Hydrol. Earth Syst. Sci. Discuss., 12, 7057–7098, 2015
www.hydrol-earth-syst-sci-discuss.net/12/7057/2015/
doi:10.5194/hessd-12-7057-2015

Hydrology and
Earth System
Sciences
Discussions
Open Access

Effectiveness of a regional model calibrated to different parts of a flow regime in regionalisation

H. S. Kim

PhD, Deputy Director, Office for Disaster Investigation and Analysis, Ministry of Public Safety and Security, Seoul, Korea

Received: 10 May 2015 – Accepted: 10 July 2015 – Published: 30 July 2015

Correspondence to: H. S. Kim (kimh0617@gmail.com)

Published by Copernicus Publications on behalf of the European Geosciences Union.

Abstract

The objective of this study was to reduce the parameter uncertainty which has an effect on the identification of the relationship between the catchment characteristics and the catchment response dynamics in ungauged catchments. A water balance model calibrated to represent the rainfall runoff characteristics over long time scales had a potential limitation in the modelling capacity to accurately predict the hydrological effects of non-stationary catchment response dynamics under different climate conditions (distinct wet and dry periods). The accuracy and precision of hydrological modelling predictions was assessed to yield a better understanding for the potential improvement of the model's predictability. In the assessment of model structure suitability to represent the non-stationary catchment response characteristics, there was a flow-dependent bias in the runoff simulations. In particular, over-prediction of the streamflow was dominant for the dry period. The poor model performance during the dry period was associated with the largely different impulse response estimates for the entire period and the dry period. The refined calibration approach was established based on assessment of model deficiencies. The rainfall–runoff models were separately calibrated to different parts of the flow regime, and the calibrated models for the separated time series were used to establish the regional models of relevant parts of the flow regime (i.e. wet and dry periods). The effectiveness of the parameter values for the refined approach in regionalisation was evaluated through investigating the accuracy of predictions of the regional models. The predictability was demonstrated using only the dry period to highlight the improvement in model performance easily veiled by the performance of the model for the whole period. The regional models from the refined calibration approach clearly enhanced the hydrological behaviour by improving the identification of the relationships between the catchment attributes and the catchment response dynamics representing the time constants in fitting recession parts of hydrograph (i.e. improving the parameter identifiability representing the different behaviour of the catchment) in regionalisation.

Title Page
Abstract Introduction
Conclusions References
Tables Figures
◀| |▶
◀ ▶
Back Close
Full Screen / Esc
Printer-friendly Version
Interactive Discussion

1 Introduction

In surface hydrology, one of the fundamental challenges is to predict streamflow from ungauged catchments (Wagener et al., 2004). Regionalisation techniques could be used to obtain appropriate parameter values representing the dynamic characteristics of the catchment response in the ungauged catchments. The regression approach is widely used as an alternative to regionalisation studies (Wagener and Wheater, 2006). In this approach, the statistical relationships between the catchment characteristics and the catchment response dynamics (i.e. the regional model) are used to derive the parameter values in the ungauged catchments after calibrating a hydrological model in the gauged catchment. Various uncertainty sources (i.e. parameter, model structure and data) have an effect on the procedure of the statistical method in regionalisation. The parameter estimation uncertainty has an influence on identifying the relationship between the catchment characteristics and the parameter values in a rainfall–runoff model (Beven and Freer, 2001; Merz and Blöschl, 2004). In particular, the parameter uncertainty is noticeably grown under the condition of the equifinality problem in model calibration (Beven and Freer, 2001).

With an increasing interest in the parameter uncertainty in regionalisation studies, some improved model calibration techniques have recently been discussed to minimise such problems with parameter identification. A regional calibration technique was proposed to circumvent the problem of poor identifiability of model parameters (Fernandez et al., 2000). This technique produces more robust model parameters over the region rather than “best” simulations in all of the individual-gauged catchments by combining two steps in the parameter estimation and establishment of regional relationships into a single process. However, there have only been a few attempts at regional calibration in catchment hydrology, and the regional calibration approach has created heated issues, particularly in the comparison of modelling philosophies (Parajka et al., 2007).

Multi-objective approaches have been introduced to enhance the parameter identifiability through increasing the information content in the hydrological data (i.e. reduction of the uncertainty in parameter estimation) (Gupta et al., 1998). When it comes to regionalisation studies, Seibert (1999) worked on several performance criteria representing the different aspects of the hydrological behaviour in Sweden. Deckers et al. (2010) examined whether large variability in catchment attributes favours regionalisation by principles of catchment similarity for the catchments distributed throughout England and Wales. The regionalisation technique using the multiple objective approach was applied to adequately simulate all aspects of the hydrograph at the ungauged catchment. Kim and Lee (2014a) demonstrated the efficiency of the regionalisation approach based on a multiple objective calibration technique to rainfall–runoff modelling. The regional model with the multiple objective approach led to improved hydrological simulations in ungauged catchments over a single-objective approach, but there was still a flow-dependent bias (i.e. a tendency towards the behaviour of underestimating and overestimating high and low flows for the wet and dry periods, respectively) in the runoff simulations.

Another possible approach to reducing uncertainty is to consider the appropriate calibration period. This process improves the parameter identifiability through increasing the amount of information relevant to the purpose of hydrological modelling. Andrews et al. (2011) evaluated the accuracy of the model on the basis of event-based analysis in hydrological modelling. Specific threshold values for the time series record were used to isolate events in rainfall and observed streamflow. The partitioning schemes based on the modeller's understanding on the hydrological properties in a catchment, the modeller's expertise in a specific model structure, data segments having similar features and a degree of parameter sensitivity were designed to assess hydrological models, which were reviewed by Wagener et al. (2003). Boyle et al. (2000) classified the drainage period in hydrograph into quick- and slow-flow-dominant periods. A simple threshold value was used to divide the drainage period. This scheme can be applied in terms of various modelling objectives on the basis of the modeller's experience, even if it is comparatively subjective. Kleissen (1990) carried out a calibration procedure only for data sets corresponding with those of high sensitive changes of the parameters in a conceptual rainfall–runoff model. This procedure does not recognise the effects of parameter dependencies even though it is a comparatively objective method (Wagener et al., 2004). Kim and Lee (2014b) divided the calibration period into 4-season to explore whether the model calibration could enhance the model accuracy dependent on the climate distributions (i.e. the seasonal climate patterns on rainfall and streamflow) when a rainfall–runoff model was only calibrated on the data segments of each 4-season.

The objective of this study was to reduce the parameter uncertainty in regionalisation studies through improving the parameter identifiability representing the different behaviour of the catchment without adding additional parameters or modification of the model structure. The work presented in this paper is a methodological advancement of the work by Kim and Lee (2014a) incorporating a seasonal calibration (Kim and Lee, 2014b), which involved the regionalisation of parameters of the IHACRES rainfall–runoff model (Jakeman and Hornberger, 1993) for the Korean catchments.

The accuracy and precision of hydrological modelling predictions was assessed to yield a better understanding for the potential improvement of the model's predictability. The variability (or consistency) of hydrologic response in model performance has been investigated to detect problems related to the spatial variability of the model accuracy. Non-parametric impulse response estimates were used to determine a model's ability related to systematic model deviation between simulated and observed behaviours. The refined calibration approach was established based on assessment of model deficiencies. The rainfall–runoff model was separately calibrated to different parts of the flow regime according to an identification of the modelling limitations in its capacity to capture the non-stationary catchment response characteristics under different climate patterns. The calibrated models for the separated time series were used to establish the regional models of relevant parts of the flow regime through the investigation of statistical relationships with the catchment attributes. The time series were partitioned according to the wet and dry periods. The effectiveness of the parameter values for the refined approach in regionalisation was evaluated through investigating the accuracy of predictions of the regional models.

2 Study site and data set

Korea is located in North-East Asia and has five major river basins (Fig. 1). There are various size reservoirs for flood control, hydropower generation and water supply in most of the rivers in Korea. The direct use of discharge time series from streams for long-term rainfall–runoff modelling is limited by the noticeable regulation for various size reservoirs. This study used streamflow gauges upstream of the reservoirs in the catchments in order to avoid reservoir regulation issues. The catchments upstream of the reservoirs are less developed and largely consist of mountainous areas. The research areas were also chosen with consideration of the time series record completeness (with less missing data) and the rainfall and streamflow data quality. The selected research areas for the major river basins are shown in Fig. 1. Table 1 lists brief information on the research sites and the available data period.

The climate characteristics in the selected catchments are shown in Figs. 2 and 3. In Korea, there are 4 seasons associated with spring (March–May.), summer (June–August), autumn (September–November) and winter (December–February). The climate has a dominant summer rainfall. The mean monthly rainfall drops sharply in the autumn (September to October excluding November). Monthly rainfall amounts during the wet period (June–September) are more than 70 % of the total annual rainfall. More than 75 % of the annual streamflow is produced during the wet period. The seasonal distribution of rainfall and streamflow is dominant across the catchment (Fig. 3). In general, the representative catchments selected from the major river basins show a high degree of similarity in the rainfall and streamflow distributions at each season where summers (including September) are wet and the other seasons are dry.

3 Modelling of the gauged catchments

The IHACRES rainfall–runoff model was used in the representation of the flow dynamics in the hydrological response of catchments. The model has been implemented in various catchments under different climate conditions (Post et al., 1996; Schreider et al., 1997; Ye et al., 1997; Littlewood, 2002) and also successfully applied in regionalisation studies based on the regression approach (Post and Jakeman, 1999; Kokkonen et al., 2003). The IHACRES is a conceptual rainfall–runoff model coupling a non-linear loss module (NLM) with a linear routing module (LRM). The conceptual NLM converts observed rainfall into effective rainfall. The LRM, which is a metric transfer function module, transforms the effective rainfall estimated from the NLM into streamflow.

Figure 4 shows the model structure. Figure 4 also lists the parameter description for the LRM and the NLM in terms of dynamic response characteristics in the catchments. The model has six parameters to be calibrated in the LRM and the NLM. The 4th parameter (υ_s) in the LRM is determined from υ_q by the constraint that the unit hydrograph has a unit volume. Jakeman and Hornberger (1993) contains a detailed examination of the model structure.

The "best" parameter sets in model calibration were selected by a multi-criteria rejection algorithm (Kim et al., 2011) with consideration of trade-offs among multi-objective functions. The multi-criteria rejection algorithm is a simple global optimisation technique. This was implemented to minimize the parameter estimation uncertainty by a single objective function. Three model performance statistics (NSE, NSE_ln (the logarithmic form of NSE) and relative bias) were applied to assess the goodness-of-fits between model simulation and observation in the calibration periods.

$$\mathrm{NSE} = 1 - \frac{\sum_{i=1}^{n}\left(Q_i^\mathrm{o} - Q_i^\mathrm{m}\right)^2}{\sum_{i=1}^{n}\left(Q_i^\mathrm{o} - \overline{Q^\mathrm{o}}\right)^2} \tag{1}$$

$$\mathrm{NSE_{ln}} = 1 - \frac{\sum_{i=1}^{n}\left[\ln\left(Q_i^{\mathrm{o}} + Q_{90}^{\mathrm{o}}\right) - \ln\left(Q_i^{\mathrm{m}} + Q_{90}^{\mathrm{o}}\right)\right]^2}{\sum_{i=1}^{n}\left[\ln\left(Q_i^{\mathrm{o}} + Q_{90}^{\mathrm{o}}\right) - \overline{\ln\left(Q^{\mathrm{o}} + Q_{90}^{\mathrm{o}}\right)}\right]^2} \tag{2}$$

$$\%\,\mathrm{bias} = \frac{\sum_{i=1}^{n}\left(Q_i^{\mathrm{o}} - Q_i^{\mathrm{m}}\right)}{\sum_{i=1}^{n} Q_i^{\mathrm{o}}} \times 100 \tag{3}$$

where Q_i^{o} is the ith observed value for streamflow, Q_i^{m} is the ith modelled value for streamflow, $\overline{Q^{\mathrm{o}}}$ is the mean value of the observed flow record, n is the observation number and Q_{90}^{o} is the 90th percentile of non-zero flows in the observation.

In order to identify deficiencies associated with the predictive error from each calibrated model, the variability (or consistency) of the model performance was investigated across all the selected catchments. Non-parametric impulse response estimates (NIREs) based on an average event unit hydrograph (total unit hydrograph incorporating both quick and slow flow components) (Croke, 2006) were used to develop an understanding of the different hydrologic response for the calibration period. The derived average event unit hydrograph represents the hydraulic properties of the catchment with the average effective rainfall pattern due to the intensity and duration over the rainfall events.

4 Regionalising a hydrological model using the regression approach

The regional models were derived from the relationships between the catchment characteristics and the catchment response dynamics using correlation analysis and multiple regression. The correlations between the variables were investigated on linear and log scales, considering statistical significance (Wagener and Wheater, 2006). Correlation analysis for variables from each calibrated model was performed to explore the impacts of parameter sets representing the catchment response dynamics on the regional relationships for the catchment characteristics. A stepwise multiple regression method was implemented to derive the linear and non-linear regional models. The coefficient of determination (R^2) measured the model performance for each regional model. The regional model producing a higher R^2 was chosen through the comparison of the R^2 on each scale.

5 Results and discussion

5.1 Assessment of the calibrated models for the entire flow regime

Calibration of the hydrological model was performed from 2003 to 2010 (an 8 year period) on a daily basis in the 11 catchments. An evaluation of modelling capacity to provide the dynamic characteristics of the catchment response was carried out through assessing the model performance consistency across the 11 catchments. The predictive error caused by model uncertainty was evaluated through analysis of the variability of the model performance. Model performance was also compared for the wet and the dry periods to investigate the capability of the model to reproduce the non-stationary catchment response characteristics under different climate patterns over the whole calibration period. Model performance statistics for wet and dry periods were calculated from the separated observed and simulated flows from the whole time series record used in calibration. The model performance variability for the entire period, the wet period and the dry period is compared in Fig. 5.

In general, the overall model performance (NSE, $\mathrm{NSE}_{\mathrm{ln}}$ and %bias) for the entire period was accurate and consistent in the all catchments. The model performance distributions in NSE, $\mathrm{NSE}_{\mathrm{ln}}$ and %bias for the wet period showed a high degree of similarity in those for the whole period. On the other hand, the rainfall–runoff model led to poorer model performance and larger variability in the values of NSE, $\mathrm{NSE}_{\mathrm{ln}}$ and %bias for the dry period when it was compared to those for the entire and the wet periods in Fig. 5. The negative NSE and $\mathrm{NSE}_{\mathrm{ln}}$ values for the dry period suggest that the magnitude of the observed discharge variance is smaller than that of the residual variance in streamflow of the rainfall–runoff model. As the calibrated models inadequately describe the streamflow behaviours in the catchments, this difference can happen. In Fig. 5, large negative biases with high variability were significant for the dry period when the model performance in %bias for the dry period was compared to the other periods. The model's ability for the dry period across all of the catchments indicates that the models calibrated to the entire flow regime do not accurately capture the effect of non-stationary catchment response dynamics that results from different climate conditions (i.e. the catchment condition as a result of decreasing rainfall).

To assess the model accuracy for the non-stationary catchment response dynamics under different climate patterns, the NIRE was implemented on the basis of the different parts of the flow regime (i.e. the entire, the wet and the dry periods). In Fig. 6, the NIREs are plotted on linear and log scales at the sample catchments (which are the top three catchments having a longer length of record in the study sites: see Table 1).

Visually, it was clear that there was a large difference in the two impulse response profiles for wet and dry periods at the catchments in Fig. 6. In general, the catchments had relatively slow recession from the peak of the impulse response and a strong slow flow component for the dry period, whereas a steeper recession from flow peak and a reduced slow flow component were observed for the wet period. The shape of the impulse response curves for the wet period was quite similar to that for the whole period in all catchments. The poor model performance during the dry period is associated with the largely different impulse response estimates for the entire period and the dry period. By contrast, the similar shapes in impulse response estimates for the whole and the wet periods lead to accurate predictions for the hydrograph's shape at low and high flows and the water balance errors (i.e. NSE, $\text{NSE}_{\ln}$ and %bias) during the wet period and the closeness of the calibration results for model performance.

5.2 Refined calibration approach to improve model deficiencies

The water balance model calibrated to represent the rainfall runoff characteristics over long time scales had difficulties calibrating the wet and dry periods at the same time well, suggesting deficiencies in the model structure. Investigation of catchment response in model performance and the NIREs clearly showed that the models calibrated over an entire flow regime had a potential limitation in the modelling capacity to accurately predict the hydrological effects of non-stationary catchment response dynamics as a result of decreasing rainfall at the catchments.

There seems to be no problem with using the parameter values of the LRM calibrated for the whole period in the wet period within the research sites because of the similar dynamics in the hydrological responses (i.e. impulse response estimates) and model performance for the whole and the wet periods in the catchments. Assuming that there is a sufficiently high degree of similarity between the LRM parameter values for the wet period and those for the whole period, the model predictions can be improved by splitting the historical time series into wet and dry periods and by calibrating data segments only for the dry period separately. The combined estimated flows for the full-time period of interest (i.e. an 8 year calibration period in this study) are then developed by splicing the estimated flows from the separate models.

The parameter values in the NLM are not changed for the wet and dry periods when calibrating to separate parts of the flow regime. The same parameter values in calibration for the whole period are applied in the NLM. Through the periods (i.e. the wet and dry periods) in calibration, the LRM parameters only vary. This strategy preserves the model conditions of antecedent wetness in a catchment when a period is shifted to another through avoiding poor initialisation of the parameter s_k (i.e. catchment wetness index at time step k) employed in the estimation of effective rainfall in each period.

5.3 Comparison of model performance from the traditional and the refined calibration methods

The study in this section investigated whether the estimation of streamflow for the dry period can be further improved by a refined approach that is based on calibration against data sets only for the dry period, as compared to the traditional calibration approach (discussed in Sect. 5.1). Table 2 provides the NLM and the LRM parameter values calibrated using the traditional approach over the entire calibration period. (Hereafter, the LRM parameters calibrated using the traditional approach over the entire calibration period refer to parameter set I.) The LRM parameters calibrated using the refined approach over the dry period (parameter set II) are also tabulated in Table 2. Figure 7 shows the range of parameter sets I and II at the 11 catchments.

The υ_s in parameter set II (mean of 0.40) were higher for the catchments than those in parameter set I (mean of 0.21) in Fig. 7. Parameter set II also provided relatively large recession time constants in both the slow and quick flow components (τ_q and τ_s) compared to those in parameter set I across all of the catchments. The larger recession time constants in parameter set II suggest that a slow recession from the flow peaks in the hydrograph series is dominant across the catchments. By contrast, the smaller recession rates of slow and quick flows in parameter set I lead to sharp flow peaks and a steep recession from the peak flows for the catchments.

Figure 8 provides the comparison of the model performance variability in NSE, NSE_{ln} and %bias from parameter sets I and II for the entire period (Fig. 8b) and the dry period (Fig. 8a). The variability of model performance from parameter sets I and II across the 11 catchments was compared for the entire period in Fig. 8b to investigate how much the errors for the dry period were veiled by those from the wet period when the model was evaluated for the entire period.

Without exception, the model performances in NSE and NSE_{ln} were clearly improved in parameter set II (i.e. more consistent and better model performance) over parameter set I. The values of the %bias were also more stable in parameter set II (SD of 10.93 in Fig. 8a) compared with parameter set I (SD of 15.63 in Fig. 8a). In particular, the predominant overestimations of the flows using parameter set I were significantly reduced by using parameter set II, as illustrated in Fig. 8a.

However, the model performance distributions in NSE for parameter set II during the entire period (mean of 0.80; SD of 0.04 in Fig. 8b) were similar to those by parameter set I for the entire period (mean of 0.79; SD of 0.05 in Fig. 8b) because the performance criteria of the model in calibration for the entire period are controlled by the wet period having a number of high flow events. The NSE is the high sensitivity to high flow events and reduces sensitivity to low flows because of the assumption of constant additive errors between the observed and simulated streamflow (Croke, 2009). As a result, larger values in a time series are strongly weighted, whereas lower values tend to be neglected (Legates and McCabe, 1999). The average value of $\mathrm{NSE}_{\ln}$ during the entire period was slightly better for parameter set II (mean of 0.64 in Fig. 8b) than for parameter set I (mean of 0.53 in Fig. 8b). The pattern of improvement in $\mathrm{NSE}_{\ln}$ for the dry period (as shown in Fig. 8a) was partially reproduced for the entire period in Fig. 8b because the logarithmic form of NSE leads to an increase in the sensitivity to the low flows dominant for the dry period when it is calculated during the whole period.

For the entire calibration period, the variability of %bias from parameter set II (SD of 4.38 in Fig. 8b) was marginally increased compared to parameter set I (SD of 3.91 in Fig. 8b). The underestimated flows in parameter set II (mean of 6.71 in Fig. 8b) were slightly larger than those in parameter set I (mean of 3.30 in Fig. 8b), even though parameter set II provided a better and more stable performance in the %bias value for the dry period than parameter set I in Fig. 8a. The relative difference in improvements in the %bias value between the whole and the dry periods is associated with negative and positive biases for the wet and dry periods in the third column of Fig. 5. The model biases associated with the noticeable overestimation and tendency toward underestimation in parameter set I across the wet and dry periods in Fig. 5 are relieved through the compensation process for each other over the whole period. As a result, the large biases for parameter set I for each of period (i.e. wet and dry periods) were veiled when the performance from parameter set I was calculated for the entire period. By contrast, the underestimation of the observed flows from parameter set II was dominant and consistent over the wet and dry periods across most of the catchments, which leads to a relative increase in the positive biases for the dry period compared to those for the entire period.

5.4 Comparison of regional models from the traditional and the refined calibration methods

Over 20 different catchment attributes were examined to find out possible relationships with the model parameter representing the dynamic characteristics of the catchment response. Of these 20 physical catchment characteristics, the catchment area (AREA), the mean catchment slope (MCS), the effective soil depth ($\mathrm{ESD}_{\mathrm{Shallow}}$) and the catchment gradient (CG) were found to be the primary drivers for representing the hydrological characteristics of the catchment response in Korea under the description of the IHACRES model parameters. A complete list and definition of these catchment attributes is contained in Kim and Lee (2014a). Here, a discussion of the underlying reasons for the different relationships for parameter sets I and II will be given. Table 3 lists the values of the catchment characteristics employed in an explanation of the hydrologic response characteristics of the catchments.

The correlation coefficients on linear and log-log scales between the LRM and the NLM parameters and the four selected catchment characteristics are shown in Table 4. Correlation analysis for variables was performed for the 9 catchments. The other remaining catchments (the Seomjin River and the Nam River catchments) were implemented to verify the regional models. To graphically distinguish the relative differences in the relationship, the main drivers against parameter sets I and II in all catchments are compared in Figs. 9 and 10, respectively.

AREA and CG were observed to be the predominant driver for representing the τ_q and the τ_s parameters in both parameter sets I and II. High positive correlations were dominant throughout the catchments. From a hydrological perspective, these relationships suggest that a large catchment has longer time in response for flow recession in hydrograph than a small catchment. It is explained by the reason that a travel distance of water to the stream and in-stream is longer in a large catchment compared to a small catchment. In the graphical comparison of parameter sets I and II for a given landscape attribute (AREA) (Fig. 9), both parameter sets I and II had a significant trend with increasing the catchment area, but steeper increasing trends in the parameters τ_q and τ_s were investigated in parameter set II. The consistent larger recession time constants in parameter set II compared to those in parameter set I indicate that the effects of the non-stationary catchment response dynamics under different climate patterns for the dry period such as low rainfall at the catchment lead to an increase in the response times for flow recession in parameter set II (i.e. low rainfall for the dry period causes a much longer travel time of surface and subsurface flows to the in-stream and stream with the increased drainage area).

In Table 4, there were negative relationships between the CG and the τ_q and the τ_s parameters along with AREA. These relationships indicate that a catchment with steep slopes has shorter time in response for flow recession than for a gentle sloping catchment. This happens as the water quickly drains in the catchments with steep slopes if there is no considerable influence of the geology (or soil) on catchment systems. Figure 10 also captured some of their different tendencies for a decrease in parameter sets I and II throughout an increase of CG. The steeper decline of the recession time constants in parameter set II against CG is due to different hydrologic response characteristics by the effect of drying at the catchment as a result of decreasing rainfall.

MCS and $\text{ESD}_{\text{shallow}}$ were identified as the major driers for representing the NLM parameters associated with the c parameter and the f parameter in the catchment. No correlation was found between the υ_s and all of the catchment characteristics investigated in Kim and Lee (2014a). A strong correlation (correlation coefficient of 0.88) at the 1 % significance level on linear and logarithmic scales existed between the c and the τ_w.

The linear and non-linear regional models (i.e. suitable statistical relationships between the catchment characteristics and the catchment response dynamics) were established based on stepwise multiple regression, according to the hydrological perspective with statistical significance. Table 5 shows the regional models and the R^2 to measure each model performance. Because of no correlations between the model parameter representing volumetric characteristics (υ_s or υ_q) and the available catchment attributes, the median values of the parameter (υ_s) from parameter sets I and II were adopted (Seibert, 1999). Based on the strong correlation with the parameter c and the parameter τ_w, the regional models for τ_w were derived from the relationship between the c and the τ_w.

5.5 Validation of the regional estimations

Validation of the regional models was performed for the Seomjin River catchment and the Nam River catchment from 2003 to 2010 (an 8 year period). In comparison of the validation results, the model performance from the regional models was compared only for the dry period to highlight the improvement of model performance from parameter set II, which is easily veiled by the performance of the model for the whole period (see Fig. 8). Hereafter, the established regional models according to the statistical relationships between the catchment characteristics and the parameter estimates in parameter sets I and II refer to the Regional model from parameter sets I and II (RMPS I and II), respectively.

Prior to performing model validation, the regional models were implemented in the 9-catchment applied to the regionalisation. The model performance from the RMPS I and II are compared in terms of the consistency of the predictions through all of the 9-catchment in Fig. 11. The RMPS II provided more accurate and consistent values in NSE and $\text{NSE}_{\ln}$ across the catchments compared with the RMPS I. The model performance variability in %bias due to the large overestimated observed flows (i.e. negative biases) in the RMPS I was significantly reduced in the RMPS II in Fig. 11.

The simulated flows from the RMPS I and II at four representative catchments chosen from each of the main river basins are compared in Fig. 12. The differences in the model responses from the RMPS I and II are demonstrated using the linear-log and log-linear scaled flow duration curves (FDCs). The bias structure from the two parameter sets is identified through plotting model residuals against observed streamflow. The RMPS II generally produced better model performance in both high and low flows compared to the RMPS I in the linear-log and log-linear scaled FDCs. In particular, low flows were significantly improved in each catchment in Fig. 12. The RMPS II reduced noticeably the overestimated middle and low flows in the RMPS I (see the residual plots in Fig. 12).

The RMPS I and II were validated at the Seomjin River and the Nam River catchments. A summary of the validation results from the RMPS I and II is listed in Tables 6 and 7. Tables 6 and 7 also provide the performance of the model and the parameter values in the validation catchments, which are estimated from the calibrated parameter sets (i.e. parameter sets I and II). This is applied to identify differences in the response between the calibrated and the regional models.

In comparison of model performance between the RMPS I and II, the RMPS II generally yielded higher model performance in NSE, $\mathrm{NSE}_{\ln}$ and %bias at the Seomjin River and the Nam River catchments. In the case of increased positive bias in the RMPS II (%bias of 20.96 in Table 7) compared to the RMPS I (%bias of 0.26 in Table 7) at the Seomjin River catchment, the increase in %bias was caused by the relative amplification of positive biases with the reduced negative bias in proportion (i.e. improvement of negative biases in a water balance error).

The accurate predictions in the RMPS II at the Nam River catchment are related to the closeness of the LRM parameter values in the calibrated and regional models in Table 6. However, there were relative differences in $\mathrm{NSE}_{\ln}$ and %bias between the calibrated ($\mathrm{NSE}_{\ln}$ of 0.40; %bias of 12.09 in Table 7) and the regional ($\mathrm{NSE}_{\ln}$ of 0.27; %bias of 20.96 in Table 7) models at the Seomjin River catchment. Only small improvement in $\mathrm{NSE}_{\ln}$ from the RMPS II was observed for the Seomjin River catchment ($\mathrm{NSE}_{\ln}$ of 0.12 and 0.27 in the RMPS I and II, respectively; see Table 7). The degraded performance with $\mathrm{NSE}_{\ln}$ and %bias between the calibrated and regional models and the only small improvement in $\mathrm{NSE}_{\ln}$ by the RMPS II at the Seomjin River catchment is caused by the relatively large gaps between τ_s in the regional and the calibrated models in Table 6.

The precision of hydrological modelling predictions for the catchments in validation is shown in Fig. 13. In the graphical comparison of modelled flows with RMPS I and II, the RMPS II provided better model fits for low and high flows for the Nam River catchment in the FDCs in Fig. 13. In particular, an improvement in the model's ability to capture low flows was clearly detected in the FDC's shape for the modelled flows at a log-linear scale for the Nam River catchment. The model biases associated with the tendency towards overestimating mid-range and low flows using the RMPS I were noticeably reduced in the RMPS II for both the Seomjin and the Nam River catchments in the residual plots of Fig. 13.

6 Summary and conclusion

The objective of this study is to reduce the parameter uncertainty in rainfall–runoff modelling, which has an influence on the identification of the relationship between the parameter values and the catchment characteristics in regionalisation. In the assessment of model structure suitability to represent catchment response, the variability (or consistency) of hydrologic response in model performance and parameter values and the NIREs have been implemented to investigate problems associated with the model accuracy in reproducing the non-stationary catchment response characteristics under different climate patterns. There was a flow-dependent bias in the runoff simulations. In particular, over-prediction of the streamflow for the dry period was much more significant. Uncertainties from these types of model errors might be accumulated through regionalisation processes, leading to influences on the identification of relationships between the calibrated parameter values and the catchment characteristics as well as runoff predictions in ungauged catchments.

The rainfall–runoff model were separately calibrated to different parts of the flow regime and the calibrated models for the separated time series were used to establish the regional models of relevant parts of the flow regime according to an identification of the shortcomings in modelling capacity. The relationships between the catchment characteristics and the parameter values in calibration were improved by the refined calibration approach. The refined approach for the dry period produced the consistently larger values in the recession time constants, leading to steeper slopes of the regression model with increasing AREA and CG. An enlargement of the τ_q and the τ_s parameters during the dry period (i.e. comparatively slow recession from the flow peaks in the impulse response profile) is related to the drying of the catchment due to rainfall decrease.

The effectiveness of the parameter values calibrated to different parts of the flow regime in regionalisation was evaluated through investigating the accuracy of predictions of the regional models. The RMPS II generally exhibited accurate predictions in NSE, NSE_{ln} and %bias at the Nam River catchment because of the closeness of the LRM parameter values in the calibrated and the regional models. However, there were relative differences in model performance for NSE_{ln} and %bias between the calibrated and the regional models (i.e. parameter set II and the RMPS II) at the Seomjin River catchment, which was mainly due to the large deviation between the calibrated and the estimated values of the τ_s. The large deviation between them is due to the relatively large variation of the τ_s values calibrated over the dry period (CV of 0.88 in Table 2). The large variation of τ_s might increase missing properties in the regional relationship between AREA and the τ_s values calibrated over the dry period. Consequently, it may influence on the performance of the model in prediction for the hydrograph's shape at low flows and the water balance errors. Given that the wide range of values in τ_s calibrated for the dry period (varying from 13.25 to 589.71 in parameter set II: see Table 2) is dominant, a large number of gauged catchments may improve the identification of the relationship between AREA and τ_s, leading to more accurate predictions of the streamflow for the dry period in ungauged catchments.

This study was focused on a reduction in the predictive uncertainty during the dry period because of the similar dynamic characteristics of the catchment response and model performances for the entire and the wet periods. The predictability was demonstrated using only the dry period to highlight the improvement in model performance easily veiled by the performance of the model during the whole period. The regional models from the refined calibration approach clearly enhanced the hydrological behaviour, which was related to a tendency towards overestimation of observed flow for the dry period by improving the identification of the relationships between the catchment characteristics (AREA and CG) and the time constants in recession parts of hydrograph (τ_q and τ_s). However, the regional models still had the weakness caused by a tendency to underestimate large flows for the wet period. This is related to the under-predicted effective rainfall from the calibrated parameters in the NLM during the wet period. Modification of the NLM may be needed to produce larger effective rainfall for larger rainfall depth during the wet period. Additionally, an suitable structure of the model having a changeable partition between slow and quick flow storages may partially contribute to increasing effective rainfall in large flows during the wet period (e.g. relating the amount of quick flow storage to seasons and rainfall depth).

References

Andrews, F. T., Croke, B. F. W., and Jakeman, A. J.: An open software environment for hydrological model assessment and development, Environ. Modell. Softw., 26, 1171–1185, 2011.

Beven, K. and Freer, J.: Equifinality, data assimilation, and uncertainty estimation in mechanistic modelling of complex environmental systems using the GLUE methodology, J. Hydrol., 249, 11–29, 2001.

Boyle, D. P., Gupta, H. V., and Sorooshian, S.: Toward improved calibration of hydrologic models: combining the strengths of manual and automatic methods, Water Resour. Res., 36, 3663–3674, doi:10.1029/2000wr900207, 2000.

Croke, B. F. W.: A technique for deriving an average event unit hydrograph from streamflow-only data for ephemeral quick-flow-dominant catchments, Adv. Water Resour., 29, 493–502, 2006.

Croke, B. F. W.: Representing uncertainty in objective functions: extension to include the influence of serial correlation, 18th World IMACS Congress and MODSIM09 International Congress on Modelling and Simulation, Cairns, Australia, July 2009, 2009.

Deckers, D. E. H., Booij, M., Rientjes, T. M., and Krol, M.: Catchment variability and parameter estimation in multi-objective regionalisation of a rainfall–runoff model, Water Resour. Manag., 24, 3961–3985, doi:10.1007/s11269-010-9642-8, 2010.

Title Page
Abstract | Introduction
Conclusions | References
Tables | Figures
◀| |▶
◀ ▶
Back | Close
Full Screen / Esc
Printer-friendly Version
Interactive Discussion

Fernandez, W., Vogel, R. M., and Sankarasubramanian, A.: Regional calibration of a watershed model, Hydrolog. Sci. J., 45, 689–707, 2000.

Gupta, H. V., Sorooshian, S., and Yapo, P. O.: Toward improved calibration of hydrologic models: multiple and noncommensurable measures of information, Water Resour. Res., 34, 751–763, doi:10.1029/97wr03495, 1998.

Jakeman, A. J. and Hornberger, G. M.: How much complexity is warranted in a rainfall–runoff model?, Water Resour. Res., 29, 2637–2649, 1993.

Kim, H. S. and Lee, S.: Assessment of the adequacy of the regional relationships between catchment attributes and catchment response dynamics, calibrated by a multi-objective approach, Hydrol. Process., 28, 4023–4041, doi:10.1002/hyp.9942, 2014a.

Kim, H. S. and Lee, S.: Assessment of a seasonal calibration technique using multiple objectives in rainfall–runoff analysis, Hydrol. Process., 28, 2159–2173, doi:10.1002/hyp.9785, 2014b.

Kim, H. S., Croke, B. F. W., Jakeman, A. J., and Chiew, F. H. S.: An assessment of modelling capacity to identify the impacts of climate variability on catchment hydrology, Math. Comput. Simulat., 81, 1419–1429, 2011.

Kleissen, F. M.: Uncertainty and identifiability in conceptual models of surface water acidification, Imperial College of Science, Technology and Medicine, London, 1990.

Kokkonen, T. S., Jakeman, A. J., Young, P. C., and Koivusalo, H. J.: Predicting daily flows in ungauged catchments: model regionalization from catchment descriptors at the Coweeta Hydrologic Laboratory, North Carolina, Hydrol. Process., 17, 2219–2238, doi:10.1002/hyp.1329, 2003.

Legates, D. R. and McCabe, G. J.: Evaluating the use of “goodness-of-fit” measures in hydrologic and hydroclimatic model validation, Water Resour. Res., 35, 233–241, 1999.

Littlewood, I. G.: Improved unit hydrograph characterisation of the daily flow regime (including low flows) for the River Teifi, Wales: towards better rainfall-streamflow models for regionalisation, Hydrol. Earth Syst. Sci., 6, 899–911, doi:10.5194/hess-6-899-2002, 2002.

Merz, R. and Blöschl, G.: Regionalisation of catchment model parameters, J. Hydrol., 287, 95–123, 2004.

Parajka, J., Blöschl, G., and Merz, R.: Regional calibration of catchment models: potential for ungauged catchments, Water Resour. Res., 43, W06406, doi:10.1029/2006wr005271, 2007.

Post, D. A. and Jakeman, A. J.: Predicting the daily streamflow of ungauged catchments in S. E. Australia by regionalising the parameters of a lumped conceptual rainfall–runoff model, Ecol. Model., 123, 91–104, 1999.

Post, D. A., Jakeman, A. J., Littlewood, I. G., Whitehead, P. G., and Jayasuriya, M. D. A.: Modelling land-cover-induced variations in hydrologic response: Picaninny Creek, Victoria, Ecol. Model., 86, 177–182, 1996.

Schreider, S. Y., Whetton, P. H., Jakeman, A. J., and Pittock, A. B.: Runoff modelling for snow-affected catchments in the Australian alpine region, eastern Victoria, J. Hydrol., 200, 1–23, 1997.

Seibert, J.: Regionalisation of parameters for a conceptual rainfall–runoff model, Agr. Forest Meteorol., 98–99, 279–293, 1999.

Wagener, T. and Wheater, H. S.: Parameter estimation and regionalization for continuous rainfall–runoff models including uncertainty, J. Hydrol., 320, 132–154, 2006.

Wagener, T., McIntyre, N., Lees, M. J., Wheater, H. S., and Gupta, H. V.: Towards reduced uncertainty in conceptual rainfall–runoff modelling: dynamic identifiability analysis, Hydrol. Process., 17, 455–476, 2003.

Wagener, T., Wheater, H. S., and Gupta, H. V.: Rainfall–Runoff Modelling in Gauged and Ungauged Catchments, Imperial College Press, London, 2004.

Ye, W., Bates, B. C., Viney, N. R., Sivapalan, M., and Jakeman, A. J.: Performance of conceptual rainfall–runoff models in low-yielding ephemeral catchment, Water Resour. Res., 33, 153–166, 1997.

Table 1. Information and characteristics of the study sites.

Basin name	Station ID	Catchment name	Available record[a]	Annual rainfall[b] (mm)	Annual streamflow[b] (mm)
Han River	1004310	Goesan	1982–2010	1227	682
	1006110	Hoengseong	2000–2010	1494	861
Nakdong River	2001110	Andong	1977–2010	1194	660
	2002110	Imha	1992–2010	1013	522
	2015110	Hapcheon	1989–2010	1304	713
	2018110	Nam River	2000–2010	1597	1110
	2021110	Miryang	2001–2010	1478	966
Geum River	3001110	Yongdam	2001–2010	1412	860
	3303110	Buan	1997–2010	1388	876
Seomjin River	4001110	Seomjin River	1975–2010	1358	744
	4007110	Juam	1991–2010	1429	670

[a] Period with no missing record.

[b] Mean annual values from the first year of available data (1990 at Goesan, Andong, Hapcheon and Seomjin River Dam) to 2010.

Table 2. Non-linear module parameters calibrated using the traditional approach and linear module parameter sets calibrated using the traditional approach (parameter set I) and the refined approach over the dry period (parameter set II) at the 11 catchments.

Catchment	Non-linear parameter			Linear parameter					
				Parameter set I			Parameter set II		
	c	τ_w	f	υ_s	τ_q	τ_s	υ_s	τ_q	τ_s
Goesan	447	79.4	1.8	0.21	1.58	79.32	0.43	2.66	228.80
Hoengseong	718	100.0	1.5	0.23	1.27	16.48	0.44	1.55	41.12
Andong	246	25.1	2.1	0.18	1.44	63.55	0.25	3.32	173.52
Imha	181	20.0	1.8	0.13	1.35	124.48	0.41	1.85	339.11
Hapcheon	398	50.1	1.4	0.24	1.34	51.06	0.57	1.36	177.42
Nam River	320	50.1	1.9	0.12	1.64	86.39	0.39	1.79	174.69
Miryang	291	63.1	2.7	0.25	0.92	13.70	0.37	1.66	19.12
Yongdam	278	31.6	2.2	0.21	0.96	28.89	0.39	1.63	187.13
Buan	372	63.1	2.4	0.24	0.64	9.00	0.40	0.71	13.25
Seomjin River	127	12.6	3.0	0.29	1.03	32.67	0.47	1.78	589.71
Juam	379	39.8	1.8	0.23	1.21	20.14	0.31	1.71	111.51
Mean	342	48.6	2.1	0.21	1.22	47.79	0.40	1.82	186.85
Median	320	50.1	1.9	0.23	1.27	32.67	0.40	1.71	174.69
SD	157	26.6	0.5	0.05	0.30	36.91	0.08	0.67	165.18
CV[*]	0.46	0.55	0.24	0.24	0.25	0.77	0.20	0.37	0.88

[*] Coefficients of variation.

Table 3. Values of the catchment attributes that are highly correlated to the calibrated non-linear and linear model parameters.

Catchment	AREA (km^2)	MCS (%)	CG	ESD$_{\text{Shallow}}$ (%)
Goesan	671	36.87	1.1	72.05
Hoengseong	209	41.13	3.3	50.71
Andong	1584	42.39	0.8	82.90
Imha	1361	40.35	1.1	86.81
Hapcheon	925	34.87	2.0	75.69
Nam River*	2285	35.36	1.7	76.19
Miryang	95	48.73	3.4	78.82
Yongdam	930	37.52	2.1	77.06
Buan	59	43.15	2.9	93.10
Seomjin River*	763	32.78	1.1	83.02
Juam	1010	31.83	1.1	73.06

* Catchments used for verification and are not used for the correlation analysis and deriving the regional models.

Table 4. Correlation coefficients between the catchment attributes and the non-linear and linear module parameters for the nine catchments on linear and log-log transformed scales (the upper value indicates a linear scale, and the lower value indicates a log-log scale).

Catchment attributes	Non-linear parameter		Linear parameter			
			Parameter set I		Parameter set II	
	c	f	τ_q	τ_s	τ_q	τ_s
AREA	–	–	0.60 0.75^b	0.67^b 0.81^c	0.63^a 0.68^b	0.78^c 0.95^c
MCS	–	0.69^b 0.63	–	–	–	–
CG	–	–	-0.67^b -0.66^b	-0.69^b -0.76^b	-0.66^b -0.70^b	-0.77^b -0.77^c
$\text{ESD}_{\text{Shallow}}$	-0.83^c -0.78^c	0.55 0.57	–	–	–	–

[a] Just outside the 5 % significance level.
[b] Significant at the 5 % level.
[c] Significant at the 1 % level.

Table 5. Regional models for the non-linear loss module and the linear routing module based on parameter sets I and II.

Model parameter		Parameter set I		Parameter set II	
		Regional model	R^{2*}	Regional model	R^{2*}
Linear module	τ_q	$e^{-0.947} \cdot \mathrm{AREA}^{0.176}$	0.57	$e^{0.830} \cdot \mathrm{CG}^{-0.551}$	0.50
	τ_s	$e^{-0.221} \cdot \mathrm{AREA}^{0.597}$	0.66	$e^{-1.122} \cdot \mathrm{AREA}^{0.914}$	0.91
	υ_s	0.23	median	0.40	median
Non-linear module	c	$1206.555 - 10.937 \cdot \mathrm{ESD}_{\mathrm{Shallow}}$			0.70
	f	$-1.157 + 0.050 \cdot \mathrm{MCS} + 0.015 \cdot \mathrm{ESD}_{\mathrm{Shallow}}$			0.64
	τ_w	$e^{-3.215} \cdot c^{1.208}$			0.78

[*] Coefficient of determination.

Table 6. Calibrated (the upper numbers) and regionalised (the lower numbers) parameter values of the IHACRES model for the validation catchments.

Catchment	Non-linear parameter			Linear parameter					
					RMPS I			RMPS II	
	c	τ_w	f	υ_s	τ_q	τ_s	υ_s	τ_q	τ_s
Nam River	320	50.1	1.9	0.12	1.64	86.39	0.39	1.79	174.69
	373	51.0	1.7	0.23	1.51	81.44	0.40	1.71	383.86
Seomjin River	127	12.6	3.0	0.29	1.03	32.67	0.47	1.78	589.71
	299	39.0	1.7	0.23	1.25	42.29	0.40	2.18	140.80

Table 7. Model performance statistics for the validation catchments using calibrated parameter values (i.e. parameter sets I and II; the upper numbers) and regionalised parameter values with the RMPS I and II (the lower numbers) in the dry period.

Catchment	RMPS I			RMPS II		
	NSE	NSE_{ln}	%bias	NSE	NSE_{ln}	%bias
Nam River	0.14	0.25	−28.59	0.68	0.65	−5.22
	0.44	0.38	−25.20	0.70	0.64	−0.35
Seomjin River	−0.43	0.10	−21.19	0.51	0.40	12.09
	0.24	0.12	0.26	0.55	0.27	20.96

HESSD
12, 7057–7098, 2015

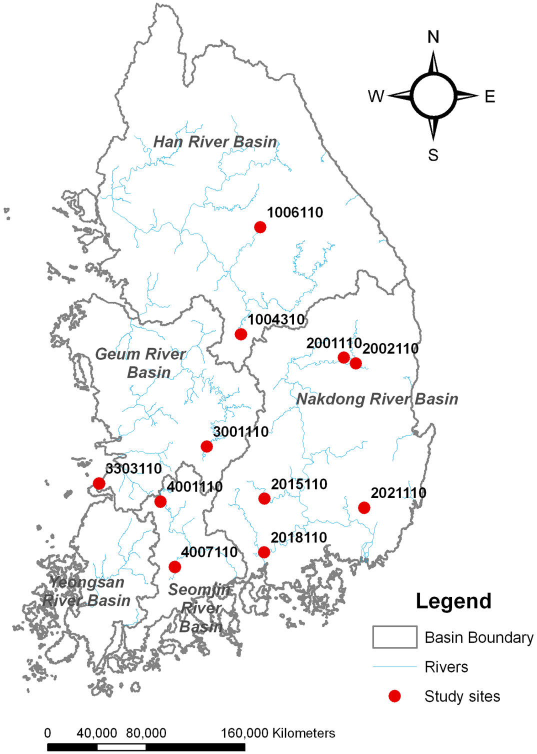


Figure 1. Locations of study sites.

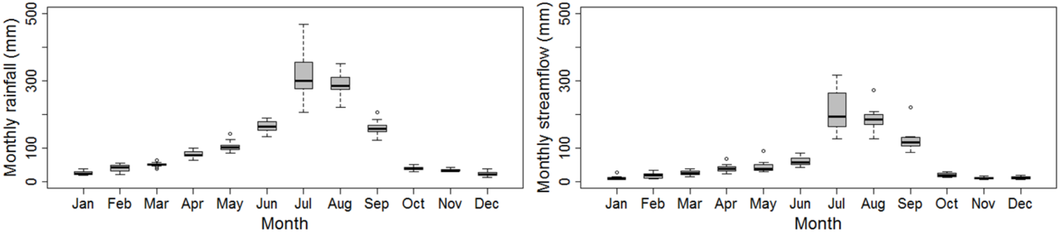


Figure 2. Variability of the mean monthly rainfall (left panel) and streamflow (right panel) for the selected catchments.

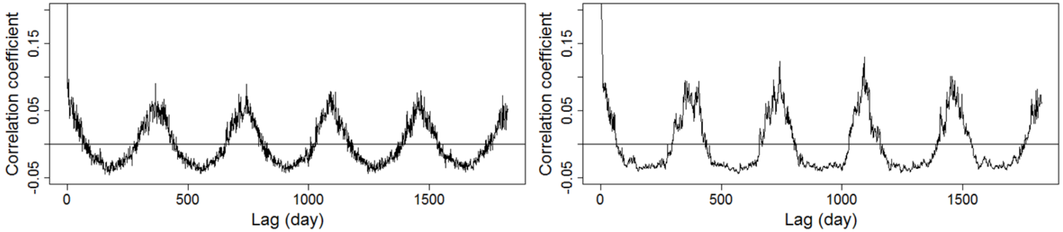
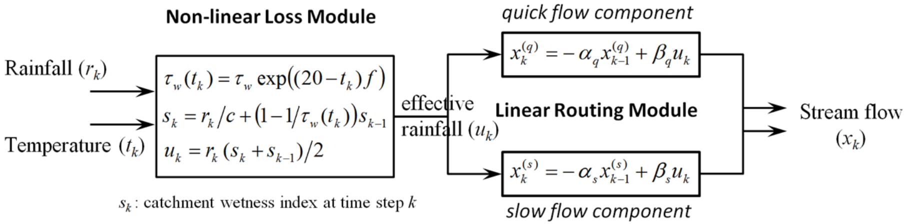


Figure 3. Seasonal effects of historical data at the Seomjin River catchment (which has the longest record in the study sites): areal rainfall (left panel) and streamflow (right panel).



Module	Parameter	Description
Non-linear	c	Maximum volume of the non-linear storage (mm)
	f	Rate of catchment water loss due to a unit change in temperature (temperature modulation factor), yielding $\tau_w(t_k)$
	τ_w	Time constant for the rate of water loss (days)
Linear	τ_s	Slow flow recession time constant (days), $\tau_s = -\Delta/\ln(-\alpha_s)$ where Δ is a time step
	τ_q	Quick flow recession time constant (days), $\tau_q = -\Delta/\ln(-\alpha_q)$
	υ_q	Relative volume of quick flow to total flow, $\upsilon_q = \beta_q/(1+\alpha_q)$
	υ_s	Relative volume of slow flow to total flow, $\upsilon_s = 1 - \upsilon_q$

Figure 4. Schematic diagram of the runoff response module and parameter description of the IHACRES rainfall–runoff model.

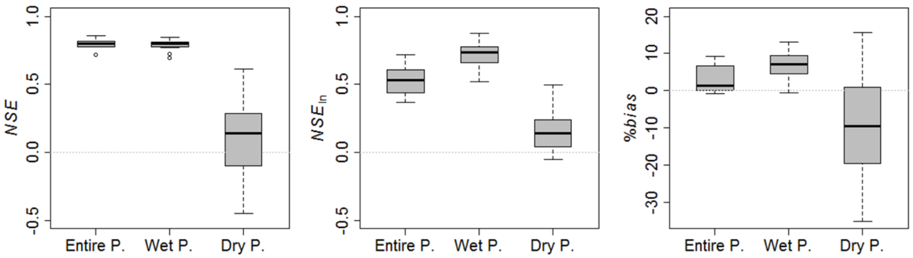
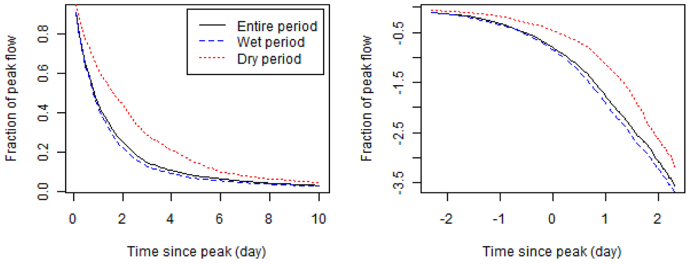
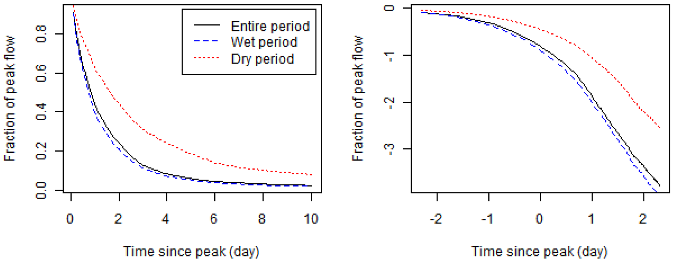


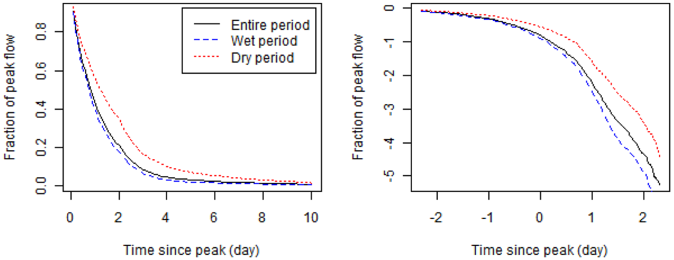
Figure 5. Variability in model performance over the entire period, the wet period and the dry period across the 11 catchments.



(a) Andong catchment; linear (left) and log-log (right) scales



(b) Goesan catchment; linear (left) and log-log (right) scales



(c) Seomjin River catchment; linear (left) and log-log (right) scales

Figure 6. NIREs during the entire period, wet period and dry period at the sample catchments.

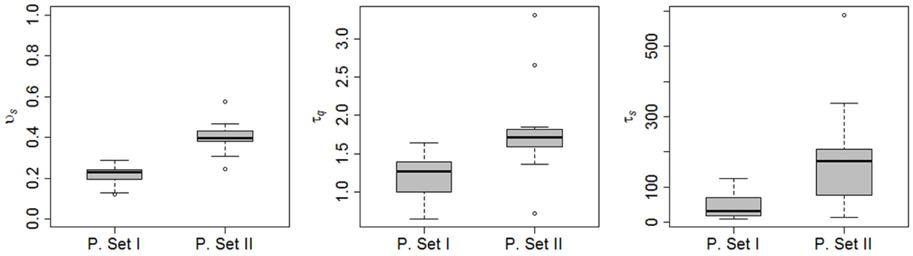
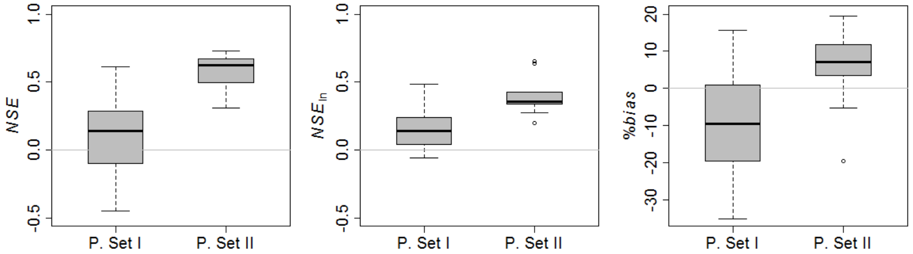
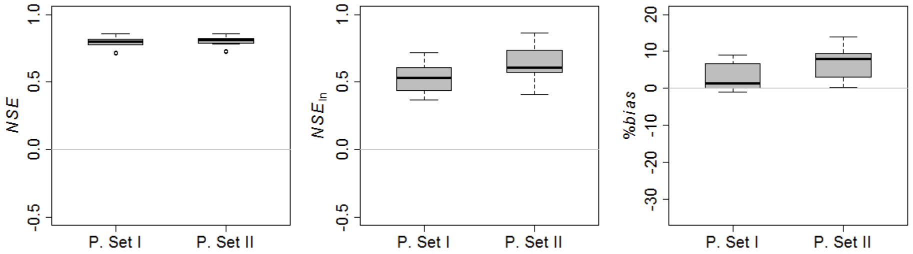


Figure 7. Comparison of the linear routing module parameter sets I and II across the 11 catchments.

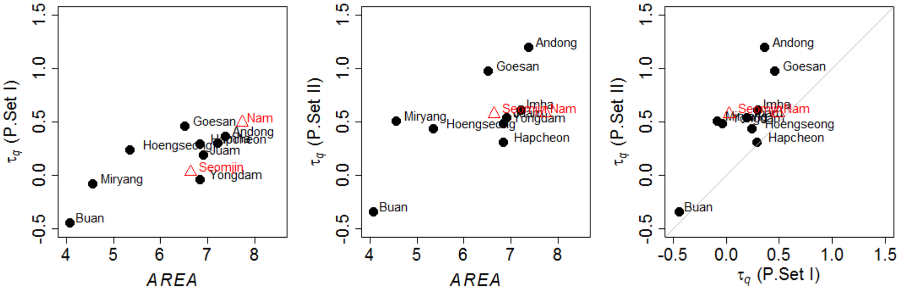


(a) Comparison based on the dry period

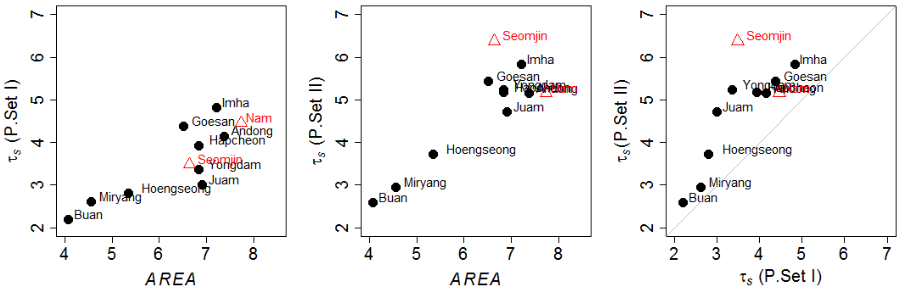


(b) Comparison based on the entire period

Figure 8. Comparison of variability in model performance using parameter sets I and II across the 11 catchments.

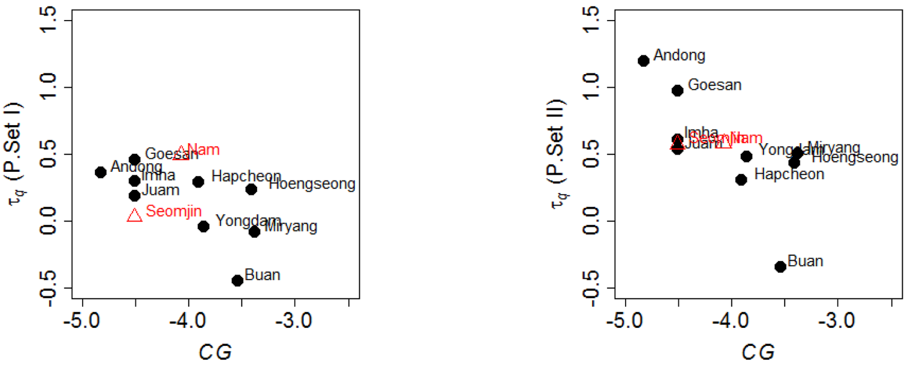


(a) *AREA* versus τ_q based on parameter set I (left) and II (middle) on a log-log scale and comparison of τ_q values from parameter sets I and II on a log-log scale (right)

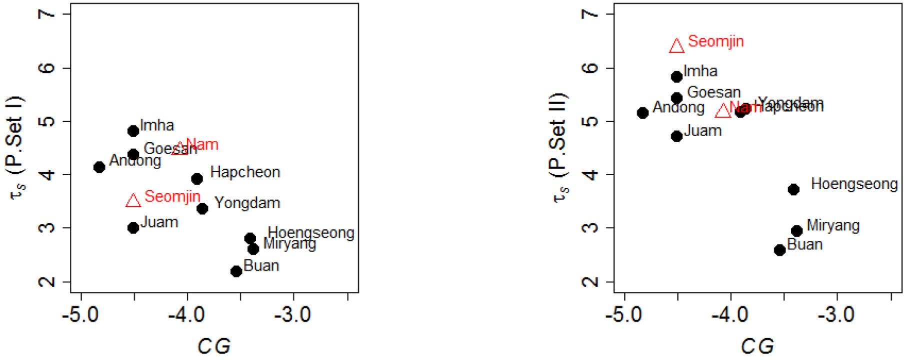


(b) *AREA* versus τ_s based on parameter set I (left) and II (middle) on a log-log scale and comparison of τ_s values from parameter sets I and II on a log-log scale (right)

Figure 9. Scatter plots for AREA and the linear module parameters in parameter sets I and II; solid dots and triangles represent values in the catchments for calibration and validation, respectively.



(a) CG versus τ_q based on parameter set I (left) and II (right) on a log-log scale



(b) CG versus τ_s based on parameter sets I (left) and II (right) on a log-log scale

Figure 10. Scatter plots for CG and the linear module parameters in parameter sets I and II; solid dots and triangles represent values in the catchments for calibration and validation, respectively.

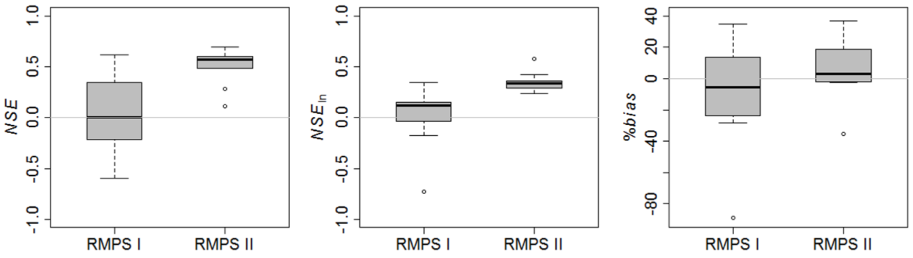
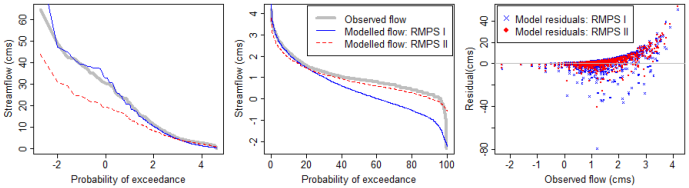
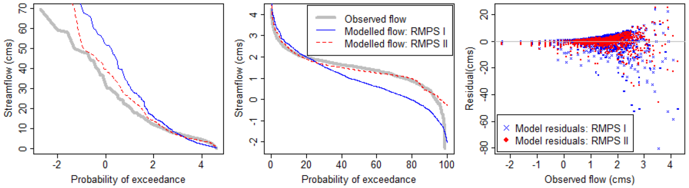


Figure 11. Performance of the RMPS I and II across the nine catchments in the dry period.

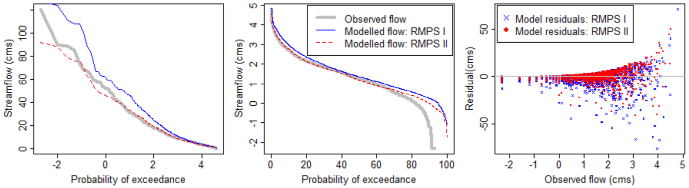
Title Page
Abstract | Introduction
Conclusions | References
Tables | Figures
◀◀ | ▶▶
◀ | ▶
Back | Close
Full Screen / Esc
Printer-friendly Version
Interactive Discussion



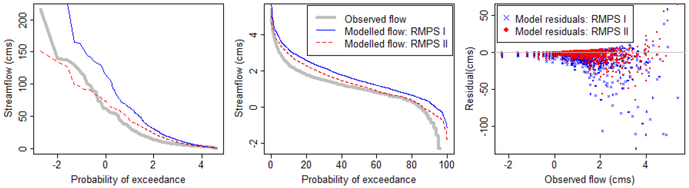
(a) Goesan catchment



(b) Hapcheon catchment

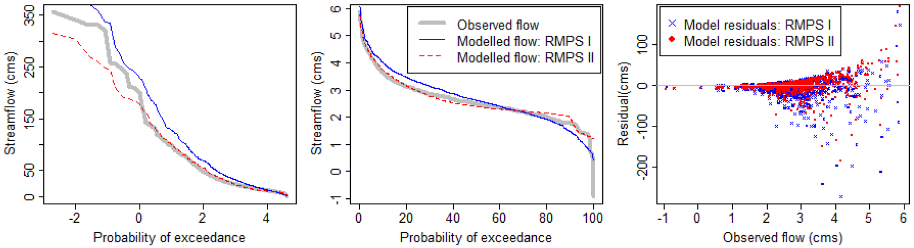


(c) Yongdam catchment

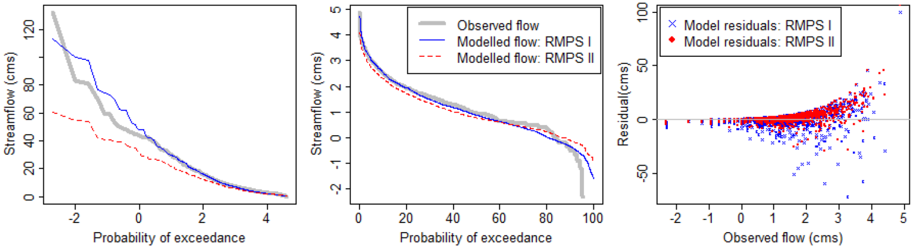


(d) Juam catchment

Figure 12. FDCs at linear-log and log-linear scales and model residuals (observed-modelled flow) from regionalised parameter values with the RMPS I and II at a linear-log scale for the representative catchments in the major river basins.



(a) Nam River catchment



(b) Seomjin River catchment

Figure 13. FDCs at linear-log and log-linear scales and model residuals (observed-modelled flow) at linear-log scale for the validation catchments based on regionalised parameter values with the RMPS I and II.

Title Page
Abstract
Introduction
Conclusions
References
Tables
Figures
◀I
▶I
◀
▶
Back
Close
Full Screen / Esc
Printer-friendly Version
Interactive Discussion