QUEENSLAND WATER MODELLING NETWORK

Climate change and variability

Modelling surface water availability to inform water security for freshwater biodiversity and human society in a changing climate

Synthesis Report prepared by Songyan Yu, Mark J. Kennard, David P. Hamilton, Ulrike Bende-Michl, Elisabeth Vogel, David Roberts, Michael Bartkow, Joel Bolzenius, Maddie George

For Queensland Water Modelling Network

Queensland Government

The Queensland Water Modelling Network (QWMN) is an initiative of the Queensland Government that aims to improve the state's capacity to model its surface water and groundwater resources and their quality. The QWMN is led by the Department of Environment and Science with key links across industry, research and government.

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Table of Contents

Executive Summary ... 5
1. Introduction ... 6
1.1. Background ... 6
1.2. Project aims ... 8
2. Impact of projected climate change on inflows to major water storages ... 9
2.1. Introduction ... 9
2.2. Methodology ... 9
2.3. Climate change impacts on inflows to 10 major storages ... 11
2.3.1. Impacts on monthly inflows to 10 major storages ... 12
2.3.2. Impact on annual inflows to 10 major storages ... 13
2.3.3. Longer-term impacts on annual inflows to 10 major storages ... 14
2.4. Key findings and implications ... 16
3. Predictions of surface water extent and prioritisation of aquatic refuge areas ... 17
3.1. Introduction ... 17
3.2. Methodology ... 17
3.2.1. Field sampling of surface water extent ... 17
3.2.2. Environmental predictor variables ... 19
3.2.3. Calibration and validation of predictive models ... 19
3.2.4. Predictions of future surface water extent ... 20
3.2.5. Spatial prioritisation of aquatic refuge areas ... 22
3.2.6. Evaluation of priority refuge network ... 24
3.3. Results ... 24
3.3.1. Calibration and validation of predictive models of surface water extent ... 24
3.3.2. Predictions of future surface water extent ... 25
3.3.3. Prioritisation of surface water refuge areas ... 27
3.4. Uncertainty in research outputs ... 31
3.5. Key findings and implications ... 31
4. Synthesis guidelines for waterhole management ... 33
4.1. Introduction ... 33
4.2. What is a waterhole? ... 33

4.3. Why are they important? ... 33
4.4. Where are they? ... 34
4.5. Threats to waterholes ... 34
4.5.1. Threats to waterhole persistence ... 34
4.5.2. Threats to waterhole quality ... 34
4.5.3. Threats to waterhole connectivity ... 34
4.5.4. Climate change impacts ... 35
4.6. Framework for waterhole management ... 35
4.6.1. Identify and classify refuges. ... 35
4.6.2. Waterhole persistence ... 36
4.6.3. Waterhole quality ... 37
4.6.4. Enforcement of laws preventing illegal pumping Waterhole connectivity ... 37
4.6.5. Monitoring and assessing refuge functions ... 37
4.7. Key findings ... 37
5. Acknowledgements ... 38
6. References ... 39

Executive Summary

Climate change is rapidly impacting the hydrological cycle and thus the availability of water resources for humans and nature. During extended dry periods, water storage in reservoirs is critical for human needs and persistent riverine pools provide essential refuges for aquatic biodiversity. However, our understanding of how surface water availability changes in response to projected increases in climate variability and extreme events such as droughts in Australia is critically lacking.

This project, for the first time, develops fine-grained, spatially-explicit predictive models of surface water availability under future scenarios of climate change throughout south-eastern Queensland river networks to inform water planning and biodiversity management. We take advantage of newly developed high resolution, downscaled future projections of gridded daily runoff (Australian Water Resources Assessment Landscape (AWRA-L) model, from the Bureau of Meteorology) to quantify variations in river discharge, routed along river networks. This is used to simulate changes in surface water inflows to water storages under future scenarios of climate change. We also use AWRA-L model projections of future rainfall, temperature, evaporation and runoff to develop innovative statistical models to predict spatiotemporal variations in riverine surface water persistence under future scenarios of climate change. This is useful to inform spatial prioritisation of riverine waterholes as potential refuges for freshwater biodiversity that can be targeted for efficient on-ground conservation management. The prioritisation-related spatial data are available via the link https://doi.org/10.25904/1912/4394.

The project delivers critical hydrologic information for water utilities to assist water resource modelling and planning for human water security under a changing climate. Working closely with key stakeholders, we also undertook a range of engagement activities including a consultation workshop that informed the development of guidelines for management of climate-resilient refuge waterholes to assist regional councils, industry groups, natural resource management groups and landholders. The project delivers real-world impact by providing hydro-ecological model outputs in user-friendly forms to support adaptation by, and building resilience of, communities and biota to climate change.

1. Introduction

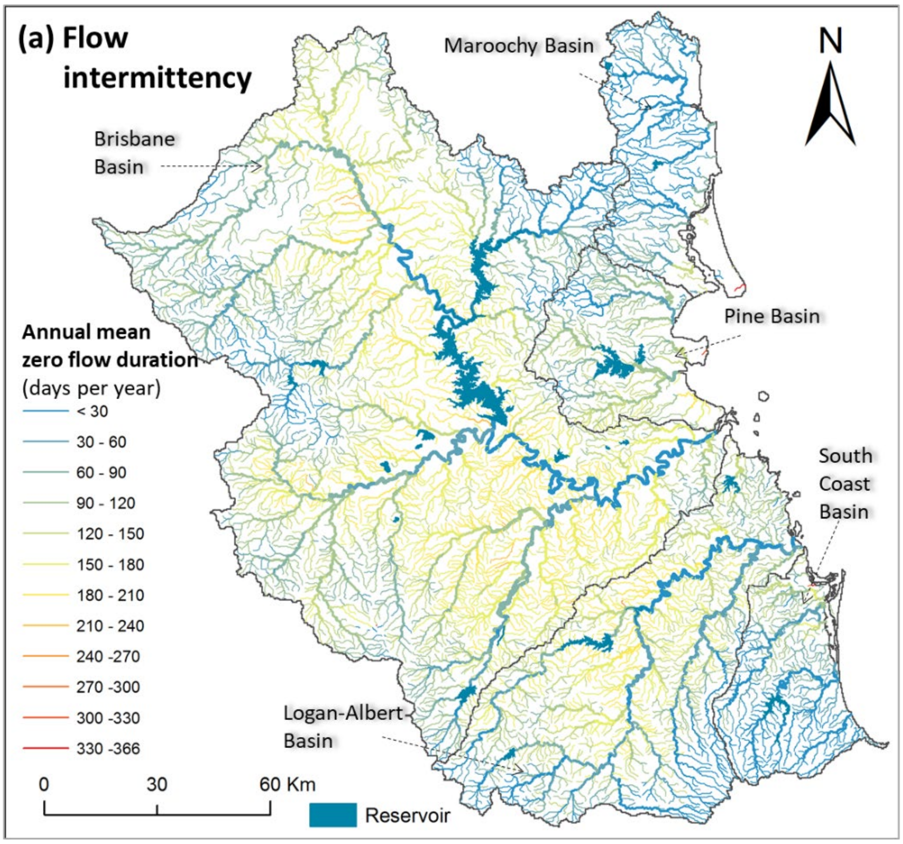
1.1. Background

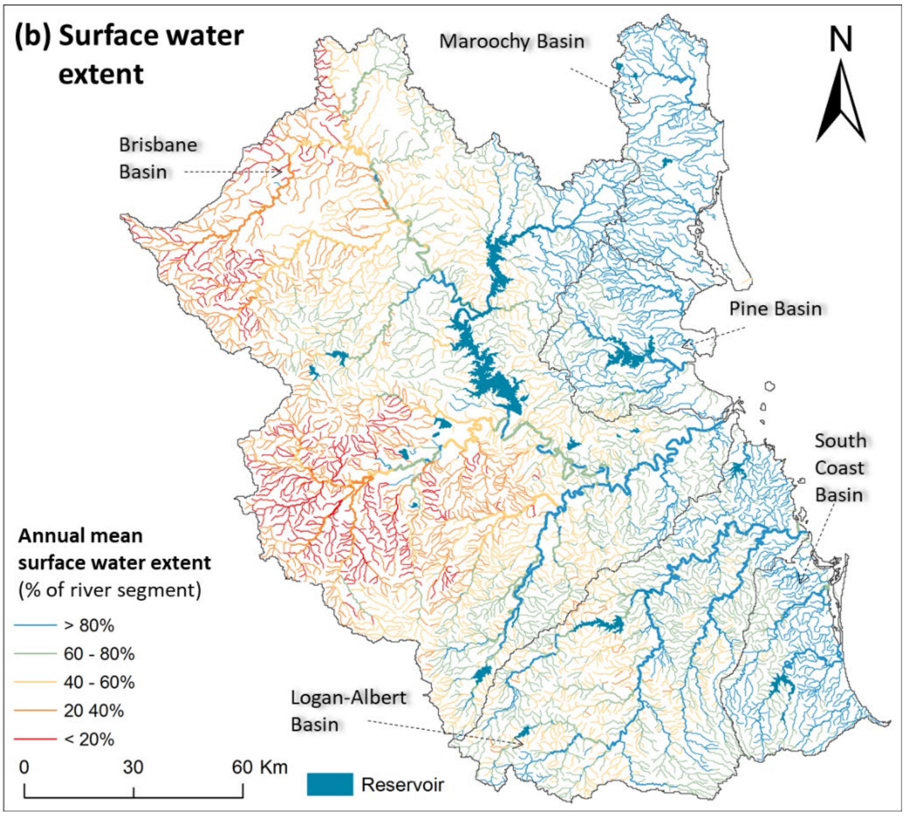
Water insecurity is a shared and widespread threat to humans and nature (Vorosmarty et al., 2010) and is likely to be exacerbated by climate change in many parts of the world, including Queensland. This poses major challenges to meeting the Sustainable Development Goal (SDG) targets to provide safe drinking water (SDG 6.1), protect and restore water-related ecosystems (SDG 6.6; 15.1), and take action to combat climate change impacts (SDG 13). SDG targets are a set of 17 interlinked global goals set up by the United Nations in 2015 to achieve a sustainable future (United Nations, 2015). Water models have a critical role to play in helping us prepare for and meet these challenges. This project uses a range of water models to deliver critical knowledge to support water resource planning and biodiversity management in south-eastern Queensland (SEQ) under an uncertain future climate.

Water availability is critical for water security. Rivers and lakes, including reservoirs, serve as key freshwater sources for human and habitats for freshwater species (Woolway et al., 2020). During extended dry periods, water stored in reservoirs is critical for human needs, while persistent riverine pools provide essential refuges for freshwater biodiversity. However, human-induced climate change is impacting the hydrological cycle and surface water availability through global increases in temperature and evapotranspiration, changes in rainfall patterns, increased hydrologic variability and extreme events such as floods and droughts (Schneider et al., 2013). These changes will significantly influence the availability, quality, and reliability of water resources for humans needs and nature (Padrón et al., 2020), and potentially cause reductions in streamflow and sustained periods of low water levels in reservoirs. This trend is projected to continue for many parts of the world, particularly in Australia, as more extreme heatwaves and increasing frequency of droughts occur as a consequence to climate change (Alexander and Arblaster, 2009).

Water levels in dams and reservoirs are predicted to be consistently lower and more variable in a future climate where rainfall-runoff will decrease and become more sporadic in many areas of Australia. These changes are likely to present major challenges for the water industry who urgently require quantitative predictions of water inflows to storages to manage changes to water quantity and the resulting changes in water quality (Frassl et al., 2019). In addition, intermittent streams constitute more than half of the global river network extent (Acuña et al., 2014) and are widespread in Australia (Kennard et al., 2010). During extended dry spells, surface water habitats in intermittent streams contract and often become restricted to disconnected pools or dry completely (Hermoso et al., 2013). Most obligate aquatic species rely on remnant aquatic habitats as refuges to survive (Arthington et al., 2005). The persistence and spatial arrangements of the remaining surface water have significant influence on the subsequent dispersal and recruitment of aquatic biota when flows resume, and thus can strongly shape biodiversity and community structure in intermittent stream systems (Dexter et al., 2014). However, our understanding of how surface water availability changes in response to projected increases in the frequency of extreme droughts in Australia is critically lacking. To better protect and manage freshwater biodiversity in riverine ecosystems, we need to understand and quantify the spatiotemporal dynamics of surface water availability across river networks, particularly during cease-to-flow periods, in order to identify priority refuges for targeted conservation management.

Our recent studies (Yu et al., 2019; Yu et al., 2020) developed statistical models to quantify the spatiotemporal dynamics of streamflow and surface water extent throughout entire river networks in SEQ over the period of 1911-2017 (Figure 1). These analyses showed that historic streamflow intermittency is widespread and areas with persistent surface water are uncommon throughout the river network. How these patterns change under future climate regimes is unknown and impedes our ability to manage freshwater biodiversity for climate resilience.


(a) Flow intermittency
Maroochy Basin
N
Brisbane Basin
Pine Basin
Annual mean zero flow duration (days per year)
< 30
30 - 60
60 - 90
90 - 120
120 - 150
150 - 180
180 - 210
210 - 240
240 -270
270 -300
300 -330
330 -366
South Coast Basin
Logan-Albert Basin
0
30
60 Km
Reservoir


(b) Surface water extent
Maroochy Basin
N
Brisbane Basin
Pine Basin
South Coast Basin
Annual mean surface water extent (% of river segment)
> 80%
60 - 80%
40 - 60%
20 40%
< 20%
Logan-Albert Basin
0
30
60 Km
Reservoir

1.2. Project aims

This project used a range of water models to predict surface water dynamics throughout river networks as a result of climate change in SEQ. Using this information, we:

1) simulated changes in surface water inflows to water storages under future scenarios of climate change and compared with climate and catchment model outputs used by Queensland government (Section 2),
2) identified and prioritised surface waterbodies as potential refuge areas for freshwater biodiversity management (Section 3), and
3) ran a range of engagement activities including a consultation workshop and developed guidelines for refuge waterhole management to assist landholders, industry groups, councils and natural resource management groups (Section 4).

2. Impact of projected climate change on inflows to major water storages

2.1. Introduction

This section provides results on the impact of projected climate change on the inflows to 10 major water supply storages (hereafter termed "10 major storages") operated by Seqwater in SEQ (Figure 2). The SEQ Water Grid is a bulk water supply network of 12 dams (termed Grid12), but two of these storages (Baroon Pocket Dam and the Six Mile Creek Dam) do not occur within our study region and are not considered further. The results are presented to allow comparison with previous analyses undertaken by the Queensland Department of Environment and Science (Vitkovsky, 2018), in which the SEQ Regional Stochastic Model (WATHNET stochastic water balance model) was used to evaluate climate change impacts on inflows to Water Grid storages.

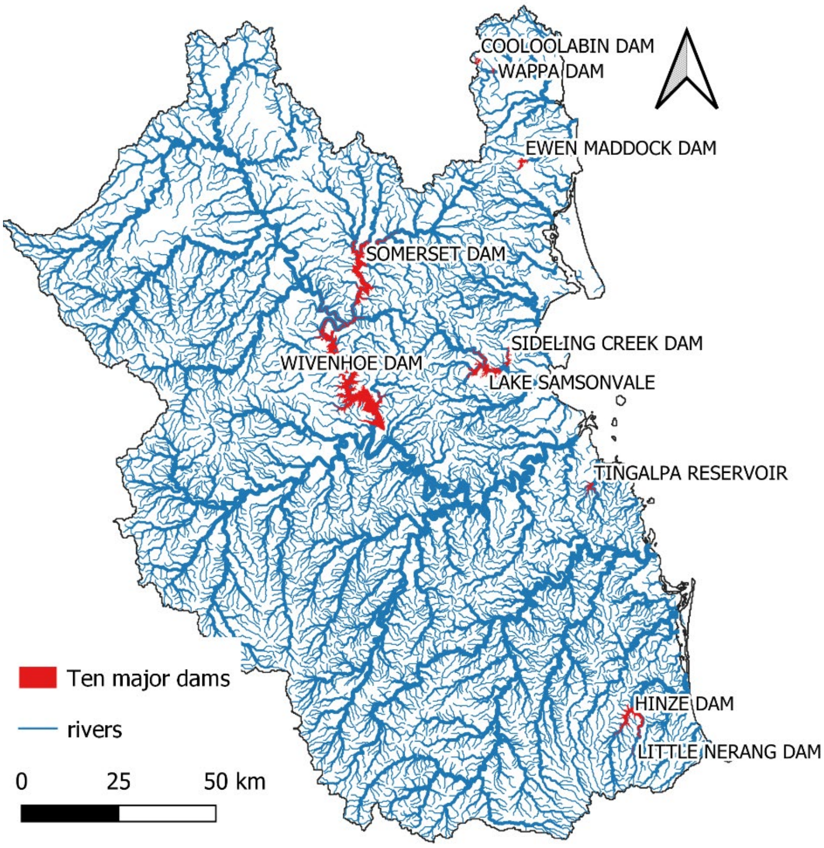
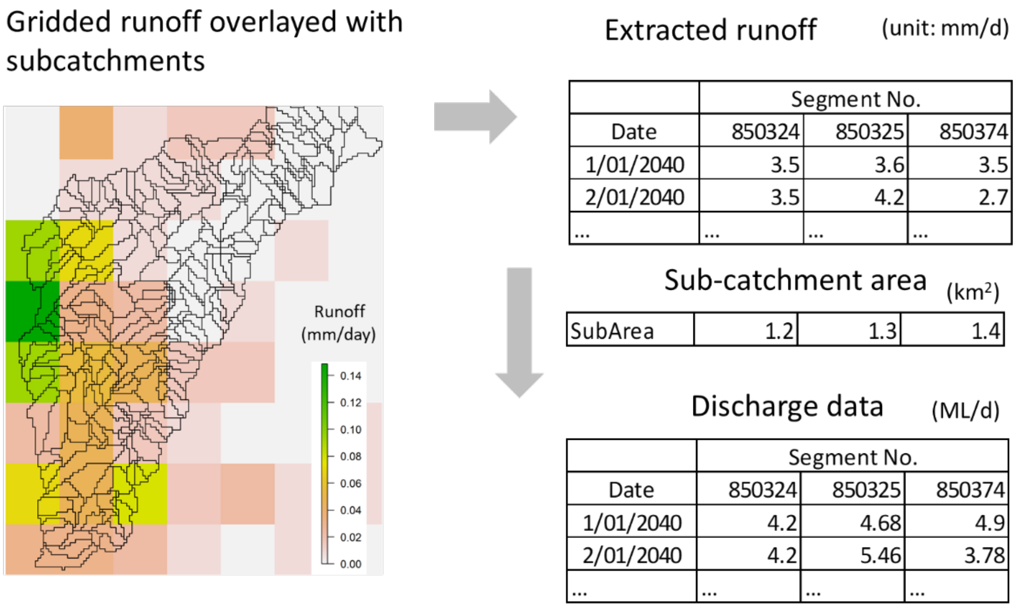


Figure 2. Location of the 10 major storages in SEQ evaluated in this report.

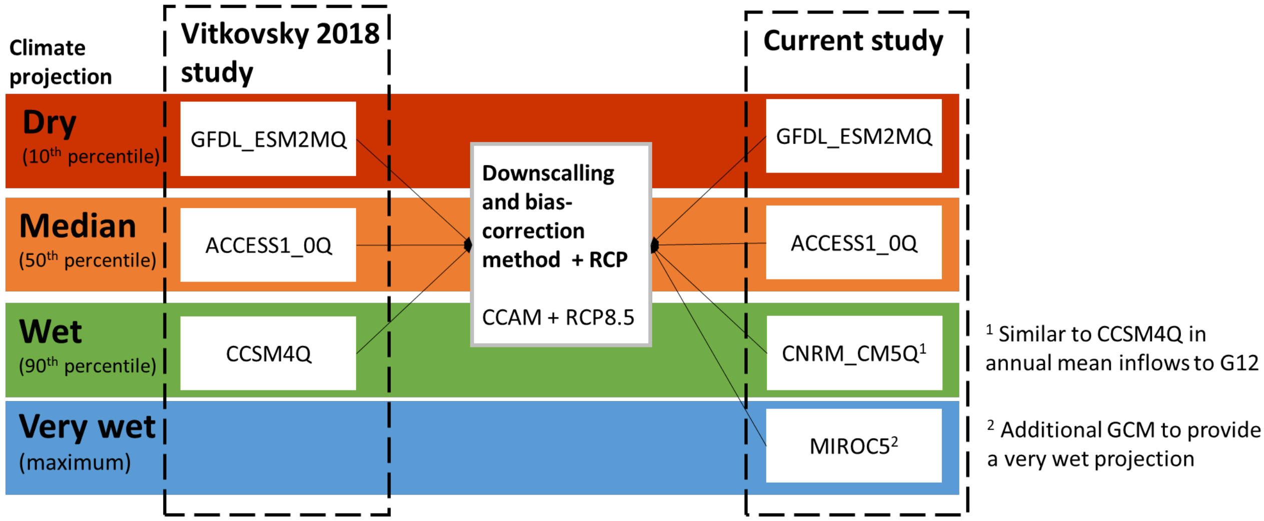
We used newly developed high resolution, downscaled future projections of daily runoff from the Australian Water Resources Assessment Landscape (AWRA-L) model (sourced from the Bureau of Meteorology (BoM)) to quantify variations in river discharge, routed along river networks. The future runoff projections were generated for 16 climate projections which were formed as the exhaustive combinations of four Global Climate Models (GCMs) and four downscaling and bias correction methods. The future runoff projections were available over the period of 2006 – 2099 under two emission scenarios of Representative Concentration Pathway (RCP 4.5 and RCP 8.5). These data are generated in a grid format and need to be converted to discharge before use for estimating inflows to the 10 major storages. We aggregated the gridded runoff with a hierarchically nested catchment framework (available in the [Australian Hydrologic Geospatial Fabric](Geofabric)), to simulate discharge throughout river networks (Figure 3). Discharge has been calculated for all SEQ sub-catchments under four future climate projections. These four projections were selected based on the calculated average annual inflows to the 10 major storages and used to represent the dry (10th percentile), median (50th percentile), wet (90th percentile), and very wet (maximum) future climate projections, respectively.



Vitkovsky (2018) reported future projections for SEQ Water Grid storage inflows from three GCMs, including CCSM4Q, ACCESS1_0Q, and GFDL_ESM2MQ, under the RCP 8.5 emission scenario. These GCMs respectively represent the wet, median, and dry climate projections for the assessment of Grid12 storages (Figure 4). All the three GCMs were downscaled and bias corrected with the CCAM model. The downscaled projections were then used to generate monthly climate change factors for rainfall change and evaporation change. In combination with a rainfall-runoff model, these monthly climate change factors were applied to alter historical streamflow measurements to generate streamflow under climate change, based on which the climate change impacts on SEQ Water Grid inflows were assessed (see the Vitkovsky 2018 report for details).

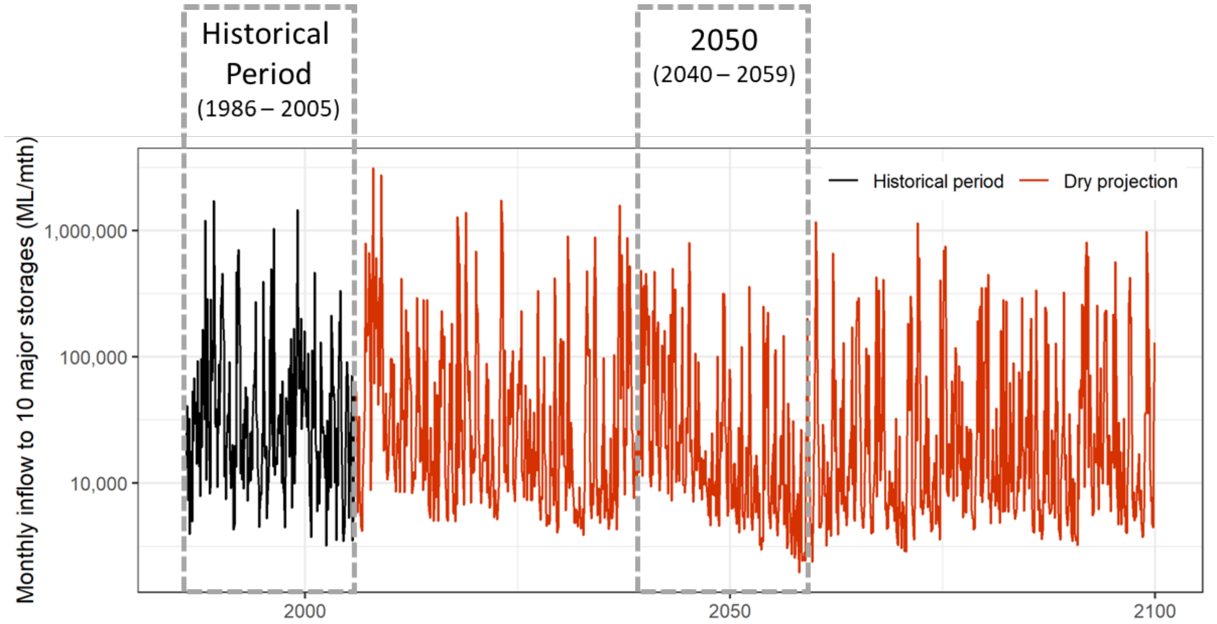
The major difference between the BoM climate change data set and those used in Vitkovsky (2018) is that the former is newly available and that its generation processes are consistent with those used in IPCC report. Assessing climate change impacts on inflows to the 10 major storages with the BoM data set provides water managers with additional independent information to better understand how reservoir inflows would change under an uncertain future.

In this study, we present projections of surface water inflows to the 10 major storages for the RCP 8.5 emission scenario using 4 GCMs representing dry to very wet future climate projections. More specifically, to make this study comparable to the Vitkovsky (2018) study, we used future projections from two GCMs (GFDL_ESM2MQ and ACCESS1_0Q) that were used in Vitkovsky (2018) (Figure 4). The BoM climate change dataset does not contain CCSM4Q GCM for the "wet" scenario. Instead, we used CNRM_CM5Q, as it has similar average annual SEQ Water Grid inflow to CCSM4Q GCM (1,500,851 ML/y vs 1,524,645 ML/y; inflow estimates sourced from Table 1 of Vitkovsky 2018). We also included an additional GCM – MIROC5 – to represent a "very wet" climate projection (2,083,211 ML/y; data source Vitkovsky 2018). The same downscaling and bias correction model (the CCAM model) and RCP emission scenario (RCP8.5) were applied for all the four GCMs used in this report.



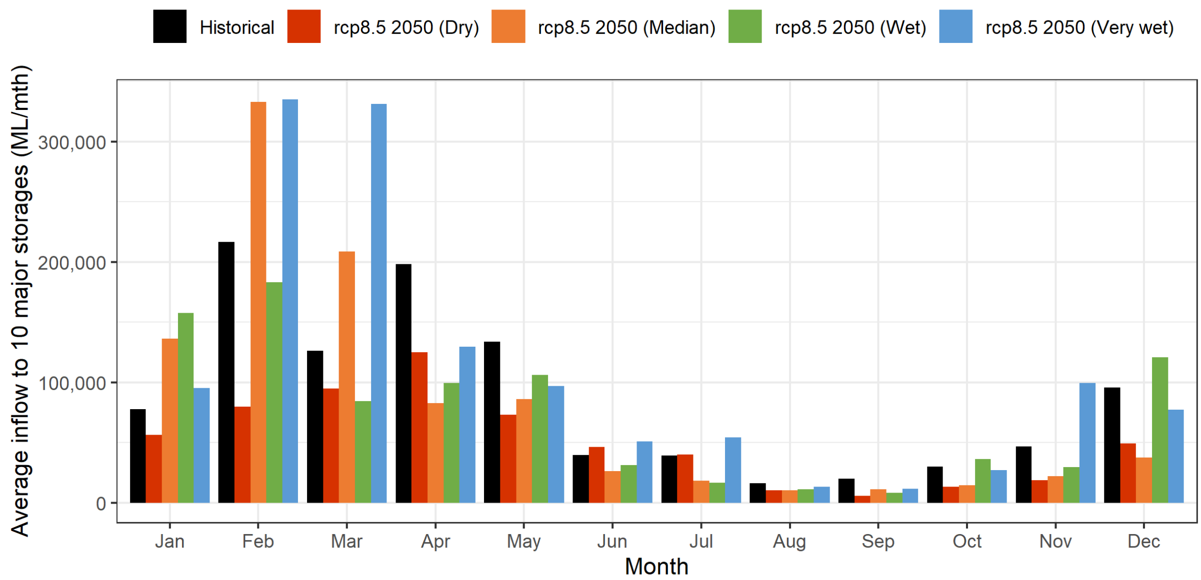
2.3. Climate change impacts on inflows to 10 major storages

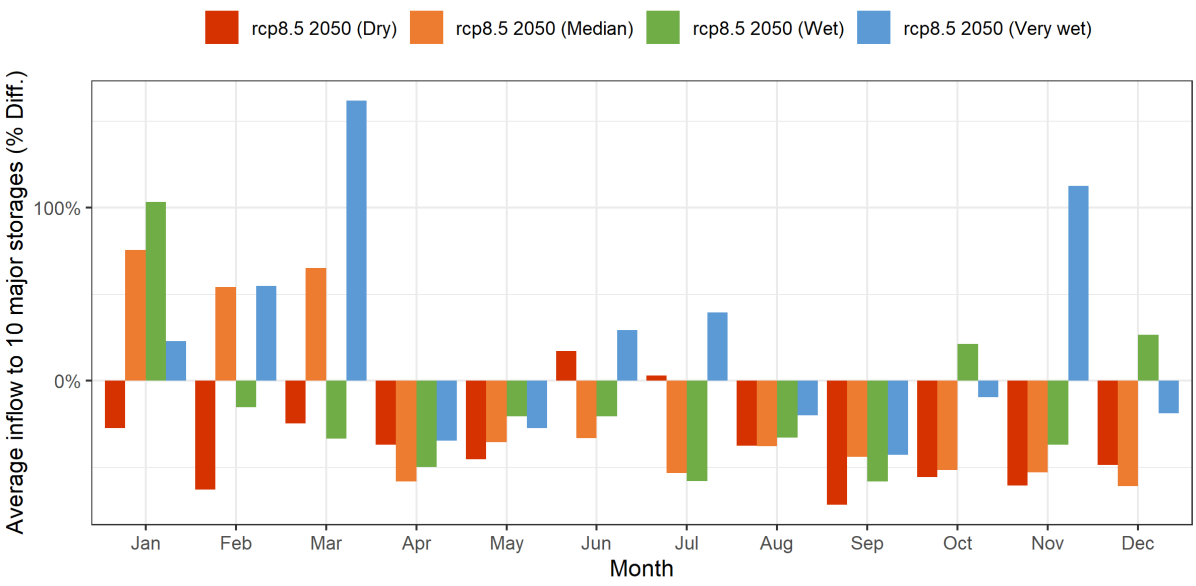
Similar to Vitkovsky (2018), we report the climate change impacts on inflows to the 10 major storages for 1) monthly inflows and 2) annual inflows. We used the period of 1986 – 2005 as the reference historical period (Figure 5). In this study, average discharge of the historical period was compared with that over the period of 2040 – 2059 (hereafter termed as "2050") to illustrate the potential impact of projected climate change on inflows to the 10 major storages (Figure 5). Note that given the data availability in the BoM climate change dataset, this analysis is applicable for other time slices of interest as well, such as the near future 2020 – 2039, mid future 2060 – 2079 and far future 2080 – 2099. We present a summary of changes in annual inflows over longer term periods as an example (see Section 2.3.3).



2.3.1. Impacts on monthly inflows to 10 major storages

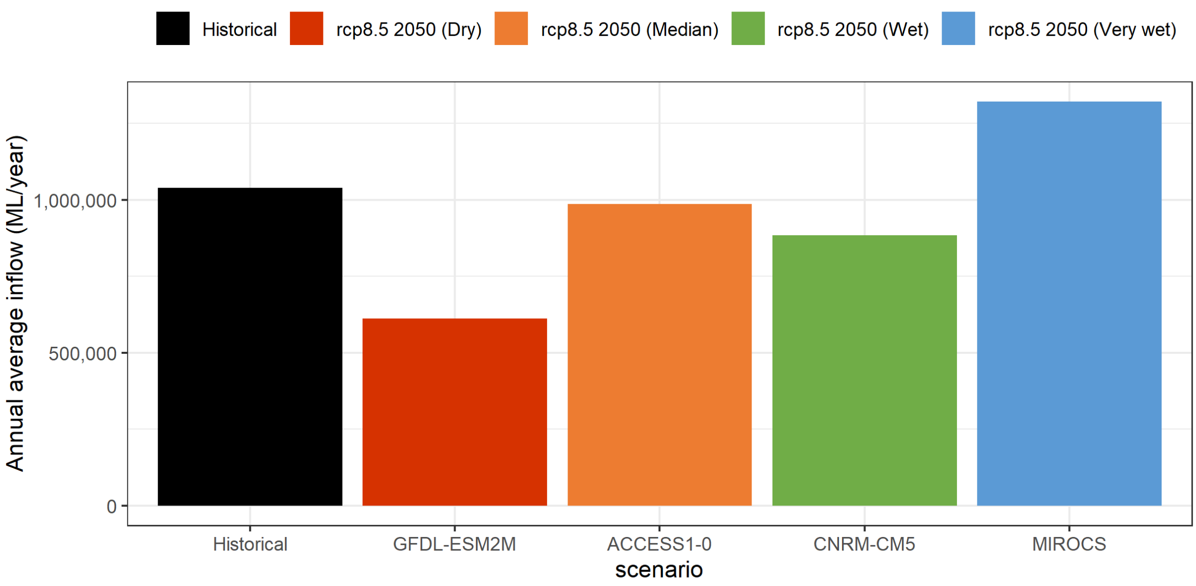
All the four future climate projections showed a similar pattern of monthly inflows to the 10 major storages to the historical average, with peak inflows in February – April and minimum inflows usually in August – September (Figure 6), but the four projections also displayed deviations from the historical average for some months. For example, monthly inflows under the dry climate projection were lower than the historical average throughout the year except for June and July. Even the very wet projection had drier months (e.g. April, May and September) than the historical average, but was 100% wetter in some other months (i.e. March and November) (Figure 6).





2.3.2. Impact on annual inflows to 10 major storages

The average annual inflows to the 10 major storages were predicted to increase only under the very wet projection (by ~25%), while the median projection had similar annual inflows to the historical average. Under the two other projections – the dry and wet projections – annual inflows to the 10 major storages were predicted to be lower than the historical average, particularly for the dry projection that showed more than 40% less of annual inflows (Figure 7). The reason why the wet projection was predicted to have less inflows than the median projection is probably because these projections were labelled as such based on their rankings on the average annual inflows to Grid12 (see Vitkovsky (2018)) not the 10 major dams as reported here. Also, it may be due to that the selected wet projections in this study were different to that used in Vitkovsky (2018) (see Figure 4), although these two projections had similar average annual inflow values.



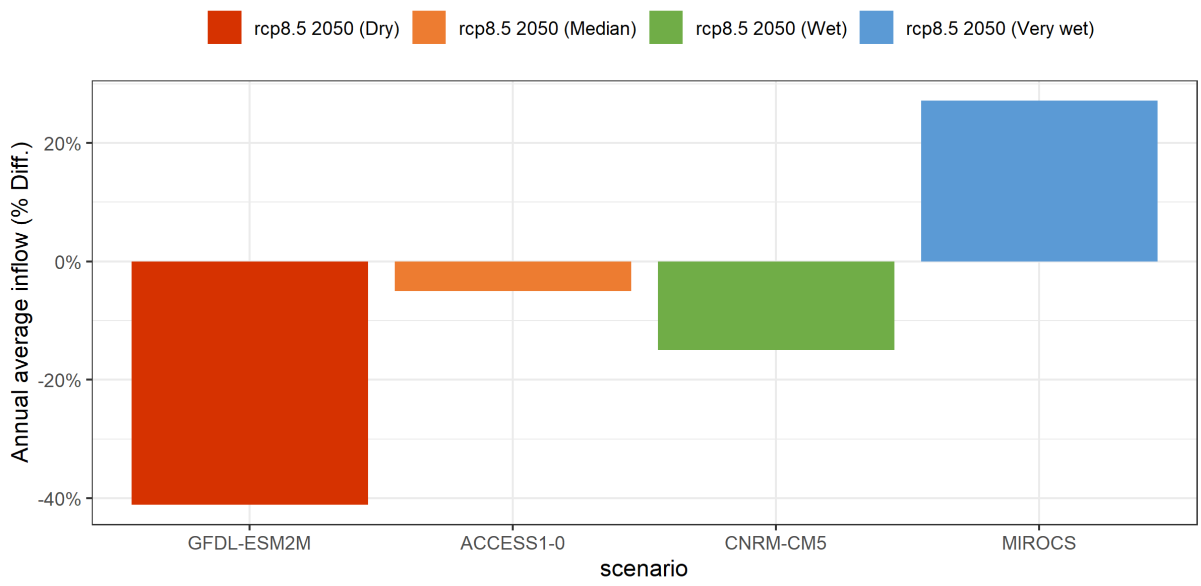
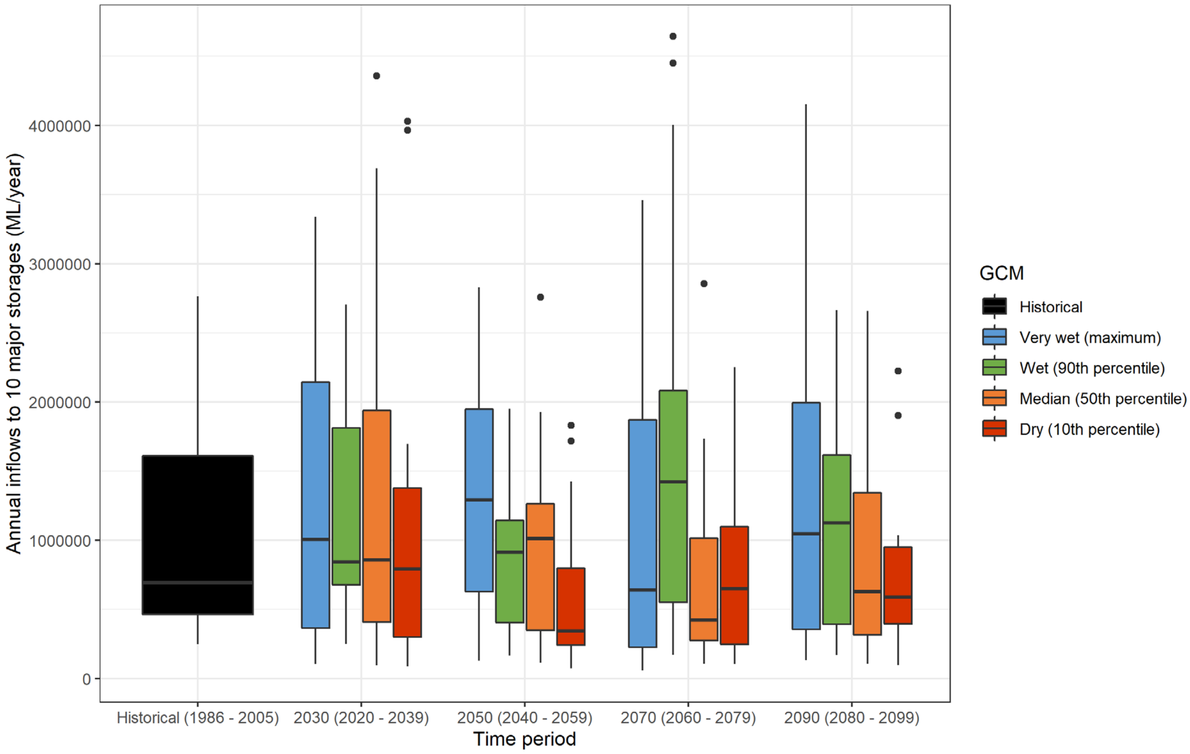
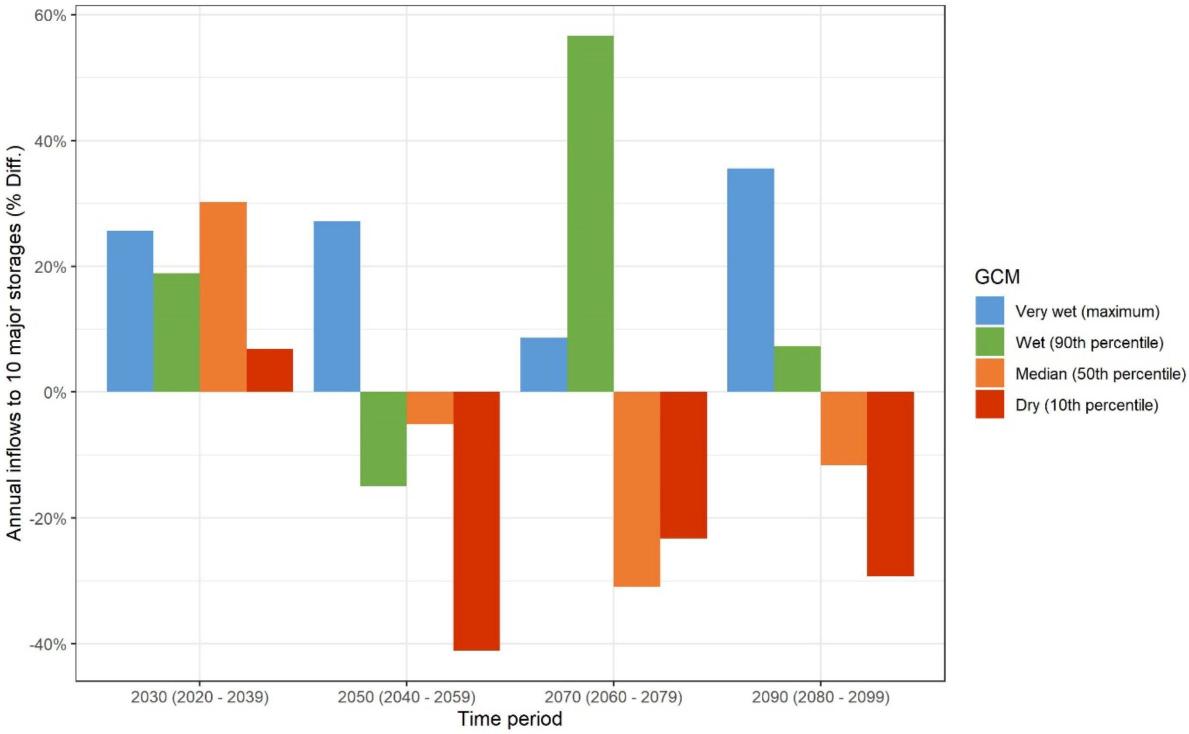


Figure 7. Average annual inflows to the 10 major storages for historical and future projections (top panel) and percentage difference from historical (bottom panel).

2.3.3. Longer-term impacts on annual inflows to 10 major storages

Inflows to the 10 major storages in the mid (2070) and far future (2090) were generally similar to those predicted for 2050, with inflows likely to be consistently lower than the historical period under the Median and Dry climate projections (Figure 8). Higher inter-annual variations in inflows to the 10 major storages were predicted under all four climate projections (Figure 8). This is particularly true for the Wet and Very Wet projections, which showed that the annual inflows to the 10 major storages could be up to 4,000,000 ML/year in extremely wet years (1,000,000 ML greater than the maximum inflows over the historical period) and down to as low as 59,677 ML in extremely dry years. Note that the predicted higher variations could be partly due to the larger uncertainty associated with the far future.


Annual inflows to 10 major storages (ML/year)
4000000
3000000
2000000
1000000
0
Historical (1986 - 2005)
2030 (2020 - 2039)
2050 (2040 - 2059)
2070 (2060 - 2079)
2090 (2080 - 2099)
Time period
GCM
Historical
Very wet (maximum)
Wet (90th percentile)
Median (50th percentile)
Dry (10th percentile)


Annual inflows to 10 major storages (% Diff.)
60%
40%
20%
0%
-20%
-40%
2030 (2020 - 2039)
2050 (2040 - 2059)
2070 (2060 - 2079)
2090 (2080 - 2099)
Time period
GCM
Very wet (maximum)
Wet (90th percentile)
Median (50th percentile)
Dry (10th percentile)

2.4. Key findings and implications

Here we applied the BoM future projections of runoff data from four GCMs to investigate the climate change impacts on the inflows to the 10 major storages in SEQ. We highlight the following key findings and implications:

1) Climate change is projected to have a significant impact on the inflows to these storages, posing significant challenges for water resources management in SEQ. Under the dry climate projections, inflows were likely to be consistently lower than the historical average across most months of the year over the period of 2050; while under the very wet projections, extremely large inflows may occur during the wet season over the period. Under the dry projection, water storage in reservoirs would have less inflows even during the wet season, making it more difficult to recover to full supply level after extended dry periods (e.g. Millennium Drought). Water storage managers might need to consider use of supplementary water sources to mitigate the anticipated drinking water shortage. Under the wet projection, extremely large inflows are more likely to occur, posing challenges for water operators to manage dam water levels during the wet season.
2) Total annual inflows to 10 of the major storage were predicted to remain similar to the historical average under the median and wet projections over the period of 2050. Additionally, total annual inflows may be 40% lower on average under the dry projection and 25% higher under the very wet projection. Under all projections, variations in annual inflows would increase over the period. Water managers might need to develop or review climate change adaptation plans to ensure drinking water safety.
3) The impacts on total annual inflows to 10 of the major storages over the mid (2070) to long term (2090) were broadly similar to those predicted for 2050.

3. Predictions of surface water extent and prioritisation of aquatic refuge areas

3.1. Introduction

Persistent surface water habitats provide critical refuges for freshwater species by facilitating their survival during extended dry periods (Bogan et al., 2019; Bond et al., 2008). Individuals that persist can then recolonize habitats when flows resume and play a key role in the long-term population viability for many species (Arthington et al., 2010). The persistence and spatial arrangements of persistent surface waters thus can strongly shape biodiversity and community structure in intermittent stream systems (Dexter et al., 2014).

Few methods have so far been developed to estimate the spatio-temporal dynamics of surface water extent throughout entire river networks, due to the limitations of many existing approaches (reviewed in Costigan et al. 2016), as well as the fact that traditional stream gauges provide little information on surface water once streamflow ceases. Our recent study developed statistical models to overcome these issues and was able to estimate the spatio-temporal dynamics of surface water extent throughout the river networks in SEQ over the past century (Yu et al., 2019). These analyses showed that historical streamflow intermittency was widespread and areas with persistent surface water were uncommon throughout the river network. However, how these patterns change under future climate regimes is unknown, which impedes our ability to manage freshwater biodiversity for climate resilience.

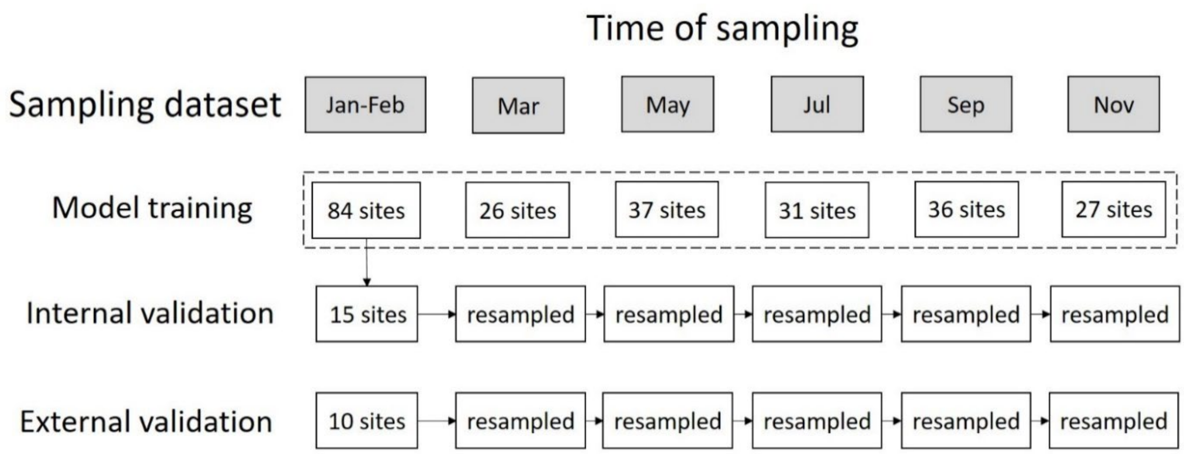
Our research presented here, for the first time, develops fine-grained, spatially-explicit predictive models of surface water extent under future scenarios of climate change throughout SEQ river networks to inform water planning and biodiversity management. We take advantage of newly developed high resolution, downscaled future projections of gridded daily rainfall, temperature, evaporation, and runoff (sourced from the AWRA-L model developed by the BoM) to develop statistical predictive models of spatio-temporal variations in riverine surface water extent under future scenarios of climate change. This information is then used to systematically identify spatial priorities for refuge waterhole management to sustain freshwater biodiversity under different climate projections. These priority areas could be considered for efficient on-ground conservation management in the future.

3.2. Methodology

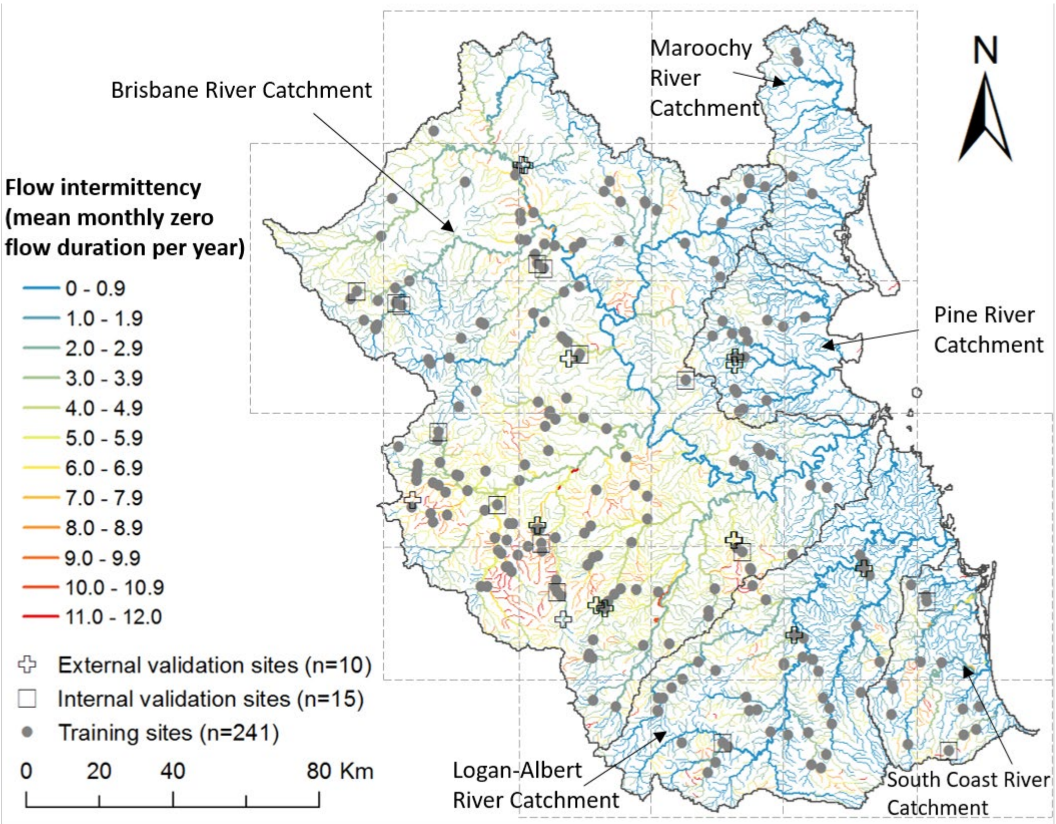
The development of predictive models of future surface water extent and spatial prioritisation of surface water refuges follows the methods described in our recent studies (Yu et al., 2019; under review). Here we extend these approaches to modelling and prioritising surface water refuges under different future climate projections. In the following, we describe details about the development of predictive models of surface water extent, predictions of surface water extent in the future, and spatial prioritisation of aquatic refuges.

3.2.1. Field sampling of surface water extent

A detailed description of the field sampling methodology is available in Yu et al. (2019) and is briefly summarised here. Field sampling of surface water extent for model training and validation was undertaken during 2018. Surface water extent was sampled at 241 sites (stream segments) between January and November in 2018 (Figure 9), using the methods described below. Eighty-four of these sites were sampled in January/February. Thereafter, bimonthly sampling of additional sites was conducted (26 – 37 sites per sampling occasion) (Figure 9). These 241 sites were used to train the predictive model (hereafter termed ‘training’ sites). We used a stratified-random sampling strategy similar to that used by Steward et al. (2012) to select candidate sampling sites. This involved dividing the SEQ study area into 24 evenly-sized cells (Figure 10) and randomly selecting candidate sampling sites with the proviso that sites could be accessed by road. This resulted in a set of sampling sites for model training that were widely dispersed throughout the study area, encompassing a representative range of stream environmental characteristics and hydrological conditions (Figure 10). A subset of 15 sites from the initial 84 sites sampled in January and February was re-sampled bimonthly and was used to evaluate the stability of model predictions through time (hereafter termed 'internal validation' sites; Figure 9; Figure 10). An additional set of 10 randomly-selected new sites (apart from the 241 training sites) were also re-sampled bimonthly and used to externally validate the model performance (hereafter termed 'external validation' sites; Figure 9; Figure 10), enabling the assessment of model predictive accuracy and transferability through space and time.



Surface water extent was estimated as the lineal extent of surface water present along the thalweg of each stream segment. A stream segment was defined as a section of DEM-derived streamline between two consecutive breaks of confluences, distributary nodes, or water bodies (Stein et al., 2014). During field sampling, if a stream segment was flowing, its surface water extent was recorded as 100%. When a stream segment was not flowing, we walked along at least 50% of the segment and estimated surface water extent by 1) making waypoints using a GPS device at the start and end point of each patch of surface water or dry stream bed, respectively, and 2) calculating in ArcGIS 10.3 (ESRI, 2002) the total length of wetted sections and expressing as a proportion of total segment length (0 ~ 100%). Only surface water pools longer than 1 m were counted as this length approximated the precision of the GPS device (Garmin Pollard GPS unit). The same person did all the measurements in the field.



3.2.2. Environmental predictor variables

We used most of the environmental predictor variables identified in Yu et al. (2019) to train surface water models in this study (Table 1). These predictor variables were selected based on their clear conceptual links to processes potentially influencing variation in the occurrence of surface water in stream channels, including the water gain/loss process. With the view to predicting future surface water extent, we keep consistent the sources of training predictor variables and those used for forecasting. We used the same water balance model AWRA-L version 6 to generate all time-varying predictor variables (e.g. rainfall, temperature, evapotranspiration, and discharge) for model training and prediction, while all the static predictor variables (e.g. stream order, stream slope) were sourced from Geofabric.

3.2.3. Calibration and validation of predictive models

We conducted Random forest (RF) modelling relating observed surface water extent to a wide range of environmental variables. Multicollinearity and spatial and temporal autocorrelation among predictors have strong impacts on identifying the relative importance of predictors (Snelder et al., 2013). We applied the procedure of Svetnik et al. (2004) to reduce the RF model to the most parsimonious set of predictors. The procedure recursively removes the least-important variable from the model based on a cross-validation process and tests whether the reduced model still has acceptable prediction performance. We used "one standard error rule" (Breiman et al., 1984) to select the reduced model that has prediction performance within the error generated from the cross-validation process for the best performance model, and that also has the least number of predictors. The reduced model was used for subsequent analysis.

The model performance was evaluated using a leave-one-out cross-validation procedure and was characterised by the mean absolute error (MAE), the root-mean-square error (RMSE), and the Nash-Sutcliffe model efficiency coefficient (NSE; Nash & Sutcliffe, 1970). MAE is the average absolute difference between the observed and predicted surface water extent. RMSE is the square root of the difference between the observed and predicted surface water extent. Both MAE and RMSE range from 0 to +∞ [%] with lower values indicating lower error. NSE was defined for hydrological models and is used to assess the predictive performance of quantitative models, including physically based and statistical models. NSE takes values from −∞ to 1 and values closer to 1 indicating greater model accuracy. According to Moriasi et al. (2007), NSE = 1.0 is the perfect fit, NSE > 0.75 is a very good fit, NSE = 0.64 to 0.74 is a good fit, NSE = 0.5 to 0.64 is a satisfactory fit and NSE < 0.5 is an unsatisfactory fit.

3.2.4. Predictions of future surface water extent

After the construction of the surface water model, we further extrapolated the model to the entire study area to forecast daily changes in surface water extent for every stream segment under future climate projections over the period of 2020 – 2099.

Three future climate projections were selected from a total of 16 projections available in the BoM climate change dataset, which were formed as exhausted combinations of four GCMs with four downscaling methods under the RCP 8.5 emission scenario. The three selected projections were ranked as the 1st, 8th, and 16th along the gradient of annual average runoff calculated for all the sampling sites over the period of 2020 – 2099. The three selected projections were intended to represent the dry, median, and wet future climates, respectively (Figure 11a). As the sampling sites were selected using a stratified-random sampling strategy, the annual average runoff for all the sites can represent the spatial variations in hydrological conditions across SEQ. Overall, the hydrological conditions in SEQ are projected to become drier under the dry climate, remain largely unchanged under the median climate, and become wetter under the wet climate (Figure 11b).

To quantify spatial patterns of surface water extent, we calculated a summary metric of annual mean surface extent for each stream segment under all three climate projections. We presented the results for a 20-year time slice of 2040 – 2059 (termed “2050”). To facilitate a comparison to the historical condition, we also estimated variations in surface water extent over a 20-year historical reference period of 1999 – 2018.

We also quantified the temporal dynamics of annual stream length with surface water in SEQ over both the historical period of 1999 – 2018 and the four 20-year future periods, including 2020 – 2039 (termed “2030”), 2040 – 2059 (termed “2050”), 2060 – 2079 (termed “2070”), and 2080 – 2099 (termed “2090”), under the three climate projections. The annual stream length is a sum of the wet length of all stream segments in SEQ, which was calculated by multiplying simulated annual mean surface extent (“%”) of a stream segment by the corresponding stream segment length.

Table 1. Table of environmental predictor variables used in the statistical modelling of surface water extent. Environmental data are sourced from Geofabric (Stein et al., 2014) except where indicated.

Group	Spatial scale	Predictor variable	Description	Unit
Water gains	Climate	CATANNRAIN	Catchment average annual mean rainfall	mm
		SubRain10, 20, 30[1]	Sub-catchment rainfall over last 10, 20, and 30 days	mm
	Catchment	RUNANNMEAN[2]	Annual mean accumulated soil water surplus	ML
		RUNANNCOFV[3]	Coefficient of variation of annual totals of accumulated soil water surplus	-
		CAT_A_KAST	Catchment average saturated hydraulic conductivity	mm/h
	Stream segment	Discharge10, 20, 30, 90, 180[4]	Mean discharge over the last 10, 20, 30, 90, and 180 days	m^3/day
Water losses	Climate	CATDRYQTEMP	Catchment average driest quarter mean temperature	°C
	Catchment	SubETA10 ,20, 30[5]	Sub-catchment actual evapotranspiration over last 10 ,20, and 30 days	mm
	Stream segment	STR-UNCONSOLIDATED	Stream and valley percentage unconsolidated rocks	mm
Catchment topography and disturbance	Catchment	CATELEMAX	Maximum upstream elevation	%
		ELONGRATIO	Catchment shape (elongation ratio)	m
		CAT_SOLPAWHC	Catchment average solum plant available water holding capacity	-
		CATSTORAGE	Catchment storage	%
	Stream segment	RDI	River disturbance index	-
		SubSlope	Segment sub-catchment average slope	°
		StrOrder	Strahler stream order	-

Data source: 1, 2, 3, 4, and 5 are calculated based on the inputs to and output from the AWRA-L version 6 model.

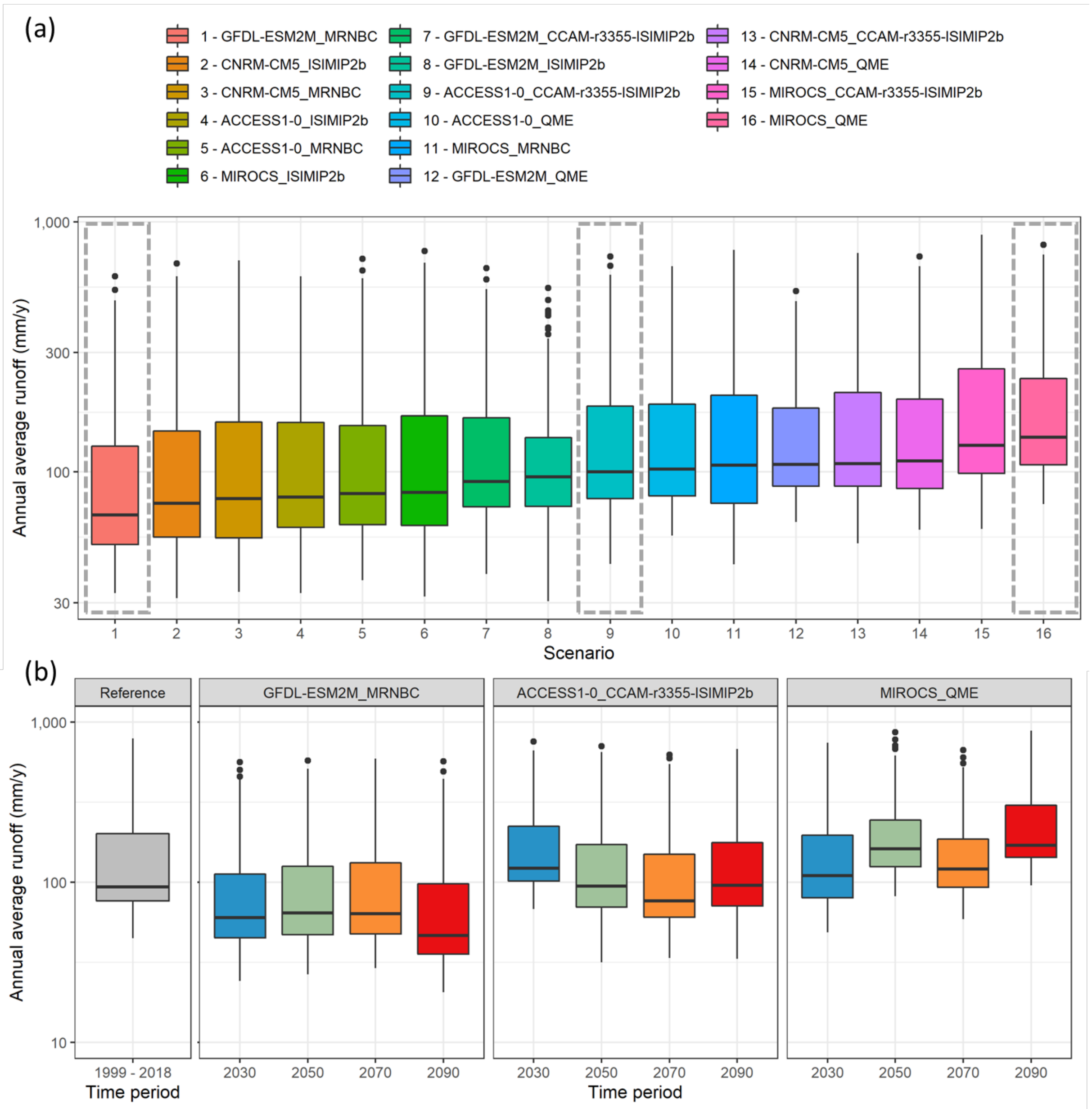


Figure 11. (a) Boxplots of predicted annual average runoff for all sampling sites over the period of 2020 – 2099 under each of the 16 climate projections, formed as combinations of four General Circulation Models and four downscaling methods. The boxplots are ordered by the median value denoted by a black horizontal line inside each box. Three climate projections ranked as the 1st, 8th, and 16th are selected for subsequent analysis and highlighted by grey dashed rectangle. (b) Predicted annual average runoff over the historical reference period of 1999 – 2018 and four 20-year time periods between 2020 and 2099 under the three selected projections (dry – GFDL-ESM2M_MRNBC; median – ACCESS1-0_CCAM-r3355-ISIMIP2b; wet – MIROCS_QME).

3.2.5. Spatial prioritisation of aquatic refuge areas

Identifying priority aquatic refuges for targeted management is critical to sustain freshwater biodiversity in intermittent stream ecosystems. The predicted variations in surface water extent provide an important basis for the prioritisation process, and three other key factors include spatio-temporal variations in hydrological connectivity (Bond et al., 2008), positional importance within a river network (Erős et al., 2011), as well as the representativeness of biodiversity of aquatic refuges (Possingham et al., 2000). In this study, taking into account all the important factors, we used a systematic prioritisation approach to find a combination of aquatic refuges to represent freshwater biodiversity in a minimum number of stream segments, while accounting for some constraints such as management cost associated with each stream segment. The methods to derive the three key factors are detailed as follows:

- **Hydrological connectivity** in intermittent streams can be facilitated by flow pulses (Bunn et al., 2006), which provide periodic opportunities for aquatic biota to disperse from refuges and recolonise dry parts of the stream network (Gallart et al., 2012). We thus used the number of flow pulses in each stream segment to quantify potential hydrological connectivity, with the assumption that stream segments experiencing a comparatively higher number of flow pulses over a given time period provide more frequent connections to other parts of the stream network. For each stream segment, we calculated the number of flow pulses for each year that equalled or exceeded the 50th percentile flow magnitude from the flow duration curve (following Gallart et al. (2016)) using modelled daily flow time series. Daily stream flow estimates for each stream segment were also sourced from the same AWRA-L model and developed by aggregating gridded runoff data with a hierarchically-nested catchment dataset.
- Several studies have highlighted the **positional importance** of habitats with high network centrality for maintaining and enhancing landscape/riverscape connectivity (Bishop-Taylor et al., 2017; Erős et al., 2011; Ribeiro et al., 2011). Here we used a network centrality metric, “betweenness centrality” (BC), to evaluate the potential importance of each stream segment within SEQ. This metric has been shown to perform better than other network centrality metrics in identifying relative positional importance (Jordán et al., 2007). In this study, BC quantifies the number of times a stream segment occurs on the shortest path of any two other stream segments in a stream network. We calculated BC for stream segments within each stream network and further normalised the BC values (0 – 1) for the purpose of comparison between different stream networks.
- Spatially-explicit distribution data for **25 target fish species** were sourced from Rose et al. (2016), who developed species distribution models relating ecologically-relevant environmental attributes to sampled fish presence/absence data at 103 least disturbed reference sites in SEQ. This model predicted the probability of fish species presence for every stream segment of the stream networks, and we chose the probability threshold of 50% to obtain the presence/absence data for the 25 fish species. We estimated the mobility capacity of each species to evaluate the potential dispersal areas from aquatic refuges using the approaches of Crook et al. (2010) and Hermoso et al. (2013), whereby each species was classified as either low, medium, or high mobility. We assumed that species with low-, medium-, and high-mobility capacity would be able to bi-directionally move 5 km, 10 km and 20 km, respectively.

To apply a systematic prioritisation approach, we first identified a list of candidate aquatic refuges for each climate projection and the historical period. Candidate aquatic refuges are expected to be able to provide both persistent surface water for species to survive extended dry periods and necessary connections to other parts of the stream network when flow resumes. We selected as candidate refuges those stream segments that meet the two following criteria for at least one year over each of the four 20-year future periods: 1) stream segments predicted to have ≥ 50% surface water extent all year, and 2) having ≥ 7 flow pulses (i.e., approximately the median value across all the climate projections).

The systematic prioritisation approach uses the “simulated annealing optimisation” technique to try to find a near-optimal combination of stream segments where all target species are represented (conservation target) in a minimum number of segments, constrained by cost and various penalties associated with each stream segment. This is done by trying to minimise the objective function

$$Objective\ function = \sum_{stream\ segments} cost + a \sum Position\ penalty + b \sum_{features} Feature\ Penalty$$

The objective function includes a cost surrogate for each stream segment, measured by the River Disturbance Index (RDI; Stein et al., 2002), a position penalty for selecting stream segments that are less important in terms of position within a stream network, measured by BC, and a feature penalty for not achieving conservation targets for all the species. RDI was computed based on flow regime disturbance caused by impoundments, flow diversions and levee banks, and catchment disturbance due to urbanization, road infrastructure and land use activities (Stein et al., 2002). The objective function considers features as objectives, so the final solution might fail to meet adequate conservation for a feature if the weighting for the feature penalty is set too low. The weight of the penalties can be controlled by parameters a and b, which determine the penalties relative to the cost of selected stream segments. Parameter a was set to 0.4 to make the weighting of position penalty in the objective function lower than cost to ensure the final solution favoured selection of stream segments with lower cost values. Parameter b was set to 0.5 to ensure as many species' conservation targets as possible could be met while high cost segments are not selected.

Conservation targets promote the design of spatially efficient conservation areas by providing a quantitative means for evaluating complementarity of candidate refuges (Nel et al., 2009). The conservation target here was set to represent 25% of each species' spatial distribution. This representation target lies between the commonly adopted target of 10% (Pressey et al., 2003) and the recently announced of 30% in the Post-2020 Global Biodiversity Framework drafted by the UN Convention on Biological Diversity (https://www.cbd.int/).

The site selection algorithm is as follows. First, an initial potential solution is created by randomly selecting a single refuge from the candidate aquatic refuges. Then, new trial solutions are generated iteratively by randomly changing the status of a single refuge and assessing the new configuration in terms of an improved or worsened objective function value. If the refuge was in the original solution and its random exclusion improves the objective function, it is excluded, if not it remains included. Similarly, if the refuge was not previously part of the proposed configuration and its random inclusion improves the objective function, then it is kept in, if not it is removed. The process terminates after 10,000 iterations have passed without improvement in the objective function value. We repeated the entire process for 100 times to find 100 solutions. We selected the best solution listing the priority refuge network with the lowest objective function score among the 100 solutions.

3.2.6. Evaluation of priority refuge network

We evaluated the effectiveness and efficiency of the identified priority refuge network under all three climate projections. The effectiveness was measured by the number of the 25 fish species meeting the conservation target in the priority network. The efficiency was calculated as the total stream length of the priority refuge network in the best solution and indicates potential management cost.

3.3. Results

3.3.1. Calibration and validation of predictive models of surface water extent

A statistical model was constructed for surface water extent. Assessment of model performance indicated that surface water extent could be predicted reasonably accurately using the constructed RF model. More specifically, the reduced RF model retained four out of the 16 predictor variables: RUNANNCOFV, Discharge30, CATDRYQTEMP, and RUNANNMEAN. The calibration performance showed an MAE value of 21%, an RMSE value of 30%, and an NSE value of 0.53 (Table 2). Based on the calibrated RF model, the internal validation displayed model performance at least as good as the calibration, except for September, which was the driest month in the year, with an overall MAE value of 16%, an RMSE value of 25%, and an NSE value of 0.74 (Table 2). The external validation showed varying degrees of model performance across different months, with November performing the best and September the worst. The overall performance for the external validation had an MAE of 29%, an RMSE of 44%, and an NSE of 0.12 (Table 2). Therefore, the updated predictive models were deemed suitable to forecast changes in surface water extent in a changing climate.

Table 2. Values of various model performance metrics for the calibrated RF model and the internal and external validations. MAE, mean absolute error [%]; RMSE, root-mean-square error [%]; NSE, Nash–Sutcliffe model efficiency coefficient.

Performance metric		MAE	RMSE	NSE
Model fit (LOOCV)		21	30	0.53
Internal validation	Mar	13	18	0.85
	May	11	14	0.91
	Jul	18	29	0.63
	Sep	25	34	0.44
	Nov	15	21	0.82
	Overall	16	25	0.74
External validation	Mar	19	30	0.60
	May	32	45	0.08
	Jul	34	52	-0.24
	Sep	45	60	-1.39
	Nov	12	19	0.79
	Overall	29	44	0.12

3.3.2. Predictions of future surface water extent

In the historical period of 1999 – 2018, streams in the coastal areas and main stems of each river catchment tended to have more and persistent surface water (i.e., annual mean surface water extent ≥ 50%) than most inland streams that had modelled annual mean surface water extent < 50% (Figure 12). Over the future period of 2050 under the dry climate projection, while inland streams were predicted to be as dry as the historical period, many coastal headwaters were predicted to have less surface water (i.e., annual mean surface water extent of < 50%) (Figure 12b). Under the median and wet climate projections, stream in the coastal areas were likely to be as wet as over the historical period, but many inland streams were predicted to be wetter with annual mean surface water extent ≥ 50% (Figure 12c, d).

The temporal variations in annual total stream length with surface water were quantified for all four future time periods under the three climate projections (Figure 13). During the period of 2030, annual stream lengths were similar among the three projections and they also showed little difference to the historical period. However, when moving into the far future, the annual stream length under the dry climate was projected to be much shorter than that during the historical period, while the wet climate would see longer stream length. In addition, the disparity in annual stream length among the three projections became larger. For example, during the 2090 period, the annual stream length under the dry projection (9,000 km) is around 30% less than under the wet projection (12,400 km). The median projection showed the least changes in annual stream length to the historical reference period among the three climate projections (Figure 13).

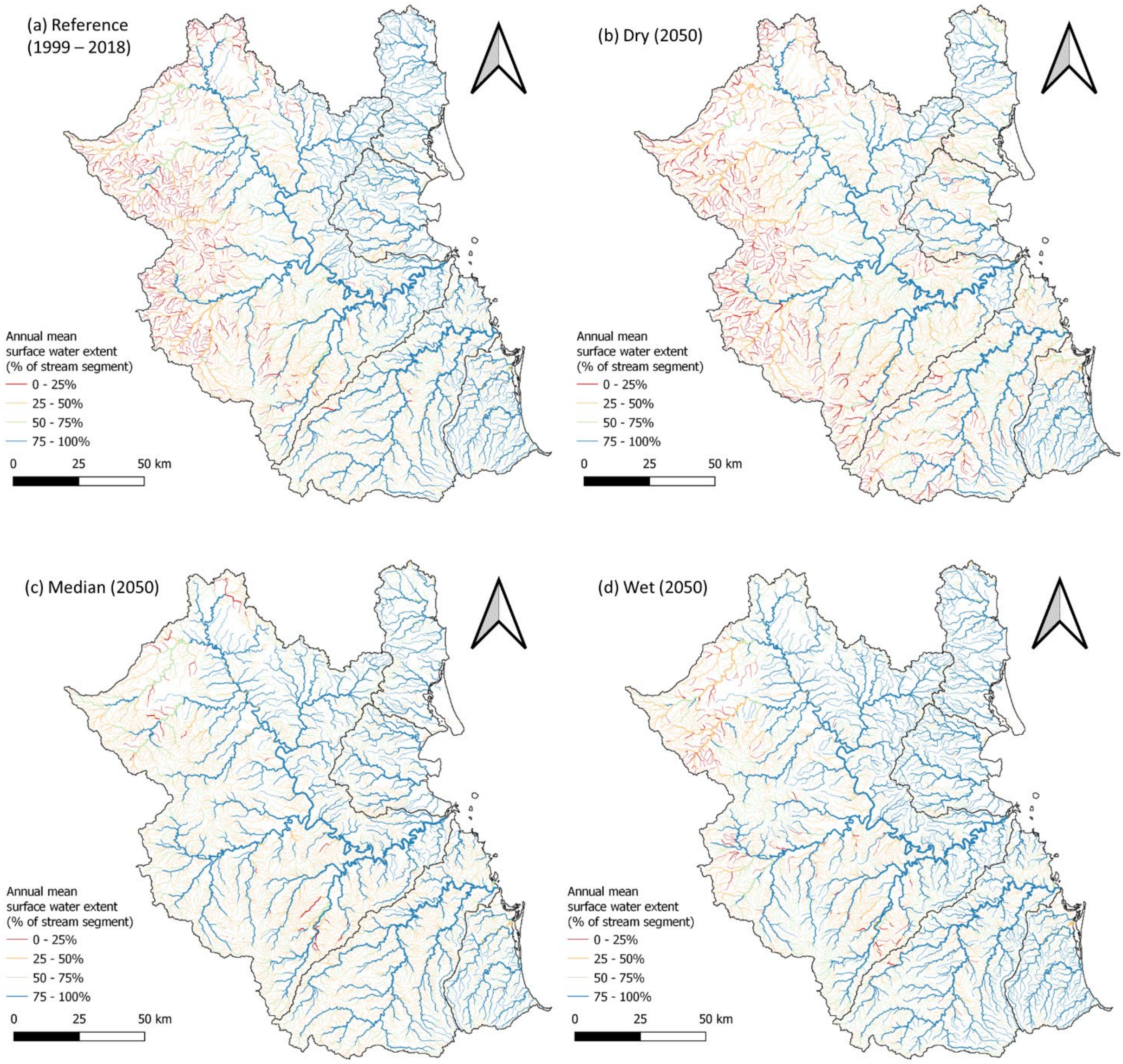


Figure 12. Predicted annual mean surface water extent (% of stream segment) over (a) the historical reference period of 1999 -2018 and the future period of 2050 (2040 – 2059) under the three climate projections: (b) dry, (c) median (c), and (d) wet.

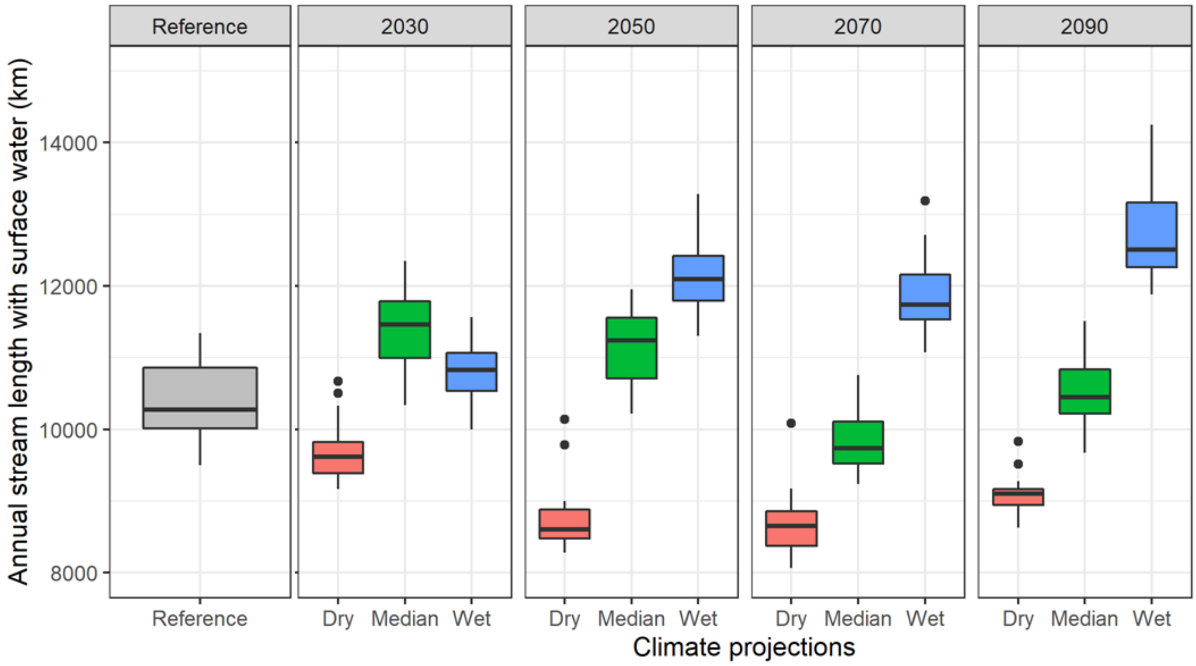


Figure 13. Boxplots of modelled annual stream length with surface water in SEQ for the historical reference period of 1999 – 2018, and four different future periods of 2020 – 2039 (2030), 2040 – 2059 (2050), 2060 – 2079 (2070), and 2080 – 2099 (2090) under the three climate projections.

3.3.3. Prioritisation of surface water refuge areas

There were substantial differences in the distribution of identified priority refuges in the best solution to meet the conservation target of 25% in SEQ among the three climate projections (Figure 14). The identified priority refuges under the dry climate were concentrated in the main stems of the upper Brisbane River catchment and the Logan-Albert River catchment as well as some coastal rivers and streams. This pattern can be explained by the drying trend of inland streams under the dry climate (Figure 14b), leaving most of them not suitable as candidate refuges. The spatial pattern of priority refuges under the dry climate limited the potentially re-colonisable areas from priority refuges and left the inland areas less re-colonised when streams were hydrologically connected. Under the median and wet climates, the distributions of priority refuges were similar to those during the historical reference period, and the potential re-colonisable areas covered the majority of the region (Figure 14c, d). Some stream segments in the main stems of the upper Brisbane River and Logan-Albert River were retained in the best solution for multiple climate projections (Figure 14e), suggesting that these segments had consistently high conservation value under various climate projections.

The differences in selection frequency of stream segments as priority refuge were also substantial among the three climate projections (Figure 15). Under the dry climate, few inland streams were selected even once, and it was the streams in the coastal areas, upper Brisbane River catchment, and Logan-Albert River catchment that were frequently selected (Figure 15b). Under the median and wet climates, many streams across the study region were selected at least once in best solutions, and the selection frequency was not as skewed to the upper Brisbane River and Logan – Albert River as under the dry climate (Figure 15c, d) and were similar to that for historical period (Figure 15a). Across the historical period and the three climate projections, there was a consistency that stream segments in the main stems of the upper Brisbane River and the Logan-Albert River were frequently selected in priority refuge solutions (Figure 15e, f), suggesting they were highly irreplaceable for meeting the conservation targets. These stream segments were almost the exact set of segments that were identified above to be retained in the best solution for more than one projection, confirming that they were of high conservation value and should be prioritised for management under climate change.

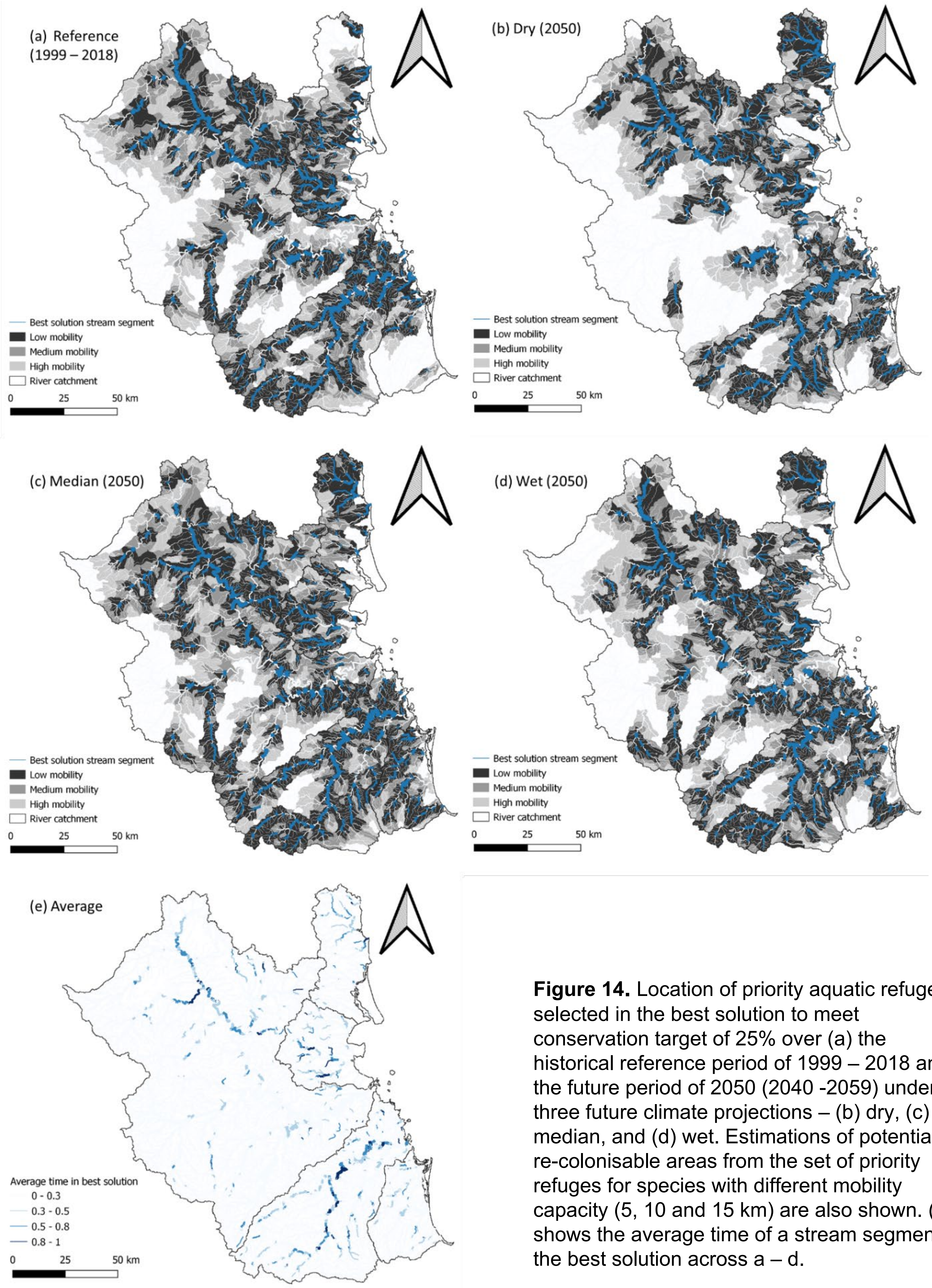


Figure 14. Location of priority aquatic refuges selected in the best solution to meet conservation target of 25% over (a) the historical reference period of 1999 – 2018 and the future period of 2050 (2040 -2059) under three future climate projections – (b) dry, (c) median, and (d) wet. Estimations of potentially re-colonisable areas from the set of priority refuges for species with different mobility capacity (5, 10 and 15 km) are also shown. (e) shows the average time of a stream segment in the best solution across a – d.

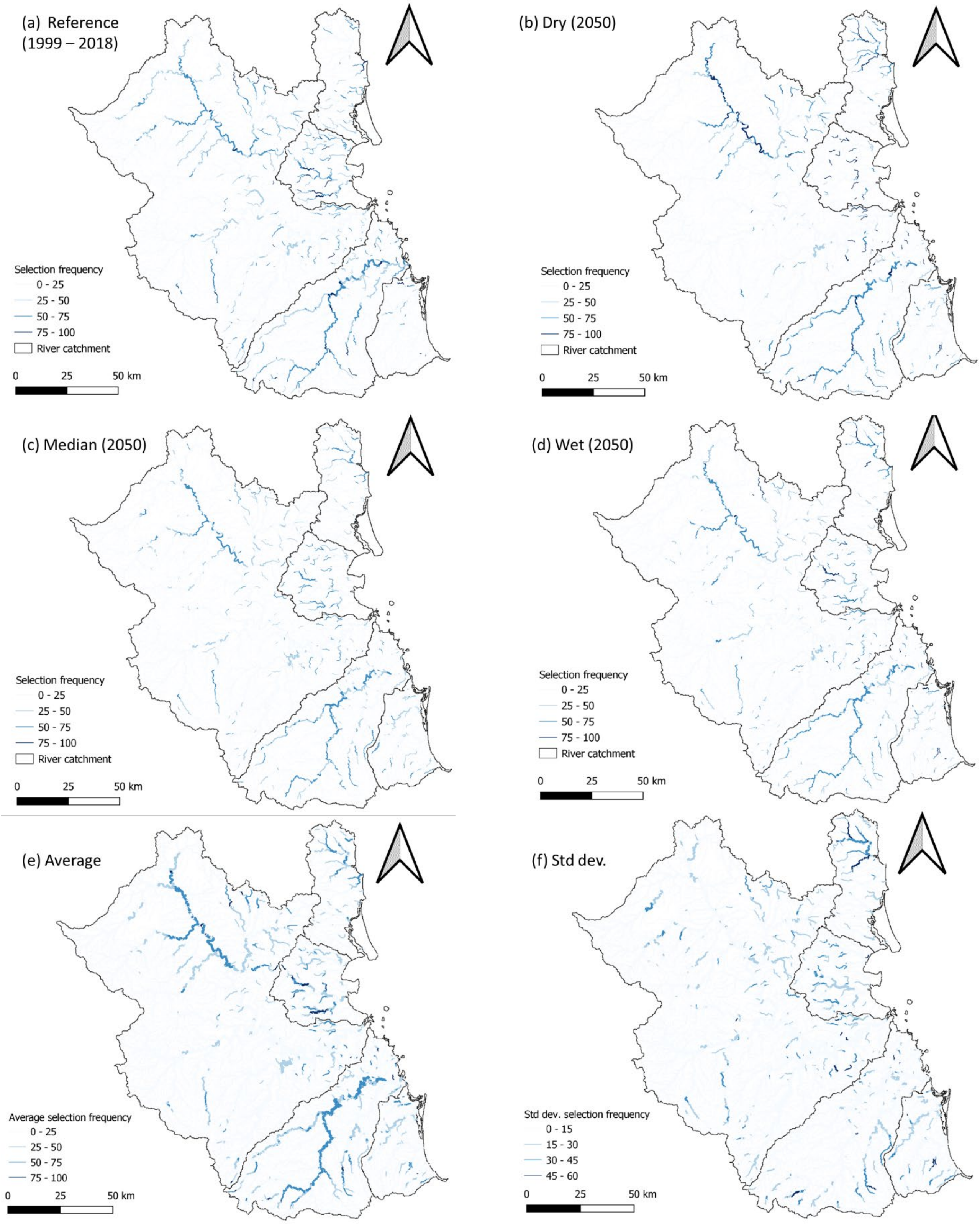


Figure 15. Selection frequency of each stream segment in SEQ among the 100 best solutions over (a) the historical reference period and the future period of 2050 under the three climate projections – (b) dry, (c) median, and (d) wet. Also shown are (e) the average selection frequency, and (f) the standard deviation of selection frequency for each stream segment across the four scenarios (historical reference + 3 future projections).

We evaluated the effectiveness and efficiency of the identified priority refuge network in terms of their ability to meet the conservation target and the number of priority refuges needed to achieve the ability. Over the historical period, the conservation target of 25% of species distribution could be met for 24 of the 25 freshwater fish species, but only for 15 – 23 species over different future periods under the dry climate projection (Figure 15a). By contrast, under the wet projection, the target could be achieved for at least 24 species. Under the median projection, the number of species meeting the target was continuously decreasing from 25 to 22 over the future periods (Figure 15a), suggesting that stream segments that played an important role in meeting the conservation target were likely to become drier over time and thus not suitable as refuges.

Corresponding to the lower species representations under the dry projection, the identified priority refuge network sizes were also lower compared to other climate projections, with the total stream lengths of refuge networks being 1,290, 1,310, 1,255, and 1,250 km over future periods of 2030, 2050, 2070, and 2090, respectively. Under the wet climate projection, a refuge network of 1,344, 1,329, 1,373, and 1,315 km long was respectively needed to achieve the high representations of ≥ 24 species over the four future periods (Figure 14b). Under the median climate, along with the lower species representation over time, the size of identified refuge networks reduced from 1,450 km through 1,370, 1,338 km to 1,321 km over 2030, 2050, 2070 and 2090, respectively. Compared to the historical period where a 1,404 km long refuge network was identified, the dry and wet climates showed consistently smaller refuge network over the four future periods for different reasons (Figure 14b).

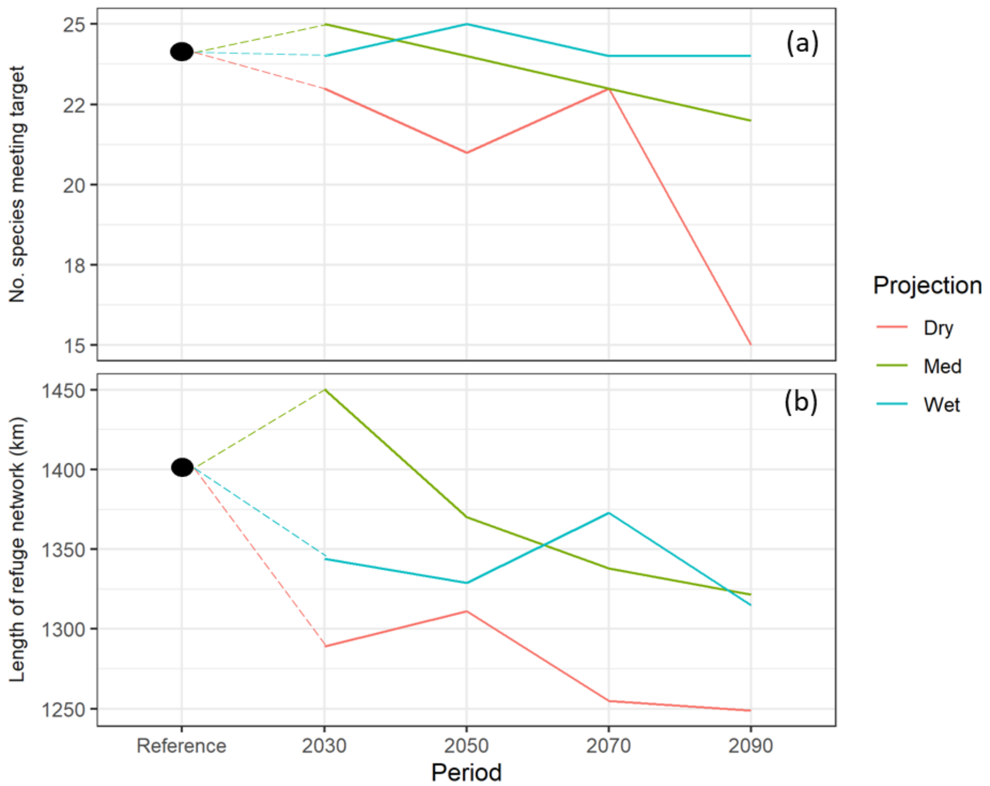


Figure 16. (a) Temporal changes in the number of species meeting the conservation target of 25% and (b) total stream lengths of priority refuge networks over the historical reference period of 1999–2018 and the four future periods of 2030, 2050, 2070, and 2090 under the three climate projections.

3.4. Uncertainty in research outputs

- **Selection of climate change projections**. The three selected climate projections were intended to cover the range of all available 16 projections in simulating annual average runoff. Although this flow metric is relevant to the research focus – surface water extent, it is acknowledged that the choice of climate projections may have differed if assessed for simulation of low flows

- **Spatial distribution of species**. We used simulated spatial distribution of species based on the historical conditions to select and prioritise stream segments for conservation management. However, species distributions are likely to change in the future in response to changing climate and hydrological conditions. Prioritisation analyses that incorporate predictions of future changes in species distributions would provide more appropriate assessment of future conservation priorities.

- **Parameter values**. Another uncertainty source is the parameter values applied in the prioritisation objective function. The set of values applied were to ensure the selected stream segments favour lower cost over relative position in the river network and that the number of species to be represented is maximum. This may not be the objectives for other refuge prioritisation cases. The research outputs here are only one possibility associated with the specific set of parameter values that are considered appropriate for this study case.

3.5. Key findings and implications

Here we developed fine-grained, spatially-explicit predictive models of surface water availability under future scenarios of climate change throughout SEQ river networks to inform water planning and biodiversity management. We identified the following key findings:

1. Three out of 16 climate projections were selected from the BoM climate change dataset to represent the dry (GFDL-ESM2M_MRNBC), median (ACCESS1-0_CCAM-r3355-ISIMIP2b), and wet (MIROCS_QME) future climates, based on the calculated annual mean catchment runoff across SEQ. The method to select typical climate projections from the BoM dataset can inform future studies where the same dataset is also used to investigate climate change impacts.

2. Surface water extent was predicted to decline in inland streams in SEQ under the dry climate projection, with most surface water restricted to the main stems of river catchments and streams in the coastal areas. However, under the wet climate, inland streams would likely to be wetter with larger surface water extent than the historical reference period. Under the median climate, the spatial patterns of annual mean surface water extent in SEQ likely remained similar to the historical period.

3. Due to the drying trend of inland streams under the dry climate projection, the priority refuge networks consisted of few inland streams and was mainly made up of the main stems of the upper Brisbane River and Logan–Albert River, and numerous coastal streams, which were predicted to be wet over the future periods. By contrast, under the median and wet climates, the identified priority refuges included many more inland streams, showing a similar pattern to that over the historical reference period.

4. The identified priority refuge networks under the dry climate projection can only meet the set conservation target for 15 – 23 out of 25 freshwater fish species, while under the wet climate projection, the conservation target can be met for 24 - 25 species, and under the median climate projection, for 22 -25 species.

5. Aligning with a smaller representation of freshwater biodiversity under the dry climate, the refuge network sizes were also smaller, up to 30% smaller than that under the wet climate in 2090. Under the wet climate, the refuge network sizes were smaller than that for the historical

period, as more candidate refuges identified under this climate lead to more efficient prioritisation.

The research methodology applied here is transferable to other areas in Australia, since the required datasets, including the BoM climate and runoff datasets and environmental attributes from Geofabric, are available at the national scale.

Our project can assist in identifying priority aquatic refuges in SEQ catchments which can be targeted for subsequent ground truthing and monitoring of water-level recession rates during dry spells. The prioritisation-related spatial data are available via the link https://doi.org/10.25904/1912/4394. This knowledge can directly inform environmental flow scenario planning and risk assessment for aquatic biodiversity resilience. It also helps refine ecohydrological rules for managing waterhole persistence and hydrologic connectivity (e.g. using the Eco Modeller tool), which can be incorporated into the Water Plan reviews for SEQ catchments. Our project also complements and extends prior work undertaken nationally and within Queensland to understand the spatial distribution, persistence and ecological functions of drought refuge waterholes in relation to changes in hydrology.

4. Synthesis guidelines for waterhole management

4.1. Introduction

Waterhole refuges are common in intermittent river systems and a vital role in allowing aquatic taxa to survive extended dry periods and to recolonise new habitats when favourable conditions return. Waterholes have three major attributes that determine their ecological values, including persistence, quality, and connectivity to other waterholes (Lobegeiger, 2011). However, these attributes are facing increasing threats from both natural processes and human activities. Surface water and groundwater extraction can reduce waterhole persistence, increasing air temperature and trampling by livestock may cause waterhole quality to decline, and constructed barriers in river channels can block the dispersal of aquatic biota. It is critical that management of waterhole refuges is enacted to support aquatic biodiversity and protect their other associated values in a changing climate.

There is a range of legislation within Queensland that provide for the protection of water and riverine habitats, including the *Water Act 2000*, *Wild Rivers Act 2005*, *Fisheries Act 1994*, and *Natural Conservation Act 1992*. Significant progress has been made by Queensland Government in better understanding waterhole refuges, particularly their three key attributes (DSITI, 2015); however, further work is required to inform water planning and refuge management in SEQ's coastal catchments.

Waterhole refuges need to be managed with the overall catchment in mind, as many of the threats are tied to the broader landscape. Here we developed synthesis guidelines for waterhole management based on literature review of relevant publications and a range of consultation activities including a consultation workshop we ran The guidelines proposed in this section were developed based on literature review of publications related to waterhole management and include guidance on the protection and management of all three waterhole attributes, from identifying and classifying waterholes, through maintenance to on-ground works, to monitoring and assessing waterhole functions. These guidelines also provide a structured approach to how waterhole refuges can be managed in an integrated way as part of a broader landscape and seeks to achieve good outcomes for both relevant stakeholder and waterholes, especially those with high values.

The guidelines outline on-ground management options for regional councils, water resource manager and landholder to manage and protect waterholes. The target audience are landholders, representative bodies (e.g. AgForce, growcom), City Councils, Queensland Government Departments, and conservation NGOs.

4.2. What is a waterhole?

According to the definition by the Queensland Government, a waterhole is a wetland where water pools in a depression within a landform element at a defined spatial scale. They usually form when rivers and streams cease to flow and become disconnected. They are most common in dryland catchments where streamflow intermittency occurs frequently, but they can also be found in sub-tropical and tropical areas, such as SEQ.

Queensland Government recently published a classification scheme for waterholes, providing a framework for classifying and typing Queensland waterholes based on a series of physical, biological and chemical attributes (Department of Environment and Science, 2020). In addition, refuge waterholes can also be classified based on how aquatic biota retreat to there and the biodiversity the waterhole supports.

4.3. Why are they important?

Waterholes provide important aquatic refuges in many river systems and allow organisms to persist during dry periods and surface water availability is limited. They also enable organisms to recolonise the broader landscape when favourable conditions, such as streamflow, return. In addition, waterholes are an important water source for terrestrial species. Waterholes also provide a source of water and recreation for human societies and can be of considerable cultural significance to First Nations people (Box et al., 2008).

There are three major attributes of waterhole refuge which contribute to their ability to sustain biota (Lobegeiger, 2011):

- *Persistence*: the length of time they retain water during no-flow events;
- *Quality*: encompassing factors such as water quality, habitat availability, and intact food webs; and
- *Connectivity* between waterholes: enabling recolonization to new habitats and gene flow.

Without a network of waterhole refuges within a catchment, each displaying all three of these attributes, the local and regional persistence of aquatic biota in temporary systems may be at risk.

4.4. Where are they?

There is currently no map of waterhole refuges in Queensland, although various methods have been proposed to identify locations of potential waterholes. One such method is remote sensing, but limitations of satellite image resolution restrict its application to floodplains or wide river channels with low vegetation canopy cover. In Section 3 of this report, a statistical modelling method was used to estimate the persistence of surface water across the entire river networks (both wide stem rivers and narrow headwaters) in SEQ. Locations of waterholes can then potentially be identified in those stream segments that were simulated to have persistent surface water presence. The identification of waterhole locations can provide important guidance on where to implement management actions to protect.

4.5. Threats to waterholes

A number of threatening processes to waterhole refuges have been identified (Lobegeiger, 2011) and are summarised below.

4.5.1. Threats to waterhole persistence

The persistence of a refuge waterhole is often measured as the length of time it contains water in the absence of rainfall and streamflow and is a key attribute that determines the maximum time obligate aquatic biota such as fish can survive in it. Waterhole persistence is controlled by its water balance involving water flowing into the pool (e.g., groundwater inflow, sub-surface flow) and out of the pool (e.g., evapotranspiration, seepage). Threats to refuge persistence include surface and groundwater extraction for irrigation and other human uses, altering streamflow regimes through dam construction, sediment infilling (Raadik, 2018).

4.5.2. Threats to waterhole quality

While waterhole persistence is mainly related to water quantity, waterhole quality encompasses not only water quality such as temperature, dissolved oxygen, and nutrients, but also conditions of riparian zones and biological interactions within pools and so on. Water quality may deteriorate as water level recedes to the point where the waterhole is no longer a suitable habitat for some species even if it still contains water. This was tragically exemplified in the mass fish death events in the lower Darling River in December 2018 and January 2019 (Lewins, 2019). Threats to refuge waterhole quality include runoff of nutrients and pesticide from surrounding areas, trampling by feral animals and livestock, clearing of riparian vegetation, water temperature increase, reduction of dissolved oxygen, channelization and de-snagging, invasive plants and animals (increasing predation and competition), salinisation, and wild fires.

4.5.3. Threats to waterhole connectivity

Waterholes not only provide refuges for aquatic biota to survive extended dry spells; the connectivity between them and other parts of the river network also plays a key role in the long-term population viability for many species at large geographic scales. Biota that survive dry spells act as population sources to recolonise suitable habitats after flow resumes. This represents a critical aspect of the population resilience in intermittent stream systems. Threats to refuge connectivity include barriers in waterways (e.g. levee banks, road crossings), altered streamflow regimes, and upstream dam construction.

4.5.4. Climate change impacts

Climate change is an overarching threat on top of all the three type of threats described above:

- Waterhole persistence. As demonstrated in Section 3, the variations in surface water extent across the river networks in SEQ were predicted to be substantial among the three climate projections. The persistence of waterholes in inland streams would become much shorter under the dry projection than the historical period, restricting potential refuge waterholes to only main stems of each river catchments or some coastal streams.
- Waterhole quality. Air temperature in SEQ is projected to increase on average by approximately 2°C by 2050 and up to 4°C by 2090 based on the Long Paddock dataset (https://www.longpaddock.qld.gov.au/). The increased air temperatures can increase waterhole water temperature through advection, potentially reducing water quality conditions (water temperatures and dissolved concentrations) in waterhole refuges. Additionally, extreme weather events such as storms are projected to be more common, potentially causing more soil erosion in catchments and sediment transport in rivers. The increase in sediment can increase turbidity and reduce primary production in waterholes; it may even fill waterholes and alter refuge availability and spatial arrangements over a short period of time.
- Waterhole connectivity. As demonstrated in Section 2, annual catchment inflows to the drinking water supply system in SEQ were predicted to be more than 40% less than the historical average. Under such a drier projection, water utilities might need to build more dams for water storage purpose, farmers might need to extract more water from streams and rivers for irrigation. These human activities would compromise the physical and hydrological connectivity of river networks, preventing survived individual species to recolonise suitable habitats when flow resumes.

4.6. Framework for waterhole management

A set of principles for managing waterhole has been developed by Robson et al. (2008). Here we linked those principles to the three major attributes of waterholes (Figure 15) and further developed a framework for waterhole management as follows.

4.6.1. Identify and classify refuges.

Waterhole refuges should be first identified and classified as the basis for management of different biota types (e.g. fish, frog, and plants). A number of documents and tools are available for identifying, characterising, and mapping refuge waterholes (Bond, 2007; Raadik et al., 2017; Shipp et al., 2018). After identification, waterholes can then be classified and prioritised for management based on surface water persistence, value for biodiversity conservation, relative position within a river network, cost of management, and other environmental conditions that are important to the resistance and resilience of aquatic biota.

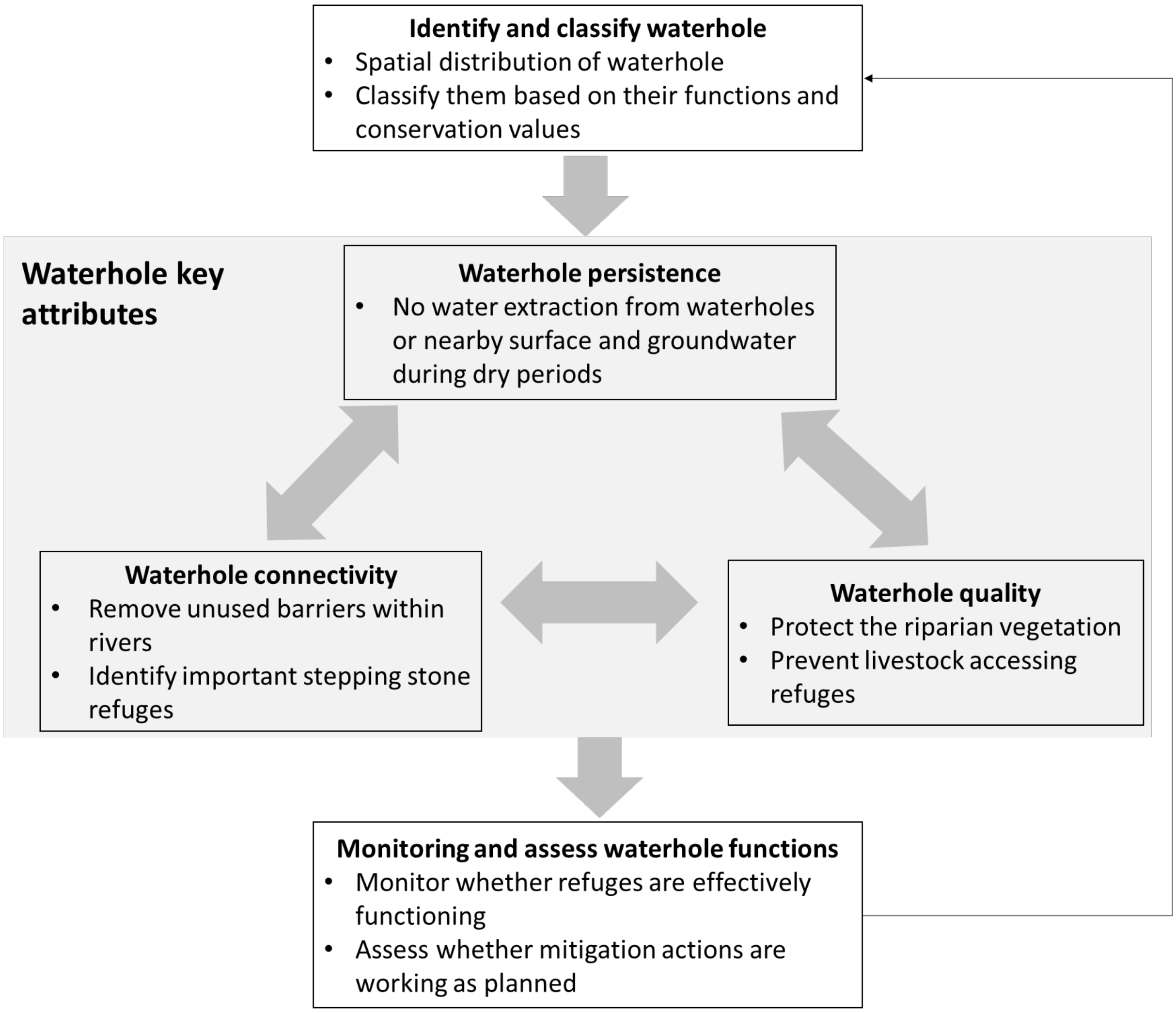


Figure 17. Framework for managing waterhole refuges.

4.6.2. Waterhole persistence

Water should not be extracted from waterholes or nearby areas during extreme dry periods to maintain waterhole persistence. Environmental flow management should be implemented to maintain life-cycle processes and dispersal pathways for aquatic plants and animal. Groundwater management also need to be considered if the waterholes are sustained by groundwater. A groundwater strategic framework has been published by the Australian Government in 2017 (i.e., National Groundwater Strategic Framework), and frameworks for groundwater management at the state level have also been established, such as in Victoria and in Queensland.

Candidate management actions to protect/improve waterhole persistence include:

- Restricting surface and ground-water extraction near or from refuge areas
- Protection of springs and groundwater recharge areas
- Fencing or restricting access by livestock
- Provision of environmental flows during non-drought years

4.6.3. Waterhole quality

The quality of waterholes and surrounding areas should be considered. It is good practice to retain intact riparian vegetation and not alienate waterholes from riparian areas. Consideration should be given to revegetation if riparian vegetation has been lost or degraded. More technical management options can be found in the Riparian Land Management Technical Guidelines by Siwan Lovett and Phil Price (https://docs.niwa.co.nz/library/public/0642267731.pdf).

Candidate management actions to address protect/improve waterhole quality include:

- Land rezoning / acquisition
- Manage invasive plants and animals
- Appropriate farm management to mitigate runoff of nutrients and pesticides
- Riparian zone management (e.g., vegetation replanting)

4.6.4. Enforcement of laws preventing illegal pumping Waterhole connectivity

Physical connections between refuges and the surrounding river channels need to be maintained to support the processes of retreat and recolonization of aquatic biota. In cases where threats to connectivity are identified, actions should be considered to remove the threats or mitigate their effect. The condition of physical connections require routine evaluation to ensure the established connections are maintained. Connections may need to be improved by setting up stepping-stone refuges to enhance the connectivity between refuges. Stepping-stone refuges are habitats that allow dispersing organisms or populations to make long-distance movements through networks by providing connections between larger groups of connected habitats (Bishop-Taylor et al., 2017).

Candidate management actions to protect/improve waterhole connectivity include:

- Remove unnecessary barriers/dams in the waterways
- Installing fish passage devices at instream barriers.

4.6.5. Monitoring and assessing refuge functions

It is important waterholes be monitored and assessed after management actions are implemented to ensure that they are functioning effectively. Monitoring and assessing are also important to identify changes of refuges in space and over time, as the position and availability of waterhole refuges are dynamic over time. For example, severe disturbance events such as floods have the potential to significantly alter streambed morphology, changing the spatial arrangement of pools. When monitoring and assessing find that the conditions of identified waterhole refuges have been changed significantly, the framework for waterhole management should be followed again to update management actions.

4.7. Key findings

Here we provided basic information about waterhole management in Queensland, including their definition and three key attributes to sustain aquatic biota. Based on the three key attributes, we further developed the set of waterhole management principles proposed by Robson (2008) to form a waterhole management framework, which starts with 1) identifying and classifying refuges, then taking actions to protect and maintain 2) waterhole persistence, 3) quality, and 4) connectivity. After management actions are implemented the refuge functions should be 5) monitored and assessed. If refuges are not functioning as expected, the framework should be followed again to update waterhole locations and associated actions. A list of various candidate management actions is outlined for waterhole stakeholders and managers to consider when following the proposed framework.

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