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Synthesis of indirect impacts of climate change on water availability in the Murray-Darling Basin

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Contents

Acknowledgments iii
Executive summary iv
1 Introduction 1
2 Methods 2
2.1 Catchments and Data 2
2.2 Modelling methods 2
3 Results 4
3.1 Landscape farm dam impacts on runoff projections 4
3.2 Effects of fire on runoff projections 4
3.3 Changing rainfall-runoff relationships 6
4 Concluding discussion 7
References 9

Figures

Figure 1 (a) Cross-validation NSE and Bias, and (b) change in mean annual flow due to a 10% reduction in rainfall and 2° local temperature increase modelled using the traditional approach (GR4J) and considering farm dams (GR4J+CHEAT1). Boxes show the interquartile range (IQR); the thick black line shows the median; whiskers show 1.5 * IQR; points show outliers. 4

Figure 2 (a) Comparison of cross-validation NSE of GR4J hydrological model with and without consideration of catchment average LAI, and (b) comparison of changes in mean annual runoff due to a 10% reduction in rainfall and 2° local temperature increase modelled using the traditional approach neglecting the effects of fire (GR4J) and considering fire impacts on LAI. ... 5

Figure 3 (a) Range of projections of mean annual runoff from different model calibration periods plotted against the projected median change; each vertical line represents a single catchment; grey lines represent a relative range of ±5%. (b) the relative range displayed geographically. 6

Figure 4 Synthesis of the range of quantified impacts of sources of non-stationarity on projections of mean annual runoff due to a 10% decline in mean annual rainfall for catchments investigated in the MDB. 7

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The authors pay respect to the Traditional Owners and their Nations of the Murray−Darling Basin. We acknowledge their deep cultural, social, environmental, spiritual and economic connection to their lands and waters.

Executive summary

Future hydrological projections are generated to support water resources planning and guide investment into water infrastructure. These projections are classically developed using calibrated rainfall-runoff models that assume hydrological processes are stationary in time. Changes in catchment rainfall-runoff relationships, such as those observed during the Millenium Drought and in response to land use changes, are often poorly predicted by rainfall-runoff models used to generate hydrological projections. Therefore, using these models may under- or over-estimate the impacts of future climate changes on catchment runoff.

Hydrological non-stationarity can manifest over different time scales and may impact future runoff projections directly or in concert with other climate changes. Transient sources of hydrological non-stationarity under a stationary climate, such as the effects of bushfires on catchment runoff, may become more permanent as climate change impacts the frequency or severity of causal events. The impacts of permanent change on rainfall-runoff relationships, such as land use change or construction of farm dams, may be amplified under a changing climate. Other sources of hydrological non-stationarity may only emerge under a changed climate, like carbon-dioxide fertilisation and vegetation evapotranspiration effects.

In this study we explore the impacts of considering hydrological non-stationarity when generating projections of future runoff under a changing climate. Where possible we use modelling methods to quantify the impacts of hydrological non-stationarity on runoff projections and compare these to projections generated using more traditional modelling approaches. Where it is not possible to provide a quantitative assessment, we discuss the possible direction and magnitude of impacts on catchment runoff projections.

1 Introduction

Water resources planning relies on long, statistically stationary time series to assess system reliability and evaluate infrastructure investments. The concept of statistical stationarity is classically related to time-invariant statistical properties of a data set, specifically the mean and variance of a time series, but can also be extended to include time-invariant relationships between variables, such as rainfall and runoff. Calibrated conceptual rainfall-runoff models, for example, often assume the relationship between rainfall and runoff is stationary. However, stationarity in hydroclimate timeseries may not hold under climate change and landscape changes (Chiew et al., 2009; Fowler et al., 2022; Potter and Chiew, 2011; Timbal and Drosdowsky, 2013). As a result, there is a need to revisit many assessments of water availability to better understand the impacts of associated climate change and the reliability and robustness of water management arrangements. To ensure such assessments provide robust insights into future water availability, there needs to be an assessment of the likely impacts of hydrologic non-stationarities.

Hydrologic non-stationarity, particularly changes in rainfall-runoff relationships, manifests in many different forms, and arises from multiple causes. Transient changes in rainfall-runoff relationships can occur following fire in forested catchments leading to short-term increases in runoff immediately following fires (Brown, 1972; Khaledi et al., 2022) and the potential for longer runoff reductions under specific conditions before an eventual return to the pre-fire condition (Benyon et al., 2023; Kuczera, 1987; Lane and Mackay, 2001). More permanent changes in rainfall-runoff relationships may be induced by the construction of farm dams (Chiew et al., 2008; Peña-Arancibia et al., 2023; Robertson et al., 2023) or land use change, e.g. from forested to grassland, or vice versa. Other sources of hydrologic non-stationarity may only emerge under a changing climate. Reductions in rainfall may lead to a reduction in groundwater recharge that ultimately may result in groundwater declining to levels where rivers transition from gaining to losing streams (Potter and Chiew, 2011). Increasing levels of atmospheric carbon-dioxide may also lead to plant physiological responses that have impacts on rates of plant growth and evapotranspiration, subsequently leading to changes in catchment water balances (Raupach et al., 2013; Ukkola et al., 2016).

In Australia, assessments of water availability have largely been undertaken with calibrated rainfall-runoff models. Future runoff projections are generated by forcing these calibrated models with climate data representing plausible future conditions. Many rainfall-runoff models that have been used in water resources assessment have been shown to poorly simulate runoff when catchments display hydrologic non-stationarity (Fowler et al., 2016; Robertson et al., 2024; Westra et al., 2014). Therefore, runoff projections generated using these models are likely to either over- or under-estimate future water availability, which can potentially lead to maladaptation. In this study, we seek to provide insights into the impacts of hydrologic non-stationarities on runoff projections in the Murray-Darling Basin (MDB). We undertake our investigation through a number of experiments that involve adapting hydrological modelling to consider the impacts of hydrological non-stationarity and compare projections of water availability generated to those produced using more traditional modelling methods.

2 Methods

2.1 Catchments and Data

For this analysis we use a subset of the Bureau of Meteorology's hydrological reference station data set (Zhang et al., 2016). We focus our analysis on 120 catchments within the Murray-Darling Basin (MDB) and derive historical timeseries of rainfall and potential evaporation from the Australian Gridded Climate Dataset (AGCD) (Frost et al., 2018; Jones et al., 2009) for each catchment. The AGCD data are available at 0.05° spatial resolution, and we obtain catchment time series by taking the area-weighted averages of all 0.05° grid cells within the catchment boundary. We focus our analysis on data for the period 1982-2018.

2.2 Modelling methods

Hydrologic modelling is undertaken using a variety of methods, but we use the GR4J rainfall-runoff model as our base model for all experiments. We choose GR4J because it has been demonstrated to perform robustly for simulating daily streamflow across Australia (Coron et al., 2012) and it has been previously used for generating runoff projections within the MDB (Zheng et al., 2024). For all modelling experiments, hydrologic models are calibrated by adjusting model parameters to minimise the NSE-Bias objective function (Viney et al., 2009) Model calibration is performed using the Shuffled Complex Evolution (SCE) (Duan et al., 1994) in the SWIFT2 streamflow modelling and forecasting software (Perraud et al., 2015).

2.2.1 Generation of projected changes.

Our primary interest in this paper is estimating changes in water availability that may occur under plausible future climate change and how different these changes are if the effects of hydrologic non-stationarity are considered. Therefore, we generate simulations from a base hydrologic model using (a) historical and (b) plausible future climate forcing and compare metrics of water availability to those generated using an enhanced modelling approach that considers the effect of a form of hydrologic non-stationarity. In all cases we investigate the sensitivity to a single future climate corresponding to a 2°C increase in mean surface air temperature over the basin and a 10% reduction in rainfall, which is equivalent to a moderate change scenario for the MDB (Zhang et al., 2020).

To investigate the effects of causes of hydrologic non-stationarity on water availability projections we undertake 3 experiments considering (a) the effects of landscape farm dams intercepting catchment runoff; (b) the effects of fire on catchment runoff, including how fire behaviour is likely to change under a future climate; (c) historical changes in rainfall-runoff relationships.

2.2.2 Modelling the effects of landscape farm dams

We model the impact of landscape farm dams on runoff generation by augmenting the GR4J hydrological model with the CHEAT1 farm dam model (Nathan et al., 2005). The CHEAT1 model represents all farm dams in a catchment using a parallel collection of 10 characteristic farm dams with representative volume-surface area-catchment area relationships. For each catchment we estimate the current number of each of the characteristic farm dams using the dataset of Malerba et al. (2021) and how the number has increased over time using the dataset of Peña-Arancibia et al. (2023). The combined GR4J+CHEAT1 model is calibrated using the time-varying number of farm dams, while runoff projections are generated using the most recent estimate of the number of farm dams. More details on the modelling method are provided by Robertson et al. (2023).

2.2.3 Modelling the effects of fire

We assume that the effects of fire on catchment runoff occurs through changes in vegetation, specifically through change in the catchment leaf area index (LAI). We modify the evapotranspiration algorithm of the GR4J model to modulate the actual evapotranspiration according to LAI using the model of Kondo (1998), in addition to the existing response to the level of the production store (Perrin et al., 2003). Historical catchment average LAI at an annual time step is estimated from the remotely sensed data set of Zhu et al. (2013) and used as hydrological model forcing data for calibration.

Gridded annual historical fire extent maps at a 0.01° spatial resolution are derived from Victorian and NSW government shapefiles. Historical daily forest fire danger index (FFDI) (McArthur, 1967; Noble et al., 1980) is derived from gridded AGCD rainfall, relative humidity and temperature data (Jones et al., 2009) and ERA5 wind speed (Hersbach et al., 2020), and summarised to the annual time step to match the LAI data. Using historical annual datasets, relationships are derived to relate (a) FFDI to burnt area for each catchment (b) FFDI to the change in LAI resulting from the occurrence of a fire and (c) the post-fire recovery of LAI with time. Projections of FFDI are for the single future climate scenario, and then used to generate projections of burnt area and catchment average LAI as forcing data to generate runoff projections.

2.2.4 Changing rainfall-runoff relationships

We examine the impact of different observed historical relationships between rainfall and runoff on the range of hydrological projections using a calibration experiment. We assume that the rainfall-runoff relationships are stationary over a 10-year calibration window. We calibrate the GR4J models for each available overlapping 10-year period in the historical record and for each set of model parameters obtained to generate 30-year runoff simulations forced by historical and future climate. For each set of historical and future runoff simulations we compute change metrics and summarise the range of projected changes.

3 Results

3.1 Landscape farm dam impacts on runoff projections

Landscape farm dams intercept catchment runoff before it reaches waterways and therefore reduces streamflow. Representing this process in rainfall-runoff modelling with the CHEAT1 farm dam model result in historical streamflow simulations with smaller cross-validation predictive errors, notably smaller bias and slightly improved NSE values, relative to a rainfall-runoff model that neglects the effects of farm dams (Figure 1a). The lower prediction errors under cross-validation principally result from the GR4J+CHEAT1 model allowing for historical temporal changes in the number of farm dams. Projections generated for a 10% reduction of rainfall, and the 2018 level of farm dam development, from the GR4J+CHEAT1 model see larger reductions in mean annual streamflow compared to those generated using the traditional modelling approach (Figure 1b). Across the catchments investigated, the median reduction in mean annual runoff is approximately 10% larger (of the projected reduction without modelling farm dams explicitly) for the model that represents farm dam interception, with the magnitude of the differences being strongly related to the density of farm dams in the catchment. Additional analysis indicates that sensitivity to farm dam water use patterns and the base hydrological model is very small (not shown for brevity).

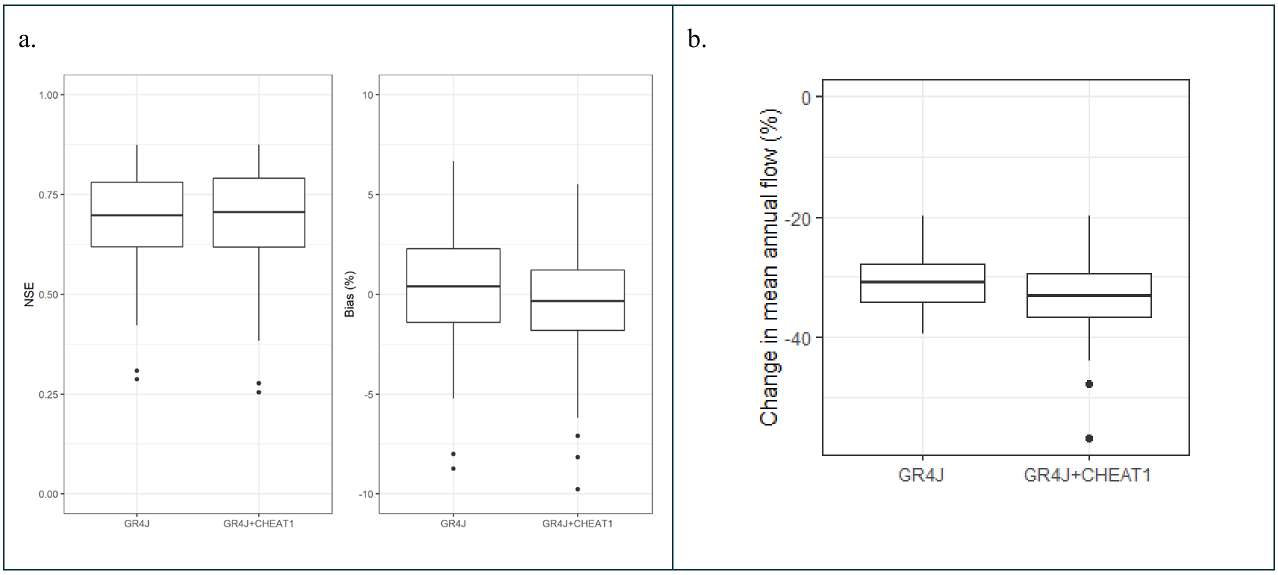

Figure 1 (a) Cross-validation NSE and Bias, and (b) change in mean annual flow due to a 10% reduction in rainfall and 2° local temperature increase modelled using the traditional approach (GR4J) and considering farm dams (GR4J+CHEAT1). Boxes show the interquartile range (IQR); the thick black line shows the median; whiskers show 1.5 * IQR; points show outliers.

3.2 Effects of fire on runoff projections

We model the impacts of fire on runoff generation by extending the GR4J hydrological model to allow actual evapotranspiration to respond to catchment average LAI. Modulating the actual evapotranspiration according to LAI leads to lower prediction errors under cross-validation for many catchments compared to the base GR4J model (Figure 2a). Improvements in cross-validation NSE by including LAI variation into the model are found to be largest in catchments that have experienced severe fires.

The impact of fire on projections of mean annual runoff in the MDB tends to be very small compared to the impact of rainfall reductions for the vast majority of catchments (Figure 2b). Accounting for the impact of fire tends to produce slightly lower reductions in mean annual runoff relative to the traditional modelling approach for the majority of catchments. Projections of the number of days of extreme FFDI conditions increase with increasing temperatures, leading to greater incidence of fire and small increases in the average annual burnt area. The occurrence of fire decreases LAI for up to 10 years, decreasing actual evapotranspiration and therefore increasing catchment runoff. However, widespread fires are relatively rare events and even when conditions are conducive to fire, e.g. when extreme FFDI values occur, the historical probability of a bushfire covering a large area is very small. Therefore, while the extent and severity of bushfires is expected to increase with climate change (Dowdy, 2020), fires large enough to have significant impacts on mean annual runoff over large regions are rare. However, while the projected changes in mean annual runoff are similar for the LAI-forced and traditional versions of the GR4J model, projections of changes in annual 5th and 95th percentile runoff with the LAI-forced model produce smaller reductions in the 95th percentile (high) flow and larger reductions in the 5th percentile (low flow) than the traditional version of GR4J (not shown). This suggests that fire is more likely to be a source of medium-term variability in future water availability rather than a cause of long-term changes in catchment runoff. However, immediately following a fire, acute impacts on surface water hydrology, such as soil surface sealing that increases erosion potential and debris flow, can create challenges for water supply management over short time horizons and may become more frequent.

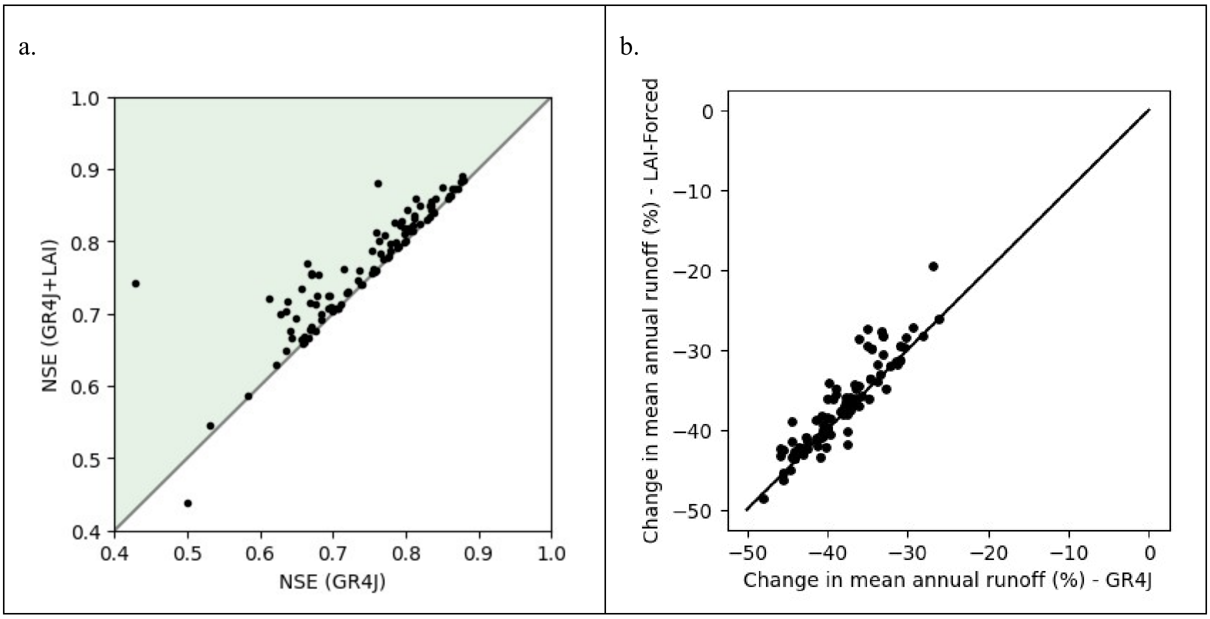

Figure 2 (a) Comparison of cross-validation NSE of GR4J hydrological model with and without consideration of catchment average LAI, and (b) comparison of changes in mean annual runoff due to a 10% reduction in rainfall and 2° local temperature increase modelled using the traditional approach neglecting the effects of fire (GR4J) and considering fire impacts on LAI.

3.3 Changing rainfall-runoff relationships

Generating runoff projections for each catchment using hydrological models calibrated to different parts of the historical record allows exploration of projection sensitivity to the range to historically observed rainfall-runoff relationships. Where the historical rainfall-runoff relationship is stationary, it is expected that the range of projections generated using models calibrated to different parts of the historical record would be small, but if the rainfall-runoff relationship is not stationary the range would be relatively large. Figure 3 shows that the range of projections varies between catchments, but for the majority of catchments the range is less that ±5% of the median projected change. There are a small number of catchments where the range of projections exceeds ±20% of the median projected change, suggesting that these catchments have seen considerable changes in the rainfall-runoff relationship during the historical period. The catchments where the range of runoff projections are smallest tend to be larger in size and located in the high runoff regions in the southeast of the MDB, while the range of projections tends to be largest in smaller catchments and those located in low runoff areas. This suggests that historically the low runoff catchments have tended to display much greater variation in rainfall-runoff relationships. In these catchments we may expect larger variations, most likely reductions, in future runoff than current rainfall-runoff models predict.

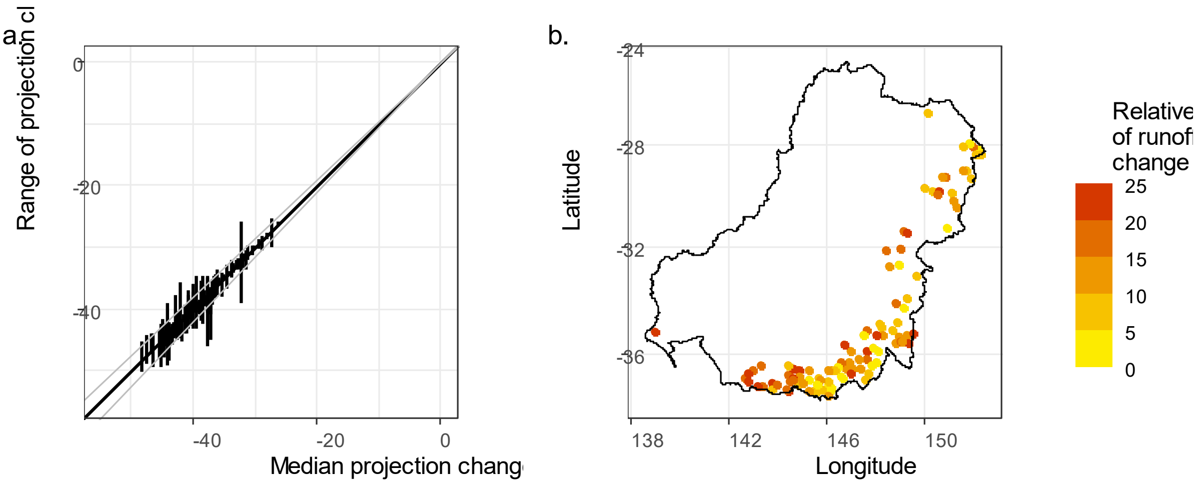

Figure 3 (a) Range of projections of mean annual runoff from different model calibration periods plotted against the projected median change; each vertical line represents a single catchment; grey lines represent a relative range of ±5%. (b) the relative range displayed geographically.

4 Concluding discussion

In this study we investigate the sensitivity of runoff projections to different sources of hydrologic non-stationarity. We summarise the key findings for a 10% rainfall decline and 2° local temperature increase in Figure 4. When modelled using a traditional approach, the median projection (for the 120 HRS catchments modelled here) is a runoff decline of close to 31% with a range that extends from a 20% decline to a 38% decline. By modelling the effects of farm dams under a changing climate it is expected that runoff declines will be larger with the median projection being a runoff decline of close to 34%. The range of runoff declines is also expected to increase when the effects of farm dams are modelled, relative to the traditional modelling approach, because farm dams intercept proportionally more runoff under a drier climate. Modelling the effects of bushfires tends to produce smaller runoff declines as the increasing frequency and intensity of fires leads to slightly lower average LAI and actual evapotranspiration, leading to slightly higher runoff. Other changes to rainfall-runoff relationships that are characteristic of the historically observed changes is expected to expand the range of projections, with larger proportional runoff declines occurring in low runoff catchments.

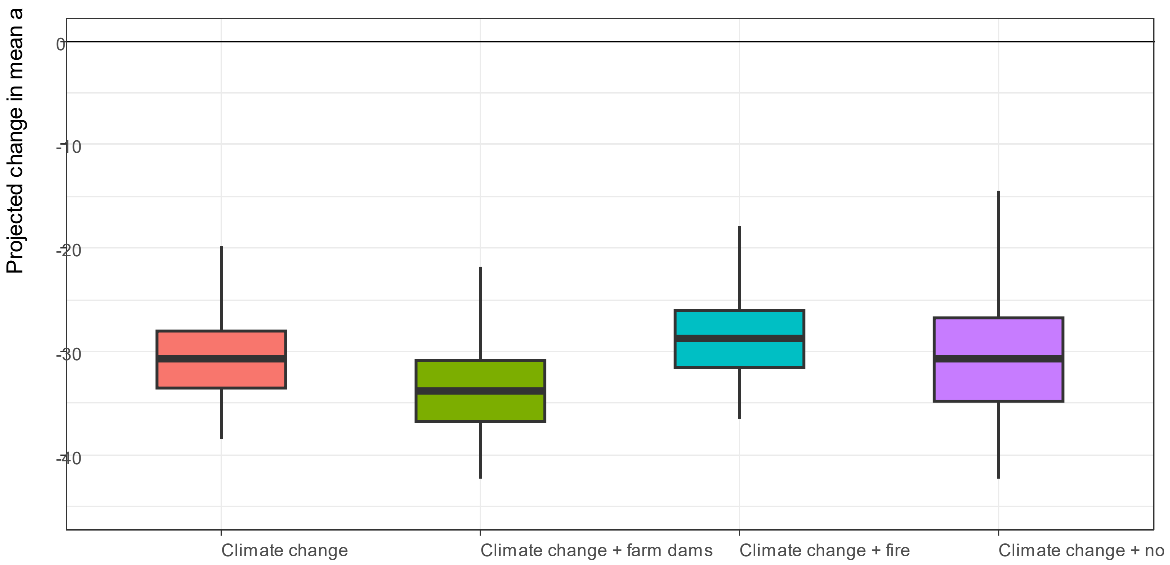

Figure 4 Synthesis of the range of quantified impacts of sources of non-stationarity on projections of mean annual runoff due to a 10% decline in mean annual rainfall for catchments investigated in the MDB.

Here we have attempted to quantify the effects of a number of sources of hydrological non-stationarity on runoff projections. However, there are a number of other sources that we have not investigated. These include the impacts of plant physiological responses to increased atmospheric carbon dioxide levels. There is considerable uncertainty in the direction as well as the magnitude of these plant physiological responses on catchment runoff. Laboratory investigations into the effects of increasing atmospheric carbon dioxide show that plant water use efficiency increases with atmospheric carbon dioxide concentration at the leaf scale. However, larger-scale field investigations suggest carbon dioxide fertilisation effects are complex and dependent on how different plant varieties interact with their growing environment. Therefore, it is difficult to upscale the knowledge gained through these experiments to provide regional assessments of the impact of carbon dioxide fertilisation on runoff due to the complex interactions and feedbacks between the controlling biological, atmospheric and hydrological processes (Chiew et al., 2008; Yang et al., 2021). As a result, the carbon dioxide fertilisation effects are likely to remain an epistemic uncertainty in projected future runoff changes.

Future land use changes are also likely to have impact on catchment runoff. Transitions from forest-like to grassland-like land uses are known to have direct impacts on catchment evapotranspiration (Zhang et al., 2001) and therefore catchment runoff. While knowledge of the hydrological response exists, the ability to predict future land use changes is relatively poor, but scenarios can be crafted based on likely changes driven by management policy.

Management can influence some sources of hydrologic non-stationarity. For example, regulations exist across the MDB that limit new development of farm dams; e.g., Victoria after the 2002 Irrigation Farm Dams Act (Parliament of Victoria, 2002). Governments are also encouraging the mitigation of the impacts of farm dams on low streamflow through low-flow bypass structures. Governments can also guide any land use changes through planning controls. However, there are also many sources of hydrologic non-stationarity where management only has limited opportunities to influence outcomes, such as the impacts of wildfire and plant physiological responses to increasing atmospheric carbon dioxide concentrations.

References

Benyon, R.G., Inbar, A., Sheridan, G.J., Lyell, C.S., Lane, P.N.J., 2023. Variable self-thinning explains hydrological responses to stand replacement in even-aged forests. Journal of Hydrology, 618: 129157. DOI:https://doi.org/10.1016/j.jhydrol.2023.129157

Brown, J.A.H., 1972. Hydrologic effects of a bushfire in a catchment in south-eastern New South Wales. Journal of Hydrology, 15(1): 77-96. DOI:https://doi.org/10.1016/0022-1694(72)90077-7

Chiew, F. et al., 2008. Rainfall-runoff modelling across the Murray-Darling Basin, CSIRO, Australia. DOI: https://doi.org/10.4225/08/585ac5cb01c1e

Chiew, F.H.S. et al., 2009. Estimating climate change impact on runoff across southeast Australia: Method, results, and implications of the modeling method. Water Resources Research, 45(10). DOI:https://doi.org/10.1029/2008WR007338

Coron, L. et al., 2012. Crash testing hydrological models in contrasted climate conditions: An experiment on 216 Australian catchments. Water Resources Research, 48(5): W05552. DOI:10.1029/2011wr011721

Dowdy, A.J., 2020. Seamless climate change projections and seasonal predictions for bushfires in Australia. Journal of Southern Hemisphere Earth Systems Science, 70(1): 120-138. DOI:https://doi.org/10.1071/ES20001

Duan, Q., Sorooshian, S., Gupta, V.K., 1994. Optimal use of the SCE-UA global optimization method for calibrating watershed models. Journal of Hydrology, 158(3-4): 265-284.

Fowler, K. et al., 2022. Explaining changes in rainfall-runoff relationships during and after Australia's Millennium Drought: a community perspective. Hydrol. Earth Syst. Sci. Discuss., 2022: 1-56. DOI:10.5194/hess-2022-147

Fowler, K., Peel, M.C., Western, A.W., Zhang, L., Peterson, T.J., 2016. Simulating runoff under changing climatic conditions: Revisiting an apparent deficiency of conceptual rainfall-runoff models. Water Resources Research, 52(3): 1820-1846. DOI:https://doi.org/10.1002/2015WR018068

Frost, A., Ramchurn, A., Smith, A., 2018. The australian landscape water balance model (awra-l v6). technical description of the australian water resources assessment landscape model version 6. Bureau of Meteorology Technical Report.

Hersbach, H. et al., 2020. The ERA5 global reanalysis. Q. J. R. Meteorol. Soc., 146(730): 1999-2049. DOI:https://doi.org/10.1002/qj.3803

Jones, D.A., Wang, W., Fawcett, R., 2009. High-quality spatial climate data-sets for Australia. Aust. Meteorol. Oceanogr. J., 58(4): 233-248.

Khaledi, J., Lane, P.N.J., Nitschke, C.R., Nyman, P., 2022. Wildfire contribution to streamflow variability across Australian temperate zone. Journal of Hydrology, 609: 127728. DOI:https://doi.org/10.1016/j.jhydrol.2022.127728

Kondo, J., 1998. Dependence of Evapotranspiration on the Precipitation Amount and Leaf Area Index for Various Vegetation Surfaces. Journal of Japanese Society of Hydrology and Water Resources, 11(7 (in Japanese with English abstract)): 679-693. DOI:10.3178/jjshwr.11.679

Kuczera, G., 1987. Prediction of water yield reductions following a bushfire in ash-mixed species eucalypt forest. Journal of Hydrology, 94(3): 215-236. DOI:https://doi.org/10.1016/0022-1694(87)90054-0

Lane, P.N.J., Mackay, S.M., 2001. Streamflow response of mixed-species eucalypt forests to patch cutting and thinning treatments. Forest Ecology and Management, 143(1): 131-142. DOI:https://doi.org/10.1016/S0378-1127(00)00512-0

Malerba, M.E., Wright, N., Macreadie, P.I., 2021. A Continental-Scale Assessment of Density, Size, Distribution and Historical Trends of Farm Dams Using Deep Learning Convolutional Neural Networks. Remote Sensing, 13(2): 319.

McArthur, A.G., 1967. Fire behaviour in eucalypt forests.

Nathan, R., Jordan, P., Morden, R., 2005. Assessing the impact of farm dams on streamflows, Part I: Development of simulation tools. Australasian Journal of Water Resources, 9(1): 1-12. DOI:10.1080/13241583.2005.11465259

Noble, I.R., Gill, A.M., Bary, G.A.V., 1980. McArthur's fire-danger meters expressed as equations. Australian Journal of Ecology, 5(2): 201-203. DOI:https://doi.org/10.1111/j.1442-9993.1980.tb01243.x

Parliament of Victoria, 2002. Water (Irrigation Farm Dams) Act 2002, Parliament of Victoria, Victoria, Australia.

Peña-Arancibia, J.L., Malerba, M.E., Wright, N., Robertson, D.E., 2023. Characterising the regional growth of on-farm storages and their implications for water resources under a changing climate. Journal of Hydrology, 625: 130097. DOI:https://doi.org/10.1016/j.jhydrol.2023.130097

Perraud, J.M., Bennett, J.C., Bridgart, R.J., Robertson, D.E., 2015. SWIFT2: Advanced Software for Continuous Ensemble Short-term Streamflow Forecasting, 2015 Hydrology and Water Resources Symposium. Engineers Australia, Hobart, Tasmania.

Perrin, C., Michel, C., Andréassian, V., 2003. Improvement of a parsimonious model for streamflow simulation. Journal of Hydrology, 279: 275-289. DOI:10.1016/S0022-1694(03)00225-7

Potter, N.J., Chiew, F.H.S., 2011. An investigation into changes in climate characteristics causing the recent very low runoff in the southern Murray-Darling Basin using rainfall-runoff models. Water Resources Research, 47(12). DOI:https://doi.org/10.1029/2010WR010333

Raupach, M.R., Haverd, V., Briggs, P.R., 2013. Sensitivities of the Australian terrestrial water and carbon balances to climate change and variability. Agricultural and Forest Meteorology, 182-183: 277-291. DOI:https://doi.org/10.1016/j.agrformet.2013.06.017

Robertson, D.E., Fu, G., Barron, O., Hodgson, G., Schepen, A., 2024. A new approach of coupled long-range forecasts for streamflow and groundwater level. Journal of Hydrology, 631: 130837. DOI:https://doi.org/10.1016/j.jhydrol.2024.130837

Robertson, D.E. et al., 2023. How sensitive are catchment runoff estimates to on-farm storages under current and future climates? Journal of Hydrology, 626: 130185. DOI:https://doi.org/10.1016/j.jhydrol.2023.130185

Timbal, B., Drosdowsky, W., 2013. The relationship between the decline of Southeastern Australian rainfall and the strengthening of the subtropical ridge. International Journal of Climatology, 33: 1021–1034. DOI:10.1002/joc.3492

Ukkola, A.M. et al., 2016. Reduced streamflow in water-stressed climates consistent with CO2 effects on vegetation. Nature Climate Change, 6(1): 75-78. DOI:10.1038/nclimate2831

Viney, N. et al., 2009. The usefulness of bias constraints in model calibration for regionalisation to ungauged catchments. In: Anderssen, R., et al. (Eds.), 18th IMACS World Congress - MODSIM09 International Congress on Modelling and Simulation, pp. 3421-3427.

Westra, S., Thyer, M., Leonard, M., Kavetski, D., Lambert, M., 2014. A strategy for diagnosing and interpreting hydrological model nonstationarity. Water Resources Research, 50(6): 5090-5113. DOI:https://doi.org/10.1002/2013WR014719

Yang, Y. et al., 2021. Low and contrasting impacts of vegetation CO2 fertilization on global terrestrial runoff over 1982–2010: accounting for aboveground and belowground vegetation–CO2 effects. Hydrol. Earth Syst. Sci., 25(6): 3411-3427. DOI:10.5194/hess-25-3411-2021

Zhang, L., Dawes, W.R., Walker, G.R., 2001. Response of mean annual evapotranspiration to vegetation changes at catchment scale. Water Resources Research, 37(3): 701-708. DOI:https://doi.org/10.1029/2000WR900325

Zhang, L., Zheng, H., Teng, J., Chiew, F.H.S., Post, D.A., 2020. Hydroclimate storylines for the Murray-Darling Basin, CSIRO, Australia.

Zhang, X.S. et al., 2016. How streamflow has changed across Australia since the 1950s: evidence from the network of hydrologic reference stations. Hydrol. Earth Syst. Sci., 20(9): 3947-3965. DOI:10.5194/hess-20-3947-2016

Zheng, H. et al., 2024. Projections of future streamflow for Australia informed by CMIP6 and previous generations of global climate models. Journal of Hydrology, 636: 131286. DOI:https://doi.org/10.1016/j.jhydrol.2024.131286

Zhu, Z. et al., 2013. Global Data Sets of Vegetation Leaf Area Index (LAI)3g and Fraction of Photosynthetically Active Radiation (FPAR)3g Derived from Global Inventory Modeling and Mapping Studies (GIMMS) Normalized Difference Vegetation Index (NDVI3g) for the Period 1981 to 2011. Remote Sensing, 5(2): 927-948.

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