A framework for seasonal variations of hydrological model parameters: Impact on model results and response to dynamic catchment characteristics

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Abstract. Previous studies have shown that the seasonal dynamics of model parameters can compensate for structural defects of hydrological models and improve the accuracy and robustness of the streamflow forecast to some extent. However, some fundamental issues for improving model performance with seasonal dynamic parameters still need to be addressed. In this regard, this study is dedicated to 1) proposing a novel framework for seasonal variations of hydrological model parameters to improve the model performance, and 2) expanding the discussion on model results and response of seasonal dynamic parameters to dynamic characteristics of catchments. The procedure of the framework is developed with (1) extraction of the dynamic catchment characteristics using current data mining techniques, (2) sub-period calibration operations for seasonal dynamic parameters, considering the effects of the significant correlation between the parameters, the number of multiplying parameters, and the temporal memory in the model states in two adjacent sub-periods on calibration operations, and (3) multi-metric assessment of model performance designed for various flow phases. The main findings are 1) the proposed framework significantly improved the accuracy and robustness of the model, 2) however, there was generally poor response of seasonal dynamic parameter set to catchment dynamics. Namely, the dynamic changes of parameters did not follow the dynamics of catchment characteristics. Hence, we deepen the discussion on the poor response in terms of (1) the evolutionary processes on seasonal dynamic parameters optimized by global optimization, considering that the possible failure in finding the global optimum might lead to unreasonable seasonal dynamic parameter values. Moreover, a practical tool for visualizing the evolutionary processes of seasonal dynamic parameters was designed using geometry visualization techniques. (2) The strong correlation between parameters, considering the dynamic changes of one parameter might be intervened by other parameters due to their interdependence. Consequently, the poor response of seasonal dynamic parameter set to dynamic catchment characteristics may be attributed in part to the possible failure in finding the global optimum and strong correlation between parameters. Further analysis also revealed that even though individual parameters cannot respond well to dynamic catchment characteristics, and a dynamic parameter set could carry the information extracted from dynamic catchment characteristics and improve the model performance.

1 Introduction

The absence of some dynamic hydrological processes is one of the common structural defects of hydrological models. For example, dynamic components in hydrological models are often oversimplified due to a poor understanding of their physical mechanisms (Xiong et al., 2019; Dakhlaoui et al., 2017; Pathiraja et al., 2016). It also manifests that the information of input data such as climate data and land-use data could not be fully utilized. However, it is difficult to change the structure of the process-driven hydrological model. With the development of current data mining technology, one of the effective approaches for overcoming the structural inadequacy of hydrological models is to integrate data mining techniques to maximize the application of input data (Firat and Güngör, 2008). In these regards, this study devotes to developing an overall framework for seasonal variations of hydrological model parameters to overcome the structural inadequacy of models and improve the model performance. The proposed framework involves the extraction of dynamic catchment characteristics, effective integration of extracted information and model calibration, and assessment of model performance. More specifically, it includes the selection and generation of hydrometeorological indices, screening for high dimensions of indices, processing of redundant information, sensitivity and correlation analysis of parameters, identification of the high dimensions of parameters, operation of the different module of models, the changes of state variables and fluxes, performance assessment in different flow phases, and assessing the transitivity of optimized dynamic in different periods.

The calibration of hydrological processes in different seasons with unique catchment characteristics is also called sub-period calibration. The static parameters are seasonally dynamized. Even though more techniques for dynamics of hydrological model parameters have been developed, such as parameters vary in time during model simulations (Motavita et al., 2019; Manfreda et al., 2018; Lan et al., 2018, 2020; Fowler et al., 2018), the proposed sub-period calibration effectively integrates into data mining techniques to compensate for the structural defects of the traditional hydrological models with static parameters. It can fully utilize the extracted information of dynamic catchment characteristics and improve the model performance. However, some specific issues for the proposed sub-period calibration are still needed to be addressed. (1) How does the potential correlation between parameters affect the sub-period calibration? Can the seasonal dynamic of a single parameter with high sensitivity or identification effectively improve the simulation performance of hydrological models without considering the correlation between parameters? (2) Given that the number of parameters increases exponentially with the number of sub-periods, will simultaneous optimization of the parameter sets in all sub-periods cause the model for crashes? 3) Due to the considerable temporal memory in the model states while shifting of the parameter set between two adjacent sub-periods, how are the fluxes and state variables in a certain sub-period affected by the previous period? In these regards, five calibration operations are designed and compared to address the above issues and the best solution for model calibration with seasonal dynamic parameters.

The response of seasonal dynamic parameters to extracted dynamic catchment characteristics is critical to elucidate the hydrological model structure and mechanism of model operation. Hence, further discussion is needed regarding the following two aspects. (1) The efficient and effective estimations for dynamic seasonal parameters in hydrological models need to use

optimization algorithms due to the measurement limits and scale issues (Beven and Kirkby, 1979; Beven et al., 1984; Beven and Freer, 2001). However, Zhang et al. (2009) stated that the possible failure in finding the global optimum might lead to abnormal or unreasonable optimal parameters, which might be the main reason for the poor response of seasonal dynamic parameters to dynamic catchment characteristics (Sorooshian et al., 1993; Vrugt et al., 2005; Zhang et al., 2009). Evolutionary

5   algorithms (EAs) are the most well-established class of global optimization algorithms for solving water resources problems (Maier et al., 2014). In each evolutionary process, four steps, including evaluation, fitness assignment, selection and reproduction, are performed. The parameter set with the best objective function value in each evolutionary process loop is recorded in the "evolutionary processes". The evolutionary process evolves toward minimizing the objective function values. The final optimum is obtained at the end of the run while satisfying the stopping criteria (Gomez, 2019). The fitness landscape,

10   as a conceptional and visualization tool, is mainly an illustration of specific settings and states in the evolutionary processes (Dawkins, 1997; Kauffman, 1993; Mitchell, 1998; Wright, 1932). However, the mapping of the fitness landscape for evolutionary processes is a challenge in hydrological model parameter optimization. The main problems include highly nonlinear, multimodal, non-convex, irregular, non-continuous, noisy, non-smooth and non-differentiable functions (Vrugt et al., 2005; Sorooshian et al., 1993; Gupta et al., 1998; Zhang et al., 2009). Besides, the hydrological simulation is not

15   analytically derivable, which also increases the difficulty of the fitness landscape presentation (Maier et al., 2014). Several measures have been previously developed for characterizing the structure of fitness functions, including the correlation length (Weinberger, 1990), objective function surface (Duan et al., 1992,1993, 1994), fitness distance correlation (Jones and Forrest, 1995), the signal-to-noise ratio in the population sizing equation (Harik et al., 1999), the spatial autocorrelation statistic (Gibbs et al., 2004) and a dispersion metric (Arsenault et al., 2014). However, the simple and practical method for hydrological

20   modeling with seasonal dynamic parameters still needs to be further explored. As developed in the field of data visualization techniques, it is given the possibility to apply these state-of-the-art techniques to overcome the limitations of traditional techniques and explain new phenomena for the application of hydrological models, as well as to discover new insights (Arora and Singh, 2013; Derrac et al., 2014; Piotrowski et al., 2017; Gomez, 2019). In these regards, we developed a novel tool for visualizing the evolutionary processes by characterizing the structures of fitness landscapes with possible properties using

25   geometry visualization techniques. (2) Moreover, due to the inability of hydrological models to accurately simulate real catchment situations, the significant correlation of parameters is inevitable (Westra et al., 2014; Klotz et al., 2017; Wang et al., 2017, 2018). The dynamic changes of one parameter might be intervened by other parameters due to their interdependence. This view is also demonstrated by Bárdossy (2007). The auther emphasized that the correlation between parameters in hydrological models would interfere the dynamic of one parameter. In this regard, the linear and nonliear correlation is

30   quantificationally analyzed to further explore the underlying mechanism of the response of dynamic parameters to catchment characteristics.

This study is aimed at proposing a novel framework for seasonal variations of hydrological model parameters to improve the model performance, and expanding the discussion on model results and response of parameters to dynamic characteristics of

catchments. The rest of the paper is organized as follows: Section 2 presents data description and analysis of the case study experiments; Section 3 presents the methods for seasonal dynamics of hydrological model parameters, including the extraction of dynamic catchment chrematistics, calibration operations for seasonal dynamic parameters, and multi-metric assessment of model performance; Section 4 presents the case study results; Section 5 discusses the potential causes for the poor response of

5   seasonal dynamic parameters to dynamic characteristics of catchments, including evolutionary processes on parameters and correlation between parameters, as well as outlines directions for future research; Section 6 summarizes the principal conclusions of the study.

2 Data description

Three basins are applied as an illustration in this study, as shown in Figure 1. The Hanzhong basin with 9,329 km^2 is located

10   in the junction of the Middle Yangtze basin. The Mumahe basin with 1,224 km^2 is characterized by low hills and moderate slopes. The Xunhe basin with 6,448 km^2 is dominated by a complex mountainous landscape, which has high temporal and spatial variability of soil moisture. Although the three basins have different rainfall-runoff characteristics, they all are located in the monsoon region of the East Asia subtropical zone. It is cold and dry in winter but warm and humid in summer (Lin et al., 2010). The seasonal variations of vegetation density and types are contemporaneous (Fang et al., 2002). Significant

15   seasonal changes in the climate and land-surface conditions allow for exploring the intra-annual dynamics of the hydrological processes. Hydrological and climatic data (including daily precipitation, temperature and streamflow data) from 1980 to 1990 were used. Nearly 73% of the data samples (1980-1987) were used for calibration, and the remainder (1988-1990) was utilized to verify the model. Moreover, the hydrometeorological data in the calibration period and the verification period are statistically consistent.
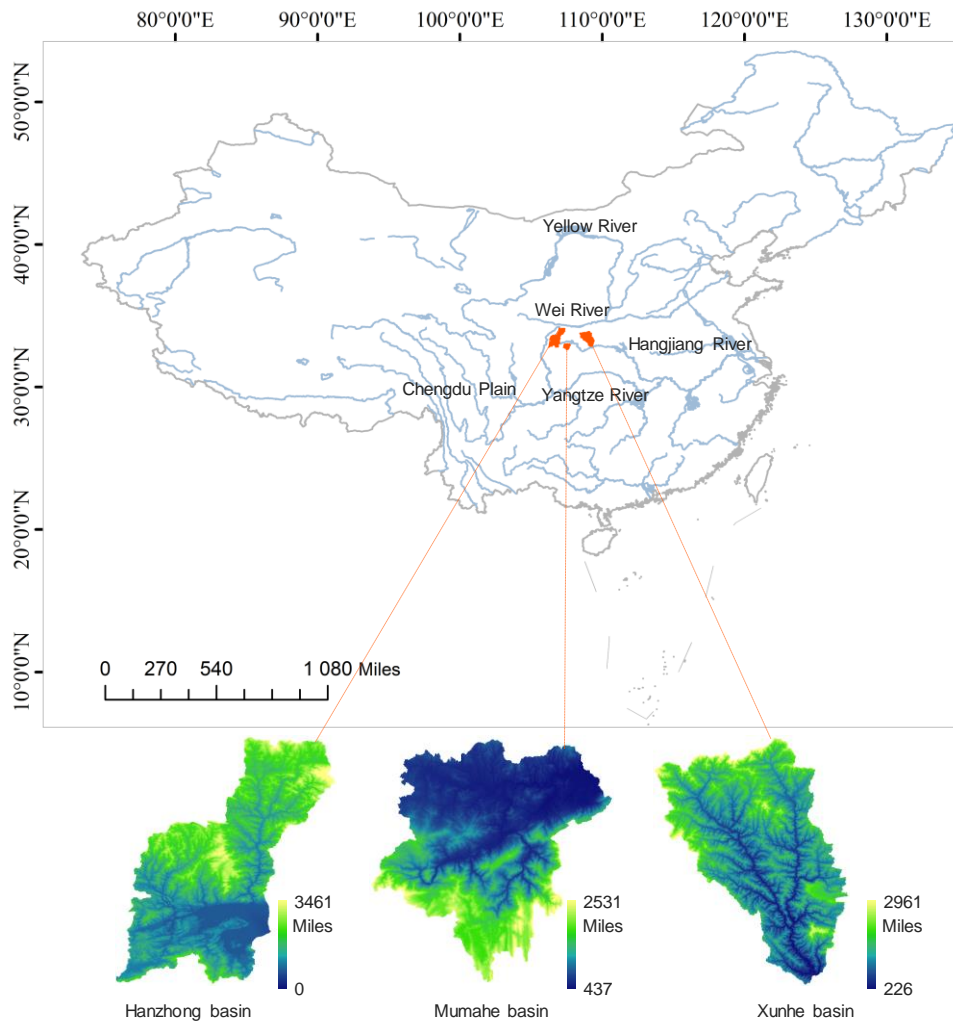
Figure 1. Locations of the study region.

3 Methods

The flowchart of the framework for seasonal dynamics of hydrological model parameters is illustrated in Figure 2 and their
5   codes are opened and attached in Supporting Information.

3.1 Extraction of dynamic catchment characteristics

A set of climatic-land surface indices was provided and preprocessed using the maximal information coefficient (MIC) and
principal components analysis (PCA). Actually, the indices are specified based on dynamic characteristics on a catchment.
The climate and land-surface indices were selected just as examples in this study. The selected climatic indices included total
10   precipitation, maximum 1-day precipitation, maximum five-day precipitation, moderate precipitation days, heavy precipitation

days, total pan evaporation, maximum 1-day pan evaporation and minimum 1-day pan evaporation. The land-surface indices included antecedent streamflow and runoff coefficient. The definition of the indices is provided in Table A1. Indeed, the indices that are independent with streamflow may damage the extraction of dynamic catchment characteristics. Hence, the selected indices should be screened first by identifying the degree of correlation between the indices and streamflow. The MIC, as a statistical metric, can indicate the linear and nonlinear correlation between the variables (Zhang et al., 2014) and is used to screen the indices in this study. The detailed introduction of the MIC metric is provided in the Supporting Information. It is assumed that the indices have a significant effect on streamflow and are picked up while the MIC value is larger than 0.35. In addition, a large amount of redundant information still exists among the screened indices and might damage the availability of the extracted information. Hence, PCA is applied to eliminate further the multicollinearity of indices (Ho et al., 2017).

Hydrological processes clustering, as a bridge, is built between extracted information of dynamic catchment characteristics and calibration operations of the hydrological model. The specific procedures are as follows. The calibration period is divided into 24 sub-annual units. The preprocessed indices in each sub-annual period for all the years are averaged. Two clustering operations were performed based on the climatic and land-surface index systems, respectively. Namely, the calibration period is partitioned into different sub-periods based on the climatic and land-surface indices, respectively. Notably, the clustering results represent the relative differences of the sub-annual periods in a basin rather than absolute differences. Moreover, it was demonstrated that the model performance was better when two sub-period clustering operations were performed based on climate indices and land-surface indices, respectively, instead of one clustering operation according to all indices (Lan et al., 2018). The reason was that, according to all indices, the unsupervised clustering method might not reasonably identify the main characteristics of sub-periods in various systems. For example, two sub-periods with similar climate conditions but not land-surface conditions might not be distinguished.

3.2 Calibration operations

In operation I (a controlled trial), the parameters are static. In operation II, the linear and nonlinear correlation between parameters is first investigated using MIC. Then, a simple but useful tool, i.e., a scatter plot (Paruolo et al., 2013), is used for identifying the sensitive parameter of hydrological models. Only the sensitive parameter is considered as of potential seasonal dynamic parameter, but other parameters are time-invariant. In operation III, simultaneous optimization of the parameter sets in all sub-periods is performed. In operation IV, only the data from the individual sub-periods are used for minimizing the objective function, while the model is run for the whole period (see the calibration operation of Figure 2 in the calibration period). For the state variables and fluxes of the hydrological model between two adjacent subperiods, the last values of the previous period are the initial values of the later period in the validation period. In operation V (the recommended calibration operation), its calibration operation is the same as operation IV. However, the simulated flow data from each sub-period are combined and compared with the observed flow in the validation period (see the calibration operation of Figure 2 in the validation period).

The HYMOD model is one of the commonly used lumped rainfall-runoff models (Yadav et al., 2007; de Vos et al., 2010; Pathiraja et al., 2018). It mainly includes soil moisture accounting mode (involving parameters H_{uz}, B and alpha) and flow routing mode (involving K_q and K_s). It is selected as illustration purposes in this study. The definitions of the five parameters, state variables and fluxes are illustrated in Table A2. Its more detailed descriptions are presented in Supporting Information.

5 An evolutionary algorithm for seasonal dynamic parameters used in this study is the so-called Shuffled Complex Evolution from the University of Arizona (SCE-UA) (Duan et al., 1993). Arsenault et al. (2014) demonstrated that SCE-UA performs better for hydrological models with low complexity, compared with other global optimization algorithms. Besides, the multiple trials are performed to ensure that the results are consistent, preventing the effects of initial values in this study. The objective function is defined as the combination of the Nash-Sutcliffe efficiency index (NSE) and its logarithmic transformation (LNSE)

10 (Nash and Sutcliffe, 1970; Nijzink et al., 2016). It is expressed as $1 - 0.5 \cdot (\text{NSE} + \text{LNSE})$. The closer the objective function value is to zero, the better the model performance. In addition, a warm-up period of one year is used in calibration and three months in the validation period. The flowchart is illustrated in Figure 2, and its codes are opened and attached in Supporting Information.

3.3 Assessment of model performance

15 Simulation performance with seasonal dynamic parameters is assessed using seven performance metrics. The metrics include NSE, LNSE and a five-segment flow duration curve (5FDC) with the root mean square error (RMSE) (Pfannerstill et al., 2014). The NSE is sensitive to peak discharges and LNSE emphasizes low flows. RMSE with FDC is used to assess the model performance in the five phrases of streamflow, including very high, high, middle, low and very low flow (Cheng et al., 2012; Pokhrel et al., 2012; Yokoo and Sivapalan, 2011). FDC is split into five segments, including below Q5, between Q5 and Q20,

20 between Q20 and Q70, between Q70 and Q95, and higher than Q95, i.e., RMSE_Q5, RMSE_Q20, RMSE_Qmid, RMSE_Q70, RMSE_Q95, as shown in Figure 2. Besides, the differences in these metrics between the calibration period and the validation period are used to assess the temporal transferability of parameters (Gharari et al., 2013; Klemeš, 1986).
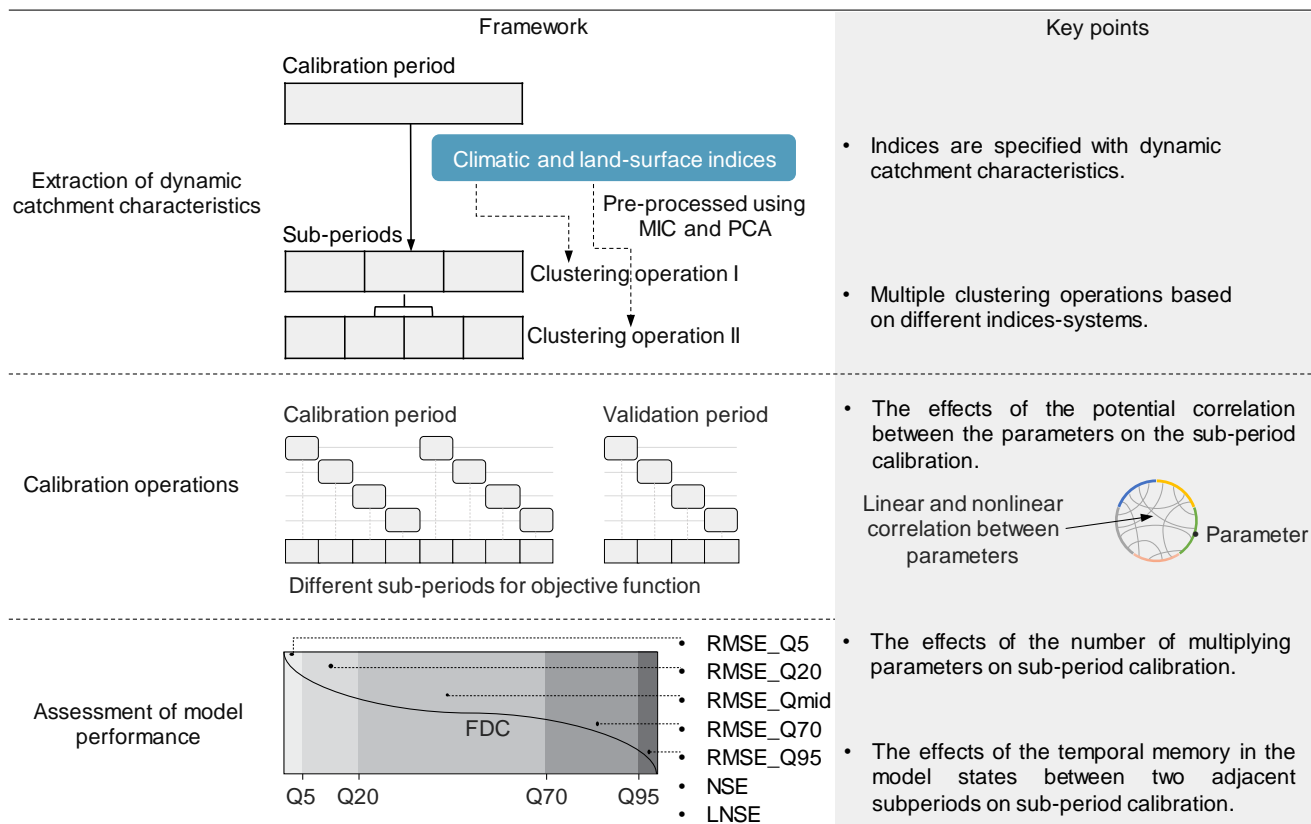
Figure 2. The developed framework for seasonal dynamics of hydrological model parameters.

4 Results

The calendar year is divided into four sub-annual periods based on hydrological/climatic similarities, as shown in Figure 3a.

5 In this way, the clustering results of the validation period are largely in agreement with the results of the calibration period. The sub-periods include the dry period, rainfall period I, rainfall period II (wettest period) and rainfall period III. Both the total amount and the variance values of all the precipitation series are minimum in the dry period and maximum in the rainfall period II. Two normal sub-annual periods (rainfall period I and rainfall period III) have similar climate conditions, but the rainfall period III has higher antecedent soil moisture content than in rainfall period I.

10 The model performance in five calibration operations is presented in Figure 3b, taking the Hanzhong Basin as an example. Compared with the operation **I** (controlled trial), the seasonal dynamics of a single parameter K_s with high sensitivity (see Figure 4a) do not significantly improve or decrease model performance in operation **II**. The result is consistent with Bárdossy (2007). The author demonstrated that one dynamic parameter might be compensated for the adjustment of other time-invariant parameters during calibration due to the strong correlation between parameters. As a result, the final performance of the model

15 with the single dynamic parameter is not significantly improved. Figure 4b verifies that there is a significant linear and

nonlinear correlation between parameters by MIC coefficients. The calibration in operation **III** has a seasonal dynamic parameter set and continuous model states. However, the multiplying number of parameters indeed leads to the crash of the model run, showing the abysmal model performance. In operation **IV**, the model performance in the validation period is not good. The shifting of the parameter set between two adjacent sub-periods may lead to the unreasonable values of model states at the junction, and further causing the model for crashes. The result is consistent with Kim and Han (2017). The operation **V** with the best model performance in various flow phases is recommended for seasonal dynamic parameters. It is also demonstrated that significant improvement in medium flow mainly benefits from the extraction of dynamic land-surface information. Namely, the clustering of the rainfall period I and rainfall period III is based on diverse soil moisture content but similar climate conditions. Besides, there was better temporal transferability of the dynamic parameters in the calibration and validation periods. Evidently, the operation **V** well utilized the extracted information of dynamic catchment characteristics and tackling the above critical issues for model calibration. Besides, the simulation performance in four sub-periods of the calibration period is shown in Figure 3c. The results show that the model performance is best in the rainfall period II (wettest period) and the poorest in the dry period.

Seasonal dynamic parameter sets in operation **V** are shown in Figure 3d. The value of K_s (slow-flow routing tanks' rate) is lowest in the dry period and highest in the wettest period in all basins. However, other parameters have no regular pattern on dynamic catchment characteristics. Most of the excess streamflow in the three rainfall periods is diverted to the slow-flow tank because the alpha values are close to zero. It means that the slow-flow tanks have a primary effect on the simulations. However, the parameter K_s does not reflect the difference between rainfall period I and rainfall period III, which have similar climate conditions but not land-surface conditions. In sum, there is generally poor response of seasonal dynamic parameter set to dynamic catchment characteristics.
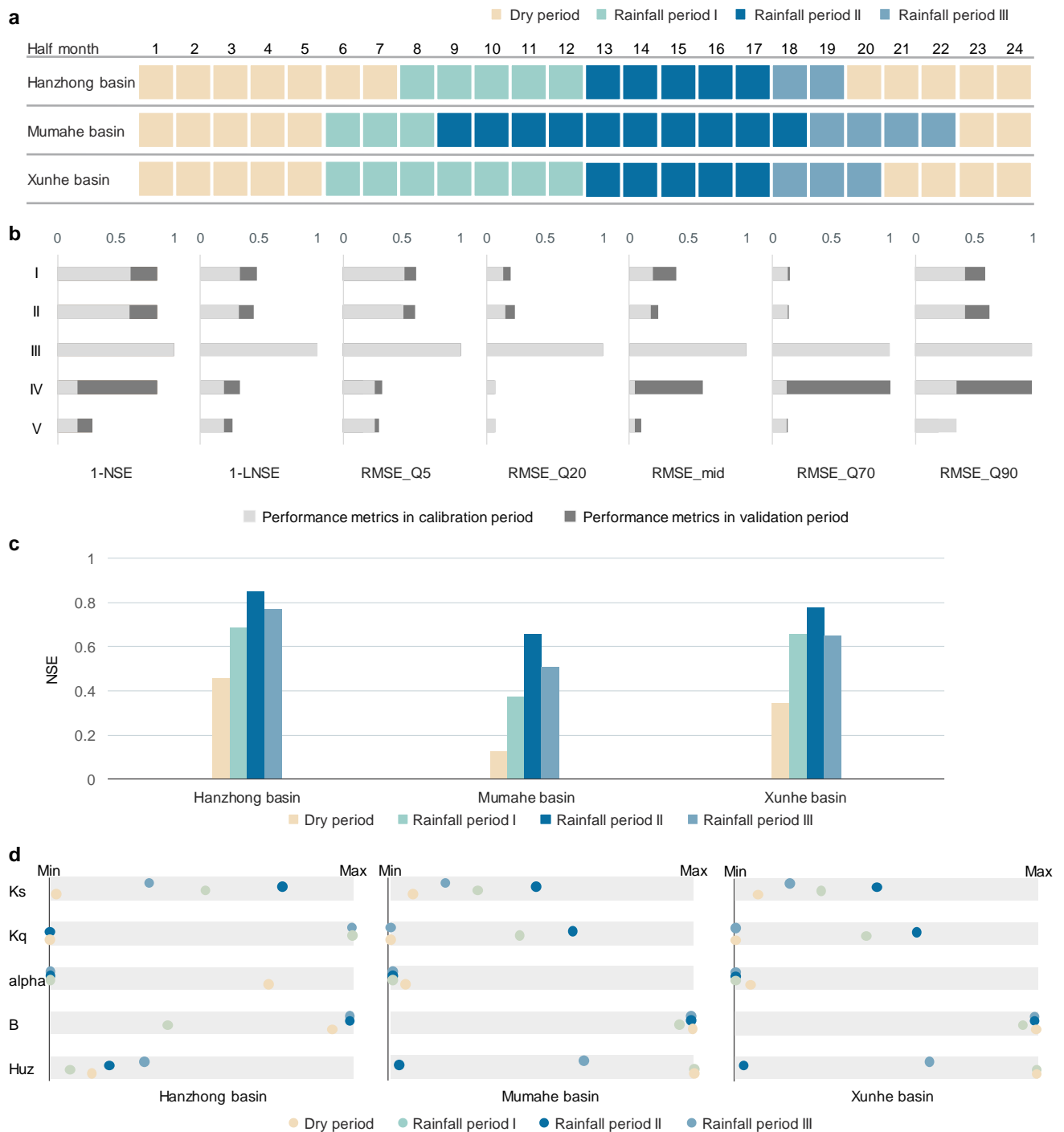
Figure 3. a) Heat map of sub-period partition. **b)** Model performance. **c)** Simulation performance in four sub-periods of the calibration period. **d)** Seasonal dynamic parameter sets.
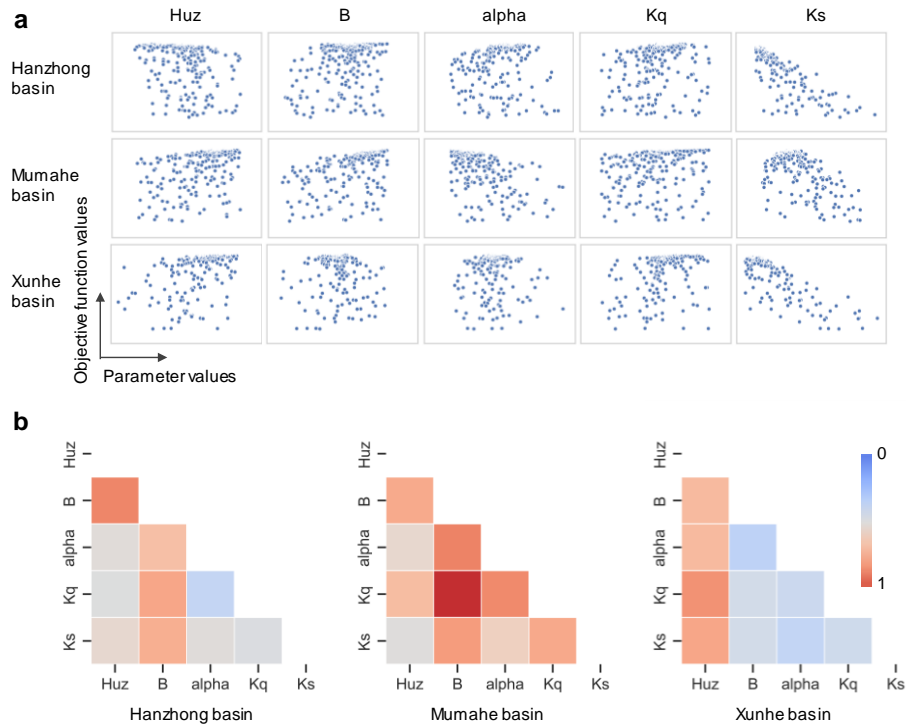
Figure 4. a) Sensitivity analysis results using scatterplots. The horizontal axis represents the sampling points, which are the parameter sets. The vertical axis represents their objective function values. **b)** The linear or nonlinear correlations between the parameters based on MIC coefficients. Red denotes the strongest correlation between parameters.

5 Discussion

The above results showed that the developed framework for seasonal variations of hydrological model parameters significantly improves model performance. However, there is generally poor response of dynamic parameter set to catchment dynamics. The potential reasons are discussed as follows.

5.1 Evolutionary processes on parameters

The intuitive sketches of three-dimensional fitness landscapes with possible properties are illustrated in Figure 5a. The vertical axis denotes the objective function values and the horizontal axes denote the parameter space. The possible properties with increasing difficulty to find global optimum are illustrated as follows: (I) Best case or low variations: an evolutionary process is ideal for estimating the global optimum. (II) Deceptiveness: a significant obstacle is a local optimum. The gradient of the deceptive objective function values may lead the optimizer away from the optima. (III) Confusion: as the local optima increase, the possible paths for finding the globally optimal solution are complicated, which makes it harder to find the global optimum. (IV) Ruggedness: if the objective function values are fluctuating, i.e., increasing or decreasing, it is difficult to determine the correct direction for the evolutionary process (Weise, 2009). To further illustrate that the overall structure of the fitness

landscapes, such as the "big bowl" shape, can easily guide the algorithm towards the global optimum, while a surface that is tough with many local optima may present difficulties (Weise, 2009; Maier et al., 2014; Kallel et al., 1998), the detailed information for the fitness landscape is provided in the Supporting Information.

The evolutionary process of dynamic parameters in individual parameter spaces is investigated (see Figure 5b) using violin plots. The violin plots are a tool to visualize the kernel density distribution of the data points (Hintze and Nelson, 1998; Piel et al., 2010). The anatomy of the violin plot and the associated information can be found in the Supporting Information. We use probability distributions of the violin plots to configure the elements of the evolution processes, representing the possible properties of the fitness landscapes. The vertical axis of the violin plot denotes parameter values; the horizontal axis denotes the probability values. With an adequate parameter space and sufficient density of coverage in individual parameters, the thinner distribution type of violin plot indicates that fewer local optimal solutions hamper evolutionary processes. For example, unimodal distribution is an ideal evolutionary process to estimate the best solution. Conversely, the multimodal or flat distribution signifies that the search is indecisive due to the prominent interference from local optima. Namely, the search may fail to find a global optimum (Dakhlaoui et al., 2017; Rahnamay Naeini et al., 2018; Vrugt and Beven, 2018). The four types of distributions of violin plots (including unimodal, bimodal, multimodal and flat distributions) with increasing the number of peaks match the properties' sketches of the fitness landscapes.

The evolutionary process of dynamic parameters in multi-parameter space is investigated regarding the entire parameter set as a whole (see Figure 5c). The parallel coordinates are a data visualization technique for multivariate data that is easy to interpret, which are applied to configure the evolutionary processes in the multi-parameter space. The polylines describe multivariate items that intersect with parallel axes. These parallel axes represent variables that can be used for the analysis of multiple properties of a multivariate data set (Heinrich and Weiskopf, 2015; Janetzko et al., 2016; Johansson and Forsell, 2016). More detailed information on the parallel coordinates is given in the Supporting Information. When used in hydrological models, the variables on the dimension axes denote individual parameters. The polylines of the parallel coordinates symbolize the parameter sets in all loops of one evolutionary process. The width of the parameter set distribution of the polylines in the parallel coordinates is used to assess the ability to find global optimum in the multi-parameter space. The higher the width of the parameter set distribution, the more difficult it is to determine the correct direction for the evolutionary process. The parameter set is challenging to converge to the global optimum. Moreover, the evolutionary process evolves toward minimizing the objective function values $f(x)$. Hence, the color changes of parallel coordinates (see Figure 5c) could represent the evolutional direction of the fitness landscapes, which is illustrated in Figure 5a (III). The direction of the arrow represents the direction of evolution. Also, the violin plot can visualize the probability distribution of each variable (i.e., parameter) along the dimension axis (Janetzko et al., 2016) (see Figures 5b and c). Interestingly, in the axis configuration of parallel coordinates, the envelope of lines between adjacent axes can be spotted to the scatter plot, which represents the relationships between parameters. Hence, the linear and nonlinear relationships between variables mapped on adjacent axes can be directly analyzed (Vrotsou et al., 2010), as shown in Figure 5d. Moreover, the multi-relational 3D parallel coordinates (Yao and Wu, 2016) (see

Figure 5e) is regarded as another approach to exhibit the relationship between any two parameters and explore new phenomena for a run of hydrological models in the ongoing research.
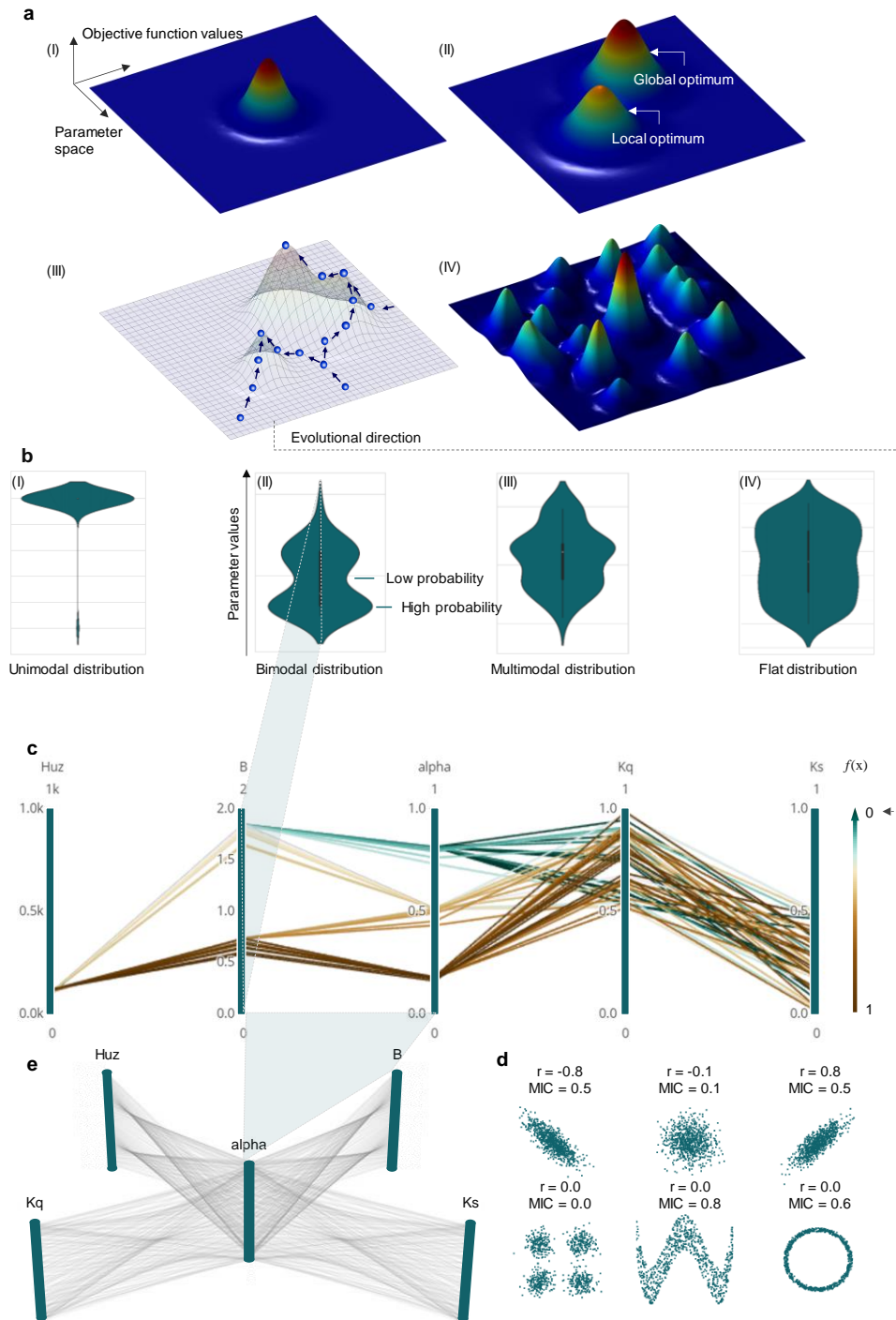
Figure 5. a) Intuitive sketches of three-dimensional fitness landscapes with possible properties. The vertical axis denotes the objective function values and the horizontal axes denote the parameter space. The arrows represent various paths that the population could follow

while evolving on the fitness landscape. **b)** Evolutionary processes in individual parameter spaces using violin plots. The vertical axis of the violin plot denotes parameter values; the horizontal axis denotes the probability values. **c)** Evolutionary processes in multi-parameter space using parallel coordinates. These parallel axes represent individual parameters. The polylines describe the parameter set. The evolutionary process evolves toward minimizing the objective function values $f(x)$. Hence, the color changes of parallel coordinates could represent the evolutional direction of the fitness landscapes. **d)** Spotting the envelope of lines between adjacent axes to scatter plot (Zhang et al., 2014). **e)** Multi-relational 3D parallel coordinate plots (Heinrich and Weiskopf, 2015).

Taking the Hanzhong basin as an example, the results for investigating the evolutionary processes of seasonal dynamic parameters in the individual parameter spaces are shown in Figure 6. The parameter K_s presents the thinner distribution of violin plots in all sub-periods, which manifests that its evolutionary processes are disturbed by fewer local optima and less hindered. However, the ability to find the global optimum of other parameters is generally poor. The results are consistent with the response of seasonal dynamic parameters to catchment characteristics shown in Figure 3d. The results in the Mumahe basin and Xunhe basin are shown in Figure S3 and Figure S4 in the Supporting Information. The results are similar to those of the Hanzhong basin.

The evolutionary processes of dynamic parameters in multi-parameter space are investigated and shown in Figures 7 and 8. Firstly, it is stated that the parameter sets from the first two loops are not investigated because their results have high uncertainties as to the warm-up of the global optimization algorithm. The direction of the evolutionary processes is analyzed according to the color changes of parallel coordinates. The polylines at K_s search to the final values with the minimum number of iterations, i.e., the fastest speed in all sub-periods. However, the polylines at other parameters are fluctuating, i.e., increasing and decreasing. It implies that it is difficult to find the right direction to determine the global optimum. In addition, the width of the parameter set distribution of the polylines decreases sequentially in the dry period, rainfall period I, rainfall period III and rainfall period II. The result indicates that the ability to find global optimum is increasing in four sub-periods, which is consistent with the simulation performance in four sub-periods (shown in Figure 3c). The results in the Mumahe basin and Xunhe basin are similar to the Hanzhong basin and shown in Figures S5-S8 in the Supporting Information.
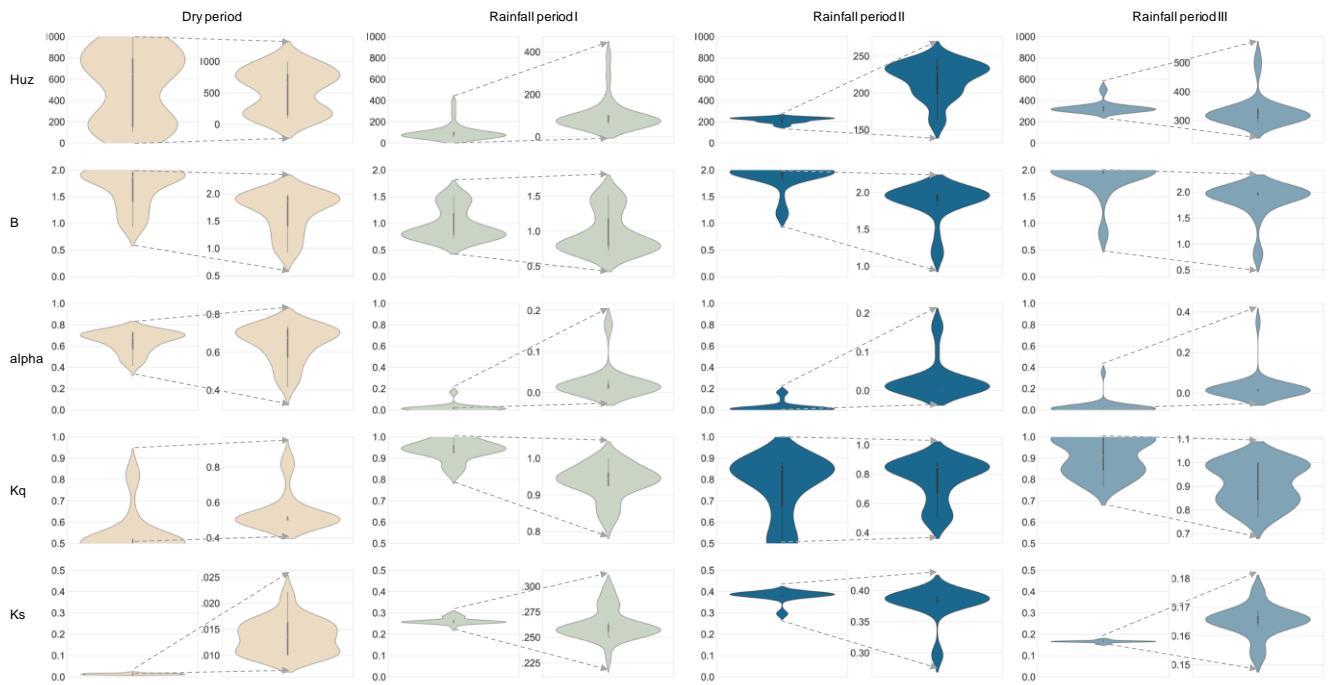
Figure 6. Evolutionary processes of seasonal dynamic parameters in the individual parameter spaces in the Hanzhong basin.
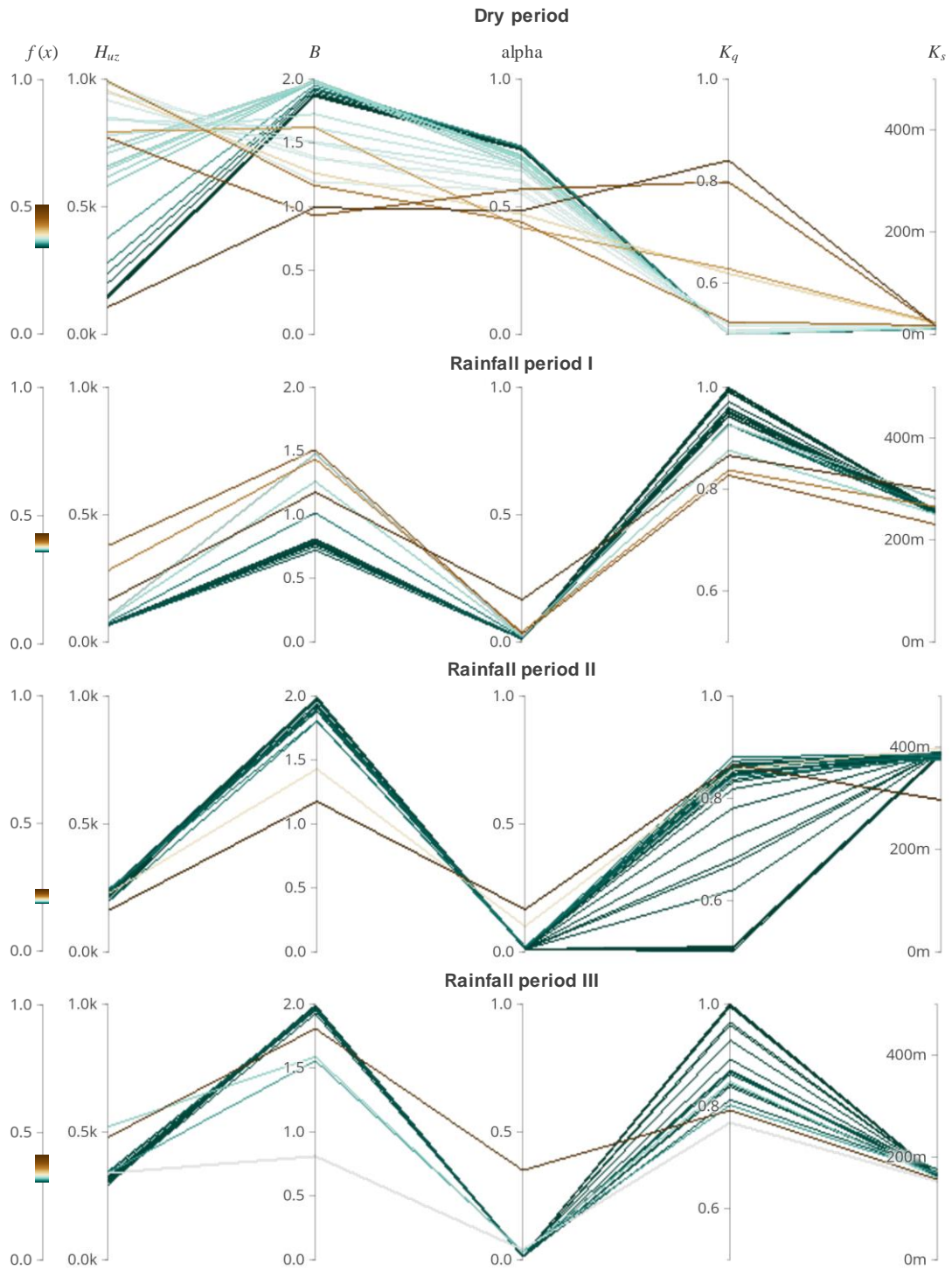
Figure 7. Evolutionary processes of seasonal dynamic parameters in multi-parameter space in the Hanzhong basin.
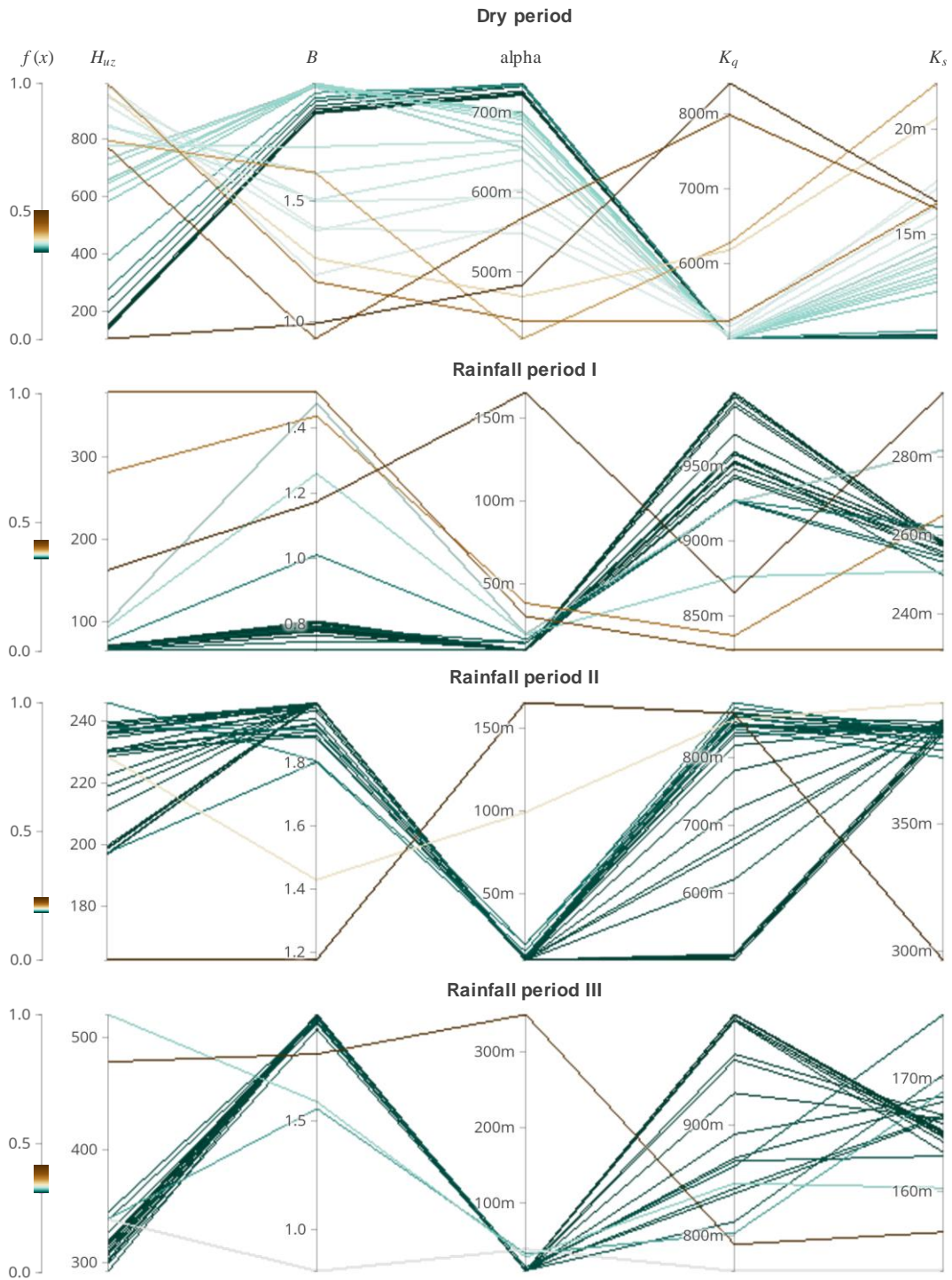
Figure 8. Evolutionary processes of seasonal dynamic parameters with magnified details on the axes in multi-parameter space in the Hanzhong basin.

5.2 Correlation between parameters

According to the values of MIC shown in Figure 4b, the significant linear and nonlinear correlation MIC existed between parameters, which verify the Bárdossy's (2007) view. Namely, the dynamic changes of one parameter might be intervened by other parameters due to their interdependence. However, according to the assessment results of model performance, the model performance with a seasonal dynamic parameter set has significant improvement. Even though individual parameters cannot respond well to dynamic catchment characteristics, a dynamic parameter set could carry the information extracted from dynamic catchment characteristics and improve the model performance.

5.3 Limitation

Still, there are several limitations, and we will address in future studies: (1) More catchments with various characteristics will be investigated to explore the impact of spatial variability of watershed features on model performance. (2) Besides seasonal-scale variability, more time scales for dynamic parameters in catchment response, such as annuals-scale variability and long-term changes, will be further studied. (3) The study uses a 5-parameter model, which is considered as a small parameter space. We would explore the higher-dimensional hydrological model using the methodology and procedure demonstrated in the ongoing study. (4) The quantifiable metrics to assess the evolutionary processes will be developed. The violin plot uses a nonparametric density estimation based on a smooth kernel function with a fixed global radius. The PDF (probability density function), CDF (cumulative distribution function) values of data can be used to quantify the violin plots in case of uniform, multimodal, skewed and clipped data (Yapo et al., 1996). Hence, the mathematical benchmark functions with PDF and CDF will be used for assessing the evolutionary processes of dynamic parameters in the next research. In addition, a dispersion metric is suggested to evaluate the polylines in the parallel coordinate and the evolutionary processes in the multi-parameter space. The metric measures average Euclidian distances, which were normalized to ensure comparability (Arsenault et al., 2014). However, the application of the quantitative evaluation metrics needs a significant amount of experiment, validation, analysis and discussion, which cannot all be considered in this study. We will clarify and investigate this critical issue in the ongoing study.

6 Conclusions

The seasonal dynamic of parameters is one of the practical considerations for compensating structural defects of hydrological models and improving model performance. In this study, a framework was proposed to extract the dynamic catchment characteristics using a series of data mining methods. The information extraction included selection and generation of climate and land-use indices, screening of indices, processing of redundant information among indices and clustering of hydrological processes based on the indices. The extracted information and model calibration were effectively integrated by sub-period calibration operations. The recommended calibration operation considered the sensitivity and correlation of parameters, the

dimensions of parameters, and considerable temporal memory in the model states between two adjacent subperiods. Multi-metric assessment of model performance was designed for various flow phases and the temporal transitivity of parameters.

The study showed that the proposed framework significantly improves the accuracy and robustness of the hydrological model. However, there was generally a poor response of seasonal dynamic parameter set to dynamic catchment characteristics. Hence,

5   the investigation for this issue was expanded considering the evolutionary processes on seasonal dynamic parameters optimized by global optimization and the intricate and significant correlation between parameters. Consequently, the poor response of seasonal dynamic parameter set to catchment dynamics might be attributed in part to the possible failure in finding the global optimum when optimizing the seasonal dynamic parameters and strong correlation between parameters. Even though individual parameters could not respond well to dynamic catchment characteristics, a dynamic parameter set could carry the

10 information extracted from dynamic catchment characteristics and improve the model performance. In addition, a novel tool for visualizing the evolutionary processes of seasonal dynamic parameters was designed using geometry visualization techniques, which was also regarded as an important tool to understand the model running with dynamic hydrological model parameters in the next research. More case studies and applications of hydrological models can be performed in the future. They are expected to yield insights into the predictive performance of hydrological models.

15 **Code and data availability**

The digital elevation model (DEM) of the study area is derived from the Advanced Spaceborne Thermal Emission and Reflection Radiometer (ASTER) global digital elevation model (GDEM) with a cell size of 30×30 m, which can be obtained from https://asterweb.jpl.nasa.gov/gdem.asp (NASA, 2019). The climatic datasets consist of daily rainfall datasets and pan evaporation datasets provided by the China Climatic Data Sharing Service System, which can be obtained from

20 https://data.cma.cn/en/?r=data/online&t=6 (CMDC, 2019). Daily streamflow used to support this paper can be made available for interested readers by contacting the corresponding author at linkr@mail.sysu.edu.cn.

Author contributions

LT, LK, XCY, LZ and CH each contributed to the development of the calibration schemes and assessment, analyzed the results, and discussed the poor model performance.

25 **Competing interests**

The authors declare that they have no conflict of interest.

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Review statement

This paper was edited by Fabrizio Fenicia and reviewed by two anonymous referees.

Appendix

Table A1. Climatic-land surface indices.

Indices	Descriptive names	Definitions	Units
R_T	Total precipitation	Current half-monthly total precipitation	mm
RX1day	Maximum 1-day precipitation	Half-monthly highest 1-day precipitation	mm
RX5day	Maximum five-day precipitation	Half-monthly highest consecutive 5-day precipitation	mm
R25pday	Moderate precipitation days	Count of days where RR (daily precipitation amount) < 25th percentile	days
R75pday	Heavy precipitation days	Count of days where $RR \geq$ 75th percentile	days
PE_T	Total pan evaporation	Current half-monthly total pan evaporation	mm
PE_x	Maximum 1-day pan evaporation	Half-monthly highest 1-day pan evaporation	mm
PE_n	Minimum 1-day pan evaporation	Half-monthly lowest 1-day pan evaporation	mm
Q_{T-1}	Antecedent streamflow	Antecedent half-monthly average streamflow	m^3/s
C	Runoff coefficient	Ratio of runoff volume to rainfall volume	

Table A2. Definitions of parameters, state variables and fluxes used in the HYMOD model (Wagener et al., 2001).

Label	Property	Range	Description
H_{uz}	Parameter	0-1000 [mm]	Maximum height of soil moisture accounting tank
B	Parameter	0-1.99	Scaled distribution function shape
alpha	Parameter	0-0.99	Quick/slow split
K_q	Parameter	0-0.99	Quick-flow routing tanks' rate
K_s	Parameter	0-0.99	Slow-flow routing tank's rate
XH_{uz}	State variable	[mm]	Upper zone soil moisture tank state height
XC_{uz}	State variable	[mm]	Upper zone soil moisture tank state contents
X_q	State variable	[mm]	Quick-flow tank states contents
X_s	State variable	[mm]	Slow-flow tank state contents
AE	Fluxes	[mm/day]	Actual evapotranspiration flux
OV	Fluxes	[mm/day]	Precipitation excess flux
Q_q	Fluxes	[mm/day]	Quick-flow flux
Q_s	Fluxes	[mm/day]	Slow-flow flux
Q_{sim}	Fluxes	[mm/day]	Total streamflow flux

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