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

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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
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.
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.
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
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 ($\theta_1$ mm), groundwater exchange coefficient ($\theta_2$ mm), 1-day-ahead maximum capacity of the routing store ($\theta_3$ mm), and the time base of the unit hydrograph ($\theta_4$ 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 $\theta_1$.

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 $\theta_1$, 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 $\theta_1$ can be induced by the periodicity in precipitation and in seasonal vegetation growth and senescence. In the present study, $\theta_1$ 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 $\theta_1$ is described by a sine function, using amplitude and phase.

Thus, for any catchment $c$, the full temporal regression function for $\theta_1$ at the data level is:

$$\theta_1(c) = \alpha(c) + \beta(c) \sin(\omega(c) t)$$  \hspace{1cm} (1)

where $\alpha$, $\beta$, $\omega$ are regression parameters for the specific DSST method, and $\alpha$ signifies the intercept, and $\{\beta, \omega\}$ represents the amplitude and phase of the sine function, respectively. If model parameter $\theta_1$ is constant then $\alpha = \beta = \omega = 0$ 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 $\theta_1$. 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:

\[
\begin{align*}
\beta(c) &= N\left(\mu_\beta, \sigma_\beta^2\right) \\
\omega(c) &= N\left(\mu_\omega, \sigma_\omega^2\right)
\end{align*}
\]

where $\mu_\beta$, $\mu_\omega$, $\sigma_\beta$, and $\sigma_\omega$ are hyper-parameters, and $N\left(\ldots\right)$ 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 $\beta$ and $\omega$ 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 $\theta_1$ 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).

$$e_i = -RMSE[\sqrt{Q}](1 + |1 + BIAS|)$$

(3)

where

$$RMSE[\sqrt{Q}] = \sqrt{\frac{1}{T} \sum_{t=1}^{T} [Q_{obs}(t) - Q_{mod}(t)]^2}$$

(4)

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

Coron et al. (2012) showed that this objective function performed well. In this function, the combination of $RMSE[\sqrt{Q}]$ 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:

$$\Lambda = \prod_{i=1}^{C} \epsilon_i \cdot \prod_{n=1}^{2} f_n (\beta, \omega | \mu_2, \sigma_2, \mu_3, \sigma_3)$$  \hspace{1cm} (5)

where the number of catchments in the region is represented by C, and the Gaussian spatial function between regression parameters $\beta, \omega$ and hyper-parameters $\mu_2, \mu_3, \sigma_2$ and $\sigma_3$ 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.
Three criteria were used to assess the projection performance for the verification periods.

1. The first criterion was $\text{NSE}_{\text{sqrt}}$, 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, $\text{NSE}_{\text{sqrt}}$ gives an intermediate, more balanced picture of the overall hydrograph fit because it can reduce the influence of high flow. It is expressed as:

$$\text{NSE}_{\text{sqrt}} = 1 - \frac{\sum_{t=1}^{T} \left[ \sqrt{Q_{\text{obs}}(t)} - \sqrt{Q_{\text{sim}}(t)} \right]^2}{\sum_{t=1}^{T} \left[ \sqrt{Q_{\text{obs}}(t)} - \bar{Q}_{\text{obs}} \right]^2}$$  \hspace{1cm} (6)$$

where $Q_{\text{sim}}(t)$ and $Q_{\text{obs}}(t)$ represent the simulated and observed daily streamflow values for the $t$th day, respectively; $\bar{Q}_{\text{obs}}$ 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.

$$\text{BIAS} = \frac{\sum_{t=1}^{T} \left[ Q_{\text{sim}}(t) - Q_{\text{obs}}(t) \right]}{\sum_{t=1}^{T} Q_{\text{obs}}(t)}$$  \hspace{1cm} (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:
DIC = \(-2 \log(p(q|\theta_{Bayes}, \xi)) + 2p_{DIC}\)  

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

\[
p_{DIC} = 2 \left(\log(p(q|\theta_{Bayes}, \xi)) + \frac{1}{S} \sum_{s=1}^{S} \log(p(q|\theta^s, \xi))\right)
\]

where posterior mean \(\theta_{Bayes} = \text{Expect}(\theta_q, \xi)\) and \(s=1,\ldots,S\), means the sequence number of the simulated parameter set \(\theta^s\) 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).
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$_{\text{sqrt}}$ 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$_{\text{sqrt}}$ 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$_{\text{sqrt}}$ reaching 0.81 during the non-dry calibration period, and then all scenarios experienced a slight decrease in performance (NSE$_{\text{sqrt}} = 0.75$) during the dry verification period. Scenario 4 (time-varying parameters
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 $\text{NSE}_{\text{sqrt}}$ rank order changed (Figure 5b). Scenario 4 had a higher
median $\text{NSE}_{\text{sqrt}}$ 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 ($\alpha$, $\beta$ and $\omega$) 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 $\beta$ and $\omega$ between different catchments,
exhibited the highest median $\text{NSE}_{\text{sqrt}}$ for all catchments with the smallest fluctuation
range. The highest median $\text{NSE}_{\text{sqrt}}$ 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 $\text{NSE}_{\text{sqrt}}$ 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 $\text{NSE}_{\text{sqrt}}$ 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 $\text{NSE}_{\text{sqrt}}$ 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 $\text{NSE}_{\text{sqrt}}$ performance but a wider variation range than scenario 5, while scenario 3 possessed the highest median $\text{NSE}_{\text{sqrt}}$ for all catchments with the smallest fluctuation range.

These results demonstrate that the time-varying scheme for model parameters improved the median $\text{NSE}_{\text{sqrt}}$ 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\textsuperscript{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\textsuperscript{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\textsuperscript{sqrt} criterion for both periods. However, the median estimates did not ensure unbiased simulations over the modeling period; one scenario with a higher NSE\textsuperscript{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 $\beta$ and $\omega$ 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 $\beta$, 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 $\omega$, 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 $\omega$, 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 $\beta$ was spatially coherent), and scenario 3 (both parameters $\beta$ and $\omega$
were spatially coherent). By considering the spatial coherence of regression parameter \( \omega \) between different catchments it was possible to narrow the variation interval of posterior distribution (see scenario 1), while adding the spatial coherence of \( \beta \) increased the variation interval of the posterior distribution of \( \omega \) (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 \( \beta \) and \( \omega \).

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 \( (\theta_1) \), 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 \( \theta_1 \) (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.

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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.

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Chen, X., Hao, Z., Devineni, N., and Lall, U.: Climate information based streamflow and rainfall


Heuvelmans, G., Muys, B., and Feyen, J.: Regionalisation of the parameters of a hydrological


<table>
<thead>
<tr>
<th>Category</th>
<th>Scenario</th>
<th>$\beta$</th>
<th>$\omega$</th>
<th>Constraints</th>
</tr>
</thead>
<tbody>
<tr>
<td>Time-varying</td>
<td>1</td>
<td>Parameter $\beta$ is region-related</td>
<td>Parameter $\omega$ is catchment-specific</td>
<td>$\theta_t = \alpha(c) + \beta(c) + \sin[\omega(c)t]$, while $\beta(c) \sim N(\mu_2, \sigma_2^2)$</td>
</tr>
<tr>
<td></td>
<td>2</td>
<td>Parameter $\beta$ is catchment-specific</td>
<td>Parameter $\omega$ is region-related</td>
<td>$\theta_t = \alpha(c) + \beta(c) + \sin[\omega(c)t]$, while $\omega(c) \sim N(\mu_3, \sigma_3^2)$</td>
</tr>
<tr>
<td></td>
<td>3</td>
<td>Parameter $\beta$ is region-related</td>
<td>Parameter $\omega$ is region-related</td>
<td>$\theta_t = \alpha(c) + \beta(c) + \sin[\omega(c)t]$, while $\beta(c) \sim N(\mu_2, \sigma_2^2)$ and $\omega(c) \sim N(\mu_3, \sigma_3^2)$</td>
</tr>
<tr>
<td>No spatial coherence</td>
<td>4</td>
<td>Parameter $\beta$ is catchment-specific</td>
<td>Parameter $\omega$ is catchment-specific</td>
<td>$\theta_t = \alpha(c) + \beta(c) + \sin[\omega(c)t]$</td>
</tr>
<tr>
<td>Time invariant</td>
<td>5</td>
<td>No parameters $\beta$ or $\omega$</td>
<td></td>
<td>$\theta_t$ is stationary</td>
</tr>
</tbody>
</table>

NB: $\theta_t$ is the production storage capacity of the catchment; $\beta$ is the slope describing long-term change during the modeling period, and $\omega$ is the amplitude of the sine function describing its seasonal variation during the modeling period; $\mu_2, \sigma_2, \mu_3, \sigma_3$ are hyper-parameters.
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.

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

Table 3. Drought identification results for the catchments.

<table>
<thead>
<tr>
<th>Catchments ID</th>
<th>Drought start</th>
<th>Drought end</th>
<th>Length</th>
<th>Mean dry period anomaly</th>
<th>% Complete</th>
<th>R1</th>
<th>R2</th>
<th>Change in runoff (%)</th>
<th>Change in rainfall (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>225219</td>
<td>1997</td>
<td>2009</td>
<td>12</td>
<td>-6.95%</td>
<td>90.4%</td>
<td>0.34</td>
<td>0.28</td>
<td>-15.98</td>
<td>-11.27</td>
</tr>
<tr>
<td>405219</td>
<td>1997</td>
<td>2009</td>
<td>12</td>
<td>-9.84%</td>
<td>98.5%</td>
<td>0.38</td>
<td>0.31</td>
<td>-18.57</td>
<td>-10.97</td>
</tr>
<tr>
<td>405264</td>
<td>1997</td>
<td>2009</td>
<td>12</td>
<td>-9.62%</td>
<td>98.5%</td>
<td>0.35</td>
<td>0.29</td>
<td>-18.23</td>
<td>-10.51</td>
</tr>
</tbody>
</table>

NB: R₁ and R₂ refer to the runoff coefficient during the non-dry and dry periods, respectively.
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.

<table>
<thead>
<tr>
<th>Category</th>
<th>Scenario</th>
<th>DIC</th>
</tr>
</thead>
<tbody>
<tr>
<td>Time-varying</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Spatial coherence</td>
<td>1</td>
<td>4961.7</td>
</tr>
<tr>
<td></td>
<td>2</td>
<td>1202.3</td>
</tr>
<tr>
<td></td>
<td>3</td>
<td>-1254.4</td>
</tr>
<tr>
<td>No spatial coherence</td>
<td>4</td>
<td>5052.8</td>
</tr>
<tr>
<td>Time invariant</td>
<td>5</td>
<td>5827.3</td>
</tr>
</tbody>
</table>

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.

<table>
<thead>
<tr>
<th>Category</th>
<th>Scenario</th>
<th>DIC</th>
</tr>
</thead>
<tbody>
<tr>
<td>Time-varying</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Spatial coherence</td>
<td>1</td>
<td>-6167.0</td>
</tr>
<tr>
<td></td>
<td>2</td>
<td>-5743.6</td>
</tr>
<tr>
<td></td>
<td>3</td>
<td>-10574.0</td>
</tr>
<tr>
<td>No spatial coherence</td>
<td>4</td>
<td>-8710.0</td>
</tr>
<tr>
<td>Time invariant</td>
<td>5</td>
<td>-7460.8</td>
</tr>
</tbody>
</table>
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).
Figure 2. Schematic of the original version of the GR4J rainfall-runoff model.
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).
Figure 4. The identified dry period in all catchments. The annual anomaly is defined as a percentage of the mean annual rainfall.
Figure 5. NSE$_{opt}$ 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<sub>eqpt</sub> 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 $Q_{\text{median}}$ 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 ($\beta$ and $\omega$) for the production storage capacity ($\theta_l$) 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 ($\beta$ and $\omega$) for the production storage capacity ($\theta_1$) 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.