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Understanding the impacts of hydrological non-stationarity on runoff projections

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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

Hydrologic non-stationary is known to challenge hydrological analysis and modelling in the Murray-Darling Basin. Non-stationarities exist in both climate and streamflow data, manifesting as short- and long-term changes in the statistical properties of time series and in the relationship between variables, e.g. rainfall and runoff. The origins of these hydrologic non-stationarities include global warming, vegetation change, water resources development activities, and the cumulative impact of interactions between changing surface and sub-surface processes. While there has been considerable research diagnosing non-stationarity in hydrological time series and simulations of rainfall-runoff models, there have been few assessments of the impacts of non-stationarity on runoff projections under climate change. This study has sought to provide insights into the likely impacts of hydrologic non-stationarity on runoff projections for the MDB, through two investigations assessing: (i) the sensitivity of runoff projections to the period used to calibrate conceptual rainfall-runoff models; and (ii) the extent to which an approach to adapt existing hydrological models to better reflect catchment rainfall-runoff process alters the model sensitivity of runoff to changes in rainfall.

In the first investigation, we show that runoff projections are sensitive to the calibration period used to fit model parameters, indicating that different rainfall-runoff relationships exist for different periods in the historical record. Ensemble simulation based on parameters calibrated for different periods showed that the range of projected changes in mean annual runoff was within ±20% of the projected median change for 90% of the catchments investigated but could be as much as 50% of the projected median change. We also found that projections from the GR4J rainfall-runoff model are less sensitive to the calibration period than projections from the more complex PDM or SimHyd models.

In the second investigation, we apply the Data Assimilation Informed model Structural Improvement (DAISI) approach, previously applied to monthly rainfall-runoff models, to adapt the daily SimHyd rainfall-runoff model to better simulate catchment rainfall-runoff processes. We find that the adapted SimHyd model produces runoff projections that are more sensitive to changes in rainfall than the base SimHyd model for more than 50% of the catchments investigated. The sensitivity of runoff projections to rainfall changes increases substantially (by more than 50%) for approximately 5% of the catchments, while the sensitivity decreases by 5% - 30% for about one-third of the catchments. Our results indicate that, on-average across the catchments investigated, SimHyd projections do not systematically over- or underestimate the sensitivity of mean annual runoff to rainfall change, but for individual catchments, projections may be substantially over- or underestimated.

Overall, we find that runoff projections are sensitive to hydrologic non-stationarity. Due to the differences in the significance of hydrologic non-stationarity across the catchments and the ability of the models in reflecting the non-stationarity, the sensitivity of runoff projections to hydrologic non-stationarity is spatially variable and model dependent. Projections generated using simpler hydrological models appear to be less sensitive to hydrologic non-stationarity, but it is well established that simpler models often are limited in their ability to simulate changes in hydrologic processes. Future research should pursue development of hydrological models that can better represent historical non-stationarities using simplified parameterisations which, based on our analysis should produce robust runoff projections.

1 Introduction

The performance of water resources system management and engineering design often assumes that systems are stationary. Stationarity is defined as a statistical process whose properties, e.g. mean, variance or correlation, do not change over time (Slater et al., 2021). In hydrology, non-stationarity can manifest in many forms with the most common being related to changes in the statistical properties of observed time series, or changes in the relationship between variables, such as the relationship between concurrent rainfall and runoff. Non-stationarities can be transient, that is changes in time series properties or relationships occur for only short periods of time, or they can be persistent, where changes in the time series are more permanent.

Non-stationarities in hydroclimate time series can exist for many reasons. The best-known source of hydroclimate non-stationarity is the increasing trend in global temperature due to anthropogenic global warming. However, there are also many other potential sources of apparent non-stationarity in hydroclimate time series including, relocation of observations sites, change in the local environment of observation sites, such as the growth of nearby vegetation, change in observation instrumentation, as well as actual change in the global or regional climate. These climate, environmental or instrumental changes can lead to abrupt step changes or trends (gradual changes) in the mean, variance or persistence of a hydroclimate time series.

Non-stationarities in streamflow time series can be induced by many of the same causes influencing hydroclimate time series and also changes in catchment characteristics. Catchment characteristics that can induce non-stationarities in streamflow time series may include changing catchment vegetation, the establishment of infrastructure such as dams or diversions weirs and irrigation. Non-stationary climate conditions may also induce changes to runoff generation processes, for example extended dry periods may lead to disconnection between the river channel and underlying groundwater systems (Potter and Chiew, 2011).

Assessments of water resources under historical and future climates rely on rainfall-runoff models to simulate streamflow for periods when observations are not available. These models are calibrated to historical observations and assume that the modelled processes are stationary in time. Where streamflow records are available that cover a wide range of climatic conditions, catchment characteristics and rainfall-runoff models are sufficiently complex then predictions from these models should reflect non-stationarities in streamflow time series. Australia's very high streamflow variability (Chiew, 2006; Chiew and Mcmahon, 2002) means that the length of records required to characterize the range of hydroclimate conditions can be very long. However, studies have found that even when these conditions are met: (a) characteristics of streamflow prediction errors can be non-constant in time, e.g. containing time-varying biases or changes in variance, (Westra et al., 2014), and (b) out-of-sample streamflow predictions can be considerably less accurate than predictions for the calibration periods when the climate of the calibration and prediction periods differ (Vaze et al., 2010).

The limited ability of hydrological models to simulate hydrologic non-stationarity has implications for generating future runoff projections under climate change. The calibration of rainfall-runoff models, and any model fitting process, seeks to provide prediction that is as highly correlated with, and therefore explains as much of the variance in, observed fitting data given the model structure and prediction variables. In the case of rainfall-runoff models the prediction variables are the forcing climate time series data and model parameters. Where the model and prediction variables cannot produce simulations that are perfectly correlated with observations, and therefore can only explain part of the variance in the observations, then model simulations will not be as responsive to changes in forcing climate data as the real system. Therefore, if hydrological non-stationarity is not well-predicted by rainfall-runoff models, then their predictions will have a damped response to climate forcing relative to the real system. In the context of generating hydroclimate projections, this will mean that future changes in runoff will be underestimated.

While there has been considerable research diagnosing non-stationarity in hydrological time series and simulations of rainfall-runoff models, there have been few assessments of the impacts of non-stationarity on runoff projections or practical improvements made to rainfall-runoff models to reduce the model prediction errors and therefore reduce underestimation of runoff projections. As the future climate of the Murray-Darling Basin is projected to be warmer and likely to be drier, understanding how hydrologic non-stationarity could potentially impact runoff projections is important for water resources planning.

In this report we describe two investigations undertaken to improve understanding of the impacts of hydrologic non-stationarity on runoff projections. The first study investigates the range of runoff projections generated using rainfall-runoff model calibrated to different periods. The rationale behind this investigation is the available streamflow records are relatively short considering the high streamflow variability in Australia. Previous studies developing runoff projections have used the entire streamflow record for model calibration. If these models cannot adequately characterise any hydrological non-stationarity, then projections are likely to underestimate future runoff changes. Shorter calibration periods are less likely to contain hydrologic non-stationarities and therefore less likely to underestimate the actual rainfall-runoff response observed during the calibration period. However, if non-stationarities do occur in the catchment, then models calibrated to different periods will characterize different rainfall-runoff responses. Generating projections using models calibrated to shorter periods then allows the sensitivity and uncertainty of projections to model calibration to be understood, providing insight into the plausible impacts of hydrologic non-stationarity.

The second study investigates using the DAISI approach (Lerat et al., 2024) to update an existing rainfall-runoff model to better represent hydrologic non-stationarities. The impacts of improving the representation of hydrologic non-stationarities on runoff projections is assessed by comparing projections generated using the original and updated rainfall-runoff models.

2 Sensitivity of hydrological projections to model calibration period

2.1 Background

Conceptual rainfall-runoff models are commonly used to generate hydrological projections. Hydrologic projections are generated by forcing calibrated models with climate data representing future conditions. Model calibration involves forcing the model with historical climate observations and then modifying the model parameters to minimize differences between simulated and observed streamflow. To generate runoff projections, models are typically calibrated to all available records, that potentially contain periods with a wide range of hydro-climatic regimes. Here we assume that (a) a rainfall-runoff relationship will be stationary over a 10-year period and (b) that 10 years is sufficient to adequately calibrate rainfall-runoff model. We then investigate the range of projected changes in a number of runoff metrics that can be produced using all possible 10-year calibration periods.

2.2 Methods

To investigate the effects of model calibration periods on runoff projections we use multiple rainfall-runoff models, specifically GR4J (Perrin et al., 2003), SimHyd (Chiew et al., 2002), PDM (Moore, 2007). The GR4J model allows for a groundwater exchange term where water can enter or leave a catchment by means other than precipitation, evaporation or streamflow, while the other models do not allow for this process. We therefore also use a simplified version of GR4J that does not permit groundwater exchange.

All hydrological models are calibrated to minimise an objective function using the Shuffled Complex Evolution algorithm (Duan et al., 1993). The adopted objective function is the NSE-bias objective (Equation 1) that has been previously used to calibrate rainfall-runoff models for climate change impact assessments (Chiew et al., 2008; Chiew et al., 2017; Viney et al., 2009).

$$OF = (1 - NSE) + 5\left(\log(1 + bias)\right)^{2.5} \tag{1}$$

where

$$NSE = 1 - \frac{\sum_{t=1}^{T}\left(Q_{s,t} - Q_{o,t}\right)^2}{\sum_{t=1}^{T}\left(Q_{o,t} - \bar{Q}_o\right)^2},$$

(2)

$$bias = \frac{\left(\bar{Q}_s - \bar{Q}_o\right)}{\bar{Q}_o},$$

(3)

and NSE is the Nash-Sutcliffe efficiency (Nash and Sutcliffe, 1970), $Q_{s,t}$ is the simulated streamflow for time step t, $Q_{o,t}$ is the observed streamflow, $\bar{Q}_s$ is the mean simulated streamflow, $\bar{Q}_o$ is the mean observed streamflow and T the total number of time steps.

For this study we use available streamflow observations for the period 1982-2018. To assess the sensitivity of hydroclimate projections to calibration periods, we calibrate the hydrological models against 10-year continuous records of streamflow data and generate projections for a range of plausible changes to climate forcing data. Model calibration is performed by running the model for the entire period 1982-2018 and setting streamflow observations outside the 10-year calibration period of interest to missing. As some of the gauges used in this study have missing data for part of the record, we only calibrate a model to a 10-year period of interest if there are at least 3 years of non-missing data.

We then force the calibrated model with scaled historical climate data to generate 37-year projections of simulated runoff. To understand sensitivities of runoff simulations to changes in rainfall and potential evaporation we examine multiple combinations of scaling factors. For rainfall we scale the historical rainfall by factors ranging from 0.8 to 1.2, which represent the range of changes in mean annual rainfall projected by the CMIP6 global circulation models for the Murray-Darling Basin. For potential evaporation, we considered only two scaling factors, 1.0 and 1.07, which are equivalent to no change in regional temperature and as approximately 2°C increase in regional temperatures.

Projected runoff for each combination of scaling factors is summarised for four flow metrics, the mean annual runoff, the mean annual 95th percentile daily runoff, the mean annual 5th percentile daily runoff and the lowest 3-year total runoff. Percentage changes in these four flow metrics, relative to the simulations generated using scaling factors of 1.0 applied to both rainfall and potential evaporation forcing, are computed for each combination of scaling factors.

Runoff projections, and therefore change factors for the four flow metrics, are generated using models calibrated to each 10-year overlapping period within the period 1982-2018. The range of changed factors generated for all calibration periods for each metric and climate scaling factors are summarised to understanding the sensitivity to calibration period.

2.3 Catchments and data

We investigate 133 catchments in the MDB where high quality streamflow observations are available to calibrate hydrological models (Figure 1). The streamflow observations and catchment delineations are obtained from the Bureau of Meteorology's Hydrologic Reference Stations (Zhang et al., 2013, see http://www.bom.gov.au/water/hrs/about.shtml). Catchment scale forcing data for the models are derived by taking area-weighted averages of gridded data estimates used to support the Australian Water Outlook (Frost et al., 2018; Jones et al., 2009).

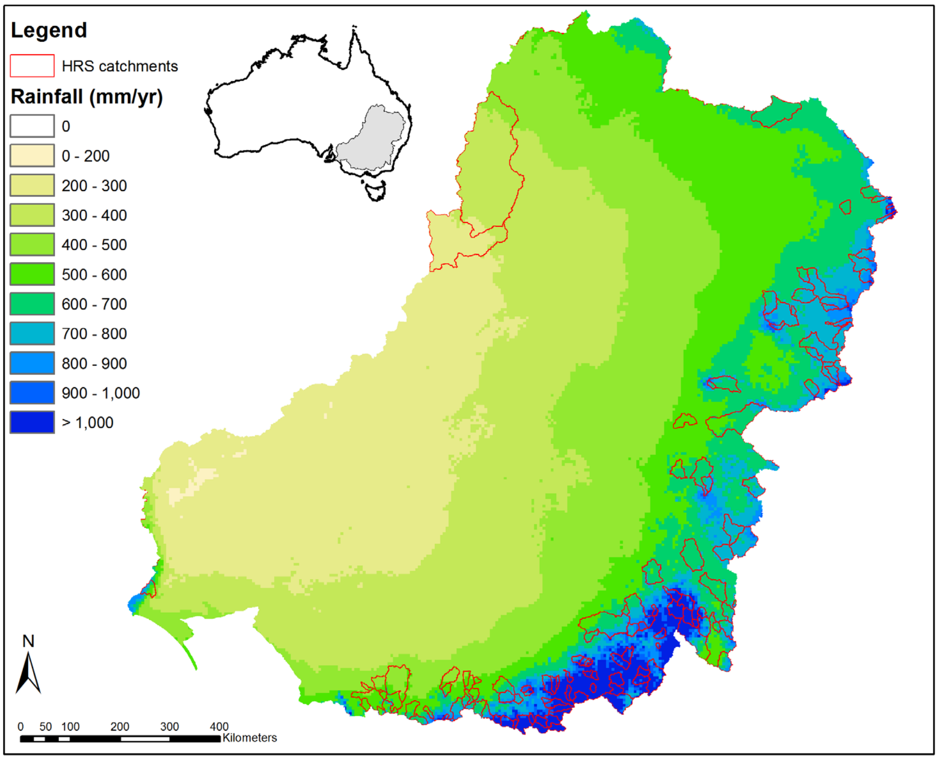

Figure 1 Location of the 133 Bureau of Meteorology's Hydrologic Reference Stations (HRS) catchment boundaries (in red) within the Murray-Darling Basin. The background colour ramp shows the mean annual rainfall).

2.4 Results

We first present results for individual catchments and then summarise results across all catchments.

2.4.1 Individual catchments

Ensemble simulation based on parameters calibrated in each 10-year period shows that the range of modelled changes in the flow metrics vary across catchments climate change scenarios and models. Figure 2 shows the range of changes in the flow metrics for projections generated using the GR4J model for two representative catchments. For both catchments shown, the range of changes in metrics increases with magnitude of the imposed climate changes. This result is expected as it is well understood that changes in rainfall and PET are amplified in streamflow. If the hydrological model represents this amplification well and it is influenced by the model calibration, larger changes in rainfall and PET would be expected to produce larger parameterization-induced differences in changes in runoff metrics.

The range of changes in flow metrics for catchment 405205 are considerably smaller than the range of changes in flow metrics for catchment 401013. This suggests that runoff projections for catchment 401013 are considerably more sensitive to the calibration period than catchment 405205.

For both catchments, the changes in high flow (mean annual 95th percentile daily runoff), tend to be less sensitive to changes in rainfall and PET than changes in mean annual flow, while changes in low flow metrics tend to be more sensitive. This is demonstrated by the relationship between rainfall and PET changes for the change in high flows being ‘flatter’ than the corresponding relationship for mean annual flow.

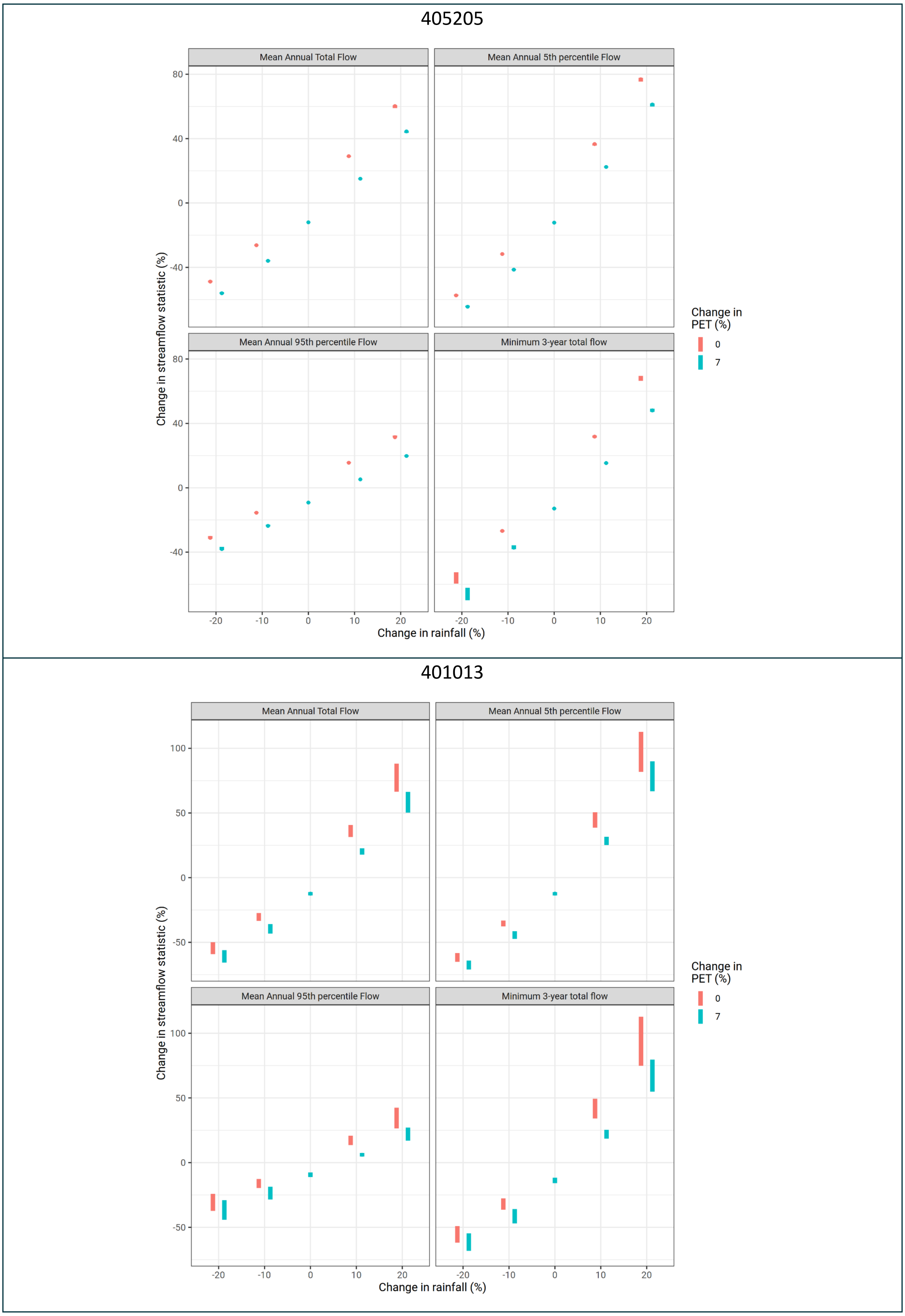

Figure 2 Sensitivity of GR4J runoff projections to calibration period for two catchments in the southern Murray-Darling Basin. Vertical bars represent the ranges of changes in metrics generated by calibrating the model to different periods for each combination of projected rainfall and PET.

However, different hydrological models display different sensitivities (Figure 3). For catchment 401013, all models show similar changes in mean annual flow in response to changes in rainfall and PET, but with the PDM model being a little less sensitive to calibration period, relative to the other models as indicated by the slightly smaller ranges in projected changes. However, PDM and SimHyd show greater changes in the high flow metric in response to rainfall and PET changes, than either version of GR4J. These two models also show greater sensitivity of the high flow metric to calibration period. SimHyd also shows a greater sensitivity of the mean annual 5th percentile flow to calibration period than all the other models examined, however the minimum 3-year total flow is less sensitive to calibration period.

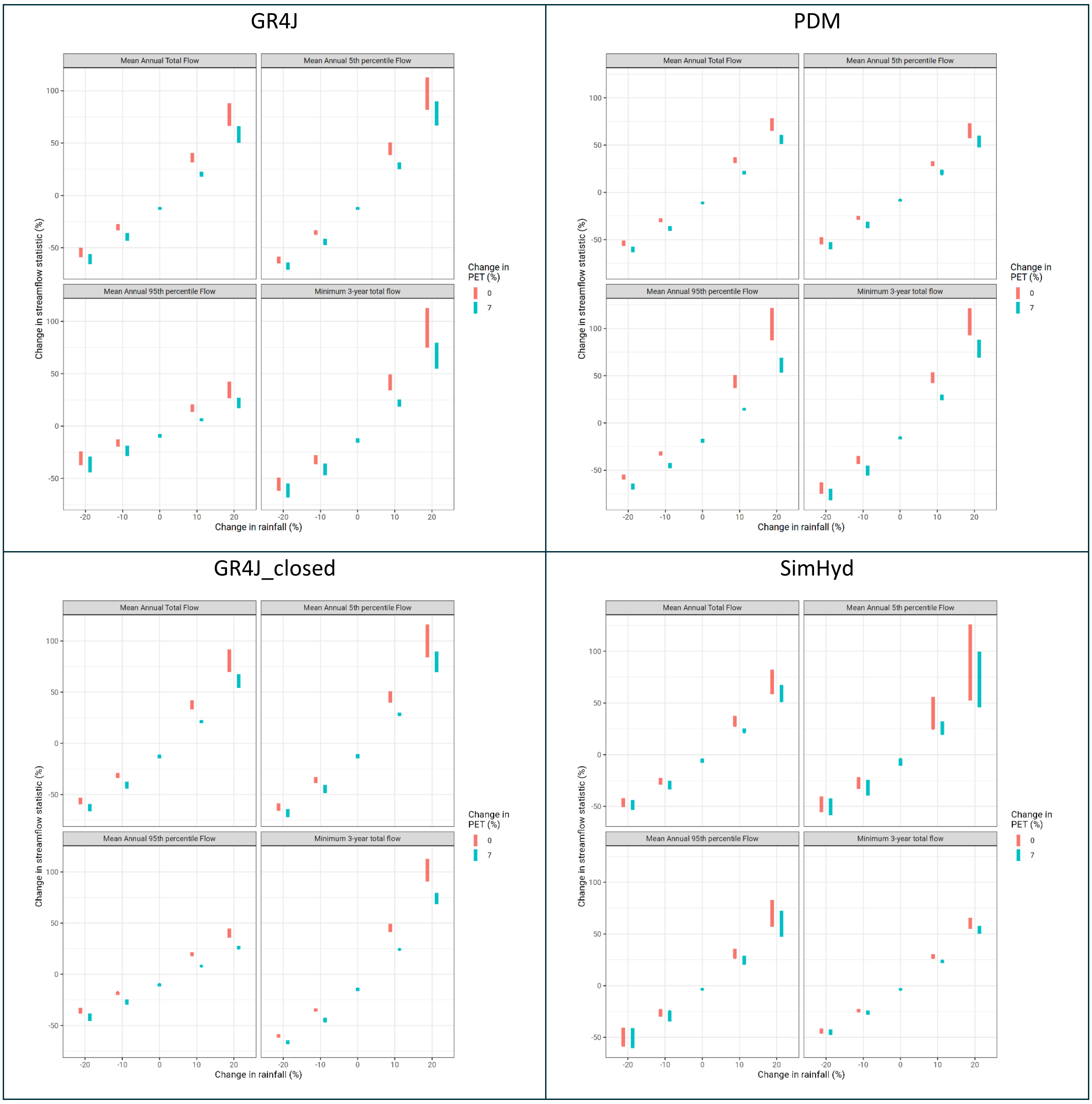

Figure 3 Sensitivity of runoff projections from different hydrological models to calibration period for catchment 401013 in the southern Murray-Darling Basin. Vertical bars represent the ranges of changes in metrics generated by calibrating the model to different periods for each combination of projected rainfall and PET. Note vertical scale is different for each hydrological model.

2.4.2 Basin wide results

We summarise the results across all the HRS catchments for three climate change scenarios: 7% increase in PET only, 10% decline in rainfall only, and a combined 10% decline in rainfall and 7% increase in PET. The median changes in runoff metrics for all catchments are all smallest for the PET change only, and largest for the combined rainfall decline and PET increase (Figure 4). Spatially, changes in all the metrics tend to be smallest in the south-east part of the MDB and larger in the northern parts of the MDB and western Victoria. Median changes tend to be smallest for the high flow metric (mean 95th percentile flow) and largest for the low flow and hydrological drought metrics (mean 5th percentile flow and 3-year minimum total flow). The median changes in runoff metrics for other models show similar spatial patterns and ordering of changes according of the climate changes presented (Appendix A.1).

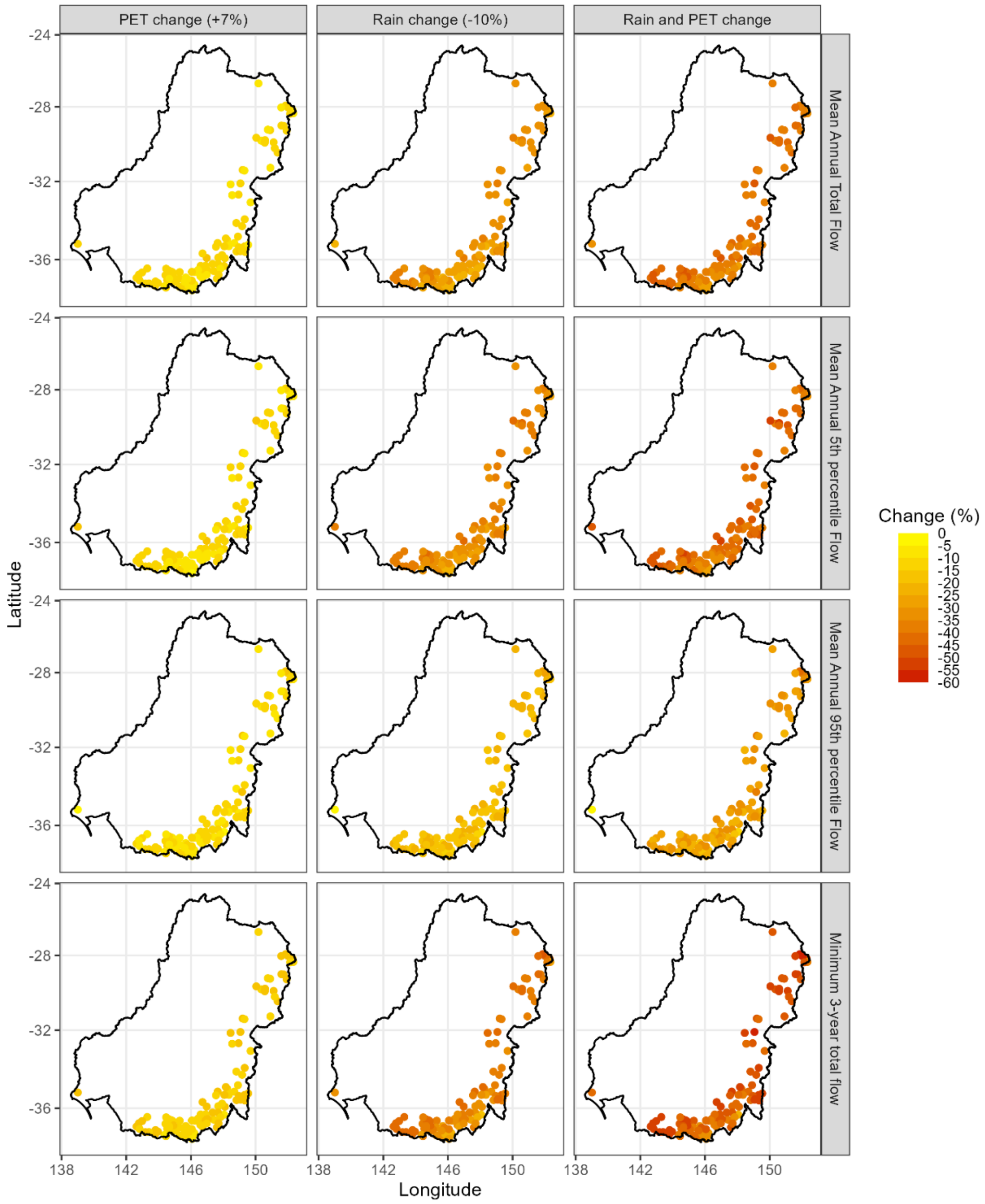

Figure 4 Median GR4J projected changes in runoff metrics for the HRS catchments for three climate change scenarios. Median change is computed across the different calibration periods.

The range of changes in runoff metrics shows similar patterns to the median projected changes. The range is smallest for the PET change only scenario and the largest for the combined rainfall and PET change. For all scenarios and metrics, the sensitivity to the calibration period is smallest in southeastern parts of the MDB. For GR4J all metrics show a similar sensitivity to calibration period, with the range of metrics extending to being as high as 15% for some catchments. The sensitivity of runoff change metrics to calibration period for other models shows a different behaviour. For PDM, the 95th percentile flow and minimum 3-year flow are much more sensitive to calibration period than other metrics, with the range of changes extending to 80%, while the other change metrics show sensitivity commensurate to GR4J (Figure 16). For SimHyd, changes in both the 5th and 95th percentile flows are more sensitive to calibration period than the other change metrics (Figure 19).

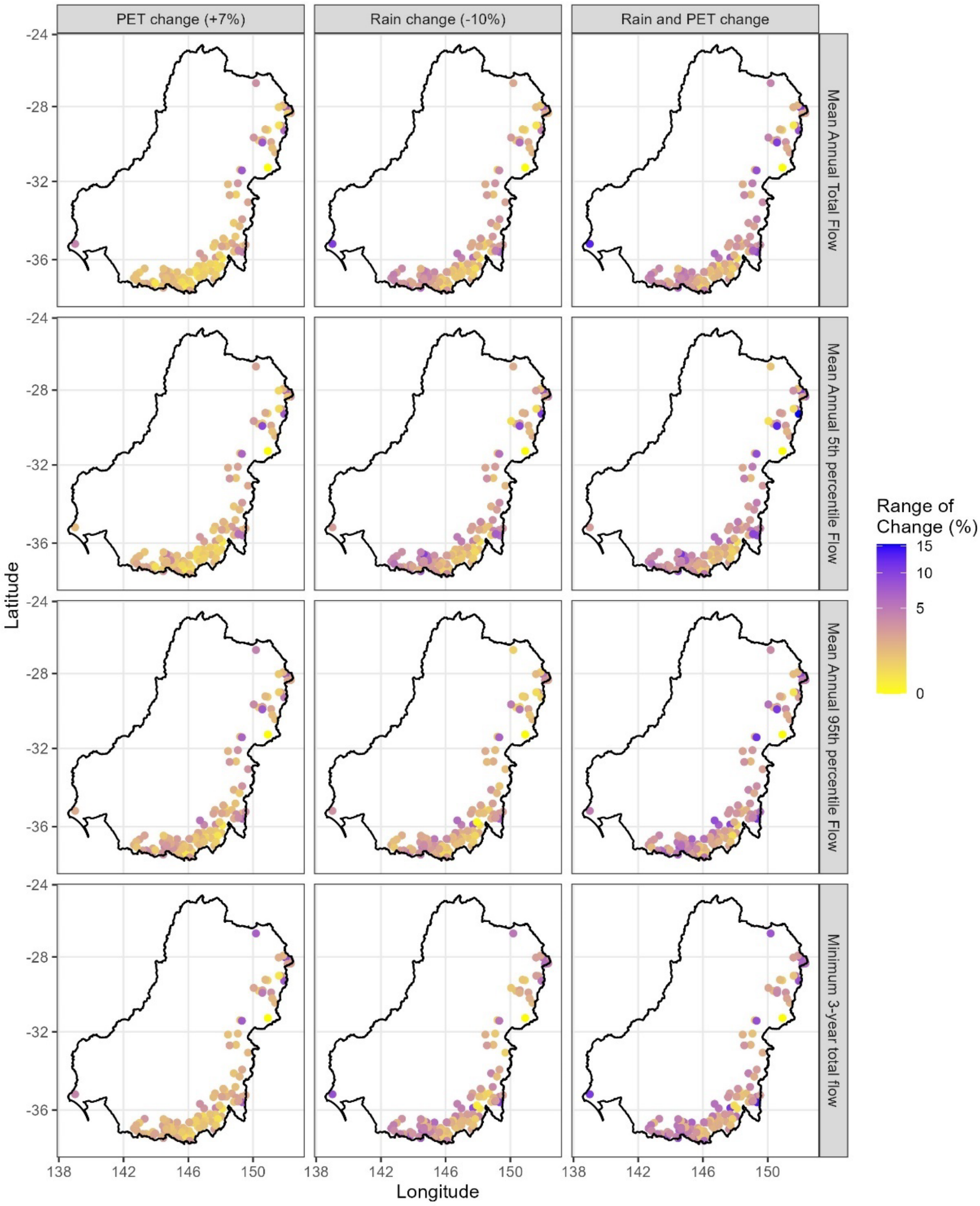

Figure 5 Sensitivity of GR4J runoff projections to calibration period for the HRS catchments for three climate change scenarios. For each point the range represents the difference between the high and lowest percentage change in the runoff metric arising from using different periods to calibrate the hydrological models.

The spatial patterns of the median and range of change show strong similarities for all metrics, we therefore examine the relationship between them (Figure 6). The relationship between the median and range of change in runoff metrics for the different climate scenarios is not necessarily very strong for all metrics. For GR4J, there appears to be a relationship between the median and range of changes in mean annual flow and 5th percentile flow, particularly for the rainfall-only climate change scenario, where catchments with larger median change tend to have larger range. However, for the other two metrics, the relationship between the median and range of change is weak to non-existent. For the other models, the relationship between the median and range of change in the metrics tends to be strong.

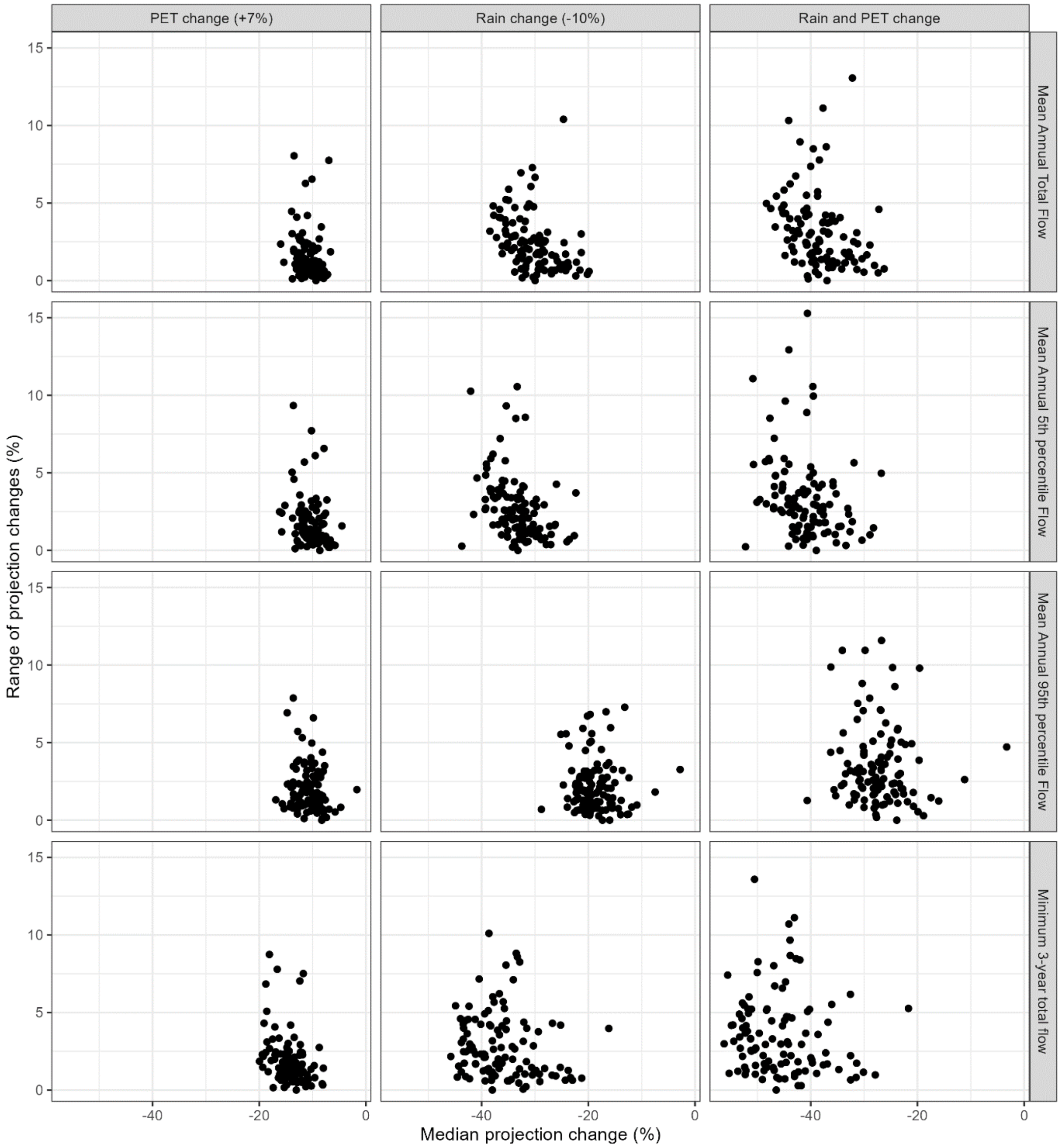

Figure 6 Relationship between median and range of changes in runoff metrics for GR4J projections for three climate change scenarios. The distributions summarised by the median and range arise from using different periods to calibrate the rainfall-runoff model.

We summarise the median projected change in the runoff metrics for three models (Figure 7). The distributions of the change in the mean annual runoff and mean annual 5th percentile daily runoff are remarkably similar for all three models, with SimHyd possibly showing slightly smaller reductions in runoff from changes in PET than the other two models. However, for the other two metrics, the GR4J models shows smaller median changes in the 95th percentile daily runoff than the other models for 50% of catchments. For the minimum 3-year total flow, SimHyd shows the smallest median change for all catchments under all climate scenarios, while PDM shows the largest change.

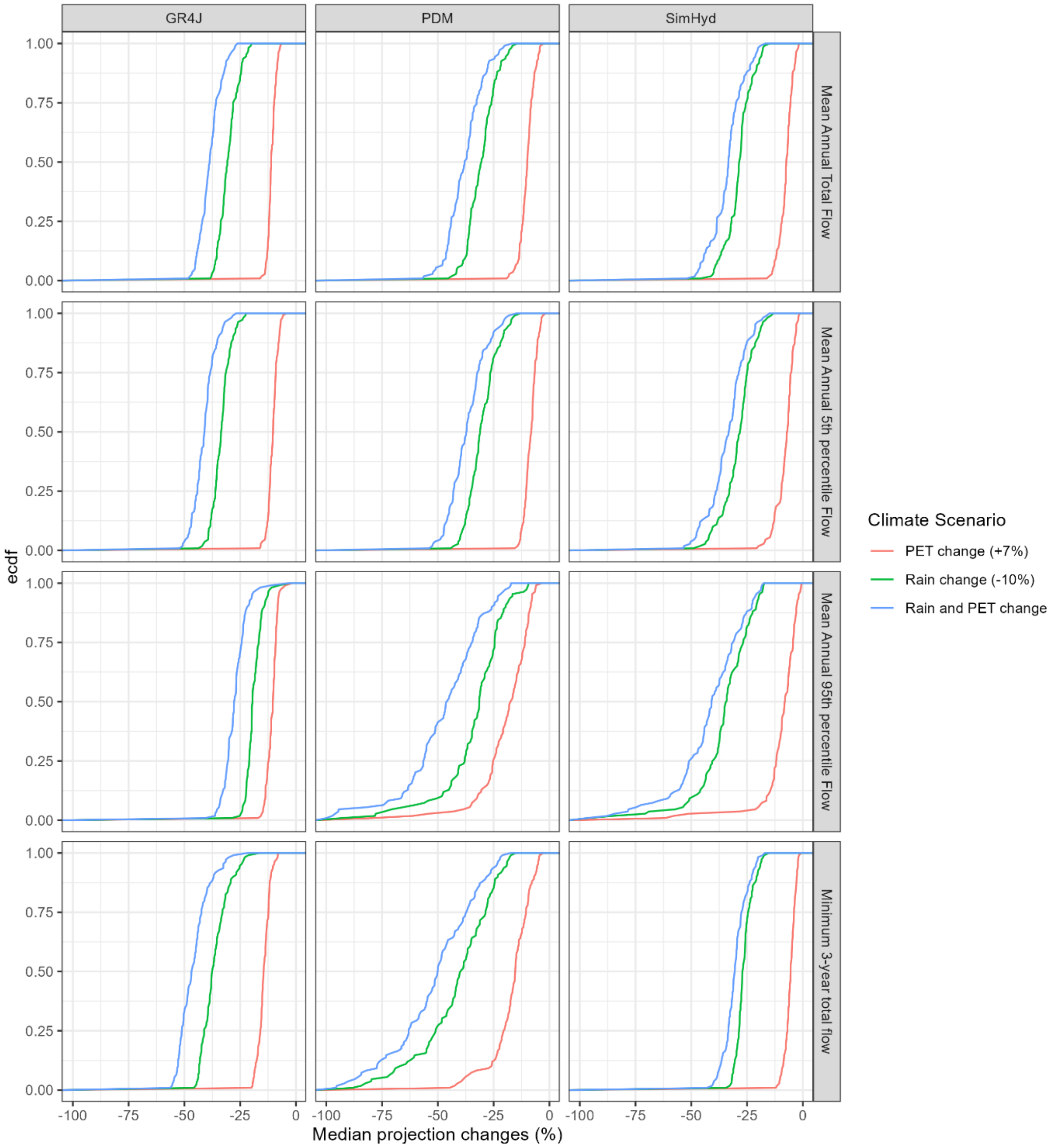

Figure 7 Empirical distributions across the catchments of the median projected changes in runoff metrics for three climate change scenarios and 3 models.

The models show differing sensitivities to calibration periods across the metrics (Figure 8). GR4J shows a similar sensitivity to calibration period across all the metrics assessed, as indicated by the very similar distributions for the range of changes, and the differences due to the climate scenarios are relatively small. The mean annual total flow metric shows relatively similar sensitivity to calibration period for all models, and for the mean annual 5th percentile flow SimHyd appears to be a little more sensitive to calibration period than the other models. The PDM model is strongly sensitive to calibration period for the mean annual 95th percentile flow and for the minimum 3-year total flow.

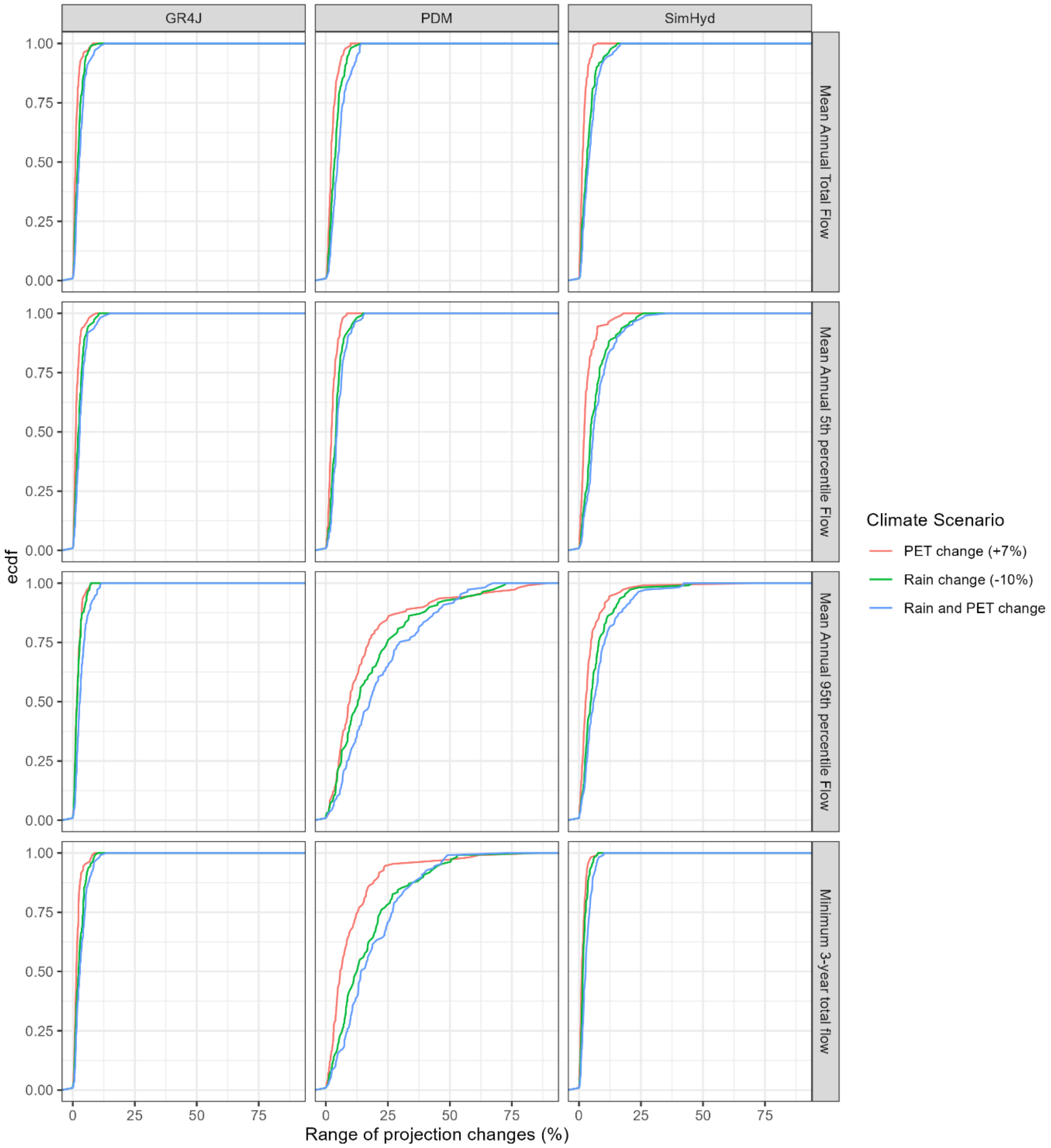

Figure 8 Empirical distributions across the catchments of the range of changes in runoff metrics due to using different calibration periods for three climate change scenarios and 3 models.

2.5 Discussion

The results presented clearly demonstrate that runoff projections are sensitive to the calibration period used to fit model parameters. This suggests that different periods in the historical record show different rainfall-runoff relationships, which can potentially be associated with hydrologic non-stationarity. The impact of calibration period on runoff projections for different climate scenarios is spatially variable, and the spatial patterns are similar across different changes in climate forcing and hydrological models. This suggests that the hydrologic non-stationarity can be catchment dependent and the models have similar ability in representing the non-stationarity.

Spatially, runoff projections for catchments in the wetter southeast of the MDB tend to show lower sensitivity to calibration period than other parts of the Basin. This suggests that the rainfall-runoff relationship in this region has been more consistent over time than in other parts of the Basin. Parts of Victoria have been shown to have rainfall-runoff relationships that have changed during the Millenium Drought and while the relationships have returned to pre-drought conditions in some regions there are still catchments left in a changed state in other regions (Peterson et al., 2021; Potter and Chiew, 2011; Fowler et al., 2022; Fowler et al., 2016). Regions of Victoria where changes in the rainfall-runoff relationships during the Millennium Drought were minimal broadly correspond to the areas in the southeast of the Basin where projections show lowest sensitivity to calibration period. Conversely, projections for regions where statistically significant changes in rainfall-runoff relationship were observed display larger sensitivity to calibration period. This suggests that the results obtained are likely to provide valid insights into the effect of hydrologic non-stationarity on runoff projections.

Changes in mean annual runoff display lower sensitivity to calibration periods than metrics representing annual high flow, and then low flow and hydrological drought. This is not unexpected as the objective function used to calibrate the models seeks to minimise bias, which will tend to ensure that the average daily, and therefore annual flow, will be well simulated. In addition, the mean annual total flow is a measure of the central tendency of the flow distribution and therefore likely to be less sensitive than other metrics. Under the climate change scenarios investigated that consider rainfall changes, the relative range of projected changes in mean annual runoff due to calibration period (range of changes / median change) is less than 0.2 for approximately 90% of catchments investigated for all models. This suggests that for projections of mean annual runoff the effects of hydrologic non-stationarity may lead to projected changes that are 20% larger or smaller than those estimated. For example, if a projected change in rainfall leads to an estimated reduction in mean annual total flow of 10%, then the expected range of the effects of hydrologic non-stationarity are considered could be an 8-12% reduction in mean annual total flow. Our results show that metrics representing high and low flow conditions are more sensitive to calibration period than mean annual total flow and therefore larger allowances for hydrological non-stationarity need to be considered in projections.

GR4J shows a lower sensitivity to calibration periods than the other models investigated. The limited sensitivity to calibration period of the GR4J model is likely related to the model parameterisation. The GR4J has fewer, only 4, parameters compared to the other models investigated, which have 10 in the case of PDM and 9 in the case of SimHyd. However, a model with fewer parameters doesn’t necessarily have lower ability to simulate streamflow than other more highly parameterised models. In many comparisons of hydrological model performance in

Australia, GR4J often is among the better performing models (Bennett et al., 2016; Coron et al., 2012), and similar results were found in this study (Figure 9). Rather, models with larger numbers of parameters often suffer from equifinality, where multiple different parameter sets can produce simulations with similar levels of performance during calibration. However, when the different parameter sets that produce similar calibration performance are used to simulate streamflow for periods climatically different to the calibration period, then very different simulations can arise (Vaze et al., 2010). Therefore, this suggests that simplified models like GR4J are likely to produce more robust projections in catchments that experience hydrologic non-stationarity because they are less sensitive to calibration periods. However, that does not mean GR4J adequately describes non-stationary hydrologic processes, as many studies have demonstrated its limitations in catchments where rainfall-runoff relationships have changed over time (Westra et al., 2014; Fowler et al., 2016). Rather, continued development of hydrological models should focus on developing simplified parameterisations that can better represent historical non-stationarities and therefore produce robust projections.

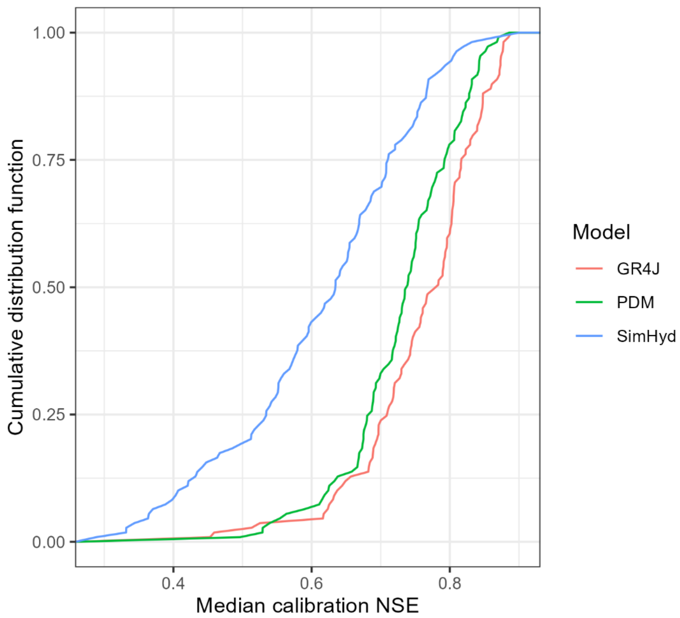

Figure 9 Median calibration Nash Sutcliffe Efficiency, computed across the different calibration periods, of the GR4J, SimHyd and PDM models.

3 Enhancing hydrological model ability to simulate hydrologic non-stationarity

3.1 Background

The previous section demonstrated that future runoff projections generated by all hydrological models investigated are sensitive to the period used for model calibration. We postulate that the sensitivity of projections to model calibration period is related to hydrologic non-stationarity where different rainfall-runoff relationships exist during the different calibration periods. Ideally, hydrological models should be able to represent the range of rainfall-runoff relationships that occur within the historical record. However, models commonly used for water resources assessment have been found to have limited ability to represent hydrologic non-stationarity (Westra et al., 2014; Fowler et al., 2016). Recently, the Data Assimilation Informed model Structural Improvement (DAISI) method was developed to improve the ability of hydrological models to simulate hydrologic non-stationarity (Lerat et al., 2024). DAISI was initially applied to the GR2M monthly rainfall-runoff model and found to improve a range of simulation performance metrics, particularly those characterising simulation performance of high and low flows and the responsiveness of simulated runoff to rainfall inputs. However, while rainfall-runoff models running at monthly time step are useful for some purposes, they are not commonly used for assessing climate change impacts in the MDB. Here we demonstrate the application of DAISI to a daily rainfall-runoff model and assess its effect of the improve model structure on runoff projections.

3.2 Methods

We firstly provide a brief overview of the DAISI approach and then describe its application to a daily rainfall-runoff model in the MDB.

3.2.1 DAISI

The DAISI approach involves using data assimilation methods to update the predictions from an existing calibrated rainfall-runoff model, uses the update predictions to define corrections to the model state equations, and then generates predictions using the rainfall-runoff model containing the updated state equations. The full details of the method are provided in Lerat et al. (2024), here we provide a high-level overview of the steps to implement the DAISI method.

1. Calibrate existing rainfall-runoff model

The DAISI approach seeks to improve an existing rainfall-runoff model and therefore the first step is to calibrate the model. The method of model calibration is not of critical importance to the implementation of DAISI; however, it is important to have a model that is able to simulate both high and low streamflow relatively well for the subsequent steps.

2. Apply data assimilation to generate updated hydrological model predictions.

A wide range of data assimilation methods exist that can generate an optimal combination of modelled predictions and observations, given simulation errors and observation uncertainties, to update the state model variables. An Ensemble Smoother related with Kalman algorithm is used by DAISI to generate probability distributions of updated predictions for an entire time series in a single updating step. To implement the Ensemble Smoother, simulations are generated using the calibrated perturbed state variables. A standard updating step similar to what is done in Kalman filtering is then applied:

$$X^a = X^f + K\left(D - HX^f\right)$$
$$K = \Sigma_{XHX}(\Sigma_D + \Sigma_{XH})^{-1} \tag{4}$$

where X^a is a matrix representing the ensemble of updated state variables, X^f is a matrix of perturbed state variables, D is a matrix of observed variables, and HX^f is a matrix of model simulations of the observed variables. The Kalman gain matrix (K) is the ratio of the covariance between the perturbed models states and the model simulations (Σ_{XHX}) to the sum of the sample covariances between the observations (Σ_D) and between the model simulations (Σ_{XH}).

The implementation of the Ensemble Smoother requires choices on which state variables are perturbed and the observations that are used for the updating procedure. For the application of DAISI, it is recommended that streamflow observations are used as the primary form of data for updating, but acknowledged other observations, such as remotely sensed actual evaporation could also be used. The state variables that are perturbed are model specific, but can included any forcing variable, model state or flux.

3. Define corrections to the model state equations

The data assimilation procedure generates updated estimates of state variables. These updated estimates are then used to define corrections to the hydrological model state equations. The corrections to the state equations are in the form of error updates:

$$\hat{y}_{n,t+1} = y_{n,t+1} + \delta_{n,t} \tag{5}$$

where $\hat{y}_{n,t+1}$ is corrected state variable *n* for time step *t+1*, $y_{n,t+t}$ is the corresponding uncorrected state variable and $\delta_{n,t}$ is the correction that is dependent on the condition of the state variable at the previous time step.

The correction is assumed to be a second order polynomial of a subset of V variables that affect variable y_n

$$\delta_{n,t} = \eta_{\,n,0} + \sum_{i=1}^{V} \eta_{\,n,i} y_{i,t} + \sum_{i=1}^{V} \eta_{\,n,V+i} y_{i,t}^2 + \sum_{1 \le i \le j \le V} \eta_{\,n,k(i,j)} y_{i,t} y_{j,t}$$

(6)

where $k(i,j) = 2V + i + (j-1)(j-2)/2$.

In total there are $1 + 2V + V(V-1)/2$ coefficients for the regression models.

The $\eta_{n,x}$ coefficients of the correction term are obtained using a maximum likelihood estimation. When estimating these coefficients, the $\delta_{n,t}$ values are approximated for each ensemble member using the state values obtained from the data assimilation for time step *t* and the state values for time step *t* generated by the hydrological model's state equations, using the state values obtained from the data assimilation for time step *t-1* and the corresponding updated perturbed forcing.

4. Generate predictions using the updated model

The output of the previous step is to generate an updated version of the hydrological model with the corrected state equations. This model can then be used to generate predictions for verification purposes and to understand the changes in sensitivity of outputs to forcing data.

3.2.2 Application of DAISI in the MDB

We apply the DAISI method to the HRS catchments in the Murray Darling Basin to understand what impact the modifications to the structure of a hydrological model have on runoff projections. The application of DAISI requires several modelling choices.

Firstly, the SimHyd model is adopted for the current analysis. We use SimHyd because in the previous analysis we identified that the SimHyd model had the lowest calibration performance of the models investigated and runoff projections were most sensitive to calibration period. This suggests there is considerable opportunity to modify the state equations of the SimHyd model to improve its ability to simulate runoff. There is also a practical aspect to the selection of the SimHyd model. Both GR4J and PDM have state equations that lead to potentially long lag relationships between internal model fluxes, through the unit hydrographs in GR4J and a cascade of two linear reservoirs in PDM. While the use of an Ensemble Smoother as the data assimilation method in DAISI does permit updating model states across multiple time steps the updating of the state equation would need to include a very large number of predictors, through all the lagged states, and therefore risks multiple co-linearity between the predictors.

Having selected the SimHyd model it is then necessary to define the configuration of DAISI, specifically characterising the data assimilation approach and state equations that are updated. The SimHyd model is firstly calibrated using the NSE-bias objective function to the entire record extending from 1982-2018.

For the data assimilation procedure, we adopted an Ensemble Smoother in line with the approach of Lerat et al. (2024) and assimilate only streamflow observations. To facilitate the ensemble data assimilation, we apply perturbations to the forcing data (rainfall and potential evapotranspiration), the two states (soil moisture store and groundwater store) and observed streamflow. We transform the forcing data, model states and streamflow observations before applying perturbations. For rainfall, potential evapotranspiration, the groundwater store, and streamflow observations a shifted log transformation is applied, with a shift of 0.1 to deal with the potential for zero values. For the soil moisture store, we adopt a shifted logit transform to modify the variable from one that is bounded between zero and the soil moisture store capacity, to one which is continuous over the real space. The shift is applied before the logit transform to ensure that the transformed variable remains finite. The covariance of the perturbations applied to the forcing data and state variables is estimated by scaling the covariance of transformed simulations of the relevant variables generated using the calibrated hydrological model by a factor of 0.01 following (Lerat et al., 2024). Similarly, we estimate the variance of perturbations applied to the transformed streamflow by scaling the observed variance by 0.01.

The Kalman gain requires estimation of the covariances of and between the simulation state variables and streamflow observations. Where there are long-time differences between the elements in the covariance matrices, there is the potential for spurious correlations to exist that arise from seasonal cycles in the state variables and observations. We therefore taper, or regularise, all covariance matrices by multiplying all elements by a squared exponential correlation function, with a time decay of 50 days.

We investigated applying updates to each of SimHyd's state equations (Appendix A.2) individually and in combination, also investigating the best set of predictors to use in the updating equation. Based on the investigation we chose to apply updates to only three: the soil moisture store, the groundwater store, and the soil evaporation (Table 1)

Table 1 SimHyd state equations updated by DAISI.

State Variable	Variables affecting the state variable	Number of update coefficients
SoilMoistureStore (SMS)	SMS, Evaporation, Rainfall	10
GroundwaterStore (groundwater)	groundwater, recharge	6
Soil Evaporation	SMS, Evaporation	6

3.3 Results

Here we firstly demonstrate the application of DAISI for a single catchment in the MDB, following the implementation steps, and then illustrate a key result from basin-wide application that has implications for the use of the SimHyd model for generating future runoff projections.

Figure 10 shows the how the data assimilation corrects the raw model predictions to more closely follow the streamflow observations. The raw hydrological model simulation, shown in green, strongly responds to small rainfall events and recedes rapidly. This rapid hydrograph rise and fall is most likely due to the NSE-bias objective function used to calibrate the model rewarding parameter sets that replicate the high flow peaks. The application of data assimilation updates the simulations to more closely follow the streamflow observations. In general, the differences between the median updated prediction and the streamflow observations are very small, with the exception of very low and high flows where differences can be larger. Where streamflow observations are missing, the spread of the ensemble tends to be considerably larger than when observations are available.

Figure 10 Demonstration of the effect of the data assimilation for a 2-year prediction window.

Updating equations were developed for the soilMoistureStore, soilET and groundwater store. Figure 11, shows the relationship between predictions from the fitted updating equations and the updates from generated by the data assimilation. For two of the three updated variables, specifically the soilMoistureStore and groundwater store, there is a strong, but imperfect, relationship between the predicted updates and those generated by the data assimilation, particularly for small values of the updates. For these variables, the range of the predicted updates is commensurate with the range of the updates generated by the data assimilation, with a small number of predicted updates being very large for the soilMoistureStore. For the soilMoistureStore, there is also a tendency to underestimate the magnitude of the assimilated updates as indicated by most points falling above the 1:1 line. However, for the soilET variable the relationship is considerably weaker, with the range of predicted updates being considerably smaller than the range of updated generated by the data assimilation and a wide spread of residuals about the 1:1 line. This suggests that updating of the soilET may not be necessary.

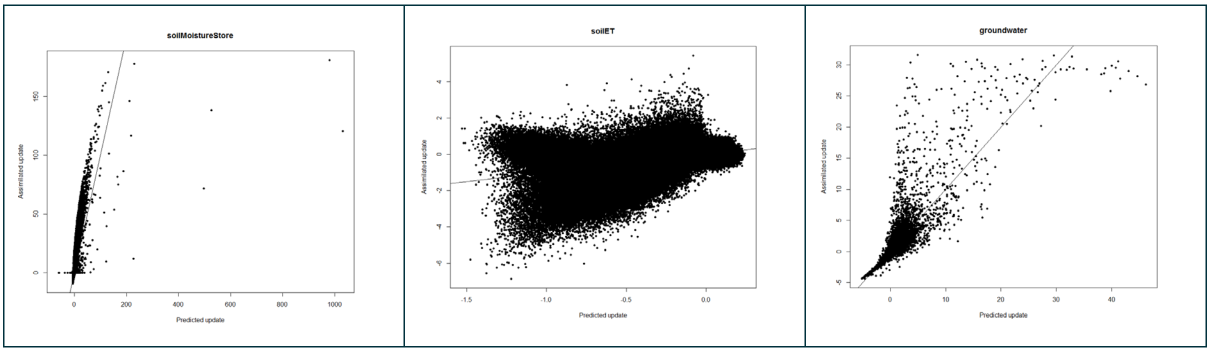

Figure 11 Relationship between the update predicted by equation (6) and the update estimated from the data assimilation, 1:1 line shown in black.

Simulations generated using the updated model show a considerably greater range than simulations generated using the original model (Figure 12). While the largest observations are underpredicted using both the original and updated models, the underprediction is considerably smaller for the updated model. The residuals of the updated model are more symmetrically distributed about the 1:1 line than the residuals for the original model. The differences in the simulations between the two models are analogous of the differences between models calibrated using different objective functions, for example calibrating to the NSE of untransformed or log-transformed streamflow, where calibrating to log-transformed streamflow will tend to better reflect simulation of low streamflow at the expense of high streamflows.

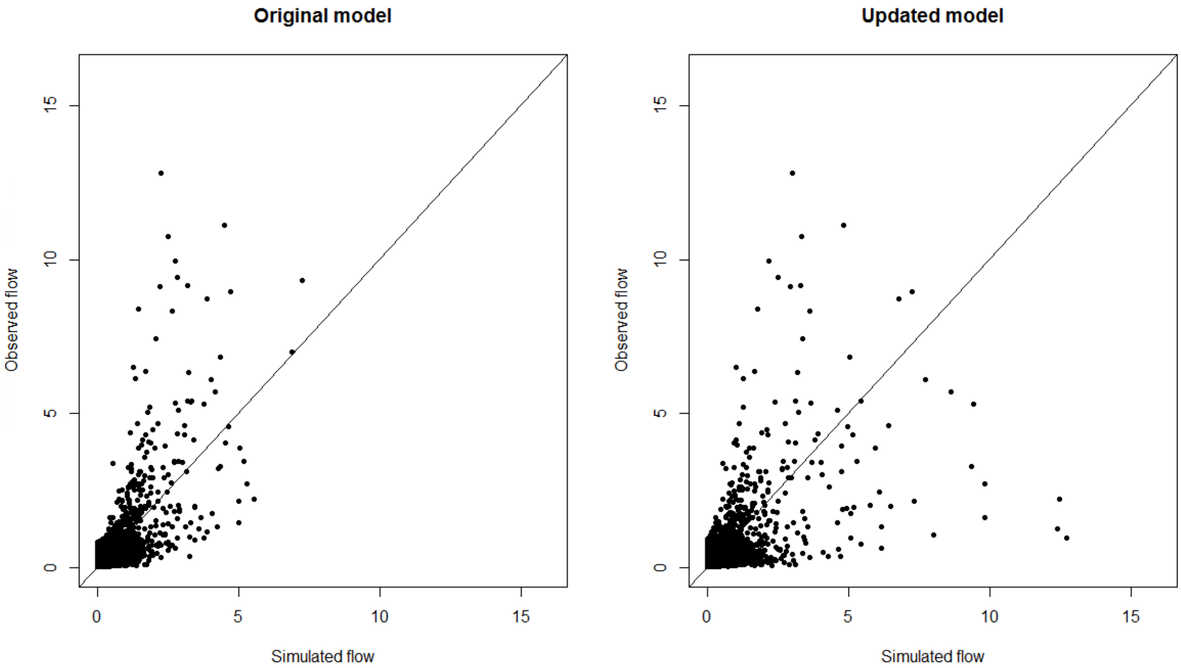

Figure 12 Relationship between simulated and observed flow for simulations generated using the original model (left panel) and updated model (right panel).

The ability of the updated model to produce simulations with a larger range than the original model results to the model displaying a greater sensitivity to changes in rainfall forcing (Figure 13). For a 10% reduction in mean annual rainfall, achieved by scaling all rainfall observations by a factor of 0.9, the original model predicted a reduction in mean annual runoff of 22%, while the updated model predicted a reduction of 25%. This represents an 12% increase in the sensitivity of the model predictions to changes in rainfall.

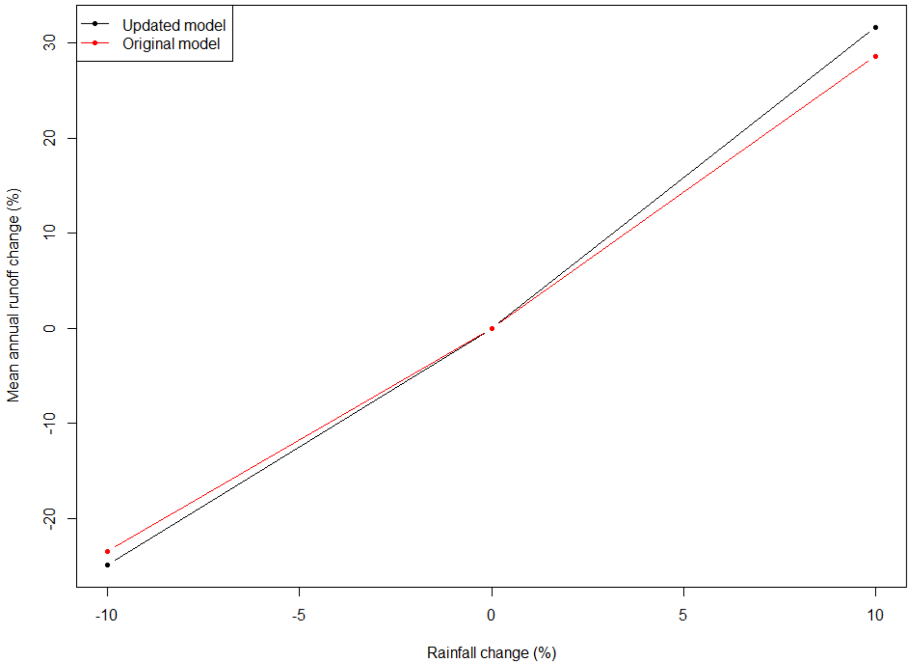

Figure 13 Sensitivity of mean annual runoff simulations to rainfall changes for the original (red) and updated (black) models.

When DAISI is applied to all the HRS catchments in the MDB it produces models that are more sensitive to rainfall declines than the original SimHyd model in more than 50% of catchments (Figure 14). Slightly more than one third of the catchments show an increase in sensitivity of mean annual runoff to rainfall reductions of more than 5%, with very large increases (>50%) in sensitivity occur in approximately 5% of catchments. Decreases in sensitivity of mean annual runoff to rainfall declines also occur, with a maximum reduction in sensitivity of approximately 30%. These results are consistent with the findings of Lerat et al. (2024), who found both that the application of DAISI could lead to both increases and decreases in the simulated elasticity of runoff to rainfall, and the relative proportion of increases and decreases depended on the objective function used for calibrating the original hydrological model.

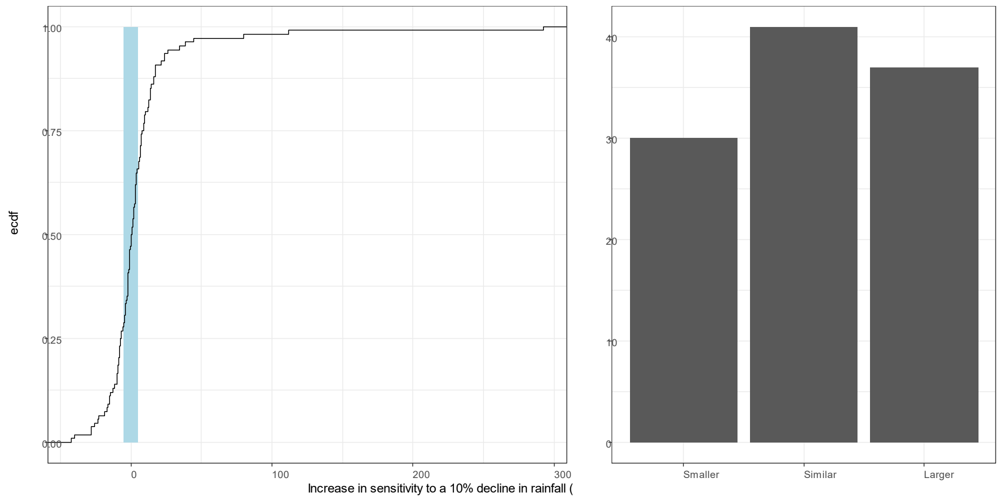

Figure 14 Increase in sensitivity of mean annual runoff to a 10% decline in rainfall of updated model simulations relative to the original model simulations. Similar sensitivity is assumed with the percentage change in mean annual runoff is within 5% of the original model.

3.4 Discussion

In this section, we have demonstrated that the DAISI approach can be used to modify an existing daily rainfall-runoff model in addition to the monthly rainfall-runoff models that were used to develop the approach (Lerat et al., 2024). For our demonstration, we adopted the SimHyd model as earlier analysis indicated that it displayed the lowest sensitivity of mean annual runoff to rainfall changes and that projected changes were most sensitive to calibration period. This suggested that DAISI was more likely to be able to improve the predictions of the SimHyd model.

The application of DAISI to the daily SimHyd model for the HRS catchments produced simulations of mean annual runoff with different sensitivities to changes in rainfall to the original SimHyd model. In slightly more than 50% of catchments the sensitivity of mean annual runoff to decreases in rainfall was found to increase, with increases in sensitivity of more than 50% occurring in 5% of catchments. Where the application of DAISI leads to changes in the sensitivity of mean annual runoff change to rainfall change, the configuration of the base SimHyd rainfall-runoff model would appear to be inadequately representing the rainfall-runoff processes in the catchment. Where DAISI increases the sensitivity of runoff change to rainfall changes, any runoff projections produced with the SimHyd model are likely to underestimate the impacts of climate change. Conversely, where DAISI decreases the sensitivity of runoff change to rainfall change, the runoff projections produced with SimHyd are likely to be overestimates. Our results indicate that, on-average across the catchments investigated, SimHyd projections do not systematically over- or underestimate the sensitivity of mean annual runoff to rainfall change, but for individual catchments, projections may be substantial over- or underestimates.

The DAISI approach to adapting hydrological models is a data driven method that directly updates the model state equations to generate simulations that better represent the catchment dynamics. As a result of the data driven nature of DAISI the corrections applied to the model state equations may be caused by hydrologic non-stationarity or simply by the inability of the existing model to adequately represent the processes driving the conversion of rainfall to runoff within a catchment. As the updates to the model state variables are applied within each time step, it is more likely that the cause of the updates will be the inability of the model to adequately represent the conversion of rainfall to runoff rather than longer-term processes related to hydrologic non-stationarity. However, there is potential to extend the current formulation of the updating equations to allow for parameterisations that vary with time or other forcing data, such as measures of vegetation cover, groundwater level or level of farm dam development, that could be more clearly support attribution of the cause of the state corrections and therefore enhancements to the model formulation. Such analysis was beyond the scope of this current study.

On applying DAISI to SimHyd we found that updating of only three of the SimHyd state equations produced updates that were statistically different to zero. The updates applied to the soilMoistureStore and groundwater store produce substantial corrections to the state variables that have an impact on streamflow predictions. Using the updated equations in SimHyd increased the range of predictions to better reflect the range of the observations but did not necessarily improve the correlation between model predictions and observations. The parameters for the updating models are estimated based on the difference between state values generated for a given time step from the data assimilation and the state values generated by the hydrological model's state equations, using the state values obtained from the data assimilation for the previous time step and the corresponding updated perturbed forcing. This parameter fitting process establishes updated models that improve model predictions for each time step given a good (updated) estimate of the state values for the previous time step and a good (updated) estimate of the forcing data. Therefore, if the updated estimates of the forcing data are different to the actual forcing, when modelling is undertaken using the actual forcing, predictions from the updated model may be poorer than those for the original model.

The current implementation of the DAISI approach assumes (i) the sequence of model state equations is appropriate, (ii) model limitations exist in the state equations, (iii) sufficient data can be generated to develop an updating model, and (iv) the second order polynomial corrections to the model state equations are appropriate. Each of these assumptions places limitations on the ability of DAISI to improve model predictions and choices need to be made on the nature of the updating equations that consider these assumptions. For example, the simulated runoff from the SimHyd model is the sum of three components: infiltration excess runoff, saturation excess runoff and baseflow runoff. We found that baseflow runoff was the dominant source of total simulated runoff for most catchments, and other sources of runoff only occurred for a small number of time steps, with zero values being returned for the majority of the time. State variables being constant for all but a few time steps leads to challenges in the data assimilation and also in the development of updating equations. The data assimilation requires an estimate of the covariance of all the state variables being updated and where state variables are constant for the majority of the time then the covariance is undefined or poorly defined. When establishing the updating models using predictor variables that are constant for the majority of time leads to the non-constant points having a very strong influence on the inferred parameters and large uncertainties in the parameter values. Therefore, we were unable to establish updating equations for directly updating the runoff components, but could only influence these indirectly through, for example, updating the state equation of the soilMoistureStore as that impacts both infiltration excess runoff and saturation excess runoff. Given the assumptions of the DAISI approach and the insights we have gained into its application, it may be better to start with simpler rainfall-runoff model structures and then use insights gained in implementing DAISI to increase model complexity.

There are many challenges in applying DAISI to daily rainfall-runoff models that may not exist when applying it to monthly models. Many hydrologic models have processes that introduce time lags into the rainfall-runoff response, for example the unit hydrograph in GR4J and the formulation of the cascade of two linear reservoirs in PDM. The output of state equations for these time lag processes are a function of inputs from multiple, and potentially a large number of, preceding time steps. State variable updating equations requires all the inputs as predictors. As a result, the number of parameters in the updating equation can become very large as the number of parameters increases with the square of the number of predictors. Establishing regression equations using large numbers of predictors, and parameters, can encounter issues with multiple co-linearity between predictors leading to large uncertainties in parameter estimates and therefore predictions. It is therefore preferable to apply DAISI to models that do not have state equations representing time lag processes dependent on multiple preceding time steps.

Applying DAISI to daily rainfall-runoff models also presents more complex numerical and computational challenges, particularly in the data assimilation step. The data assimilation step requires estimation of the covariances between the simulation state variables and streamflow observations. The size of these covariance matrices is proportional to the product of the number of time steps and number of updated state variables squared. Therefore, moving from a monthly time step to a daily time step increases the size of the covariance matrices by a factor of 900 (assuming a 30-day month) without considering difference in the number of model state variables. Using such large covariance matrices can create numerical instabilities in matrix operations, some of which can be resolved by matrix regularisation techniques, such as tapering of the covariance matrix applied in this study.

4 Concluding discussion

Hydrologic non-stationary is known to challenge hydrological analysis and modelling in the Murray-Darling Basin. Non-stationarities exist in both climate and streamflow data, manifesting as short- and long-term changes in the statistical properties of time series and in the relationship between variables, e.g. rainfall and runoff. The sources of these non-stationarities are wide ranging, but include global warming, vegetation change, water resources development activities, and interactions between changing surface and sub-surface processes, e.g. surface-groundwater interactions.

Many hydroclimate records, particularly streamflow observations, are relatively short, which places constraints on the ability to understand and differentiate low-frequency hydroclimate variability from many of the impacts of landscape change and water resources development. As a result, hydrological models, particularly those calibrated to historical streamflow observations, typically characterise hydrologic non-stationarities poorly. Nevertheless, there is a need to use hydrological models to generate projections of future water availability to support water resources planning and management. While there has been considerable research diagnosing non-stationarity in hydrological time series and simulations of rainfall-runoff models, there have been few assessments of the impacts of non-stationarity on runoff projections. This study has sought to provide insights into the likely impacts of hydrologic non-stationarity on runoff projections for the MDB.

To understand the potential impacts of hydrologic non-stationarity on the sensitivity of model simulations to changes in rainfall, we followed two lines of inquiry. The first inquiry investigates the sensitivity of runoff projections to the period used to calibrate conceptual rainfall-runoff models. The second inquiry investigates the extent to which an approach to adapt existing hydrological models to better reflect catchment rainfall-runoff process alters the model sensitivity of runoff to changes in rainfall.

We show that runoff projections are sensitive to the calibration period used to fit model parameters, indicating that different rainfall-runoff relationships exist for different periods in the historical record. The impact of calibration period on mean annual runoff tends to be smaller than metrics of annual high or low flows and hydrological drought. The range of projected changes in mean annual runoff was found to be less than 20% of the median change for 90% of the catchments investigated but could be as much as 50% of the projected median change. For example, if a projected change in rainfall leads to a 10% decrease in mean annual runoff, then allowing for the possibility of hydrologic non-stationarity would yield decreases in mean annual runoff that are in the range of 8%-12% based on 90% of catchments, or as much as 5%-15% considering the complete data set. We also find that projections from the GR4J rainfall-runoff model are less sensitive to calibration period than projections from the more complex PDM or SimHyd models.

We apply the DAISI approach, previously applied to monthly rainfall-runoff models, to adapt the daily SimHyd rainfall-runoff model to better simulate catchment rainfall-runoff processes. We find that the adapted SimHyd model produces runoff projections that are more sensitive changes in rainfall than the base SimHyd model for more than 50% of the catchments investigated. The sensitivity of runoff projections to rainfall changes increases substantially (by more than 50%) for approximately 5% of the catchments, while the sensitivity decreases by 5% - 30% for about 20% of the catchments. Our results indicate that, on-average across the catchments investigated, SimHyd projections do not systematically over- or underestimate the sensitivity of mean annual runoff to rainfall change, but for individual catchments, projections may be substantial over- or underestimates.

Overall, we find that runoff projections are sensitive to hydrologic non-stationarity. The sensitivity of runoff projections to hydrologic non-stationarity is spatially variable and model dependent. Projections generated using simpler hydrological models appear to be less sensitive to hydrologic non-stationarity, but it is well established that simpler models often are limited in their ability to simulate changes in hydrologic processes. Future research should pursue development of hydrological models that can better describe historical non-stationarities using simplified parameterisations which, based on our analysis should produce robust runoff projections.

5 References

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A.1 Appendix

This appendix presents additional results for section 2 for the SimHyd and PDM models.

A.1.1 PDM results

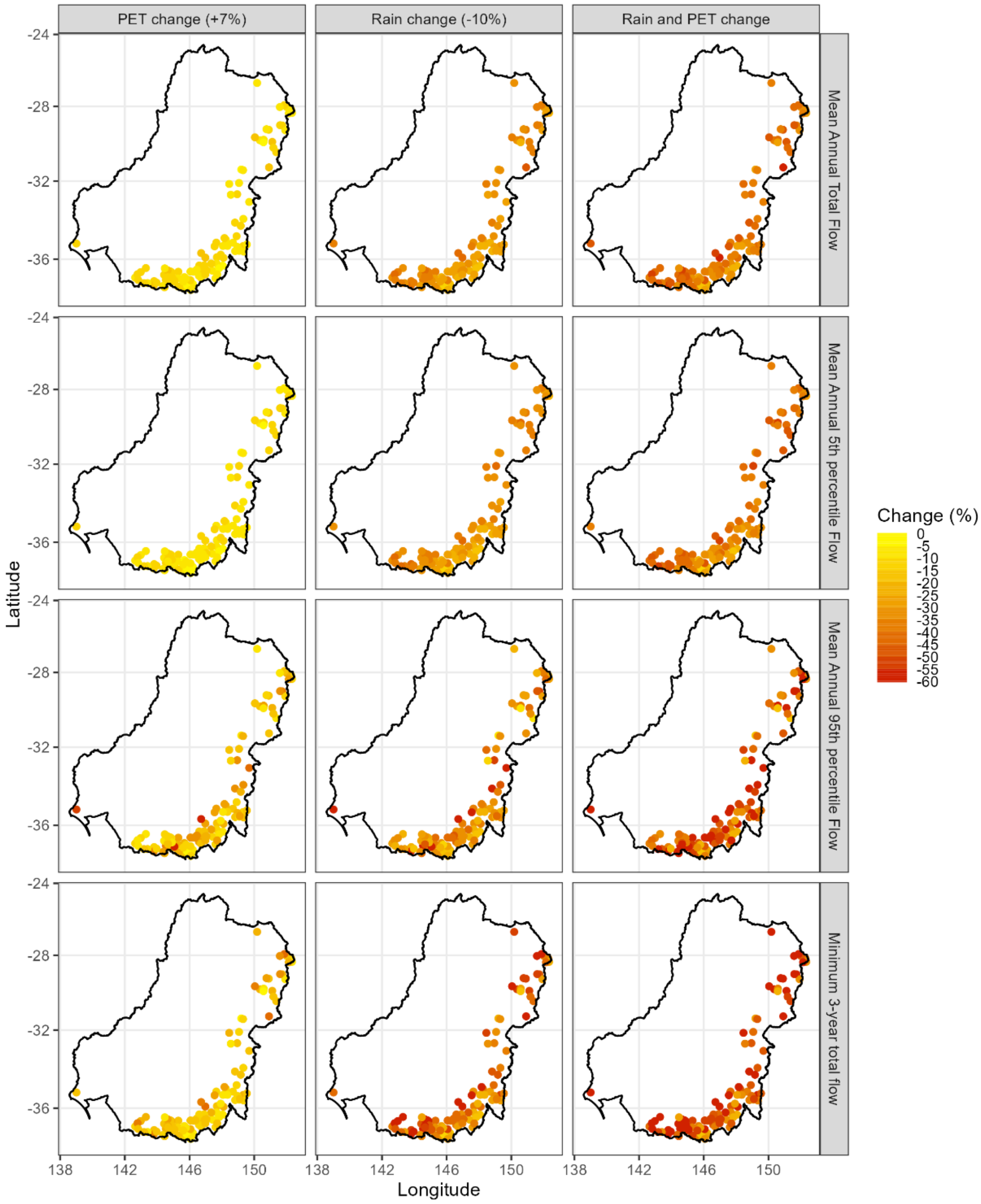

Figure 15 Median PDM projected changes in runoff metrics for the HRS catchments for three climate change scenarios. Median change is computed across the different calibration periods.

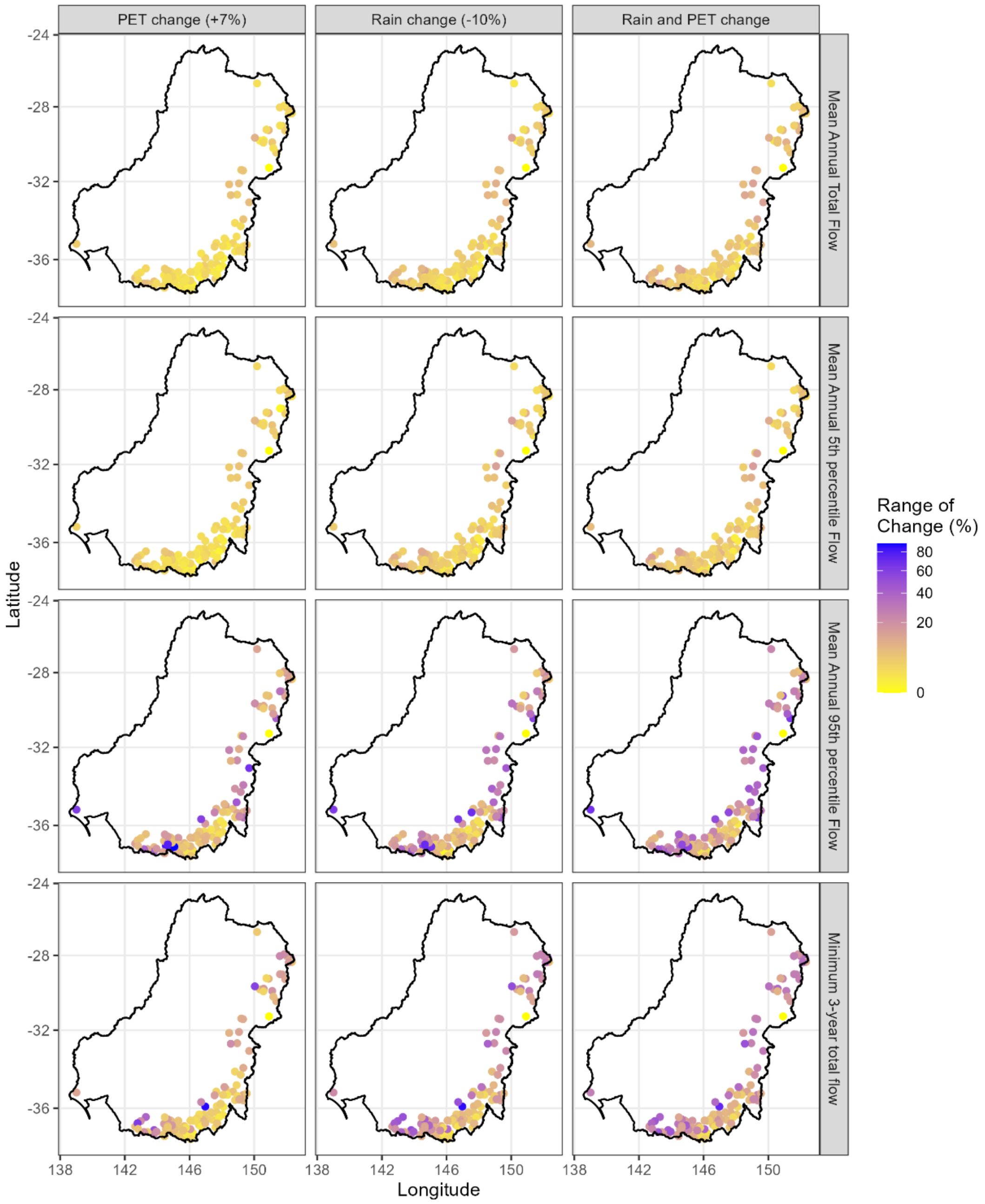

Figure 16 Sensitivity of PDM runoff projections to calibration period for the HRS catchments for three climate change scenarios. For each point the range represents the difference between the high and lowest percentage change in the runoff metric arising from using different periods to calibrate the hydrological models.

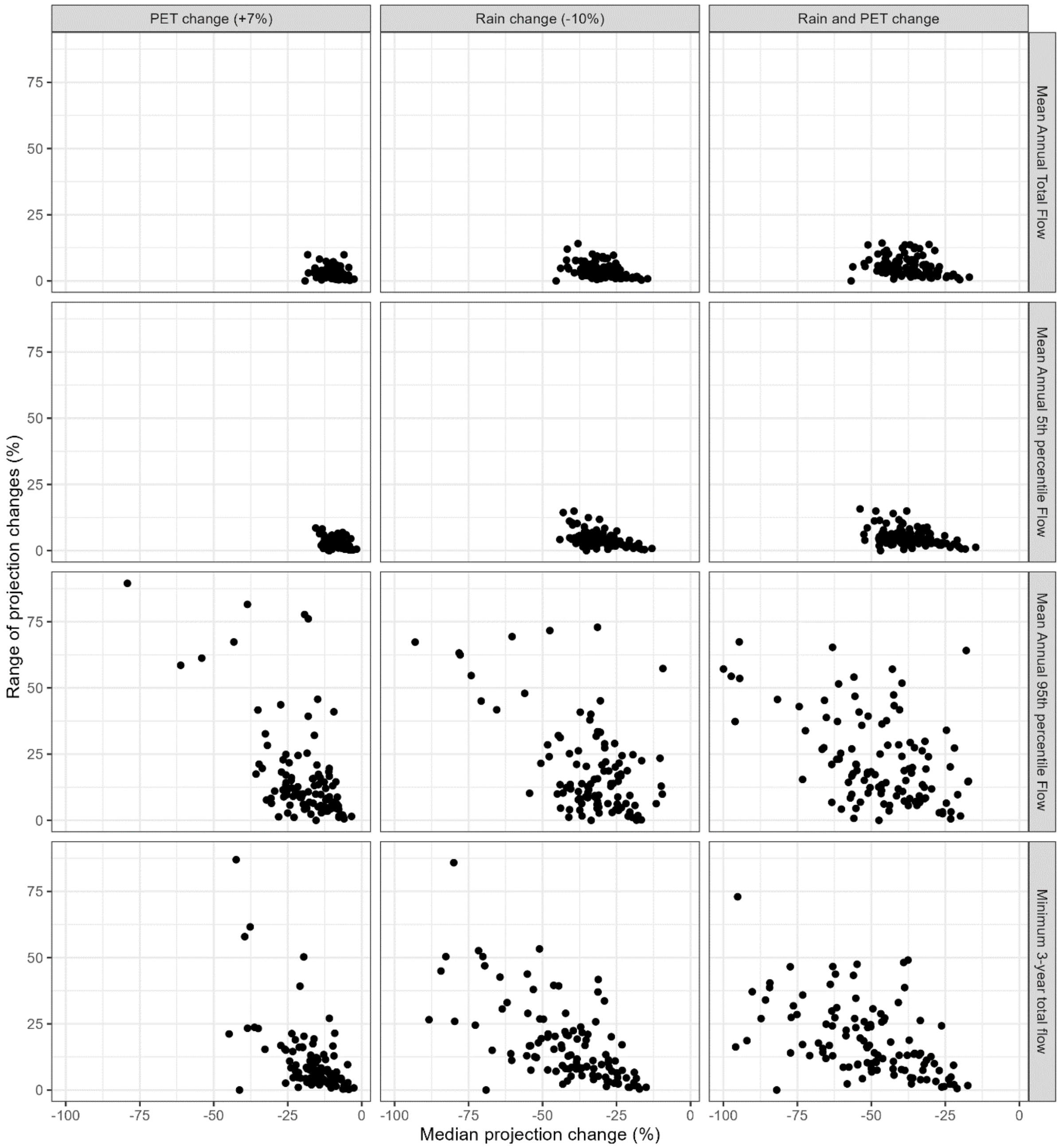

Figure 17 Relationship between median and range of changes in runoff metrics for PDM projections for three climate change scenarios. The distributions summarised by the median and range arise from using different periods to calibrate the rainfall-runoff model.

A.1.2 SimHyd Results

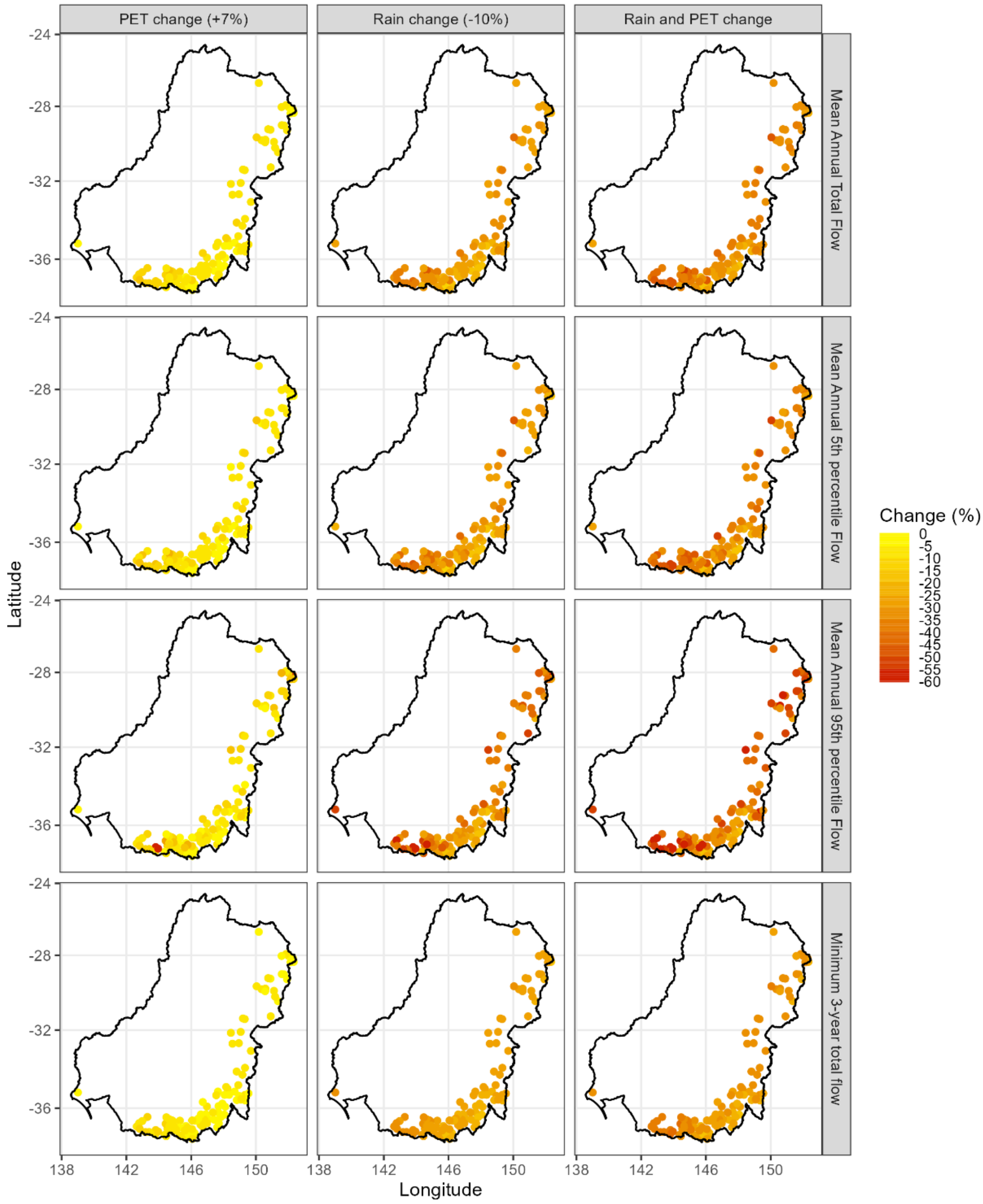

Figure 18 Median SimHyd projected changes in runoff metrics for the HRS catchments for three climate change scenarios. Median change is computed across the different calibration periods.

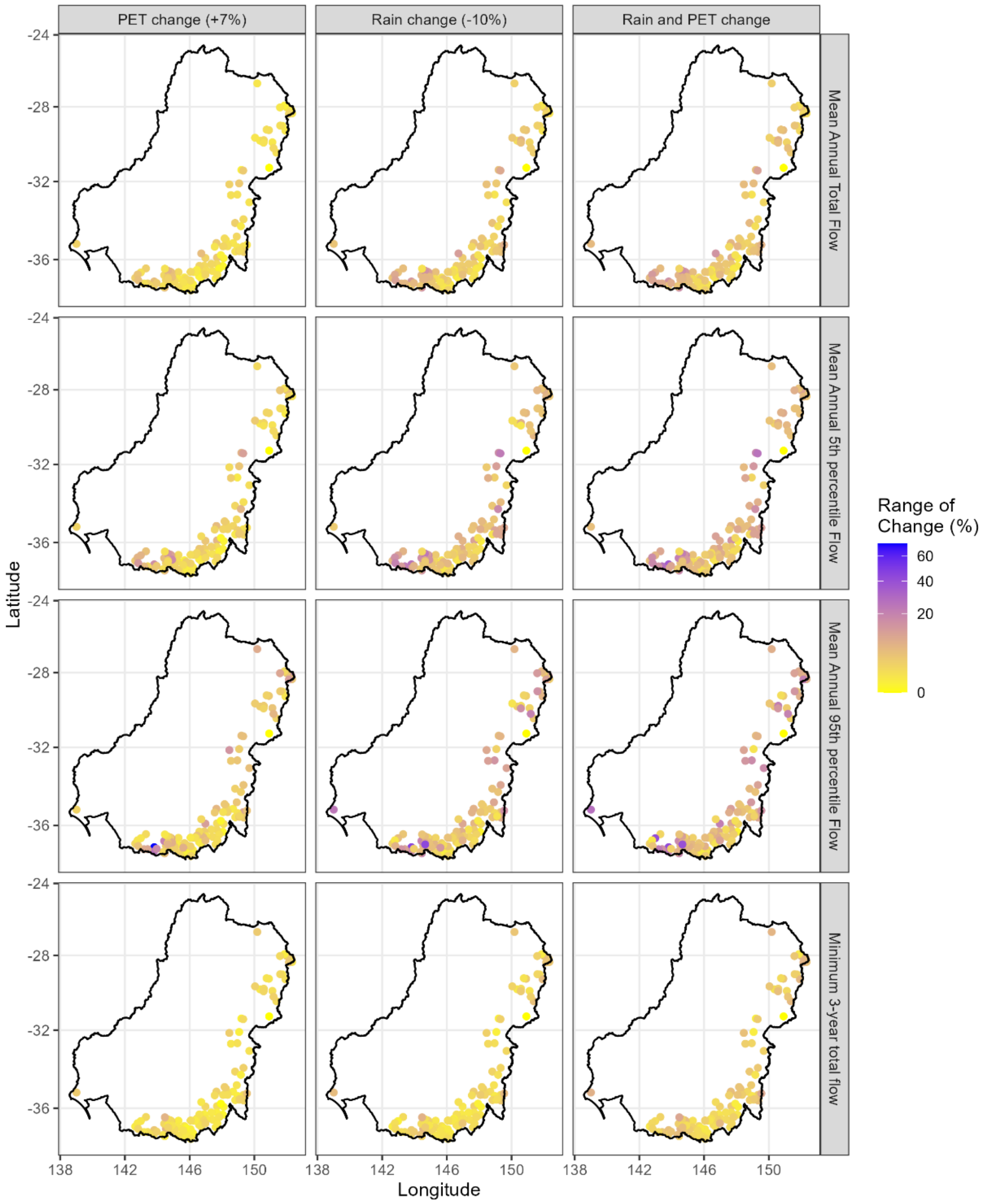

Figure 19 Sensitivity of SimHyd runoff projections to calibration period for the HRS catchments for three climate change scenarios. For each point the range represents the difference between the high and lowest percentage change in the runoff metric arising from using different periods to calibrate the hydrological models.

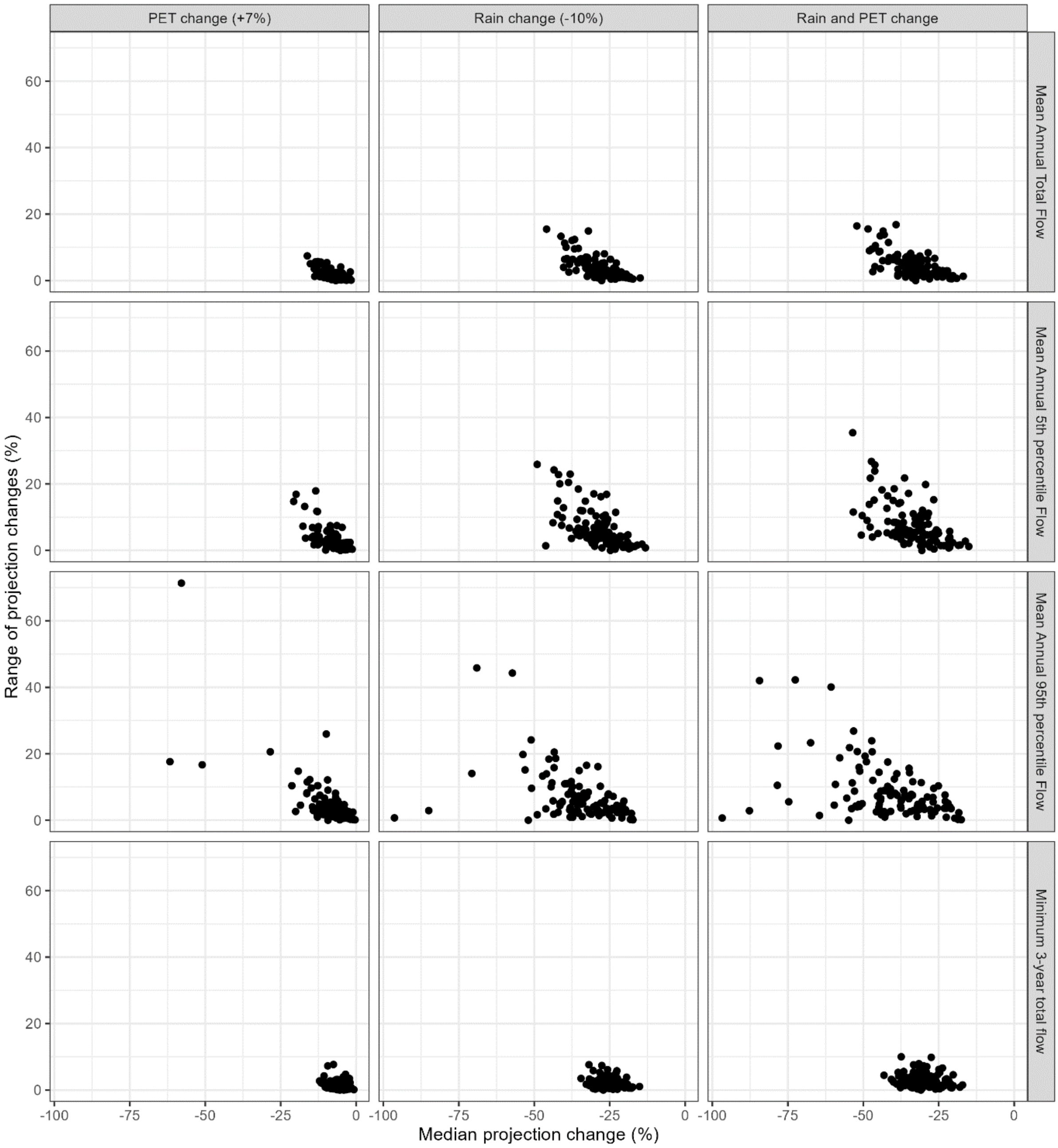

Figure 20 Relationship between median and range of changes in runoff metrics for SimHyd projections for three climate change scenarios. The distributions summarised by the median and range arise from using different periods to calibrate the rainfall-runoff model.

A.2 SimHyd model and its implementation

This appendix presents the full formulation of SimHyd model, a schematic is provided in Figure 21, followed by the full listing of the state equations and a table of model parameters that are adjusted during calibration (Table 2).

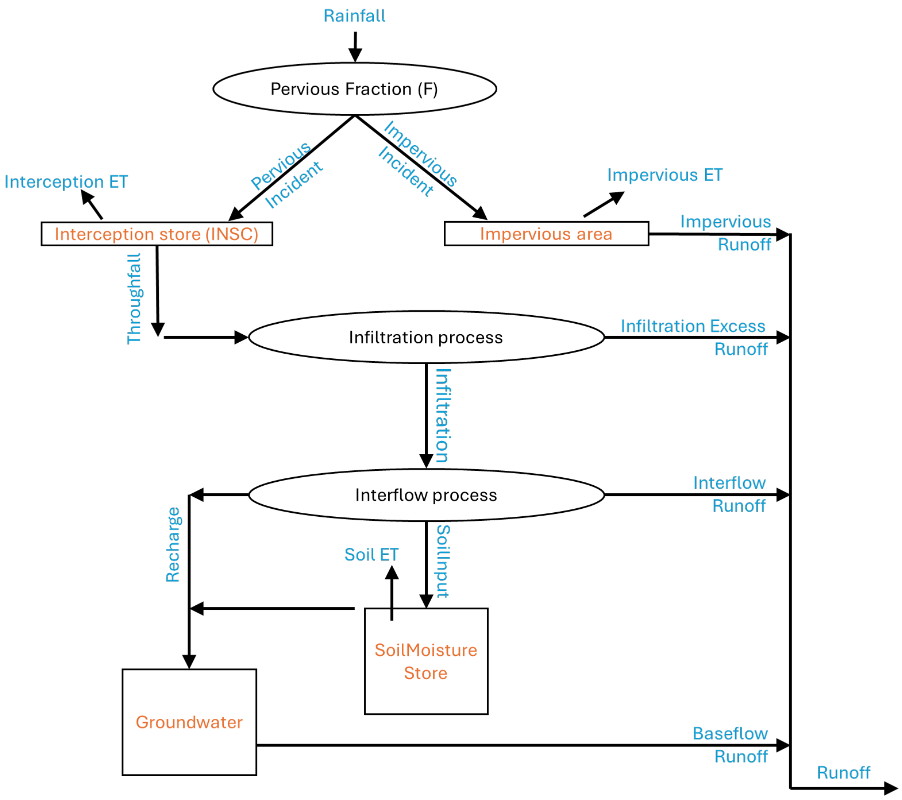

Figure 21 Schematic of the SimHyd model (Chiew et al., 2002)

Formulation of the SimHyd model state equations

$$imperviousET = \min(IMT, R)$$

$$imperviousRunoff = R - imperviousET$$

$$interceptionET = min(perviousIncident, E, INSC)$$

$$throughfall = max(0, P - interceptionET)$$

Infiltration process

$$infiltrationCapacity = F_p I_C exp\left(I_s.\frac{SMS}{SMSC}\right)$$

$$infiltration = min(throughfall, infiltrationCapacity)$$

$$infiltrationExcessRunoff = throughfall - infiltration$$

Interflow process

$$interflowRunoff = SUB.\frac{SMS}{SMSC}.infiltration$$

$$recharge = CRAK.\frac{SMS}{SMSC}.(infiltration - interflowRunoff)$$

$$soilInput = infiltration - interflowRunoff - recharge$$

$$baseflowRunoff = K.groundwater$$

Soil moisture process

$$soilET = min\left(soilMoistureStore, \min\left(E - interceptionET, 10.0\frac{SMS}{SMSC}\right)\right)$$

$$SMSChange = soilInput - soilET$$

$$groundwaterChange = \begin{cases} recharge - baseflowRunoff & if\ SMS + SMSChange < SMSC \\ recharge - baseflowRunoff + SMSChange & otherwise \end{cases}$$

$$SMS = max(SMS + SMSChange, SMSC)$$

$$groundwater = groundwater + groundwaterChange$$

$$runoff = (1 - F).imperviousRunoff + F.(infiltrationExcessRunoff + interflowRunoff + baseflowRunoff)$$

Table 2 SimHyd parameters

	Symbol	Default value	Minimum	Maximum
PerviousFraction	F	NA	0	1
BaseflowCoefficient	K	0.3	0	1
ImperviousThreshold	IMT	1	0	5
InfiltrationCoefficient	I_C	200	0	400
InfiltrationShape	I_s	3	0	10
InterflowCoefficient	SUB	0.1	0	1
PerviousFraction	F_p	0.9	0	1
InterceptionStoreCapacity	$INSC$	1.5	0	5
RechargeCoefficient	$CRAK$	0.2	0	1
SoilMoistureStoreCapacity	$SMSC$	320	1	500

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