Hydrol. Earth Syst. Sci. Discuss., https://doi.org/10.5194/hess-2019-6
Manuscript under review for journal Hydrol. Earth Syst. Sci.
Discussion started: 4 February 2019

Hydrology and Earth System Sciences
Discussions
Open Access

Improving hydrological projection performance under contrasting climatic conditions using spatial coherence through a hierarchical Bayesian regression framework

Zhengke Pan[a,b], Pan Liu[a,b,*], Shida Gao[a,b], Jun Xia [a,b,c], Jie Chen [a,b], Lei Cheng [a,b]

[a]State Key Laboratory of Water Resources and Hydropower Engineering Science, Wuhan University, Wuhan 430072, China

[b]Hubei Provincial Collaborative Innovation Center for Water Resources Security, Wuhan 430072, China

[c]Chinese Academy of Sciences, Beijing 100864, China

*Corresponding author. Email: liupan@whu.edu.cn; Tel: +86-27-68775788; Fax: +86-27-68773568

Hydrol. Earth Syst. Sci. Discuss., https://doi.org/10.5194/hess-2019-6
Manuscript under review for journal Hydrol. Earth Syst. Sci.
Discussion started: 4 February 2019

Hydrology and Earth System Sciences
Discussions

ABSTRACT

Understanding the projection performance of hydrological models under contrasting climatic conditions supports robust decision making, which highlights the need to adopt time-varying parameters in hydrological modeling to reduce the performance degradation. Many existing literatures model the time-varying parameters as functions of physically-based covariates; however, a major challenge remains finding effective information to control the large uncertainties that are linked to the additional parameters within the functions. This paper formulated the time-varying parameters for a lumped hydrological model as explicit functions of temporal covariates and used a hierarchical Bayesian (HB) framework to incorporate the spatial coherence of adjacent catchments to improve the robustness of the projection performance. Four modeling scenarios with different spatial coherence schemes, and one scenario with a stationary scheme for model parameters, were used to explore the transferability of hydrological models under contrasting climatic conditions. Three spatially adjacent catchments in southeast Australia were selected as case studies to examine validity of the proposed method. Results showed that (1) the time-varying function improved the model performance but also amplified the projection uncertainty compared with stationary setting of model parameters; (2) the proposed HB method successfully reduced the projection uncertainty and improved the robustness of model performance; and (3) model parameters calibrated over dry periods were not suitable for predicting runoff over wet periods because of a large degradation in projection performance. This study improves our understanding of the spatial coherence of time-varying parameters, which will help improve the projection performance under differing climatic conditions.

Keywords: Climate change; Hierarchical Bayesian; Hydrological model parameters; Spatial coherence; Streamflow projection; Contrasting climatic conditions

Hydrol. Earth Syst. Sci. Discuss., https://doi.org/10.5194/hess-2019-6
Manuscript under review for journal Hydrol. Earth Syst. Sci.
Discussion started: 4 February 2019

1. INTRODUCTION

Long-term streamflow projection is an important part of effective water resources planning because it can predict future scarcity in water supply and help prevent floods. Streamflow projections typically involve the following: (i) calibrating hydrological model parameters with partial historical observations (e.g., precipitation, evaporation and streamflow); (ii) projecting streamflow under periods that are outside of those for model calibration; and (iii) evaluating the model projection performance with certain criteria. One of the most basic assumptions of this process—that the calibrated model parameters are stationary and can be applied to predict catchment behaviors in the near future, has been widely questioned (Brigode et al., 2013;Broderick et al., 2016;Chiew et al., 2014;Chiew et al., 2009;Ciais et al., 2005;Clarke, 2007;Cook et al., 2004;Coron et al., 2012;Deng et al., 2016;Merz et al., 2011;Moore and Wondzell, 2005;Moradkhani et al., 2012;Moradkhani et al., 2005;Pathiraja et al., 2016;Pathiraja et al., 2018;Patil and Stieglitz, 2015;Westra et al., 2014;Xiong et al., 2019;Zhang et al., 2018).

Many previous studies have explored the transferability of stationary parameters to periods with different climatic conditions. They have concluded that hydrological model parameters are sensitive to the climatic conditions of the calibration period (Chiew et al., 2014;Chiew et al., 2009;Coron et al., 2012;Merz et al., 2011;Renard et al., 2011;Seiller et al., 2012;Vaze et al., 2010). For instance, Merz et al. (2011) calibrated model parameters using six consecutive 5-year periods between 1976 and 2006 for 273 catchments in Austria and found that the calibrated parameters representing snow and soil moisture processes showed significant trend in the study

Hydrol. Earth Syst. Sci. Discuss., https://doi.org/10.5194/hess-2019-6
Manuscript under review for journal Hydrol. Earth Syst. Sci.
Discussion started: 4 February 2019

area. Other studies have found that degradation in model performance was directly related to the difference in precipitation between calibration and verification periods (Coron et al., 2012;Vaze et al., 2010). One proposal for managing this problem is to calibrate model parameters in periods with similar climatic conditions to the near future, but future streamflow observations are unavailable. Thus, it is still necessary to reduce the magnitude of performance loss and improve the robustness of the projection performance using calibrated parameters based on the historical records, even though the climatic conditions in the future may be dissimilar to those used for model calibration.

Several recent studies have found that hydrological models with time-varying parameters exhibited a significant improvement in its projection performance compared with the stationary parameters (Deng et al., 2016;Deng et al., 2018;Westra et al., 2014). The functional method is one of the most promising ways to model time-varying parameters and shows its excellence in improving the model projection performance (Guo et al., 2017;Westra et al., 2014;Wright et al., 2015). This method models the time-varying parameter(s) as function(s) of physically-based covariates (e.g., temporal covariate and Normalized Difference Vegetation Index). Generally, the hydrological model is run with various assumed functions, the best functional forms of time-varying parameters can be obtained by comparing the evaluation criteria. However, a major challenge for the application of the functional method remains finding effective information to control the large uncertainties that are linked to the additional parameters describing these regression functions.

Hydrol. Earth Syst. Sci. Discuss., https://doi.org/10.5194/hess-2019-6
Manuscript under review for journal Hydrol. Earth Syst. Sci.
Discussion started: 4 February 2019

Similarity of adjacent catchments, has been verified its validity in controlling the estimation uncertainty of model parameters (Bracken et al., 2018;Cha et al., 2016;Cooley et al., 2007;Lima and Lall, 2009;Najafi and Moradkhani, 2014;Sun and Lall, 2015;Sun et al., 2015;Yan and Moradkhani, 2015). The level of similarity of different catchments is known as spatial coherence. For instance, Sun and Lall (2015) used the spatial coherence of trends in annual maximum precipitation in the United States, and successfully reduced the parameter estimation uncertainty in their at-site frequency analysis. In general, there are three methods to consider the spatial coherence between different catchments in parameter estimation, i.e., no pooling, complete pooling and hierarchical Bayesian (HB) framework (also known as partial pooling). In these three approaches, the HB framework has been proved as the most efficient method to incorporate the spatial coherence to reduce the estimation uncertainty because it has the advantage of shrinking the local parameter toward the common regional mean and including an estimation of its variance or covariance across the catchments (Bracken et al., 2018;Sun and Lall, 2015;Sun et al., 2015). In the field of hydrological modeling, most proceeding literatures were focused on no pooling models that neglect the spatial coherence between catchments (Heuvelmans et al., 2006;Lebecherel et al., 2016;Merz and Bloschl, 2004;Oudin et al., 2008;Singh et al., 2012;Tegegne and Kim, 2018;Xu et al., 2018); little attention has been paid to the HB framework. Thus, we want to fill this gap and explore the applicability of the spatial coherence through the HB framework in hydrological modeling with the time-varying parameters.

The objectives of this paper were to: (1) verify the effect of the time-varying model parameter scheme on model projection performance and uncertainty analysis compared with stationary model parameters; (2) verify the projection performance of considering spatial coherence of adjacent catchments through the HB framework compared with spatial incoherence; and (3) compare the model projection performance for different climatic transfer schemes.

This paper is organized as follows. Section 2 introduces the differential split sample test (DSST) for segmenting the historical series, the hydrological model, and the two-level HB framework for incorporating spatial coherence from adjacent catchments. Section 3 provides a case study of the proposed methodology for improving hydrological projection performance under contrasting climatic conditions. Section 4 summarizes the main conclusions of the study.

2. METHODOLOGY

The methodology is outlined by a flowchart in Figure 1, and is summarized as follows:

(1) A temporal parameter transfer scheme is implemented (described in section 2.1) using a classic DSST procedure in which the available data are divided into non-dry and dry periods;

(2) A daily conceptual rainfall-runoff model is used (outlined in section 2.2);

(3) A two-level HB framework is used to incorporate spatial coherence in hydrological modeling (described in section 2.3). The data level (first level) of the framework models the temporal variation in the model parameters using a time-varying function, while the process level (second level) models the spatial coherence of the

Hydrol. Earth Syst. Sci. Discuss., https://doi.org/10.5194/hess-2019-6
Manuscript under review for journal Hydrol. Earth Syst. Sci.
Discussion started: 4 February 2019

regression parameters in the time-varying function. Four modeling scenarios with different spatial coherence schemes, and one scenario with a stationary scheme for the model parameter, are used to evaluate the transferability of hydrological models under contrasting climatic conditions;

(4) Likelihood function and parameter estimation methods are applied (outlined in section 2.4); and

(5) The criteria are used to evaluate the model performance for various model scenarios (described in section 2.5).

2.1 Differential split sampling test

To verify the projection performance of the rainfall-runoff model under contrasting climatic conditions (non-dry and dry periods), a classic DSST using annual rainfall records was adopted.

2.1.1 Dry period identification

Two separate tasks were needed to develop the DSST method into a working system. The first step was to define the "dry period". The method to define the dry period is adopted from Saft et al. (2015), and is a rigorous identification method that treats autocorrelation in the regression residuals, undertakes global significance testing, and defines the start and end of the droughts individually for each catchment. In the second step, the non-dry period was defined as the complement of the dry period in the historical records. A similar approach to define the dry and non-dry periods was used by Fowler et al. (2016).

2.1.2 Verification method

In the DSST method, the model parameters calibrated in the non-dry period were evaluated in the dry period, and vice versa. The projection performance of the calibrated parameters for different transfer schemes was evaluated using the criteria illustrated in section 2.5.

2.2 The rainfall-runoff model

The hydrological model used in this study is the GR4J (modèle du Génie Rural à 4 paramètres Journalier), which is a lumped conceptual rainfall-runoff model (Perrin et al., 2003). The original version of the GR4J model (Figure 2) comprised four parameters (Perrin et al., 2003): production store capacity (θ_1 mm), groundwater exchange coefficient (θ_2 mm), 1-day-ahead maximum capacity of the routing store (θ_3 mm), and the time base of the unit hydrograph (θ_4 days). More details on the GR4J model can be found in Perrin et al. (2003).

The GR4J model is a parsimonious, but efficient model. The model has been used successfully across a wide range of hydro-climatic conditions across the world, including the crash testing of model performance under contrasting climatic conditions (Coron et al., 2012), and the simulation of runoff for revisiting the deficiency in insufficient model calibration (Fowler et al., 2016). In addition, Fowler et al. (2016) verified that conceptual rainfall-runoff models were more capable under changing climatic conditions than previously thought. These characteristics make the GR4J particularly suitable as a starting point for implementing modifications and/or improving predictive ability under changing climatic conditions.

2.3 The HB framework for the time-varying model parameter

In this study, various versions were constructed for evaluating the projection capabilities of models for contrasting climatic conditions (non-dry and dry periods), and for considering the temporal variation and spatial coherence of parameter θ_1.

2.3.1 Data level: temporal variation of the model parameter

As described in the literature (Perrin et al., 2003;Renard et al., 2011;Westra et al., 2014), the parameter θ_1, which represents the primary storage of water in the catchment, is the most sensitive parameter in the GR4J model structure, and stochastic variations of this parameter have the largest impact on model projection performance (Renard et al., 2011;Westra et al., 2014). In addition, the temporal variation in the catchment storage capacity was physically interpretable. Periodic variations in the production store capacity θ_1 can be induced by the periodicity in precipitation and in seasonal vegetation growth and senescence. In the present study, θ_1 was constructed to account for the periodical variation that had a significant impact on the extensionality of the model. The periodical variation in catchment storage capacity θ_1 is described by a sine function, using amplitude and phase.

Thus, for any catchment *c*, the full temporal regression function for θ_1 at the data level is:

Data lever: $$\theta_1(\mathrm{c}) = \alpha(\mathrm{c}) + \beta(\mathrm{c})\sin\left[\omega(\mathrm{c})t\right] \quad (1)$$

where α, β, ω are regression parameters for the specific DSST method, and α signifies the intercept, and $\{\beta, \omega\}$ represents the amplitude and phase of the sine function, respectively. If model parameter θ_1 is constant then α=β=ω=0 suffices in Eq.1 and the resulting model simplifies to a stationary hydrological model.

2.3.2 Process level: spatial coherence of regression parameters

For a heterogeneous region that is distinctly non-uniform in climatic and geologic conditions, different catchments within the region typically have different catchment storage capacities and different values of production store capacity θ_1. For a homogeneous region prescribed by similar climatic and geologic conditions in each part, the production store capacity (in Eq. 2) is expected to the same among different catchments of the region. The model could be improved by considering spatial input, i.e., the spatial coherence of parameters across adjacent catchments (Chen et al., 2014;Lima et al., 2016;Merz and Bloschl, 2004;Oudin et al., 2008;Patil and Stieglitz, 2015;Renard et al., 2011;Sun et al., 2014).

At the process level, independent Gaussian prior distributions were used for the regression parameters $\{\beta,\omega\}$ as follows:

Process level:
$$\beta(\mathrm{c}) = N\left(\mu_2, {\sigma_2}^2\right)$$
$$\omega(\mathrm{c}) = N\left(\mu_3, {\sigma_3}^2\right) \qquad (2)$$

where μ_2, μ_3, σ_2 and σ_3 are hyper-parameters, and $N(.)$ represents the hyper-distribution, i.e., a Gaussian distribution. Independent Gaussian distributions were assumed for the regression parameters $\{\beta,\omega\}$ that were used to model spatial coherence based on practical considerations. The process level of the HB framework aims to describe the variation of $\{\beta,\omega\}$ in space by means of a Gaussian spatial process in which the mean value depends on covariates describing regional characteristics. Regression parameters β and ω are the most important parameters in the regression function and can reflect the spatial connection of variation and cyclicity of catchment production storage capacity among catchments. A similar setting was made in Sun and Lall (2015) and Sun et al. (2015).

2.3.3 Modeling scenarios

Five modeling scenarios (Table 1) were carried out to assess the effect of spatial coherence on the time-varying function. Different levels of spatial coherence of $\{\beta, \omega\}$ were assumed in scenarios 1 to 4, while in scenario 5 parameter θ_1 was set to be constant to provide a comparison.

2.4 Estimation and projection

The objective function and parameter inference methods were used to derive the posterior distribution of all unknown quantities, as illustrated below.

2.4.1 Likelihood function

For a specific catchment, the model parameters were calibrated to minimize the following objective function, which was adopted from Coron et al. (2012).

$$\varepsilon_c = -RMSE\left[\sqrt{Q}\right]\left(1+\left|1+BIAS\right|\right) \quad (3)$$

where

$$RMSE\left[\sqrt{Q}\right] = \sqrt{\frac{1}{T}\sum_{t=1}^{T}\left[Q_{sim}(t)-Q_{obs}(t)\right]^2} \quad (4)$$

and $RMSE\left[\sqrt{Q}\right]$ refers to the root-mean-square error.

Coron et al. (2012) showed that this objective function performed well. In this function, the combination of $RMSE\left[\sqrt{Q}\right]$ and $BIAS$ (Eq.7) gives weight to dynamic representation as well as the water balance. Using square-root-transformed flows to compute the RMSE reduces the influence of high flows during the calibration period and provides a good compromise between alternative criteria.

In the case of multiple catchments, the objective function of the HB framework was written as follows:

$$\Lambda = \prod_{c=1}^{C} \varepsilon_c \bullet \prod_{n=1}^{2} f_N\left(\beta, \omega \middle| \mu_2, \sigma_2, \mu_3, \sigma_3\right) \quad (5)$$

where the number of catchments in the region is represented by C, and the Gaussian spatial function between regression parameters β, ω and hyper-parameters μ_2, μ_3, σ_2 and σ_3 are denoted by $f_N()$.

2.4.2 Inference

The likelihood functions defined in Eqs. 3 and 5 pose a computational challenge because their dimensionality grows (primarily related to the number of catchment-specific parameters) with the number of catchments considered. The unknown parameters are estimated using the Shuffled Complex Evolution Metropolis (SCEM-UA) sampling method (Ajami et al., 2007;Vrugt et al., 2003;Vrugt et al., 2009), which is a widely used Markov Chain Monte Carlo algorithm for simulating the posterior probability distribution of parameters that are conditional on the current choice of parameters and data. When compared with traditional Metropolis-Hasting samplers, the SCEM-UA algorithm more efficiently reduces the number of model simulations needed to infer the posterior distribution of parameters, (Ajami et al., 2007;Duan et al., 2007;Liu et al., 2014;Liu and Gupta, 2007;Vrugt et al., 2003). Convergence is assessed by evolving three parallel chains, while verifying that the posterior distribution of parameters results in a value smaller than a Gelman-Rubin convergence value of 1.2

Hydrol. Earth Syst. Sci. Discuss., https://doi.org/10.5194/hess-2019-6
Manuscript under review for journal Hydrol. Earth Syst. Sci.
Discussion started: 4 February 2019

(Gelman et al., 2013).

2.5 Model performance criteria

Three criteria were used to assess the projection performance for the verification periods.

(1) The first criterion was NSE_{sqrt}, known as the arithmetic square root of Nash-Sutcliffe Efficiency (Coron et al., 2012;Moriasi et al., 2007;Nash and Sutcliffe, 1970). When compared with the classic NSE, NSE_{sqrt} gives an intermediate, more balanced picture of the overall hydrograph fit because it can reduce the influence of high flow. It is expressed as:

$$NSE_{sqrt} = 1 - \frac{\sum_{t=1}^{T}\left[\sqrt{Q_{obs}(t)} - \sqrt{Q_{sim}(t)}\right]^2}{\sum_{t=1}^{T}\left[\sqrt{Q_{obs}(t)} - \sqrt{\overline{Q}_{obs}}\right]^2} \tag{6}$$

where $Q_{sim}(t)$ and $Q_{obs}(t)$ represent the simulated and observed daily streamflow values for the t^{th} day, respectively; $\overline{Q}_{obs}$ is the mean of the observed daily streamflow for the calculation interval; and T refers to the length of the calculation period.

(2) The second criterion is the BIAS, which is a part of the objective function.

$$BIAS = \frac{\sum_{t=1}^{T}\left[Q_{sim}(t) - Q_{obs}(t)\right]}{\sum_{t=1}^{T}\left[Q_{obs}(t)\right]} \tag{7}$$

(3) The third criterion is the Deviance information criterion (DIC), which was defined by Spiegelhalter et al. (2002). It is a widely used and popular measure designed for Bayesian model comparison and is a Bayesian alternative to the standard Akaike Information Criterion. The DIC value for a Bayesian scenario is obtained as:

Hydrol. Earth Syst. Sci. Discuss., https://doi.org/10.5194/hess-2019-6
Manuscript under review for journal Hydrol. Earth Syst. Sci.
Discussion started: 4 February 2019

$$DIC = -2\log\left(p\left(q\middle|\theta_{Bayes},\xi\right)\right) + 2p_{DIC} \tag{8}$$

where p_{DIC} is the effective number of parameters, defined as

$$p_{DIC} = 2\left(\log\left(p\left(q\middle|\theta_{Bayes},\xi\right)\right) - \frac{1}{S}\sum_{s=1}^{S}\log\left(p\left(q\middle|\theta^{s},\xi\right)\right)\right) \tag{9}$$

where posterior mean $\theta_{Bayes} = \text{Expect}\left(\theta\middle|q,\xi\right)$ and s=1,…,S, means the sequence number of the simulated parameter set θ^{s} by the adopted SCEM-UA algorithm. According to Spiegelhalter et al. (2002), scenarios with smaller DIC would be preferred to scenarios with larger DIC.

3. CASE STUDY

3.1 Study area and data

To evaluate the model performance, we used daily precipitation (mm/day), evapotranspiration (mm/day), and streamflow (mm/day) time series records for three unregulated and unimpaired catchments in south-eastern Australia, taken from the national dataset of Australia (Zhang et al., 2013), covering 1976–2011. The streams were unregulated: they were not subject to dam or reservoir regulations, which can reduce the impact of human activity. The observed streamflow record contained at least 11835 daily observations (equivalent to a record integrity of greater than 90%) for 1976–2011, with acceptable data quality. The first complete year of data was used for model warm-up to reduce the impact of the initial soil moisture conditions during the calibration period.

The attributes of the south-eastern Australian catchments are shown in Table 2 and Figure 3. The IDs of these catchments are 225219 (Glencairn station on the Macalister

River: mean annual rainfall, potential evapotranspiration, and runoff are 1064 mm, 1142 mm, and 350 mm, respectively), 405219 (Dohertys station on the Goulburn river: mean annual rainfall, potential evapotranspiration, and runoff are 1169 mm, 1193 mm, and 422 mm, respectively), and 405264 (D/S of Frenchman Ck Jun station on the Big river: mean annual rainfall, potential evapotranspiration, and runoff are 1406 mm, 1157 mm, and 469 mm, respectively). These catchments are adjacent to each other and satisfy the homogeneity assumption. All catchments experienced a severe multiyear drought around the end of the millennium. Saft et al. (2015) identified that the rainfall-runoff relationship in these catchments was altered during the long-term drought.

3.2 Results and discussion

Results from the DSST were used to assess the model projection performance for five scenarios under contrasting climatic conditions. First, a DSST was conducted in each catchment to divide original records into non-dry and dry periods. Then, the projection performance for the five scenarios and associated parameter uncertainties were evaluated using the criteria described above.

3.2.1 Dry period identification

As illustrated in Table 3 and Figure 4, the drought definition method identified that the three catchments had similar dry period characteristics, with the same drought start (1997) and end (2009) points. The mean dry period anomaly was less severe in the Macalister catchment (225219), with a 6.95% reduction in the mean dry period anomaly while the other two catchments experienced reductions of 9.84% (405219) and 9.62% (405264).

Hydrol. Earth Syst. Sci. Discuss., https://doi.org/10.5194/hess-2019-6
Manuscript under review for journal Hydrol. Earth Syst. Sci.
Discussion started: 4 February 2019

In terms of changes in rainfall, both catchments had a reduction from the non-dry to the dry periods of 11% on average, which was within the range that Vaze et al. (2010) recommended for acceptable model simulations. Vaze et al. (2010) tested four conceptual rainfall-runoff models in 61 catchments in southeast Australia using the stationary scheme of model parameters, and found that the calibrated parameter sets generally gave acceptable simulations provided rainfall changes were not too large (no more than 15% dryer or 20% wetter than rainfall in the calibration period).

3.2.2 Model performance in five scenarios

Generally, the calibrated model parameters provided good simulation performance over the calibrated periods for all criteria (Broderick et al., 2016;Coron et al., 2012;Fowler et al., 2016;Thirel et al., 2015;Vaze et al., 2010).For example, the mean NSE_{sqrt} score during the calibration period across these catchments remained close to about 0.7 or slightly higher, regardless of which scenario was chosen. However, when the same parameter sets were verified by simulating streamflow over drier or wetter periods, the model performance was degraded, including both the robustness and accuracy of projection performance. Furthermore, the magnitude of performance loss increases along with the variation between the calibration and verification periods.

Figure 5 shows the NSE_{sqrt} performance for calibration in a non-dry period and verification in a dry period for each scenario in all catchments. All scenarios performed well in all catchments with the mean NSE_{sqrt} reaching 0.81 during the non-dry calibration period, and then all scenarios experienced a slight decrease in performance (NSE_{sqrt} = 0.75) during the dry verification period. Scenario 4 (time-varying parameters

Hydrol. Earth Syst. Sci. Discuss., https://doi.org/10.5194/hess-2019-6
Manuscript under review for journal Hydrol. Earth Syst. Sci.
Discussion started: 4 February 2019

without spatial inputs) and scenario 5 (temporally stable parameters) generally performed better during the calibration period than the scenarios that considered different levels of spatial coherence for the regression parameters. During the verification period, the NSE_{sqrt} rank order changed (Figure 5b). Scenario 4 had a higher median NSE_{sqrt} performance, but a wider variation range, than scenario 5, which indicates the validity of the time-varying scheme for improving the model performance. However, the introduction of additional regression parameters (α, β and ω) at the same time amplified the model projection uncertainty. Fortunately, the appropriate adoption of spatial coherence alleviates this problem. Scenario 3, which considered spatial coherence of regression parameters β and ω between different catchments, exhibited the highest median NSE_{sqrt} for all catchments with the smallest fluctuation range. The highest median NSE_{sqrt} performance in scenarios 4 and 5 during the calibration period did not guarantee the same superior performance during the verification period. This illustrates the deficiency of time-varying and stationary schemes of model parameters when spatial inputs from adjacent catchments are not considered.

Similarly, Figure 6 illustrates the NSE_{sqrt} performance for each scenario in all catchments for calibration in the dry period and verification in the non-dry period. All scenarios performed well for all catchments with the mean NSE_{sqrt} reaching 0.75 in the dry calibration period and 0.79 in the non-dry verification period. As shown in Figure 5, models experienced a slight improvement in NSE_{sqrt} performance when transferred from the dry period to the non-dry period. However, the projection performance calibrated using a contrasting climatic condition was inferior to the simulation performance that was directly calibrated from the climatic condition. By comparing scenarios in the calibration period, it was found that scenarios 4 and 5 exhibited the highest performance, followed successively by scenario 3, scenario 2, and scenario 1. During the verification period, however, scenario 4 had a higher median NSE_{sqrt} performance but a wider variation range than scenario 5, while scenario 3 possessed the highest median NSE_{sqrt} for all catchments with the smallest fluctuation range.

These results demonstrate that the time-varying scheme for model parameters improved the median NSE_{sqrt} performance but also amplified the projection uncertainty compared with the results from the stationary scheme for model parameters. Compared with other model scenarios, the incorporation of spatial coherence of both regression parameters in scenario 3 reduced the projection uncertainty and improved the robustness of the model performance, with the smallest fluctuation ranges under the contrasting climatic conditions. It indicates that the spatial setting of model parameters between different catchments provided a clear input for reducing the uncertainty of the model projection performance during the verification period. In addition, it also should be noted that model parameters calibrated over dry periods, contrastively, were not suitable for predicting runoff over wet periods because of a larger degradation in projection performance than the scheme with the adverse calibration-verification direction.

Compared the DIC results for both DSST schemes in Table 4 and Table 5, the best DIC value is achieved by scenario 3, which incorporates the spatial coherence of both regression parameters and is the most complex scenario in the comparison. This finding is consistent with the results by the NSE_{sqrt} criterion, and showed the validity of the spatial coherence of both regression parameters in ensuring the robustness of the hydrological projection performance. In addition, when compared DIC results of scenarios 4 and 5, the setting of time-varying functions improved the DIC performance in both DSST schemes. This finding also agreed with the results by the NSE_{sqrt} criterion, and indicated the positive implications by the time-varying model parameters on the projection performance.

Figure 7 shows the BIAS estimates for the median of the posterior distribution of model parameters for all modeling scenarios across all catchments when transferability between the non-dry and dry periods was examined. Although the BIAS was a component of the objective function (Eq. 3), the 10-year rolling average BIAS still deviated considerably from a value of 1 for all the scenarios in the two DSST schemes. The median estimates of the posterior distribution in both scenarios performed well in the NSE_{sqrt} criterion for both periods. However, the median estimates did not ensure unbiased simulations over the modeling period; one scenario with a higher NSE_{sqrt} criterion may have an altered BIAS during the modeling period. The BIAS results in catchments 225219 and 405219 showed some similarity: all scenarios tended to underestimate streamflow along the time sequence in both DSST schemes. Conversely, all scenarios tended to overestimate the streamflow in catchment 405264 in both schemes. By comparing the BIAS performance for the five scenarios, it was observed that the spatial setting of modeling scenarios generally tended to enlarge the BIAS in all catchments, while the difference between scenarios 4 and 5 was very small.

3.2.3 Parameter uncertainty analysis

The uncertainty of the parameters was characterized by the posterior distribution of the regression parameters and was derived by the MCMC iteration. As mentioned in section 2.3.2, regression parameters β and ω were assumed to have different levels of spatial coherence in each modeling scenario (Table 1); these scenarios in each DSST regime are compared in Figs. 7 and 8. It should be mentioned that there was no regression parameter in scenario 5. Upper and lower ranges in the boxplot are given by the 25th and 75th percentiles of the posterior distribution. The whiskers extend to values defining 1.5-standard deviations of the sample. Small dots (gray) denote the arithmetic average of the posterior distribution. Values beyond the whiskers are marked as outliers and denoted as small squares. In the upper plots in Figures 7 and 8, it can be clearly seen that the first three scenarios had a much smaller variation interval than scenario 4 in terms of regression parameter β, which denotes the amplitude of the sine function. The median values in the first three scenarios were close to zero while the median values in the fourth scenario varied significantly between catchments. With regards to the regression parameter ω, which denotes the phase of the sine function (in the lower figures of Figures 7 and 8), absolute values in the four scenarios differ notably. Scenario 1, which only considered the spatial coherence of the regression parameter ω, has the lowest median value and the narrowest interval for all catchments, followed successively by scenario 4 (no parameter was spatially coherent) scenario 2 (only parameter β was spatially coherent), and scenario 3 (both parameters β and ω

were spatially coherent). By considering the spatial coherence of regression parameter ω between different catchments it was possible to narrow the variation interval of posterior distribution (see scenario 1), while adding the spatial coherence of β increased the variation interval of the posterior distribution of ω (see scenario 3).

In conclusion, by combining the results of parameter uncertainty estimation and model projection performance evaluation, the incorporation of spatial coherence successfully improved the robustness of the projection performance in both DSST schemes by controlling the estimation uncertainty of regression parameters β and ω.

4. CONCLUSIONS

In this study, a two-level HB framework was used to incorporate the spatial coherence of adjacent catchments to improve the hydrological projection performance of sensitive time-varying parameters for a lumped conceptual rainfall-runoff model (GR4J) under contrasting climatic conditions. Firstly, a temporal parameter transfer scheme was implemented, using a DSST procedure in which the available data were divided into non-dry and dry periods. Then, the model was calibrated in the non-dry periods and evaluated in the dry periods, and vice versa. In the first level of the proposed HB framework, the most sensitive parameter in the GR4J model, i.e., the production storage capacity (θ_1), was allowed to vary with time to account for the periodic variation that had significant impacts on the extensionality of the model. The periodic variation in catchment storage capacity was represented by a sine function for θ_1 (parameterized by amplitude and phase). In the second level, four modeling scenarios with different spatial coherence schemes, and one scenario with a stationary scheme of catchment storage capacity, were used to evaluate the transferability of hydrological models under contrasting climatic conditions. Finally, the proposed method was applied to three spatially adjacent, unregulated, and unimpaired catchments in southeast Australia. Results showed that: (1) the time-varying function improved the model performance but also amplified the projection uncertainty compared with stationary setting of model parameters; (2) the proposed HB method successfully reduced the projection uncertainty and improved the robustness of model performance; and (3) model parameters calibrated over dry periods were not suitable for predicting runoff over wet periods because of a large degradation in projection performance. This study improves our understanding of the spatial coherence of time-varying parameters, which will help improve the projection performance under differing climatic conditions. However, there are several unsolved problems that need to be addressed. First, the spatial setting of regression parameters may expand the BIAS between the simulation and streamflow observation with a single objective function; the potential physical mechanism behind this result should be explored further. Secondly, this study was confined to spatially coherent catchments that are similar in climatic and hydrogeological conditions; further research is needed to determine which factors have the most significant impacts on model projection performance when considering obvious inputs from other catchments.

ACKNOWLEDGMENTS

This study was supported by the National Key Research and Development

Program (2018YFC0407202), the National Natural Science Foundation of China (51861125102; 51879193), and the Natural Science Foundation of Hubei Province (2017CFA015). The numerical calculations were done on the supercomputing system in the Supercomputing Center of Wuhan University. The authors would like to thank the editor and anonymous reviewers for their comments, which helped improve the quality of the paper.

AUTHOR CONTRIBUTIONS

All of the authors helped to conceive and design the analysis. Zhengke Pan and Pan Liu preformed the analysis and wrote the paper. Shida Gao, Jun Xia, Jie Chen and Lei Cheng contributed to the writing of the paper and made comments.

COMPLIANCE WITH ETHICAL STANDARDS

Conflict of interest: The authors declare that they have no conflict of interest.

REFERENCES

Ajami, N. K., Duan, Q. Y., and Sorooshian, S.: An integrated hydrologic Bayesian multimodel combination framework: Confronting input, parameter, and model structural uncertainty in hydrologic prediction, Water Resour. Res., 43, 10.1029/2005wr004745, 2007.

Bracken, C., Holman, K. D., Rajagopalan, B., and Moradkhani, H.: A Bayesian Hierarchical Approach to Multivariate Nonstationary Hydrologic Frequency Analysis, Water Resour. Res., 54, 243-255, 10.1002/2017wr020403, 2018.

Brigode, P., Oudin, L., and Perrin, C.: Hydrological model parameter instability: A source of additional uncertainty in estimating the hydrological impacts of climate change?, J. Hydrol., 476, 410-425, 10.1016/j.jhydrol.2012.11.012, 2013.

Broderick, C., Matthews, T., Wilby, R. L., Bastola, S., and Murphy, C.: Transferability of hydrological models and ensemble averaging methods between contrasting climatic periods, Water Resour. Res., 52, 8343-8373, 10.1002/2016wr018850, 2016.

Cha, Y., Park, S. S., Lee, H. W., and Stow, C. A.: A Bayesian hierarchical approach to model seasonal algal variability along an upstream to downstream river gradient, Water Resour. Res., 52, 348-357, 10.1002/2015wr017327, 2016.

Chen, X., Hao, Z., Devineni, N., and Lall, U.: Climate information based streamflow and rainfall forecasts for Huai River basin using hierarchical Bayesian modeling, Hydrol. Earth Syst. Sci., 18, 1539-1548, 10.5194/hess-18-1539-2014, 2014.

Chiew, F. H. S., Teng, J., Vaze, J., Post, D. A., Perraud, J. M., Kirono, D. G. C., and Viney, N. R.: Estimating climate change impact on runoff across southeast Australia: Method, results, and implications of the modeling method, Water Resour. Res., 45, 17, 10.1029/2008wr007338, 2009.

Chiew, F. H. S., Potter, N. J., Vaze, J., Petheram, C., Zhang, L., Teng, J., and Post, D. A.: Observed hydrologic non-stationarity in far south-eastern Australia: implications for modelling and prediction, Stoch. Environ. Res. Risk Assess., 28, 3-15, 10.1007/s00477-013-0755-5, 2014.

Ciais, P., Reichstein, M., Viovy, N., Granier, A., Ogee, J., Allard, V., Aubinet, M., Buchmann, N., Bernhofer, C., Carrara, A., Chevallier, F., De Noblet, N., Friend, A. D., Friedlingstein, P., Grunwald, T., Heinesch, B., Keronen, P., Knohl, A., Krinner, G., Loustau, D., Manca, G., Matteucci, G., Miglietta, F., Ourcival, J. M., Papale, D., Pilegaard, K., Rambal, S., Seufert, G., Soussana, J. F., Sanz, M. J., Schulze, E. D., Vesala, T., and Valentini, R.: Europe-wide reduction in primary productivity caused by the heat and drought in 2003, Nature, 437, 529-533, 10.1038/nature03972, 2005.

Clarke, R. T.: Hydrological prediction in a non-stationary world, Hydrol. Earth Syst. Sci., 11, 408-414, 10.5194/hess-11-408-2007, 2007.

Cook, E. R., Woodhouse, C. A., Eakin, C. M., Meko, D. M., and Stahle, D. W.: Long-term aridity changes in the western United States, Science, 306, 1015-1018, 10.1126/science.1102586, 2004.

Cooley, D., Nychka, D., and Naveau, P.: Bayesian spatial modeling of extreme precipitation return levels, J. Am. Stat. Assoc., 102, 824-840, 10.1198/016214506000000780, 2007.

Coron, L., Andreassian, V., Perrin, C., Lerat, J., Vaze, J., Bourqui, M., and Hendrickx, F.: Crash testing hydrological models in contrasted climate conditions: An experiment on 216 Australian catchments, Water Resour. Res., 48, 17, 10.1029/2011wr011721, 2012.

Deng, C., Liu, P., Guo, S. L., Li, Z. J., and Wang, D. B.: Identification of hydrological model parameter variation using ensemble Kalman filter, Hydrol. Earth Syst. Sci., 20, 4949-4961, 10.5194/hess-20-4949-2016, 2016.

Deng, C., Liu, P., Wang, D. B., and Wang, W. G.: Temporal variation and scaling of parameters for a monthly hydrologic model, J. Hydrol., 558, 290-300, 10.1016/j.jhydrol.2018.01.049, 2018.

Duan, Q. Y., Ajami, N. K., Gao, X. G., and Sorooshian, S.: Multi-model ensemble hydrologic prediction using Bayesian model averaging, Adv. Water Resour., 30, 1371-1386, 10.1016/j.advwatres.2006.11.014, 2007.

Fowler, K. J. A., Peel, M. C., Western, A. W., Zhang, L., and Peterson, T. J.: Simulating runoff under changing climatic conditions: Revisiting an apparent deficiency of conceptual rainfall-runoff models, Water Resour. Res., 52, 1820-1846, 10.1002/2015wr018068, 2016.

Gelman, A., Carlin, J., Stern, H., Dunson, D., Vehtari, A., and Rubin, D.: Bayesian Data Analysis, third ed ed., CRC Press, 2013.

Guo, D. L., Westra, S., and Maier, H. R.: Impact of evapotranspiration process representation on runoff projections from conceptual rainfall-runoff models, Water Resour. Res., 53, 435-454, 10.1002/2016wr019627, 2017.

Heuvelmans, G., Muys, B., and Feyen, J.: Regionalisation of the parameters of a hydrological model: Comparison of linear regression models with artificial neural nets, J. Hydrol., 319, 245-265, 10.1016/j.jhydrol.2005.07.030, 2006.

Lebecherel, L., Andreassian, V., and Perrin, C.: On evaluating the robustness of spatial-proximity-based regionalization methods, J. Hydrol., 539, 196-203, 10.1016/j.jhydrol.2016.05.031, 2016.

Lima, C. H. R., and Lall, U.: Hierarchical Bayesian modeling of multisite daily rainfall occurrence: Rainy season onset, peak, and end, Water Resour. Res., 45, 14, 10.1029/2008wr007485, 2009.

Lima, C. H. R., Lall, U., Troy, T., and Devineni, N.: A hierarchical Bayesian GEV model for improving local and regional flood quantile estimates, J. Hydrol., 541, 816-823, 10.1016/j.jhydrol.2016.07.042, 2016.

Liu, P., Li, L. P., Chen, G. J., and Rheinheimer, D. E.: Parameter uncertainty analysis of reservoir operating rules based on implicit stochastic optimization, J. Hydrol., 514, 102-113, 10.1016/j.jhydrol.2014.04.012, 2014.

Liu, Y. Q., and Gupta, H. V.: Uncertainty in hydrologic modeling: Toward an integrated data assimilation framework, Water Resour. Res., 43, 18, 10.1029/2006wr005756, 2007.

Merz, R., and Bloschl, G.: Regionalisation of catchment model parameters, J. Hydrol., 287, 95-123, 10.1016/j.jhydrol.2003.09.028, 2004.

Merz, R., Parajka, J., and Bloschl, G.: Time stability of catchment model parameters: Implications for climate impact analyses, Water Resour. Res., 47, 17, 10.1029/2010wr009505, 2011.

Moore, R. D., and Wondzell, S. M.: Physical hydrology and the effects of forest harvesting in the Pacific Northwest: A review, J. Am. Water Resour. Assoc., 41, 763-784, 2005.

Moradkhani, H., Hsu, K. L., Gupta, H., and Sorooshian, S.: Uncertainty assessment of hydrologic model states and parameters: Sequential data assimilation using the particle filter, Water Resour. Res., 41, 17, 10.1029/2004wr003604, 2005.

Moradkhani, H., DeChant, C. M., and Sorooshian, S.: Evolution of ensemble data assimilation for uncertainty quantification using the particle filter-Markov chain Monte Carlo method, Water Resour. Res., 48, 13, 10.1029/2012wr012144, 2012.

Moriasi, D. N., Arnold, J. G., Van Liew, M. W., Bingner, R. L., Harmel, R. D., and Veith, T. L.: Model evaluation guidelines for systematic quantification of accuracy in watershed simulations, Trans. ASABE, 50, 885-900, 2007.

Najafi, M. R., and Moradkhani, H.: A hierarchical Bayesian approach for the analysis of climate change impact on runoff extremes, Hydrol. Process., 28, 6292-6308, 10.1002/hyp.10113, 2014.

Nash, J. E., and Sutcliffe, J. V.: River flow forecasting through conceptual models part I — A discussion of principles, J. Hydrol., 10, 282-290, https://doi.org/10.1016/0022-1694(70)90255-6, 1970.

Oudin, L., Andreassian, V., Perrin, C., Michel, C., and Le Moine, N.: Spatial proximity, physical similarity, regression and ungaged catchments: A comparison of regionalization approaches based on 913 French catchments, Water Resour. Res., 44, 15, 10.1029/2007wr006240, 2008.

Pathiraja, S., Marshall, L., Sharma, A., and Moradkhani, H.: Detecting non-stationary hydrologic model parameters in a paired catchment system using data assimilation, Adv. Water

Resour., 94, 103-119, 10.1016/j.advwatres.2016.04.021, 2016.

Pathiraja, S., Moradkhani, H., Marshall, L., Sharma, A., and Geenens, G.: Data-Driven Model Uncertainty Estimation in Hydrologic Data Assimilation, Water Resour. Res., 54, 1252-1280, 10.1002/2018wr022627, 2018.

Patil, S. D., and Stieglitz, M.: Comparing Spatial and temporal transferability of hydrological model parameters, J. Hydrol., 525, 409-417, 10.1016/j.jhydrol.2015.04.003, 2015.

Perrin, C., Michel, C., and Andreassian, V.: Improvement of a parsimonious model for streamflow simulation, J. Hydrol., 279, 275-289, 10.1016/s0022-1694(03)00225-7, 2003.

Renard, B., Kavetski, D., Leblois, E., Thyer, M., Kuczera, G., and Franks, S. W.: Toward a reliable decomposition of predictive uncertainty in hydrological modeling: Characterizing rainfall errors using conditional simulation, Water Resour. Res., 47, 21, 10.1029/2011wr010643, 2011.

Saft, M., Western, A. W., Zhang, L., Peel, M. C., and Potter, N. J.: The influence of multiyear drought on the annual rainfall-runoff relationship: An Australian perspective, Water Resour. Res., 51, 2444-2463, 10.1002/2014wr015348, 2015.

Seiller, G., Anctil, F., and Perrin, C.: Multimodel evaluation of twenty lumped hydrological models under contrasted climate conditions, Hydrol. Earth Syst. Sci., 16, 1171-1189, 10.5194/hess-16-1171-2012, 2012.

Singh, S. K., Bardossy, A., Gotzinger, J., and Sudheer, K. P.: Effect of spatial resolution on regionalization of hydrological model parameters, Hydrol. Process., 26, 3499-3509, 10.1002/hyp.8424, 2012.

Spiegelhalter, D. J., Best, N. G., Carlin, B. R., and van der Linde, A.: Bayesian measures of model complexity and fit, J. R. Stat. Soc. Ser. B-Stat. Methodol., 64, 583-616, 10.1111/1467-9868.00353, 2002.

Sun, X., Thyer, M., Renard, B., and Lang, M.: A general regional frequency analysis framework for quantifying local-scale climate effects: A case study of ENSO effects on Southeast Queensland rainfall, J. Hydrol., 512, 53-68, 10.1016/j.jhydrol.2014.02.025, 2014.

Sun, X., and Lall, U.: Spatially coherent trends of annual maximum daily precipitation in the United States, Geophys. Res. Lett., 42, 9781-9789, 10.1002/2015gl066483, 2015.

Sun, X., Lall, U., Merz, B., and Dung, N. V.: Hierarchical Bayesian clustering for nonstationary flood frequency analysis: Application to trends of annual maximum flow in Germany, Water Resour. Res., 51, 6586-6601, 10.1002/2015wr017117, 2015.

Tegegne, G., and Kim, Y. O.: Modelling ungauged catchments using the catchment runoff response similarity, J. Hydrol., 564, 452-466, 10.1016/j.jhydrol.2018.07.042, 2018.

Thirel, G., Andreassian, V., Perrin, C., Audouy, J. N., Berthet, L., Edwards, P., Folton, N., Furusho, C., Kuentz, A., Lerat, J., Lindstrom, G., Martin, E., Mathevet, T., Merz, R., Parajka, J., Ruelland, D., and Vaze, J.: Hydrology under change: an evaluation protocol to investigate how hydrological models deal with changing catchments, Hydrol. Sci. J.-J. Sci. Hydrol., 60, 1184-1199, 10.1080/02626667.2014.967248, 2015.

Vaze, J., Post, D. A., Chiew, F. H. S., Perraud, J. M., Viney, N. R., and Teng, J.: Climate non-stationarity - Validity of calibrated rainfall-runoff models for use in climate change studies, J. Hydrol., 394, 447-457, 10.1016/j.jhydrol.2010.09.018, 2010.

Vrugt, J. A., Gupta, H. V., Bouten, W., and Sorooshian, S.: A Shuffled Complex Evolution Metropolis algorithm for optimization and uncertainty assessment of hydrologic model parameters, Water Resour. Res., 39, 18, 10.1029/2002wr001642, 2003.

Vrugt, J. A., ter Braak, C. J. F., Diks, C. G. H., Robinson, B. A., Hyman, J. M., and Higdon, D.: Accelerating Markov Chain Monte Carlo Simulation by Differential Evolution with Self-Adaptive Randomized Subspace Sampling, International Journal of Nonlinear Sciences and Numerical Simulation, 10, 273-290, 2009.

Westra, S., Thyer, M., Leonard, M., Kavetski, D., and Lambert, M.: A strategy for diagnosing and interpreting hydrological model nonstationarity, Water Resour. Res., 50, 5090-5113, 10.1002/2013wr014719, 2014.

Wright, D. P., Thyer, M., and Westra, S.: Influential point detection diagnostics in the context of hydrological model calibration, J. Hydrol., 527, 1161-1172, 10.1016/j.jhydrol.2015.05.047, 2015.

Xiong, M., Liu, P., Cheng, L., Deng, C., Gui, Z., Zhang, X., and Liu, Y.: Identifying time-varying hydrological model parameters to improve simulation efficiency by the ensemble Kalman filter: A joint assimilation of streamflow and actual evapotranspiration, J. Hydrol., 568, 758-768, 10.1016/j.jhydrol.2018.11.038, 2019.

Xu, Q., Chen, J., Peart, M. R., Ng, C. N., Hau, B. C. H., and Law, W. W. Y.: Exploration of severities of rainfall and runoff extremes in ungauged catchments: A case study of Lai Chi Wo in Hong Kong, China, Sci. Total Environ., 634, 640-649, 10.1016/j.scitotenv.2018.04.024, 2018.

Yan, H. X., and Moradkhani, H.: A regional Bayesian hierarchical model for flood frequency analysis, Stoch. Environ. Res. Risk Assess., 29, 1019-1036, 10.1007/s00477-014-0975-3, 2015.

Zhang, X. J., Liu, P., Cheng, L., Liu, Z. J., and Zhao, Y.: A back-fitting algorithm to improve real-time flood forecasting, J. Hydrol., 562, 140-150, 10.1016/j.jhydrol.2018.04.051, 2018.

Zhang, Y. Q., Viney, N., Frost, A., and Oke, A.: Collation of australian modeller's streamflow dataset for 780 unregulated australian catchments, Water for a healthy country national research flagship, 115pp, 2013.

Hydrol. Earth Syst. Sci. Discuss., https://doi.org/10.5194/hess-2019-6
Manuscript under review for journal Hydrol. Earth Syst. Sci.
Discussion started: 4 February 2019

Hydrology and Earth System Sciences
Discussions
Open Access

TABLES

Table 1. Different spatial coherence scenarios for regression parameters β and ω in the time-varying functional form of model parameter θ_1. To explore the performance of spatial coherence within the time-varying function, different levels of spatial coherence for regression parameters β and ω were assumed for the first three scenarios; in contrast, no spatial coherence is assumed in scenario 4, and a temporally stable θ_1 is assumed in scenario 5.

Category		Scenario	β	ω	Constraints
Time-varying	Spatial coherence	1	Parameter β is region-related	Parameter ω is catchment-specific	$\theta_1=\alpha(c)+\beta(c)+\sin[\omega(c)t]$, while $\beta(c)=N(\mu_2, \sigma_2^2)$
		2	Parameter β is catchment-specific	Parameter ω is region-related	$\theta_1=\alpha(c)+\beta(c)+\sin[\omega(c)t]$, while $\omega(c)=N(\mu_3, \sigma_3^2)$
		3	Parameter β is region-related	Parameter ω is region-related	$\theta_1=\alpha(c)+\beta(c)+\sin[\omega(c)t]$, while $\beta(c)=N(\mu_2, \sigma_2^2)$ and $\omega(c)=N(\mu_3, \sigma_3^2)$
	No spatial coherence	4	Parameter β is catchment-specific	Parameter ω is catchment-specific	$\theta_1=\alpha(c)+\beta(c)+\sin[\omega(c)t]$
Time invariant		5	No parameters β or ω		θ_1 is stationary

NB: θ_1 is the production storage capacity of the catchment; β is the slope describing long-term change during the modeling period, and ω is the amplitude of the sine function describing its seasonal variation during the modeling period; μ_2, σ_2, μ_3, σ_3 are hyper-parameters.

Hydrol. Earth Syst. Sci. Discuss., https://doi.org/10.5194/hess-2019-6
Manuscript under review for journal Hydrol. Earth Syst. Sci.
Discussion started: 4 February 2019

Hydrology and Earth System Sciences Discussions
Open Access

Table 2. Comparison of catchments attributes in terms of mean annual rainfall (mm), mean annual evaporation (mm), and mean annual runoff (mm) for 1976–2011.

Catchments ID	River Name	Observations start	Observations end	Mean annual rainfall	Mean annual potential evapotranspiration	Mean annual runoff
225219	Macalister	1/1/1976	30/12/2011	1064	1142	350
405219	Goulburn	1/1/1976	30/12/2011	1169	1193	422
405264	Big	1/1/1976	30/12/2011	1406	1157	469

Table 3. Drought identification results for the catchments.

Catchments ID	Drought start	Drought end	Length	Mean dry period anomaly	% Complete	R_1	R_2	Change in runoff (%)	Change in rainfall (%)
225219	1997	2009	12	-6.95%	90.4%	0.34	0.28	-15.98	-11.27
405219	1997	2009	12	-9.84%	98.5%	0.38	0.31	-18.57	-10.97
405264	1997	2009	12	-9.62%	98.5%	0.35	0.29	-18.23	-10.51

NB: R_1 and R_2 refer to the runoff coefficient during the non-dry and dry periods, respectively.

Hydrol. Earth Syst. Sci. Discuss., https://doi.org/10.5194/hess-2019-6
Manuscript under review for journal Hydrol. Earth Syst. Sci.
Discussion started: 4 February 2019

Hydrology and Earth System Sciences Discussions
Open Access

Table 4. Comparison of five scenarios in terms of the deviance information criterion (DIC) when model parameters were calibrated in the non-dry period and verified in the dry period.

Category		Scenario	DIC
Time-varying	Spatial coherence	1	4961.7
		2	1202.3
		3	-1254.4
	No spatial coherence	4	5052.8
Time invariant	No spatial coherence	5	5827.3

Table 5. Comparison of five scenarios in terms of the deviance information criterion (DIC) when model parameters were calibrated in the dry period and verified in the non-dry period.

Category		Scenario	DIC
Time-varying	Spatial coherence	1	-6167.0
		2	-5743.6
		3	-10574.0
	No spatial coherence	4	-8710.0
Time invariant	No spatial coherence	5	-7460.8

FIGURES

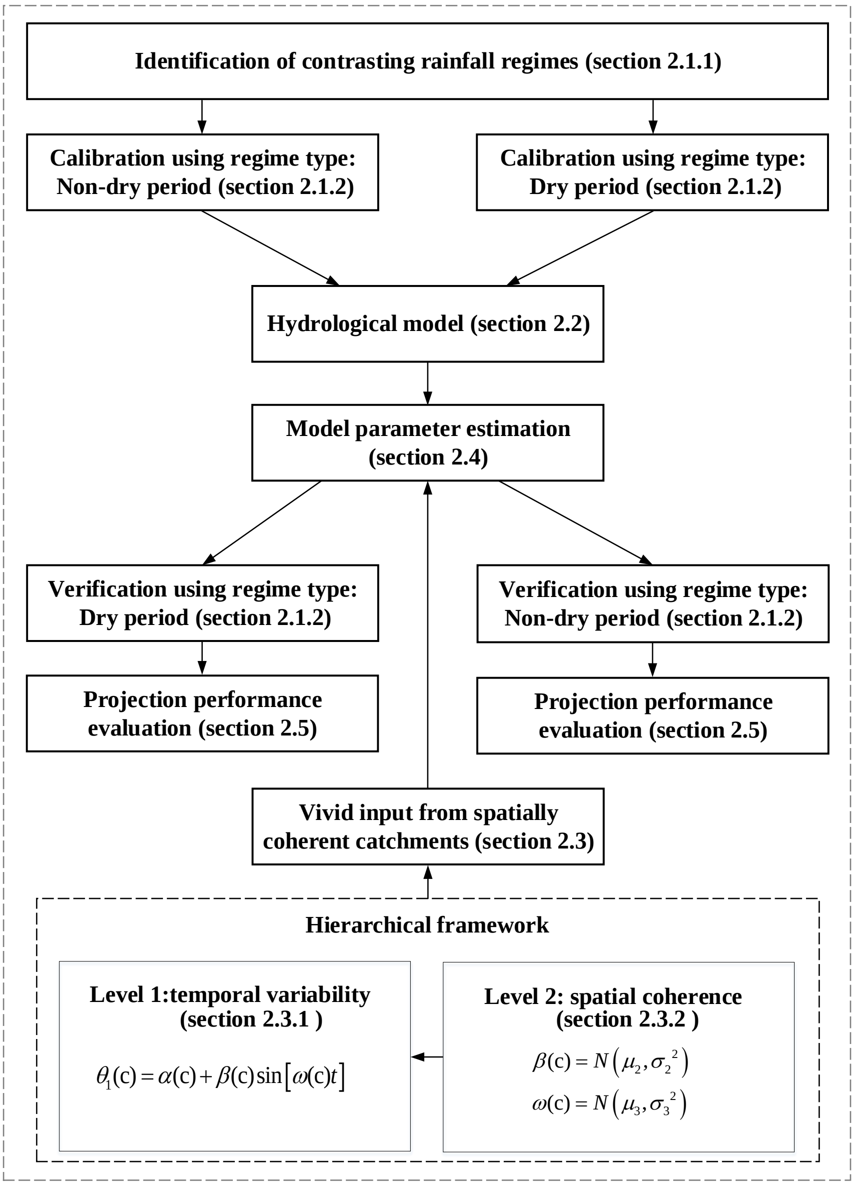

Figure 1. Flow diagram of the methodology for integrating inputs from spatially coherent catchments and temporal variation of model parameters into a hydrological model under contrasting climatic conditions (non-dry and dry periods).

Hydrol. Earth Syst. Sci. Discuss., https://doi.org/10.5194/hess-2019-6
Manuscript under review for journal Hydrol. Earth Syst. Sci.
Discussion started: 4 February 2019

Hydrology and Earth System Sciences
Open Access
Discussions

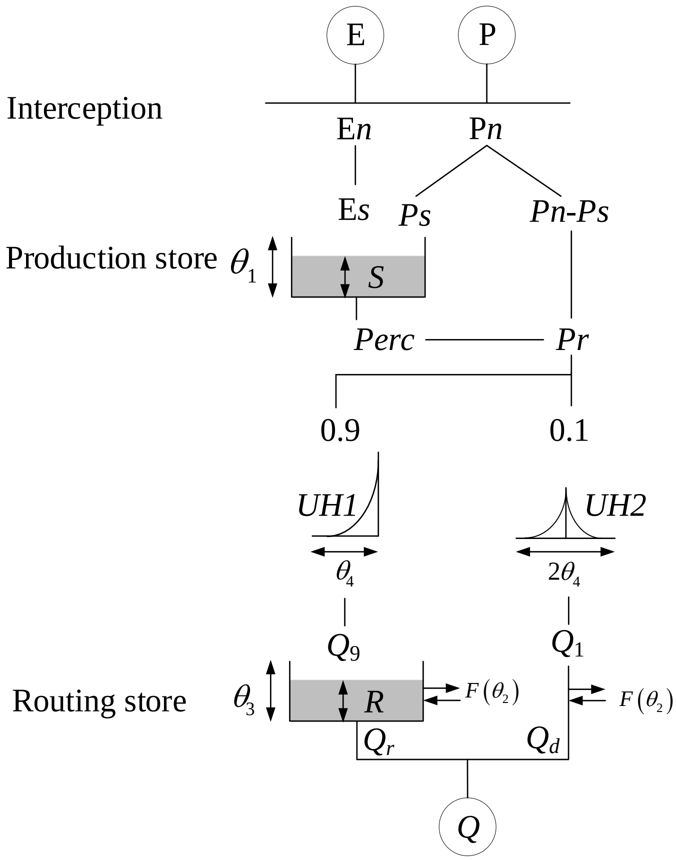

Figure 2. Schematic of the original version of the GR4J rainfall-runoff model.

Hydrol. Earth Syst. Sci. Discuss., https://doi.org/10.5194/hess-2019-6
Manuscript under review for journal Hydrol. Earth Syst. Sci.
Discussion started: 4 February 2019

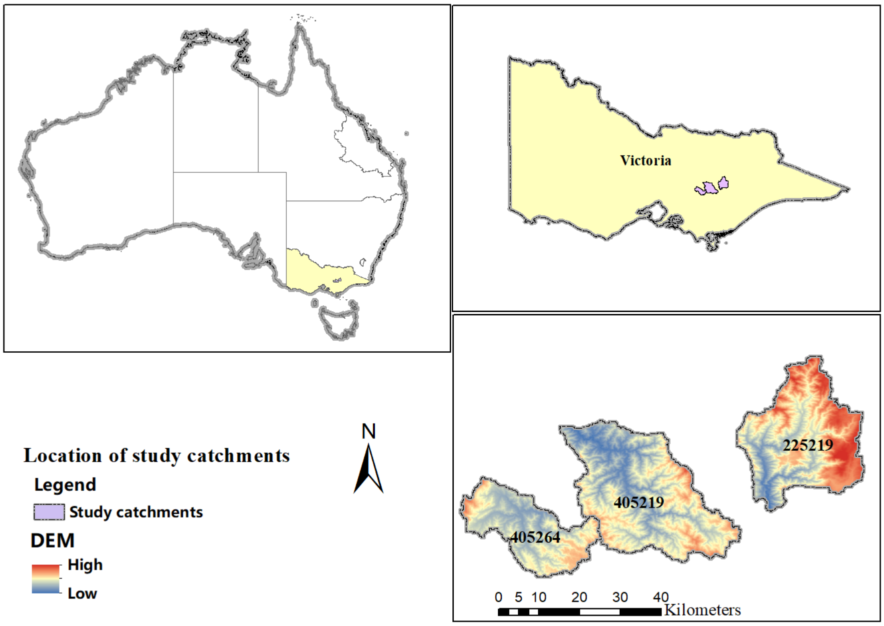

Figure 3. Locations of study catchments in Victoria, Australia. The catchment IDs are 225219 (Macalister River catchment), 405219 (Goulburn River catchment), and 405264 (Big River catchment).

Hydrol. Earth Syst. Sci. Discuss., https://doi.org/10.5194/hess-2019-6
Manuscript under review for journal Hydrol. Earth Syst. Sci.
Discussion started: 4 February 2019

Hydrology and Earth System Sciences
Open Access
Discussions

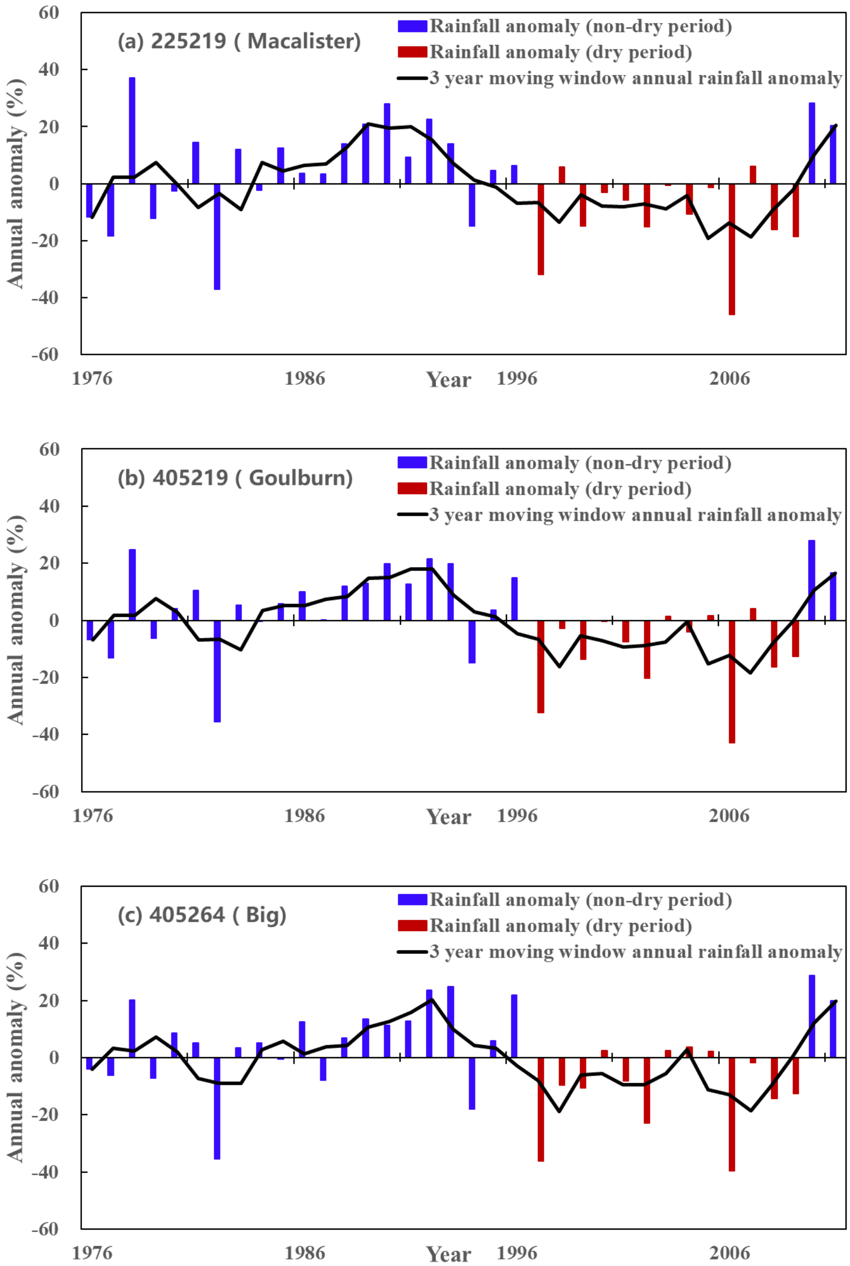

Figure 4. The identified dry period in all catchments. The annual anomaly is defined as a percentage of the mean annual rainfall.

Hydrol. Earth Syst. Sci. Discuss., https://doi.org/10.5194/hess-2019-6
Manuscript under review for journal Hydrol. Earth Syst. Sci.
Discussion started: 4 February 2019

Hydrology and Earth System Sciences
Discussions

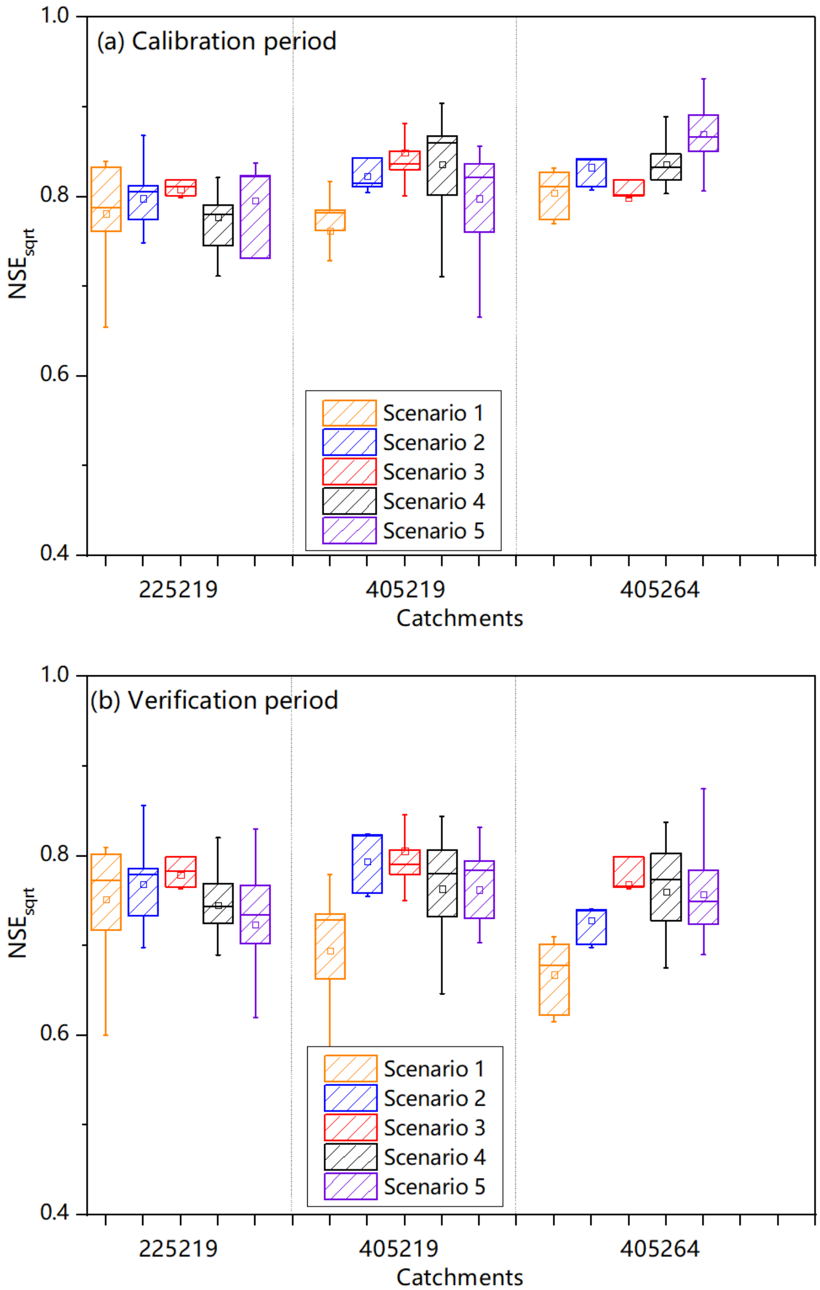

Figure 5. NSE_{sqrt} for each of the five scenarios for each catchment during (a) the calibration period (non-dry period) and (b) the verification period (dry period).

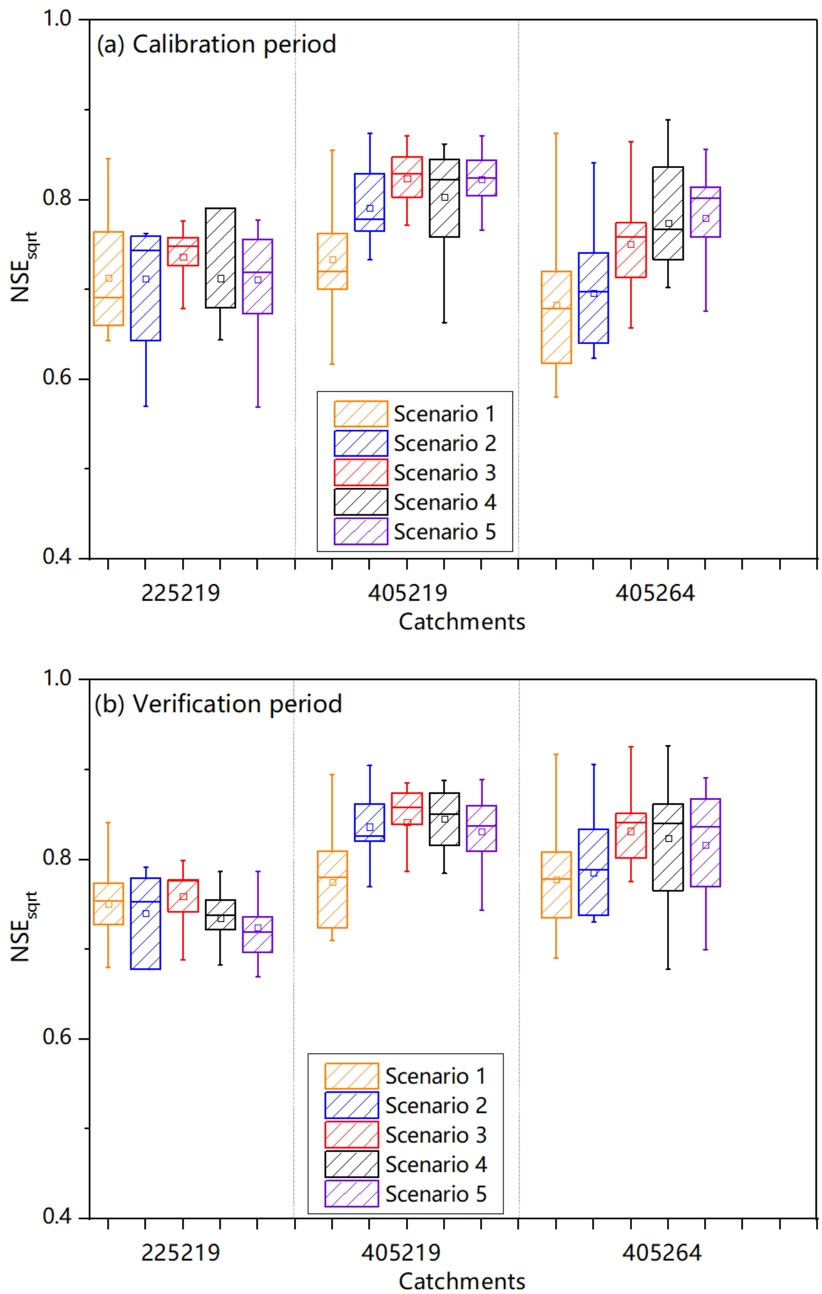

Figure 6. NSE_{sqrt} for each of the five scenarios for each catchment during (a) the calibration period (dry period) and (b) the verification period (non-dry period).

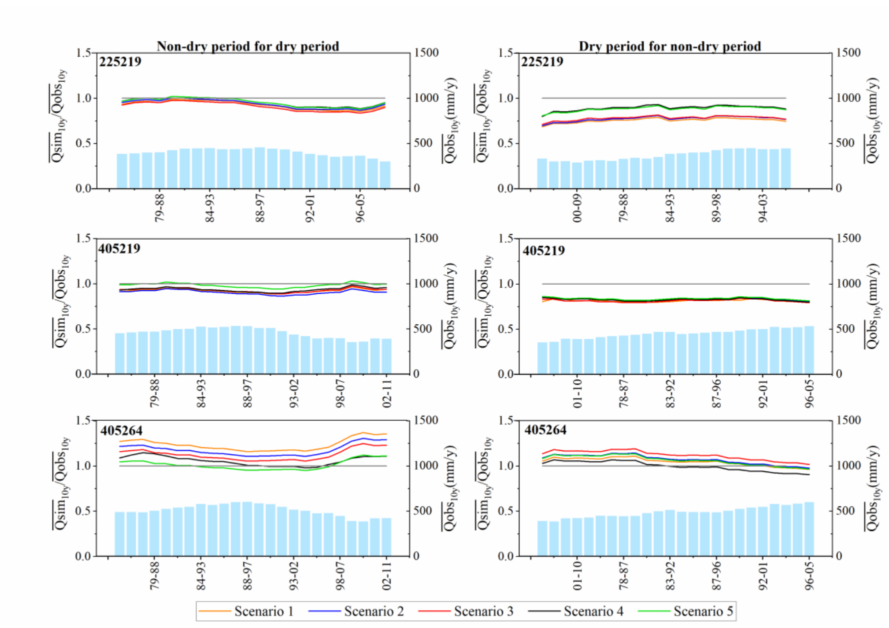

Figure 7. Long-term simulation BIAS of Q_{median} for five scenarios in all catchments. Simulation BIAS is plotted as a 10-year moving average, and 10-year moving average streamflows are plotted for reference. The left-hand three graphs are calibrated in the non-dry period and then verified in the dry period, while the opposite sequence applies to the right-hand graphs.

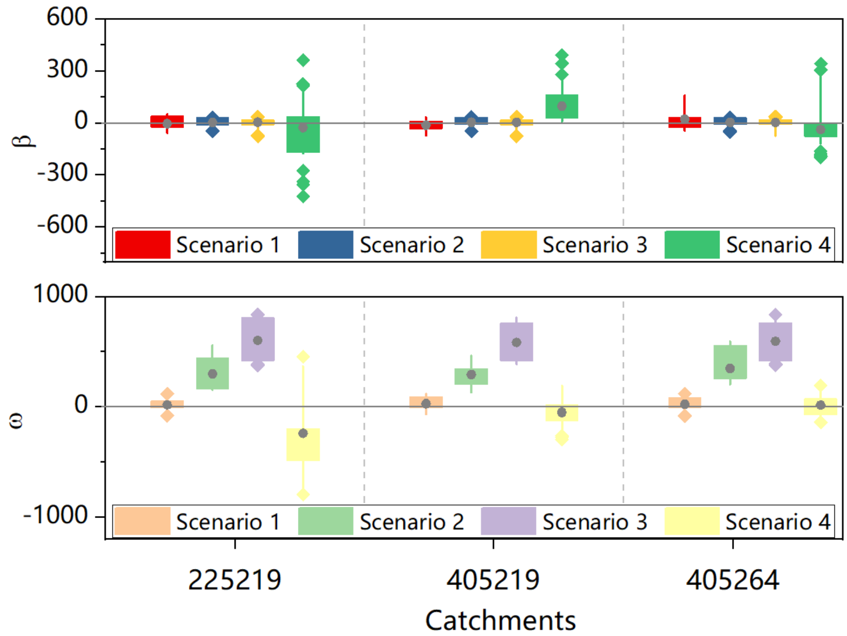

Figure 8. Posterior distributions of the regression parameters (β and ω) for the production storage capacity (θ_1) for the four model scenarios in each catchment when calibrated in the non-dry period and verified in the dry period. Upper and lower ranges are given by the 25th and 75th percentiles of the posterior distribution. The whiskers extend to values defining 1.5-standard deviations of the sample. Small dots (gray) denote the arithmetic average of the posterior distribution of this parameter. Values beyond the whiskers are marked as outliers and denoted as small squares.

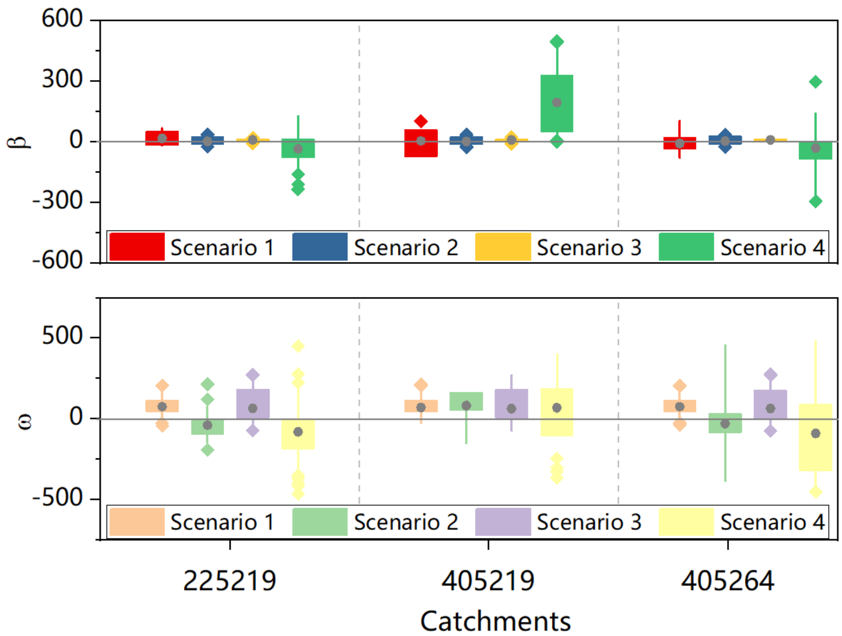

Figure 9. Posterior distributions of the regression parameters (β and ω) for the production storage capacity (θ_1) for the first four model scenarios in each catchment when calibrated in the dry period and verified in the non-dry period. Upper and lower ranges are given by the 25th and 75th percentiles of the posterior distribution. The whiskers extend to values defining 1.5-standard deviations of the sample. Small dots (gray) denote the arithmetic average of the posterior distribution of this parameter. Values beyond the whiskers are marked as outliers and denoted as small squares.