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Improved Model Parameter Transferability Method for Hydrological Simulation with SWAT in Ungauged Mountainous Catchments

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Abstract: The sustainability of water resources in mountainous areas has a significant contribution to the stabilization and persistence of the ecological and agriculture systems in arid and semi-arid areas. However, the insufficient understanding of hydrological processes in ungauged mountainous catchments (UMCs) is not able to scientifically support the sustainable management of water resources. The conventional parameter transferability method (transplanting the parameters of the donor catchment model with similar distances or attributes to the target catchment model) still has great potential for improving the accuracy of the hydrological simulation in UMC. In this study, 46 river catchments, with discharge survey stations and multi-type catchment characteristics in Xinjiang, are separated into the target catchments and donor catchments to promote an improved model parameter transferability method (IMPTM). This method synthetically processes the SWAT model parameters based on the distance approximation principle (DAP) and the attribute similarity principle (ASP). The performance of this method is tested in a random gauged catchment and compared with other traditional methods (DAP and ASP). The daily runoff simulation results in the target catchment have relatively low accuracy by both the DAP method ($NS = 0.27$, $R^2 = 0.55$) and ASP method ($NS = 0.36$, $R^2 = 0.65$), which implies the conventional approach is not capable of processing the parameters in the target regions. However, the simulation result by IMPTM is a significant improvement ($NS = 0.69$, $R^2 = 0.85$). Moreover, the IMPTM can accurately catch the flow peak, appearance time, and recession curve. The current study provides a compatible method to overcome the difficulties of hydrological simulation in UMCs in the world and can benefit hydrological forecasting and water resource estimation in mountainous areas.

Keywords: ungauged catchment; hydrological simulation; parameter transfer; SWAT model

1. Introduction

The hydrological model is an essential tool to understand the hydrological process of catchments under the various climate input and land management [1], which includes a lumped conceptual model, and semi-distributed or distributed hydrological models, e.g., the Xin'anjiang model [2,3],

the TOPMODEL model [4,5], and the SWAT model [6–8]. These models have to satisfy the accuracy requirements of the hydrological process's simulation with measurement flow data by parameter calibration and validation. However, many watersheds in mountainous areas are data-deficient or ungauged, which are difficult to apply to models to conduct the proper management of water resources [9–11], especially when the snow-cover and icecaps on high-altitude mountains [12] contribute melting water downstream [13]. Therefore, proper parameterization is one of the key processes to achieve accurate hydrological simulation in the data-deficient or ungauged catchments.

Hydrology simulation in ungauged catchments has caught the attention of hydrologists for a long time. The International Association of Hydrological Sciences (IAHS) also put forward the International Hydrological Plan (PUB) in 2003, with the aim of strengthening hydrological process modeling and forecasting in ungauged catchments [14]. At present, the main methods conducted in ungauged catchments are mathematical statistics and hydrological modeling [2,3,15]. The mathematical statistics method can get the runoff rapidly and roughly. However, it neglects the physical mechanism of the hydrologic process and cannot describe the temporal and spatial variations of the hydrological elements [16]. The distributed model has obvious advantages for the hydrological process simulation in ungauged catchments. Some authors have proposed many methods to parameterize the ungauged (target) catchments based on the gauged (donor) by using the distance approximation principle [16–18], the attribute similarity principle [19,20] and the regression analysis method [21,22]. However, these three parameter transferability methods ignore the differences of climatic or physical properties between target catchment and donor catchment, such as mean elevation and catchment area, which creates great uncertainty on the simulated results. Therefore, it is a huge challenge to properly parameterize the ungauged mountainous catchments (UMC).

Due to the drawback of direct parameter transferring based on the closest or similar attributes, many scholars have noticed the relationship between model parameters and catchment characteristics [23–26]. Grabowski et al. explored the linear relationship between stream temperature and areal average landscape variables (average elevation, average slope, curve number) [27]. Athira et al. analyzed the relationship between the model parameters and the catchment characteristics of 8 catchments in the US and concluded that there is a nonlinear relationship between them [28]. However, the parameter transfer approach still has great potential to regionalize to mountainous alpine catchments for satisfactory results. Therefore, the development of new methods for model parameter transferability for ungauged catchments still has meaning in practice.

Xinjiang province is located in the arid and semi-arid areas of northwest China, which suffers from a serious shortage of water resources due to low precipitation and high evapotranspiration [29,30]. However, most of its headwater regions are situated in high-altitude mountainous areas [31,32], and the snow-melting and ice-melting runoff are the major components of water source for the plain areas [33–35]. Due to global warming, the frequencies and intensities of mountainous floods and debris flow have increased significantly and threaten the local population [36–38]. However, the vast and complex terrain in Xinjiang results in very low densities of meteorological and hydrological measurement stations (about one station every 3000 km²). Therefore, it becomes extremely difficult in UMCs to conduct the proper simulation or forecasting for mountainous stream flows [39,40]. The accurate simulation for UMCs is not only helpful to learn about the hydrological conditions of the alpine catchment, but also to provide technical support for the sustainable use of downstream water resources (such as hydropower production, agricultural irrigation, flood and disaster prevention, and flood resource utilization).

The classic parameter transferability approaches suggested by previous studies are not fully capable of model parameterization when only a few flow data in surrounding catchments are available. This paper provides an alternative approach of model parameter transferability for the ungauged mountainous catchments to reduce the uncertainties of model parameters. In this study, the soil and water assessment tool (SWAT) model is applied to simulate hydrological processes for 46 mountain river catchments with discharge gauging stations in Xinjiang. This alternative approach intends to

make full use of the topographic, climatic characteristics, and SWAT model parameter sets to grasp the statistical relationships between the ungauged (target) and gauged (donor) catchments. By doing so, the authors aim to provide an alternative method for the accurate simulation of hydrological processes in UMCs and to generate accurate simulation results for water authorities.

2. Data and Methods

2.1. Catchments

This proposed alternative method was established and tested on sample catchments to guarantee the applicability and robustness. A parameter library with a large number of sample parameter sets could also catch the internal relations among these properties. Therefore, in this study, we used a set of 46 small to medium-size catchments in Xinjiang (Figure 1 and Table S1). Xinjiang is an arid and semi-arid region located in the northwest of China ($73^{\circ}40' \text{ E} \sim 96^{\circ}18' \text{ E}$, $34^{\circ}25' \text{ N} \sim 48^{\circ}10' \text{ N}$). This region has a complex topography, with the elevation of -216 to 8587 m [29]. Tianshan divides Xinjiang into two regions, namely, southern Xinjiang and northern Xinjiang, with an average annual precipitation of 106 and 255 mm , respectively. Alpine catchment in Xinjiang contributes more than 80% of surface runoff, among which glacier and snow-melt runoff accounts for greater than 45% of total runoff [41]. These 46 small and medium-sized rivers were selected from the three mountains, Altai Mountain, Tianshan Mountain, and Kunlun Mountain, respectively. These watersheds have the common characteristics of high average altitude ($1844.58\sim 4920.50 \text{ m}$), a large height difference, and replenishment of snow-melt water runoff. In addition, the watershed area ranges from 163.20 to 14578.74 km^2 . The types of runoff replenishment include precipitation type, snow melting type, ice melting type, mixed type and so on. The geographical positions of catchments are shown in Figure 1.

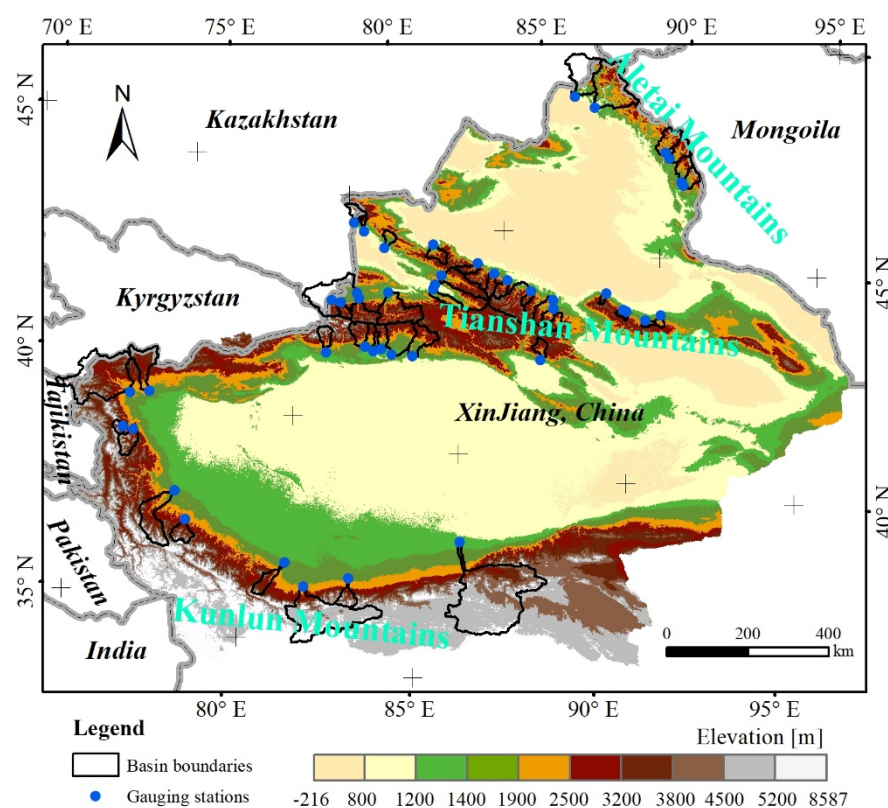


Figure 1. Location of the 46 Xinjiang catchments used in this study (blue dots indicate the gauging stations and solid lines the catchment boundaries).

2.2. Data Sources

The data needed for this study are mainly used in the model build, calibration, and validation of these catchments' SWAT hydrological models. The digital elevation model (DEM), soil data, land use/cover data, and meteorological data (e.g., maximum and minimum temperatures, precipitation) are collected as model-driven data, while the measured runoff data are used to model calibration and validation. In order to reduce the differences caused by the driving data, models of the 46 catchments in Xinjiang are built using the same set of DEM, soil, land use/cover data with a unified projection coordinate system. DEM data is derived from the ASTER GDEM with the spatial resolution of 30 m (<http://www.gisat.cz/content/en/products/digital-elevation-model/aster-gdem>), while the soil data used the FAO-HWSD products with a grid size of 1 km² (<http://www.fao.org/soils-portal/soil-survey/soil-maps-and-databases/harmonized-world-soil-database-v12/en/>). Land use/cover data were interpreted by human-computer interaction techniques from the Key Laboratory of Remote Sensing and Geographic Information System, Xinjiang Institute of Ecology and Geography, Chinese Academy of Sciences. Meteorological data, including daily maximum and minimum air temperatures and daily precipitation data, were provided by China Meteorological Science Data Sharing Service Network (<http://data.cma.cn/>). In addition, other data, such as daily solar radiation, daily relative humidity, and wind speed, were generated by the simulation of SWAT built-in weather generator. The measured runoff data of hydrological stations were derived from the Hydrological Yearbook of Xinjiang.

2.3. SWAT Model

The soil and water assessment tool (SWAT) model, which is a semi-distributed hydrological model with a strong hydro-physical process mechanism, has been applied successfully worldwide [42]. The SWAT model, which includes snow melting module, confluence module, groundwater module, vegetation interception, and evaporation module, is commonly used to simulate the complex cyclic processes of water, pesticides, and sediment under the intricate and variable soil types, land-use patterns, and management measures at different scales [43]. It was also successfully applied in the high-altitude mountainous catchments in Xinjiang, such as the Kaidu [29], Hotan [31,32], Aksu [7,34], and Tizinafu river catchments [44], and other parts of the world, such as Karnali river catchment in Nepal [45], Chungju dam catchment in South Korea [46], and Damma glacier catchment in Switzerland [47].

The parameter sensitivity analysis is indispensable to determine the most sensitive parameters of the SWAT model before calibration and validation. Parameter sensitivity analysis of the SWAT model in this study is based on the sequential uncertainty fitting (SUFI-2) [48] algorithm. SUFI-2 is a global sensitivity analysis method in which the parameter sensitivity input required for the next calibration is counted at this calibration. Based on statistical theory studies, if *t-stat* of the hypothesis test samples in comparison with the critical value of a parameter has a higher value, then the corresponding simulation effect will be better. The main function of the *t*-test is to determine the relative significance of all single samples. *P*-value is the significant probability value of *t*-test results, and the result comes from the look-up table, which mainly reflects the significance degree of *t*-test statistics. The sensitivity reference value of the SUFI-2 method is the absolute value of *t-stat*. The smaller the absolute value of *t-stat* is, the lower the sensitivity will be and the corresponding value of *p*-value indicates whether *t-stat* is significant. The closer the *p*-value is to 0, the stronger the significance will be.

Nash efficiency coefficient (*NS*), correlation coefficient (*R*²), and relative average deviation (*RE*) are used to evaluate the simulation results. The formulas are as follows:

$$NS = 1 - \frac{\sum_{i=1}^n (Q_o - Q_m)^2}{\sum_{i=1}^n (Q_o - \overline{Q_o})^2}, \quad (1)$$

where *Q_o* represents the daily measured runoff, *Q_m* represents the daily simulated runoff, $\overline{Q_o}$ represents the multi-year average measured runoff, and *n* represents the simulated time length. The value range

of the NS efficiency coefficient is $(-\infty, 1]$. The closer the value is to 1, the higher the simulation accuracy will be. The formula of R^2 and RE are as follows.

$$R^2 = \frac{[\sum_{i=1}^n (Q_o - \overline{Q_o})(Q_m - \overline{Q_m})]^2}{\sum_{i=1}^n (Q_o - \overline{Q_o})^2 \sum_{i=1}^n (Q_m - \overline{Q_m})^2}, \quad (2)$$

$$RE = 1 - \frac{\overline{Q_o} - \overline{Q_m}}{\overline{Q_o}} \quad (3)$$

where $\overline{Q_m}$ represents the multi-year average measured runoff. The R^2 range is $[0,1]$, and the closer the value is to 1, the better the simulation result will be. The closer the value of RE is to 0, the smaller the mean difference between the simulated runoff and the measured runoff.

2.4. Traditional Model Parameter Transferability Methods

2.4.1. Theoretical Basis

The regulation of regional differentiation, also known as the regulation of spatial geography, refers to the relative consistency of the geographical environment as a whole and its components in a certain direction while showing some differences in another direction [49]. In this study, there are similar distributions of land cover or vertical climate change in the adjacent catchment in the same latitudinal zone and equivalent mountain range, but there are some differences in slope aspect and elevation range between different catchments, which leads to exclusive climatic and hydrological characteristics of each catchment.

2.4.2. Traditional Parameter Transfer Methods

The model parameter transferability method is to transfer one or more parameters of a donor catchment model into the ungauged target catchment model according to certain rules as its model parameters. In the process of parameter transfer, the selection of donor catchment is associated with the simulated results of the target catchment model to some extent. Generally, the closer the two catchments are, the more similar the hydrological processes of the two catchments will be, due to the more semblable attributes of climate and geography conditions. Therefore, the accuracy of the traditional parameter transferability method heavily depends on the similarity between the donor catchment and target catchment.

(1) Distance approximation principle

The distance approximation principle (DAP) is to select the donor catchment that is closest to the target catchment in space, and then apply the parameters of the donor catchment model directly to the target catchment model. This method only considers the absolute distance between the donor catchments and the target catchment [17,18].

(2) Attribute similarity principle

Attribute similarity principle (ASP) chooses some attributes of the catchment, such as meteorology and topography, to calculate the similarity between the target catchment and other multi-donor catchments. The main catchment attributes for model parameters' transformation involved in runoff yield and concentration in a mountainous catchment, including catchment area (A), average slope (S), average elevation (E), annual average precipitation (P), and average temperature (T), which can be used to calculate the similarity of the hydrological process. The formula for calculating the similarity of attributes between river catchments is as follows.

$$\varnothing = \sum_{i=1}^n \frac{|X_i^G - X_i^U|}{X_i^U} \times 100, \quad (4)$$

where \varnothing is the attribute similarity between the two catchments; X_i^G and X_i^U are the i th attribute value of the donor catchment and the target catchment, respectively. The smaller the value of \varnothing is, the more similar the two catchments will be.

The attribute similarity principle can determine the catchment with the highest attribute similarity and then transfer the parameters of this catchment model to the target catchment model [19,20].

3. Improved Model Parameter Transferability Method

3.1. Basic Idea and Overall Design

The basic idea of the improved model parameter transferability method proposed in this research is to establish a statistical relationship between the sensitive parameters of multiple river catchment models and the characteristics of catchment meteorology, hydrology, and terrain based on DAP and ASP to obtain a new set of parameter transfer rules. Then, the effectiveness of this alternative method is verified. The detailed process is as follows (Figure 2).

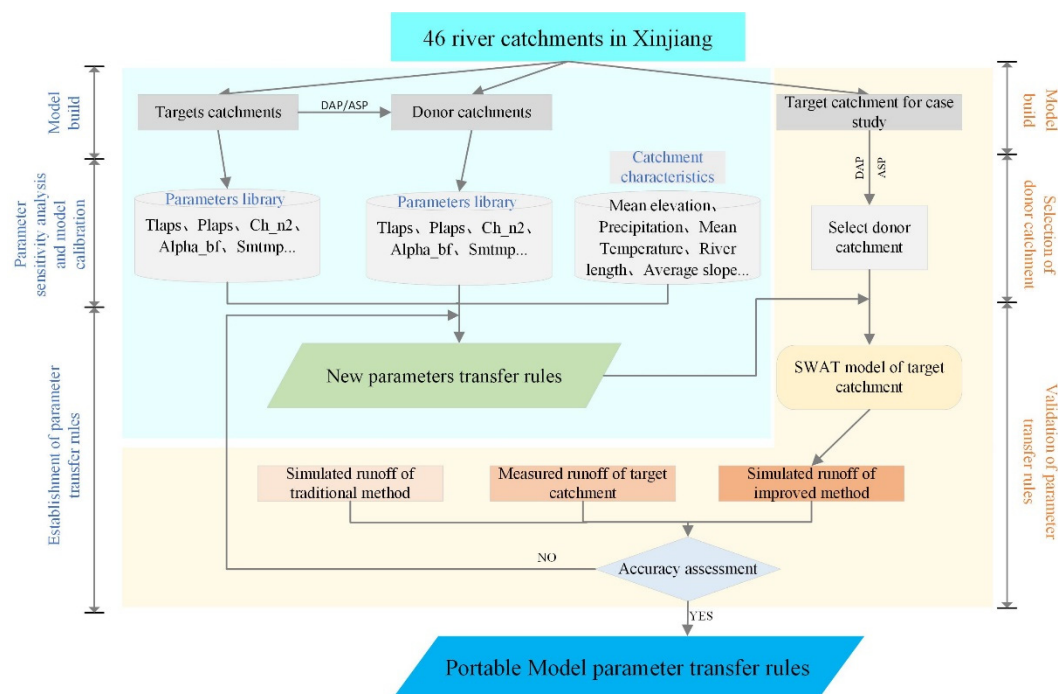


Figure 2. Flowchart of the overall design.

Firstly, using the DEM, land use/cover, soil, and meteorology data, SWAT models of 46 river catchments with hydrological stations in Xinjiang were built. The sensitivity analysis of 27 parameters of each catchment model was carried out by the SUFI-2 method, and the parameter sensitivity ranking was obtained. We selected some of the top comprehensive ranking parameters based on the significance of the p-value, which is sensitive and rational to most catchment models. These sensitive parameters were primarily adjusted so that the NS efficiency coefficient and correlation coefficient R^2 of each catchment model were above 0.6.

Secondly, in order to avoid the reuse of the target catchment and the donor catchment, 23 catchments in Xinjiang were randomly selected as the target catchments (one of which was used as a case study), and the corresponding donor catchments of these target catchments were selected by using DAP and ASP. The relationship of parameters between target catchment models and donor catchment models, and the average elevation, temperature, precipitation, river length, and catchment area were analyzed in a statistical way; then, we summarized the parameter transfer rules between target catchment and donor catchment.

Finally, we sought the optimal donor catchment of the remaining target catchment in the case study according to the DAP or ASP, and based on the established parameter transfer rules, the model parameter sets of target catchment were generated. We compared with the measured runoff in the target catchment and the simulated results, which generated the model parameters in accordance with the parameter transfer rules, and the applicability of the new parameter transfer rules was verified. If the improved simulation results are better than those of the original method, it can be shown that the new model parameter transferability method can effectively improve the accuracy of runoff simulation in the target catchment.

3.2. Parameter Sensitivity Analysis

We calibrated and verified 46 river catchment SWAT models and obtained satisfactory results (Figures S1 and S2). In the current study, 27 parameters of SWAT models for the 46 catchments were selected for sensitivity analysis by using the SUFI-2 method, and then the sensitivity order was obtained by composite average. As can be seen from Figure 3 and Table 1, the precipitation lapse rate (PLAPS), temperature lapse rate (TLAPS), melt factor for snow on 21 June (SMFMX), baseflow alpha-factor (ALPHA_BF), Manning's "n" value for the main channel (CH_N2) are the five top sensitive parameters. The absolute value of the *t-stat* value is relatively large; the *p*-value is close to 0. The results show that the sensitivity parameters of the top 5 in high-altitude mountainous areas are greatly associated with precipitation, temperature, snow melting, as well as flow concentration of river channel.

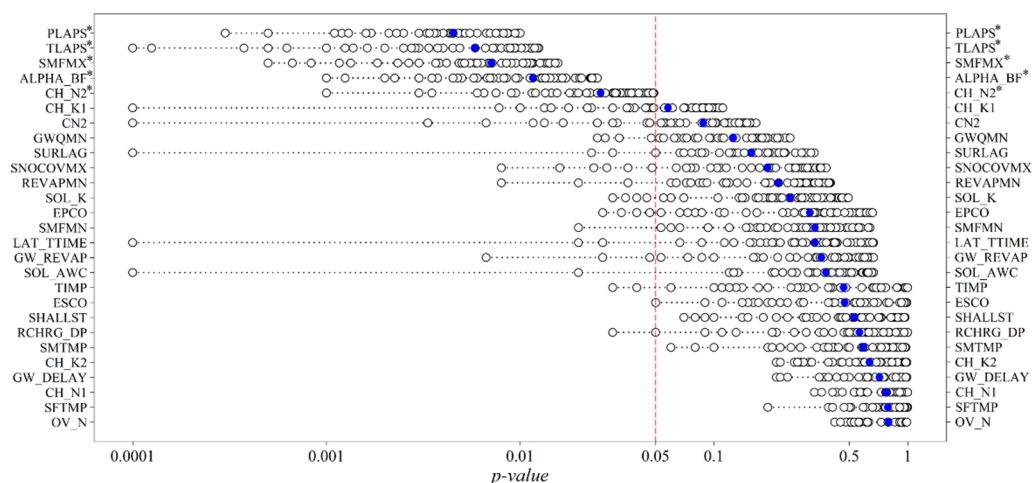


Figure 3. The *p*-value (circles) of the two-sample test for the SWAT parameters sensitivity of 46 Xinjiang catchments. The red dotted line represents a significance level of 5% (α). The blue solid circle is the mean *p*-value of parameters of all catchments' model. The mean *p*-value smaller than α implies that the parameter is sensitive to most catchment models.

Table 1. Comprehensive ranking for the soil and water assessment tool (SWAT) parameters sensitivity of 46 Xinjiang catchments.

Parameter	Physical Meaning of Parameters	Ranges	<i>t-stat</i>	<i>p-value</i>
PLAPS	Precipitation lapse rate (mm H ₂ O/km)	−1000~1000	−12.41	0.005
TLAPS	Temperature lapse rate (°C/km)	−10~10	−3.49	0.006
SMFMX	Melt factor for snow on June 21(mm H ₂ O/°C-day)	0~20	2.88	0.007
ALPHA_BF	Baseflow alpha factor (1/days)	0~1	−2.51	0.012
CH_N2	Manning’s “n” value for the main channel	−0.01~3	−2.29	0.026
CH_K1	Effective hydraulic conductivity in tributary channel alluvium (mm/hr)	0~300	1.9	0.058
CN2	Initial SCS runoff curve number for moisture condition II	35~98	−1.76	0.088
GWQMN	Threshold depth of water in the shallow aquifer required for return flow to occur (mm H ₂ O)	0~5000	1.57	0.126
SURLAG	Surface runoff lag coefficient	0.05~24	1.48	0.156
SNOCVMX	Minimum snow water content that corresponds to 100% snow cover, SNO100 (mm H ₂ O)	0~500	−1.36	0.190
REVAPMN	Threshold depth of water in the shallow aquifer for “revap” or percolation to the deep aquifer to occur (mm H ₂ O)	0~500	−1.27	0.215
SOL_K	Saturated hydraulic conductivity (mm/hr)	0~2000	−1.21	0.248
EPCO	Plant uptake compensation factor	0~1	−1	0.313
SMFMN	Melt factor for snow on December 21(mm H ₂ O/°C-day)	0~20	0.98	0.333
LAT_TTIME	Lateral flow travel time (days)	0~180	−0.96	0.332
GW_REVAP	Groundwater “revap” coefficient	0.02~0.2	−0.93	0.359
SOL_AWC	Available water capacity of the soil layer (mm H ₂ O/mm soil)	0~1	0.89	0.379
TIMP	Snow pack temperature lag factor	0~1	0.79	0.468
ESCO	Soil evaporation compensation factor	0~1	0.68	0.473
SHALLST	Initial depth of water in the shallow aquifer (mm H ₂ O)	0~50000	0.66	0.532
RCHRG_DP	Deep aquifer percolation fraction	0~1	−0.48	0.565
SMTMP	Snow-melt base temperature (°C)	−20~20	−0.48	0.593
CH_K2	Effective hydraulic conductivity in main channel alluvium (mm/hr)	−0.01~500	−0.46	0.636
GW_DELAY	Groundwater delay time (days)	0~500	0.22	0.716
CH_N1	Manning’s “n” value for the tributary channel	0.01~30	0.19	0.778
SFTMP	Snowfall temperature (°C)	−20~20	−0.11	0.791
OV_N	Manning’s “n” value for overland flow	0.01~30	0.11	0.813

3.3. Improved Model Parameter Transferability Method

3.3.1. PLAPS and TLAPS

By simulating the parameters of TLAPS, PLAPS, and the average elevation (H_{ave}) of the catchment, the corresponding parameters of the donor catchment and the target catchment were statistically correlated. In this study, TLAPS/ H_{ave} of the donor catchment and TLAPS/ H_{ave} of the target catchment (Figure 4a), PLAPS/ H_{ave} of the donor catchment, and PLAPS/ H_{ave} of the target catchment (Figure 4b) were analyzed based on their correlation. It was found that TLAPS and PLAPS were significantly correlated with the average elevation (H_{ave}) of the catchment, and TLAPS and PLAPS of the donor catchment and the target catchments were similar. The R^2 of TLAPS is about 0.70,

p -value < 0.05 (significant), and the R^2 of PLAPS is about 0.66, p -value < 0.05 (significant). According to the results of the study, the TLAPS transfer rule is as follows:

$$TLAPS_T = (TLAPS_D / H_{ave_D}) \times H_{ave_T}, \quad (5)$$

where $TLAPS_T$ and $TLAPS_D$ are the target catchment TLAPS and donor catchment TLAPS ($^{\circ}\text{C}/\text{km}$); H_{ave_T} and H_{ave_D} are the target catchment average elevation and donor catchment average elevation (m).

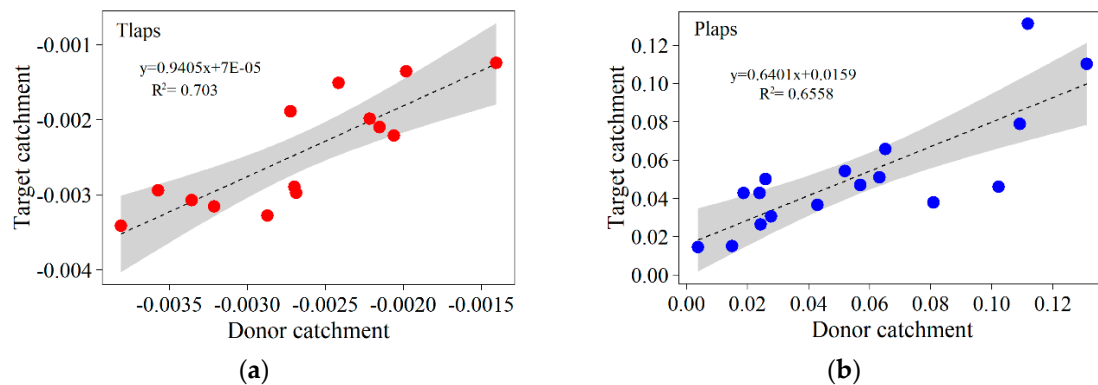


Figure 4. Relationship of temperature lapse rate (TLAPS) and precipitation lapse rate (PLAPS) parameters between the donor catchment and the target catchment.

PLAPS transfer rule is as follows:

$$PLAPS_T = (PLAPS_D / H_{ave_D}) \times H_{ave_T}, \quad (6)$$

where $PLAPS_T$ and $PLAPS_D$ are the target catchment PLAPS and donor catchment PLAPS (mm/km).

3.3.2. SMFMX

According to the relationship between the SMFMX and the average elevation (H_{ave}) of all calibrated catchment models, the logarithmic relationship between them is observed, and the fitting result is shown in Figure 5. The SMFMX parameter increases as the increase of H_{ave} of the catchment, and the fitting degree of SMFMX and H_{ave} R^2 are about 0.49, p -value < 0.05 (significant). According to the results of the study, the SMFMX transfer rule is as follows:

$$SMFMX = 7.9685 \times \ln(H_{ave}) - 56.991, \quad (7)$$

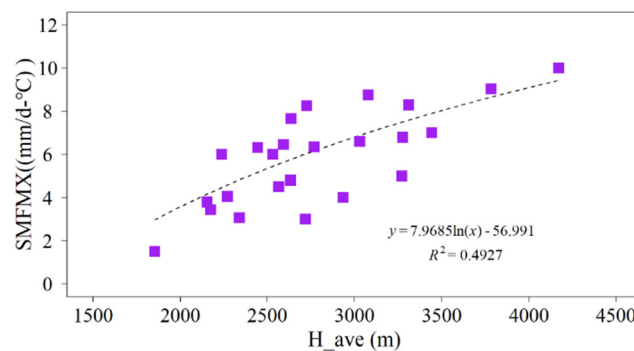


Figure 5. Fitting relationship between melt factor for snow on 21 June (SMFMX) and average elevation (H_{ave}) of all river catchment models.

3.3.3. CH_N2

Manning's "n" value for the main channel (CH_N2) is a coefficient that reflects the influence of the roughness of the river channel on runoff comprehensively. The CH_N2 is influenced by many factors, and its value is usually measured by experimental data. In this study, it is correlated to the average slope (Slope_ave) and river channel length (L_reach) of the catchment. And it is found that the CH_N2 is significantly correlated with the ratio of L_reach to Slope_ave (Figure 6). The two have a power exponential relationship. R^2 is about 0.74, and p -value < 0.05 (significant). According to the study results, the CH_N2 parameter transfer rule is as follows.

$$\text{CH_N2} = 0.873 \times (\text{L_reach}/\text{Slope_ave})^{-0.75}, \quad (8)$$

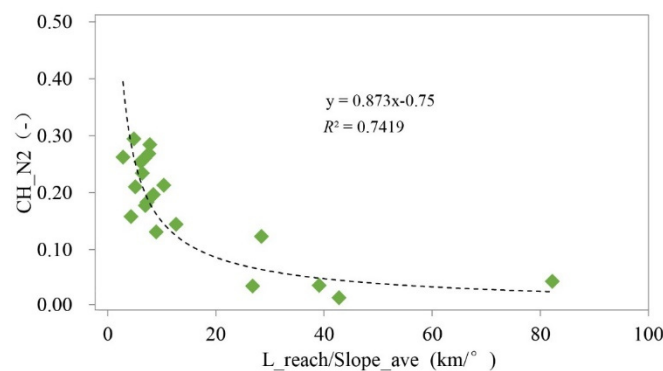


Figure 6. Fitting relationship between Manning's "n" value for the main channel (CH_N2) and the ratio of river channel length (L_reach) and average slope (Slope_ave) of the catchment.

3.3.4. ALPHA_BF

On the basis of the existing study, the statistical correlation between the ALPHA_BF and the Manning's "n" value for the main channel (CH_N2) shows that the coefficient of ALPHA_BF exhibits a rising trend with the increase of the CH_N2, and there is a binomial relationship between them (Figure 7), R^2 is about 0.59, and p -value < 0.05 (significant). According to the results of this study, the ALPHA_BF parameter transfer rule is as follows.

$$\text{ALPHA_BF} = 13.281 \times (\text{CH_N2})^2 - 2.5862 \times \text{CH_N2} + 0.1385, \quad (9)$$

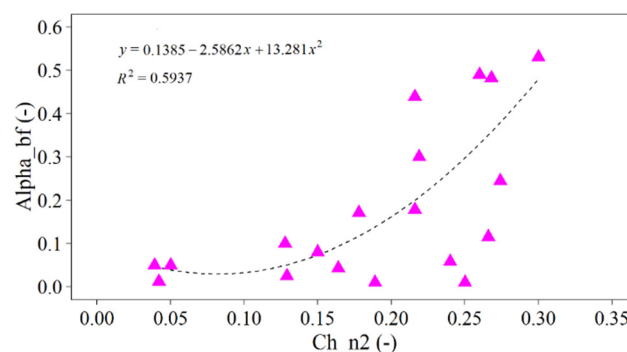


Figure 7. Fitting relationship between the baseflow alpha-factor (ALPHA_BF) and CH_N2 of the river channel.

3.3.5. Alternative Model Parameter Transfer Rules

Based on the DAP and ASP, the relationships between the parameters of the SWAT model and climate/topography of 44 catchments in Xinjiang were combined for the donor catchment selection and parameter's transfer rules determination. The main sensitive parameters of each donor catchment model and corresponding target catchment model are correlated with the catchment characteristic factors such as average elevation, slope aspect, and river length. Afterwards, the relationship between these 22 couples of sensitive parameters and catchment characteristic factors is further analyzed, and a set of improved parameter transfer rules is summarized, which are as follows:

- a. The DAP method is used to initially select 2–3 standby donor catchments,
- b. The ASP method is used to determine the closest attributes of the candidate donor catchments as the donor catchments,
- c. Correlate the model parameter set of the donor catchment with the closest attributes to the target catchment model,
- d. According to the average elevation of the donor catchment and target catchment, and TLAPS of the donor catchment, the TLAPS transfer rule of the target catchment is as follows:

$$TLAPS_T = (TLAPS_D / H_{ave_D}) \times H_{ave_T}, \quad (5)$$

- e. According to the average elevation of the donor catchment and target catchment, and PLAPS of the donor catchment, the PLAPS transfer rule of the target catchment is as follows:

$$PLAPS_T = (PLAPS_D / H_{ave_D}) \times H_{ave_T}, \quad (6)$$

- f. According to the average elevation of the target catchment, the SMFMX transfer rule of the target catchment is as follows:

$$SMFMX = 7.9685 \times \ln(H_{ave}) - 56.991, \quad (7)$$

- g. According to the river channel length and average slope of the target catchment, the CH_N2 transfer rule of the target catchment is as follows:

$$CH_N2 = 0.873 \times (L_{reach}/Slope_{ave})^{-0.75}, \quad (8)$$

- h. According to Manning's "n" value for the main channel of the target catchment, the ALPHA_BF transfer rule of the target catchment is as follows:

$$ALPHA_BF = 13.281 \times (CH_N2)^2 - 2.5862 \times CH_N2 + 0.1385, \quad (9)$$

where $TLAPS_T$ and $TLAPS_D$ are the target catchment TLAPS and donor catchment TLAPS ($^{\circ}\text{C}/\text{km}$); H_{ave_T} and H_{ave_D} are the target catchment average elevation and donor catchment average elevation (m); $PLAPS_T$ and $PLAPS_D$ are the target catchment PLAPS and donor catchment PLAPS (mm/km); L_{reach} is the length of river channel (km); $Slope_{ave}$ is the average slope of the catchment, in the unit of degrees.

4. Case Study

4.1. Selection of Donor Catchment

In order to verify the applicability of the improved parameter transferability rules, the Kuyiersite (KU) river catchment in Altay Mountain was selected as the target catchment for case analysis and the other 45 catchments as the undetermined donor catchments. Firstly, based on the distance

approximation principle, we determined the donor catchment, which is close to the target catchment, including the Kelan (KL) river catchment and the Kayiersite (KA) river catchment. According to the attribute similarity principle, six attributes, including the distance (D), catchment area (A), the average slope (Slope_ave), the average elevation (H_ave), the average annual precipitation (P), and the average temperature (T) of the target catchment and the donor catchment, were calculated. The results are shown in Table 2. To sum up, the attributes of the KL river catchment are more similar to those of the KU river catchment ($\varnothing = 26.87$), and the attributes of the KA river catchment are quite different from those of the KU river catchment ($\varnothing = 66.11$), while KA river catchment is closest distance to the KU river catchment.

Table 2. The similarity of hydrological characteristics and attributes of the target catchment and the donor catchment.

River	Distance (km)	Catchment Area (km ²)	Average Slope (°)	Average Elevation (m)	Average Annual Precipitation (mm)	Average Annual Temperature (°C)	Attribute Similarity (\varnothing)
KU	-	1967.14	20.70	2540.94	220.16	5.32	-
KL	159.50	2359.87	20.18	2429.38	206.29	5.29	26.87
KA	38.61	1624.98	15.75	2200.04	222.38	5.48	66.11

In virtue of the traditional model parameter transferability method, the model parameters of the donor catchment are transplanted directly into the KU river catchment, and the results of the model simulation are presented in Table 3. The *NS* coefficient transferred by the KA river parameter with approximate distance is 0.27, while it equals 0.36 when transferred by the model parameters of KL river catchment with similar attributes. The results show that the accuracy of the simulated runoffs are relatively low when the parameters of the donor catchment with approximate distance (DAP) and the donor catchment with high attribute similarity (ASP) are transplanted to KU river catchment, but the result of parameter transplantation based on ASP is better than that based on DAP. The donor catchment chosen by DAP and ASP cannot reflect the characteristics of the target catchment very well. As a result, the simulation results of the two parameter transferability methods have not achieved good simulation results in accordance with the two methods and the theoretical basis mentioned above. However, it is more appropriate to select the KL river with highly similar attributes as the donor catchment of the target catchment.

Table 3. Order of the donor catchments and their simulation results.

		Target Catchment—KU River		
		Distance Proximity	Attribute Similarity	Evaluation Indicator (<i>NS</i> / <i>R</i> ²)
Donor catchment	KA river (DAP)	1	2	0.27/0.55
	KL river (ASP)	2	1	0.36/0.65

4.2. Validation of the Improved Model Parameter Transferability Method

By using the improved model parameter transferability rules proposed in Section 3.3.5, the model parameter of KU river catchment is generated by the model parameters of KL river catchment according to the characteristics of the catchment area and the average elevation of KU river catchment (the parameters are detailed in Table S2). The simulated results are shown in Table 4. The accuracy of the simulated results is improved significantly by the modified model parameters of the KL river catchment are applied in the KU river catchment model: the *NS* efficiency coefficient is increased from 0.36 to 0.69, and the correlation coefficient *R*² is increased from 0.65 to 0.85. The simulated result is satisfactory.

Table 4. Comparison results for the parameter transfer of the different donor catchments.

Parameter Transfer Scheme	Evaluation Indicator	
	NS	R^2
KL river catchment model parameters (ASP)	0.36	0.65
KA river catchment model parameters (DAP)	0.27	0.55
Modified KL river catchment model parameters (IMPTM)	0.69	0.85

By further analyzing the simulation of the runoff curve with different parameter schemes, as shown in Figure 8, it can be seen that the accuracy of the simulated runoff after the model parameters' transplantation in the KL river catchment is higher than that of the KA river, but the simulation of the parameters' transplantation in the KL river is not good for flow peak's capture, especially for the autumn flood peaks; the simulation effect on the winter base flow is good. The model parameters' transplantation of KA river catchment can capture the flood peak, but the simulation accuracy of the peak value is not good. The simulation effect is significantly improved by modifying the model parameters of KL river catchment according to the improved parameter transfer rules, which not only capture the flood peaks well but also improve the simulation accuracy of the peak value.

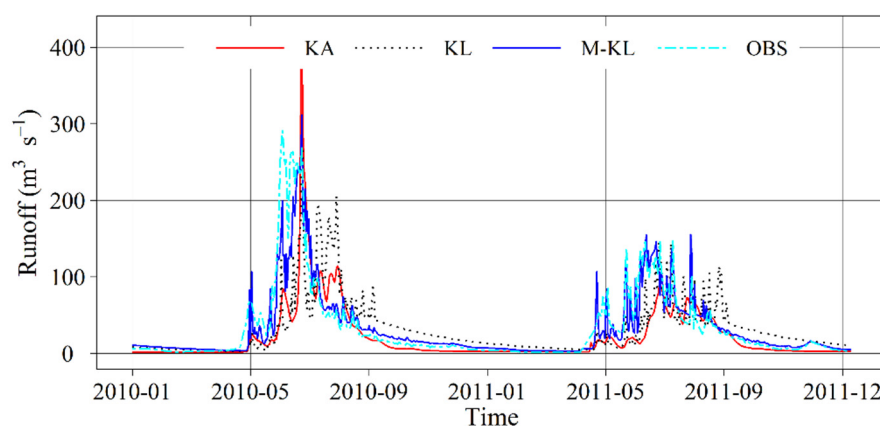


Figure 8. The daily discharge hydrographs for the measured runoff (OBS) and simulation runoff based on the different model parameter transplantation schemes (KA model parameters (KA), KL model parameters (KL), and modified KL model parameters (M-KL)) in KU river catchment.

Figure 9 exhibits the comparison between the simulated daily runoff accumulation and the measured daily runoff accumulation of the three parameters transfer simulation schemes of KU river in 2010 and 2011. The trends of daily runoff accumulation calculated by the three parameters transfer schemes are basically the same, but the results of ASP schemes (KL catchment), DAP schemes (KA catchment), and M-KL schemes were lower than the measured values, especially in summer. The simulated runoff accumulative total amount of the parameters' transfer results of the KL river catchment is similar to that of the measured, while the runoff accumulative total amount of the parameters' transfer results of the KA catchment is much lower than that of the measured ones. The cumulative total amount of daily runoff calculated by improved parameters' transfer rules of the KL river catchment after transplantation is closer that of the measured amount, but it accurately grasps the flow peak amount during the spring snow melting periods. However, in autumn and winter, the total amount of simulation is lower than the measured value.

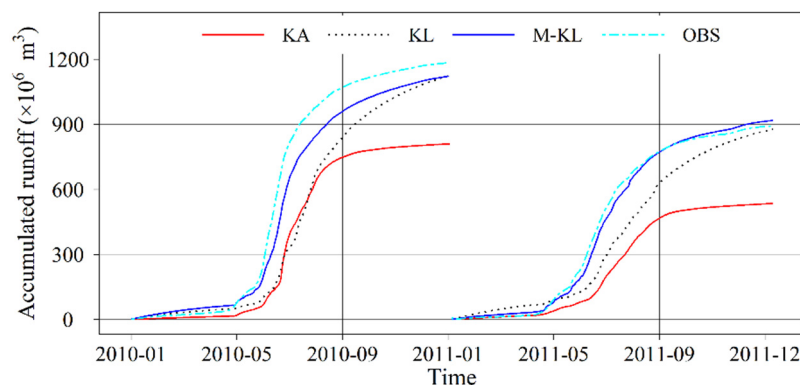


Figure 9. The daily accumulation discharge hydrographs for the measured runoff (OBS) and simulation runoff based on the different model parameter transplantation schemes (KA model parameters (KA), KL model parameters (KL), and modified KL model parameters (M-KL)) in KU river catchment in 2010 and 2011.

5. Discussion

5.1. Sensitivity Analysis

In order to improve the calibration efficiency, the sensitivity identification for key parameters is carried out beforehand. In the current study, we identified 27 parameters of the SWAT model related to flows, snowmelt, groundwater, and evapotranspiration in the sub-basin scale by using the SFUI-2 method. TLAPS, PLAPS, CH_N2, SMFMX, ALPHA_BF were found as the most sensitive parameters (Table 1 and Figure 3), with the mean p -value passing the 5% confidence test (p -value < 5%) in all catchments. The analysis results are similar to previous studies [7,32,50].

Top five sensitive parameters played vital roles for the mountainous catchments in Xinjiang. TLAPS and PLAPS are utilized to adjust temperature and precipitation according to elevation bands, which directly determine the spatial patterns and total amounts of precipitation and temperature [51,52]. They indirectly influence the occurrence time of floods, magnitudes of streamflow, evapotranspiration, and even water budgets. CH_N2 is a characterization of the roughness of the river channel, which has a great influence on flow routing. The higher the value of CH_N2, the stronger the scouring ability of the natural channel [53]. The SMFMX parameters of the snowmelt module are very essential for mountain watershed models. The reason why SMFMX is sensitive to alpine watersheds may be due to the relatively large contribution of snowmelt in mountain runoff, especially in summer [54]. ALPHA_BF is a parameter of the groundwater module and is a direct index of groundwater flow response to changes in recharge [51]. Not all the snowmelt water in the mountainous area directly generates surface runoff and recharge to the river. Usually, it slowly melts and infiltrates into the ground. Subsequently, a large proportion of groundwater (17–66%) is supplied to the river [7]. The similar catchment properties were also confirmed by Me et al. [43] in their catchment.

The hydrologic parameters that were not sensitive in the model were mainly the parameters such as SHALLST, RCHRG_DP, SMTMP, CH_K2, GW_DELAY, CH_N1, SFTMP, and OV_N. Initial depth of water in the shallow aquifer (SHALLST) and deep aquifer percolation fraction (RCHRG_DP) are the initial settings of the groundwater module in the SWAT model. This result indicates that deep groundwater flow does not significantly impact runoff, probably because the mountainous areas have steep slopes, sparse surface vegetation, and poor water holding capacity, so it is hard to influence the streamflow [55]. CH_N1 or OV_N is the Manning's "n" value for the tributary channel or overland flow, which are parameters that characterize the roughness of the surface [51]. Due to the large amount of precipitation and the relatively low temperature in high-altitude mountainous areas, most of them exist in the form of snowfall. After the temperature rises, they will slowly infiltrate into the ground, resulting in a reduction in the proportion of runoff contributed by overland flow throughout the

year [7]. Therefore, these parameters have low sensitivity to hydrological simulation in high-altitude mountain catchments.

5.2. The Difference of Model Parameter Transferability Method

The improved model parameter transferability method is based on the principles of DAP and ASP, supported by the easy-to-obtain geographic features such as river basin elevation and channel length so that the parameters of the donor catchment can be properly converted into the target catchment model. Application results of IMPTM show that the accuracy of runoff simulation has been significantly improved (Table 4 and Figure 8). In contrast, for the conventional approach, DAP is the most straightforward approach of parameter transferring, which only considers the distance between the donor catchment and the target catchment, and ignores the characteristics of the catchment itself. ASP considers the similarity between the characteristics of the target catchment and the donor catchment, and then the model parameters from similar donor watersheds will be directly implanted into the target model. Even though the catchment attributes are similar, there are still some differences. Cheng et al. [17] also confirmed that ASP is similar to DAP which is not capable of improving the simulation accuracy in the target catchment.

The improved model parameter transferability method not only considers the distance and characteristics between the target catchment and the donor catchments but also analyze the relationship among the parameters and the characteristics of the catchment. Thereby, the five most sensitive parameters of the donor catchment model are further localized in the target catchment model according to the new transferring rules (Section 3.3.5). A large number of studies have also shown that TLAPS, PLAPS, and SMFMX are highly correlated to catchment elevation [8,45,54]. CH_N2 is a coefficient that comprehensively reflects the influence of a rough river on the runoff. Channel length and slope potentially affect the channel CH_N2 coefficient [56,57], while CH_N2 has an effect on alpha to some extent [58]. Based on the vast amount of calibrated model parameters and catchment attributes, some statistical relationships are established to obtain the new model parameter transfer rules, which can be universally applied for hydrological simulation in mountainous basins.

All sample catchments in this study have the common characteristics of high average altitude and large altitude difference. Therefore, this method would have poor applicability to the plain catchments in relatively low altitudes. The altitude difference of the plain catchment is small, and TLAPS or PLAPS even may not be sensitive and become less important. In addition, low-altitude catchments in tropical or subtropical climate regions are rarely covered with snow, and SMFMX will lose its effect in those regions [59,60]. Therefore, the application of the new approach certainly has its limitations and suitable environments.

6. Conclusions

In this study, we built the SWAT models of 46 river catchments with discharge gauging stations in Xinjiang. Twenty-two river catchments were selected as the target catchments, and the corresponding donor catchments of each individual target catchment were selected based on the distance approximation principle and the attribute similarity principle. The parameter transfer rules were obtained based on the relationship between model parameters and catchment characteristics. Finally, a sample target catchment was selected to evaluate the applicability of the SWAT model with newly implanted parameters. The results of this study show that (1) the parameters such as TLAPS, PLAPS, SMFMX, CH_N2, and ALPHA-BF are more sensitive in high-altitude catchments. (2) It is not ideal to directly transfer the model parameters either from the closest catchment or from the most similar one. For instance, the target catchment (KU catchment) does not have acceptable simulation results based on either the closest distance approach (parameters directly from KA catchment) or the similarity approach (parameters directly from KL catchment), with *NS* and *R*² less than 0.60. (3) The new rules of parameter transfer achieved better performance on the target catchment (KU catchment), with proper timing and value of flood peaks. Its *NS* coefficient can be increased from 0.36 to 0.69,

and R^2 from 0.65 to 0.85. Validation results of the SWAT model in high-altitude catchment present the acceptable performance and confirm the adaptation of the IMPTM model. However, since the IMPTM in this study only tested some parameters which are sensitive to the current study region, the relations between other parameters and catchment properties are absent in this study. There is still great potential for improving the simulation accuracy of the hydrological process in ungauged mountainous catchments in further study.

Supplementary Materials: The following are available online at <http://www.mdpi.com/2071-1050/12/9/3551/s1>, Figure S1: Measured and simulated hydrographs of the 44 catchments in Xinjiang. Figure S2: Model performance (NS , R^2 , and RE) of the 44 catchments in Xinjiang. Table S1: Overview of 46 catchments in Xinjiang. Table S2: Parameters of the different parameter transplantation schemes (KA model parameters (KA-DAP), KL model parameters (KL-ASP), and modified KL model parameters (M-KL-IMPTM)).

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