

Proportional coefficient method applied to TRMM rainfall data: case study of hydrological simulations of the Hotan River Basin (China)

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ABSTRACT

A low-density rain gauge network is always a major obstacle for hydrological modelling, particularly for alpine and remote regions. The availability of the Tropical Rainfall Measuring Mission (TRMM) rainfall products provides an opportunity for hydrological modelling, although the results must be validated and corrected before they can be used in further applications. In this paper, the combination of proportional coefficients with cross-checking by hydrological modelling was proposed as a method to improve the quality of TRMM data in a rural mountainous region, the Hotan River Basin. The performance of the Soil and Water Assessment Tool (SWAT) model was examined using streamflow and snow cover measurements. The corrected results suggest that the proportional coefficient approach could effectively improve the TRMM data quality. A verification of the hydrological model outputs indicated that the simulated streamflow was consistent with the observed runoff. Moreover, the modelled snow cover patterns presented similar spatial and temporal variations to the remotely sensed snow cover, and the correlation coefficient ranged from 0.63 to 0.98. The results from the TRMM correction and hydrological simulation approach indicated that this method can significantly improve the precision of TRMM data and can meet the requirements of hydrological modelling.

Key words | Hotan River Basin, proportional coefficient method, snow cover, SWAT, TRMM

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INTRODUCTION

Precipitation is commonly considered the most important driving factor in regional hydrological cycles, and it provides vital input data for hydrological modelling (Adler *et al.* 2000; Su *et al.* 2008). In addition, precise measurements of precipitation affect the reliability of watershed hydrological simulations and predictions (Kurtzman *et al.* 2009; Li *et al.* 2012). Spatially distributed precipitation information is conventionally obtained from a high-density network of rain gauge stations (Collischonn *et al.* 2008), and a lack of sufficient

precipitation data leads to significant limitations for hydrological modelling and introduces unavoidable uncertainty (Taesombat & Sriwongsitanon 2009). In addition, maintaining weather observation sites in north-western China is complicated by the complex topography, hostile weather and remote nature of the area. The majority of stations are installed in local towns with elevations below 2 km.

With the rapid development of geographic information systems and remote sensing (RS) technology, remotely

sensed data have been widely applied in many disciplines, such as ecology, hydrology and meteorology, and the information partially overcomes the lack of essential data in rural areas. Many satellite precipitation products, such as the Global Satellite Mapping of Precipitation (GSMaP), Global Precipitation Climatology Project (GPCP), Tropical Rainfall Measuring Mission (TRMM) and Climate Prediction Center's morphing technique (CMORPH), have achieved various spatial and temporal resolutions and have been widely used in hydrological simulations (Shrestha *et al.* 2008; Stisen & Sandholt 2010; Bitew & Gebremichael 2011; Gosset *et al.* 2013). Among the RS precipitation products, the TRMM satellite merits credit for its long service duration and stable quality performance since January 1998 (Li *et al.* 2012). Significant work has been conducted to evaluate the suitability of TRMM rainfall products as replacements for station-based (SB) precipitation, and the majority of the results have indicated that the application of TRMM rainfall data achieves acceptable results for simulations with relatively long time steps (Tobin & Bennett 2009; Li *et al.* 2012; Strauch *et al.* 2012). However, TRMM data are problematic in mountainous and arid areas, particularly for daily runoff simulations that might affect peak flow extremes (Su *et al.* 2008; Li *et al.* 2012, 2015).

Many studies have evaluated the performance of TRMM rainfall data in the north-western arid areas of China, and the results have suggested that TRMM rainfall data require spatial and temporal corrections before their application (Mu & Jiang 2010; Ji & Luo 2013; Yang & Luo 2013). Cheema & Bastiaanssen (2012) used a regression and geographical differential analysis to calibrate TRMM rainfall data and achieved good results with a high efficiency and small error rate in complex mountainous terrains. Yang & Luo (2014) extracted terrain variables to establish a stepwise regression model and a back-propagation neural network to adjust the TRMM rainfall data, and both approaches exhibited better results at the watershed scale. Qu *et al.* (2014) introduced a TRMM correction method based on the water balance and obtained several quantifiable improvements. However, these methods are highly dependent on the skill of the investigator and do not necessarily correspond to gauging data.

The precision of TRMM data can be improved by meteorological station data and topography; and therefore, the objective of this study is to correct TRMM data

based on the proportional coefficient method. Furthermore, the corrected TRMM data are used to improve the calibration of hydrological simulations using the Soil and Water Assessment Tool (SWAT). The latter can be used to improve our understanding of the hydrological functioning of dryland basins in north-western China. As rain gauge stations are not available in the study area, a larger region with additional stations outside the Hotan area was proposed for obtaining the appropriate spatial distribution information. Hence, 10 meteorological gauging stations on the northern slope of the Karakorum-Kunlun Mountains were selected for the TRMM rainfall data corrections and subsequent accuracy validations. The corrected TRMM rainfall data show greater consistency with the SB data. Furthermore, the corrected TRMM rainfall data over the Hotan River Basin were used to force the SWAT model, which was validated by MODIS snow cover data and discharge observations. The acceptable SWAT output for streamflow and snow cover indirectly confirmed the feasibility of the proposed correction approach.

STUDY AREA AND MATERIALS

Study area

The study area was the Hotan River Basin, which is a semi-arid mountainous catchment in the Xinjiang Uygur Autonomous Region of north-western China. The basin is approximately 4.88×10^4 km² (Figure 1). The Hotan River originates from the northern slope of the Karakorum-Kunlun Mountains, which have the most mid- and low-latitude glaciers in the world. The Hotan River Basin has a complex topography that includes woodlands, grasslands, deserts and alpine mountains, and has elevations that range between 1,192 m and 6,858 m.

This region has a typical semi-arid continental climate. The perennial mean temperature is approximately 12.2 °C, the estimated annual precipitation is approximately 5.4–89.6 mm, and the annual pan evaporation is approximately 2,159–3,137 mm in the lower regions (Xu *et al.* 2008) (Figure 2). The Hotan River Basin has abundant water resources with an annual average of 4.378×10^9 m³, and

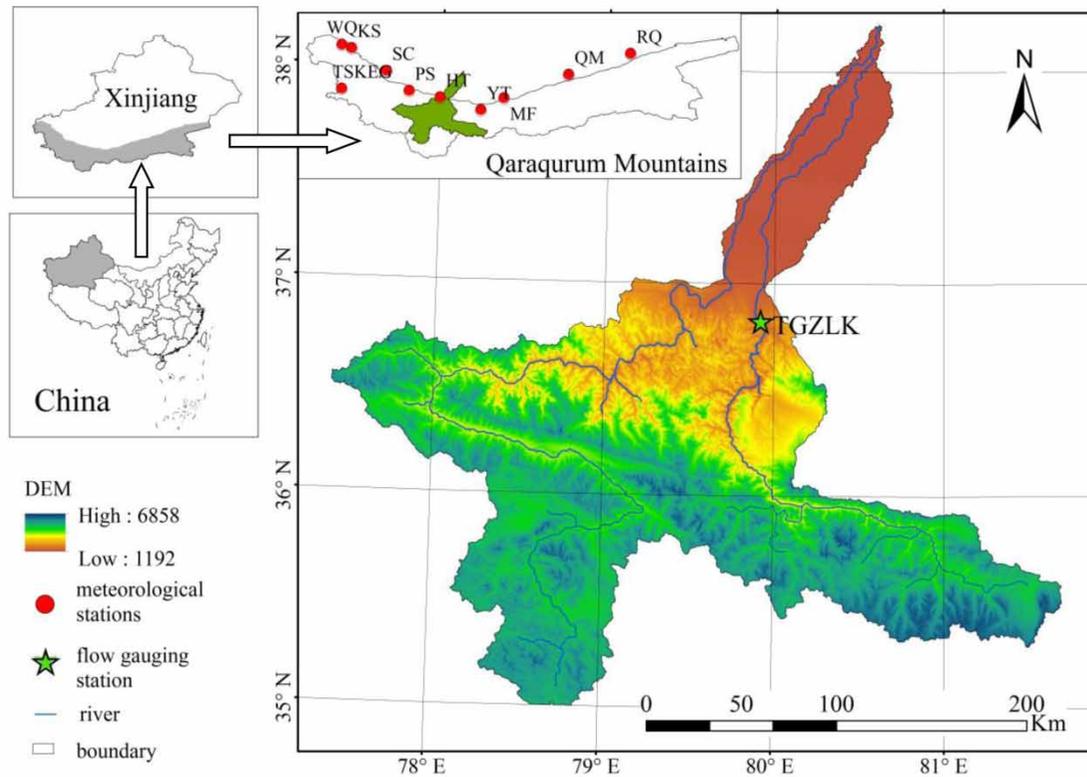


Figure 1 | Location of the Hotan River Basin, flume and nearby meteorological gauge stations.

these resources are primarily recharged by glacier melt in the high mountains, seasonal snowmelt and rainfall in the middle and high mountain regions (Wu *et al.* 2006). Due to there being no meteorological station in the Hotan River Basin, two meteorological stations (HT and PS) located near the basin were selected for the assessment.

Data

The TRMM Multi-Satellite Precipitation Analysis (TMPA) was jointly developed by the USA's National Aeronautics and Space Administration (NASA) and Japan's National Space Development Agency (NASDA) (Lonfat *et al.* 2004).

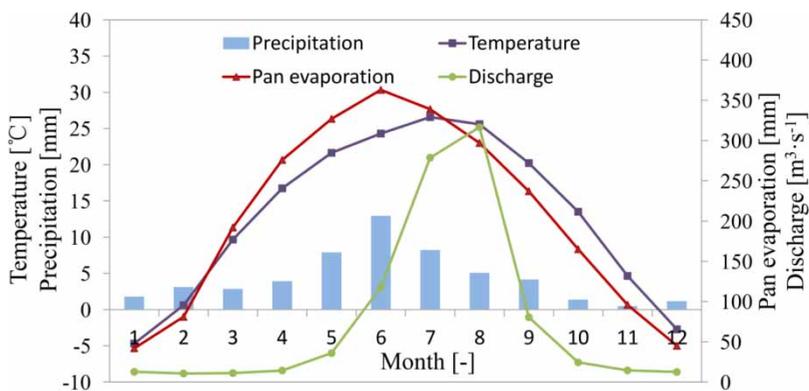


Figure 2 | The monthly precipitation, temperature and pan evaporation at HT station and discharge at TGZLK station.

TMPA provides a calibration-based sequential scheme for combining precipitation estimates from multiple satellites and gauge analyses (where feasible) at fine spatial and temporal scales ($0.25^\circ \times 0.25^\circ$ and 3 hourly) over 50°S to 50°N (Smith *et al.* 2007). Two types of TMPA products are available: a near-real-time version (3B42RT) and a post-real-time research version (TMPA 3B42) (Narayanan *et al.* 2005). TMPA 3B42 includes two versions: version 6 and version 7 (3B42V6 and 3B42V7; the latter is the most recent). The TRMM rainfall sensor is not sensitive to observe light rain as well as snowfall events due to its highly inclined orbit, combined with its minimum detectable signal of near 18 dBZe (Kulie & Bennartz 2009). The TRMM 3B42 V7 data set has been validated by utilizing stations into Global Precipitation Climatology Centre (GPCC) data sets to improve the observation accuracy of the light rain and solid precipitation. Hence, version 7 of TRMM Multi-Satellite Precipitation Analysis (TMPA 3B42) data set of daily research products from 2000 to 2010 were utilized in this study.

With the exception of the TRMM rainfall data mentioned above, the precipitation time series from the 10 meteorological gauge stations on the northern slope of the Karakorum-Kunlun Mountains were included to correct the TRMM rainfall data (Figure 1). As there are no meteorological stations in the Hotan River Basin, the HT and PS stations located near the basin were selected to provide additional meteorological information (except precipitation) for the SWAT model, such as maximum temperature, minimum temperature, wind speed, relative humidity and solar radiation. The corrected TRMM rainfall data were used to drive the SWAT model to replace the conventional SB precipitation time series and provide a proper description of the spatial heterogeneity of precipitation in mountainous areas. There are 69 TRMM grid cells covering the Hotan River Basin. The precipitation time series at each TRMM pixel was extracted and modified using the correction coefficient. The 69 corrected precipitation time series act as station records for input to the SWAT model.

To set up the SWAT model, topographic data, land use data and soil data were processed. A digital elevation model (DEM) with a grid size of $90 \times 90 \text{ m}^2$ was used as the elevation input data. A global land cover map for the year 2000 (GLC2000) at a resolution of $1 \times 1 \text{ km}^2$ from the European Commission Joint Research Centre (JRC) for

Space Applications (SAI) was used as the land use data. The soil data were derived from the Harmonized World Soil Database (HWSD) using the Food and Agriculture Organization (FAO) of the United Nations soil classification system. The SWAT model accepted different input data sets with their own unique resolutions because of the flexibility of the model structure, as long as all the spatial input data have the unified coordinate system. Therefore, DEM ($90 \text{ m} \times 90 \text{ m}$), land use ($1 \text{ km} \times 1 \text{ km}$) and soil ($1 \text{ km} \times 1 \text{ km}$) data were preprocessed before model setup by processes of image mosaic, clip and reprojection. Then, all the three spatial input data used to drive the SWAT model were entered in the model with their initial resolution to divide the hydrological response units (HRUs). Being defined as homogeneous spatial units characterized by similar geomorphologic and hydrological properties (Flügel 1995), HRUs were divided according to a unique combination of homogeneous land use, soil properties and slope. Considering the spatial distinction, different HRUs do have variable sizes. This study also used the daily and monthly runoff data from the TGZLK hydrological station for calibration and validation, which was obtained from the Tarim Water Resources Management Bureau. The meteorological data for these stations were obtained from the China Meteorological Data Sharing Service System (<http://cdc.cma.gov.cn>). The remotely sensed MODIS 10A2 product with 8-day intervals and a resolution of 500 m was obtained from NASA and used as a validation reference for the spatially variable results. Table 1 lists the various data sets used for the SWAT model in this study.

METHODOLOGY

TRMM rainfall data calibration

To maximize information from the available data, a relatively straightforward method was proposed to ensure the realities of the spatially distributed data. Sokol (2003) developed a method to estimate actual precipitation using rain gauge data to adjust the radar precipitation data through a proportional coefficient equation. As an adaptation to the arid conditions in north-western China, this paper applied the proportional coefficient method to integrate the

Table 1 | Required data for establishing the SWAT model

Data type	Data source	Primary parameters involved
DEM	CGIAR-CSI	Elevation, gradient, slope length
Land use	JRC	Land use types
Soil	FAO;IIASA	Soil type and their properties
Runoff	CAS	Daily and monthly runoff data
TRMM	NASA	Daily precipitation data
Meteorological data	CMA	Daily maximum and minimum temperature, wind speed, relative humidity, solar radiation
MODIS 10A2	NASA	Snow cover

TRMM rainfall and stationary data into one variable, P_i , to improve the data accuracy of the TRMM rainfall data. The P_i value was defined as follows:

$$P_i = \frac{G_i + \lambda}{T_i + \lambda}, \quad i = 1, 2, 3, \dots, n \quad (1)$$

where λ is a positive constant that is typically assumed to be 10 mm (Sokol & Bližňák 2009), G_i and T_i represent the rain gauge stations' data and the TRMM rainfall data in the same pixel, respectively, and n represents the number of rain gauge stations used for the special interpolation.

To obtain the spatial distribution of P_i , the co-kriging method was used to interpolate P_i for the entire research area. Co-kriging is a common interpolation method that involves one or more secondary variables that are correlated with the variable of interest and assist in improving the interpolation precision (Nalder & Wein 1998). Considering the correlation between precipitation, elevation and complex topography in the research area, the co-kriging method using the relationship between altitude and precipitation was adopted in this study. Then, the proportional coefficients of the precipitation data (P_{ij}) that possessed spatial distribution characteristics were obtained. The calibrated rainfall data can be defined as follows:

$$P_{ij}^{mer} = \max(P_{ij} * (T_{ij} + \lambda) - \lambda, 0) \quad (2)$$

where P_{ij}^{mer} represents the calibrated rainfall data in pixels (i, j), and T_{ij} represents the TRMM rainfall data in the same pixel as P_{ij}^{mer} . In addition, the cross-validation method was used to examine the effects of the interpolation. Cross-validation (Simon et al. 2003) is a method used to evaluate the quality of interpolations; it extracts a certain

portion of the measured data for interpolation and leaves the remaining data for examining the effect of the interpolation process (Hornung et al. 2014). The relative error (RE) (Janssen & Heuberger 1995) and correlation coefficient (CC) were calculated to evaluate the quality of the TRMM rainfall data both before and after adjustment. The relevant formulas are as follows:

$$RE = \frac{\bar{G} - \bar{T}}{\bar{G}} \quad (3)$$

$$CC = \frac{\sum_{i=0}^n (G_i - \bar{G})(T_i - \bar{T})}{\sqrt{\sum_{i=0}^n (G_i - \bar{G})^2 \sum_{i=0}^n (T_i - \bar{T})^2}}, \quad 0 \leq CC \leq 1 \quad (4)$$

where G_i and T_i are the observation stations' data and radar rainfall data in the same pixel mentioned in Equation (1), with \bar{G} and \bar{T} corresponding to the mean values, respectively.

Seven meteorological gauge stations, including WQ, KS, TSKEG, HT, MF, QM and RQ, were filtered for interpolation, and three meteorological gauging stations, including SC, PS and YT, were used for cross-validation.

SWAT model setup

As the average annual precipitation at the HT station was approximately 35 mm and the frequency and intensity of precipitation in the mountains show pronounced differences from that of the plains, using the precipitation data from the plain stations was not reasonable or realistic for the model simulations even after correcting for the precipitation lapse rate (Plaps) in the SWAT model. After the correction of the TRMM rainfall data, these data were used to force

the SWAT hydrological model. The validation of the SWAT model indirectly confirmed the reasonability of the corrected TRMM data. The SWAT model is a well-established, semi-distributed hydrological model developed by the United States Department of Agricultural Research Service (USDA-ARS) (Arnold *et al.* 1998). The model is commonly used to simulate and forecast the circulation process of water, sediment, nutrients and pesticides (Douglas-Mankin *et al.* 2010; Arnold *et al.* 2012). The SWAT model includes a strong physical basis and is a representative semi-distributed hydrological model that has been successfully applied worldwide (Jayakrishnan *et al.* 2005; Wang *et al.* 2014; Yasin & Clemente 2014; Meng *et al.* 2015), such as in America (Watson & Putz 2014; White *et al.* 2014), Europe (Piniewski *et al.* 2014; Roebeling *et al.* 2014; Zabaleta *et al.* 2014), Australia (Saha *et al.* 2014; Brown *et al.* 2015) and Asia (Shope *et al.* 2014; Wang *et al.* 2016). There have also been many notable study cases carried out in Xinjiang Province (Lu *et al.* 2012; Meng *et al.* 2016), even in the Tarim River Basin (Huang *et al.* 2015; Liu *et al.* 2016). For instance, the SWAT model was used in Xinjiang Province by Yu *et al.* (2011) in the Manas River Basin and by Song *et al.* (2013) in Ili Kashi River Basin to reveal hydrological behaviours. Furthermore, the SWAT model has also been used to assess the climate change impact on water resources in the headwater region of the Tarim River (Fang *et al.* 2015). Many of these study cases confirmed the simulation capacity of the SWAT model in arid and semi-arid regions. Moreover, the advantages of the SWAT model, such as fast computing time, easy setup, flexible model structure, various practice modules, make it favourable for regional studies. Despite the fully distributed models, such as MIKE SHE having options of stronger physical basics, the limited input data make the model setup rickety; in other words, they are used inherently in a lumped way. With the consideration of data availabilities, model setup, model calibration and validation, the SWAT model was used in this study. The spin-up period ranged from 2000 to 2003, the calibration period was from 2004 to 2008, and the validation period was from 2009 to 2010.

For the calibration and sensitivity analyses in this study, the Sequential Uncertainty Fitting (SUFI-2) program (Abbaspour *et al.* 2007) in the SWAT Calibration Uncertainty Procedure (SWAT-CUP) calibration package (Arnold *et al.*

2012) was used to accelerate the model calibration process. Thirty parameters commonly used for calibration were selected in this research. According to the results of the parameter sensitivity analysis, 17 parameters were calibrated for this research, and default values were used for the others.

RESULTS AND DISCUSSION

Results of the corrected TRMM data

Table 2 shows the effect of the cross-validation process at three stations (SC, PS and YT). The evaluation indices (CC and RE) improved at different levels, although not all of the values reached the ideal effect. The RE value of the three stations ranged from -0.14 to 0.16 , and the CC value was between 0.54 and 0.77 . These values indicate that the estimated and observed data are more consistent. In addition, a relatively poor correction result was observed at the PS station, which may have been caused by the poor data quality before correction. This result indirectly suggests that the correction effect is influenced by the data quality.

For demonstration purposes, only the results of the PS (Figure 3) meteorological station are presented in this paper. According to Figure 3(a), the corrected monthly peak precipitation based on the TRMM data was similar to that of the rain gauge data. For the annual precipitation, the corrected TRMM rainfall data were more similar to the SB data, which can be seen in Figure 3(b). In conclusion, the corrected TRMM rainfall data were more consistent with the SB data relative to the TRMM rainfall data before adjustment, and they may reflect the more accurate spatial distribution of precipitation. As the high-altitude

Table 2 | Monthly and annual cross-validation results between the rain gauge stations and the corrected TRMM rainfall data

Stations	Correction value	RE	CC	RE	CC
		Monthly		Annual	
SC	Before	-0.09	0.68	-0.09	0.47
	After	-0.01	0.77	-0.01	0.92
PS	Before	-0.86	0.35	-0.86	0.45
	After	-0.09	0.56	-0.09	0.87
YT	Before	0.47	0.50	0.47	0.85
	After	0.16	0.85	0.16	0.97

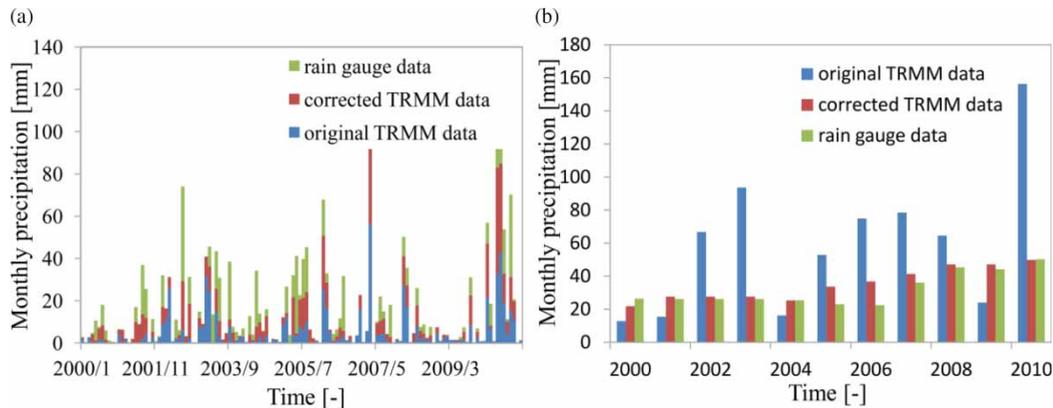


Figure 3 | Monthly and annual precipitation from the rain gauge data and the corrected TRMM data at the PS station from 2000 to 2010: (a) monthly; (b) annual.

precipitation could not be directly validated through *in situ* data or field observations, the data reasonability can only be indirectly validated via hydrological simulations.

Results of the SWAT model

Table 3 shows the calibration results of the SWAT parameters. All of these parameters are applied globally to all HRUs which makes the SWAT model very flexible to fit all kinds of practical situations. However, considering their

own unique combination of land use, soil properties, and slope of different HRUs, the bio-physical parameters are not uniform over the catchment. The temperature lapse rate (Tlaps) is the most sensitive parameter in the Hotan River Basin because the basin is primarily recharged by glaciers and snow melting. The snowmelt base temperature (SMTMP), melt factor for snow on June 21 (SMFMX), snowfall temperature (SFTMP) and melt factor for snow on December 21 (SMFMN) also play important roles in the snowmelt-runoff process. Precipitation is one of the most

Table 3 | Calibration results of the SWAT model parameters

Parameters	Parameter name	Range	Calibrated value
TLAPS	Temperature lapse rate ($^{\circ}\text{C}/\text{km}$)	-10-10	-5.2
PLAPS	Precipitation lapse rate ($\text{mm H}_2\text{O}/\text{km}$)	0-500	200
LAT_TIME	Lateral flow travel time (days)	0-180	4
TIMP	Snow pack temperature lag factor	0-1	0.008
ALPHA_BF	Base flow alpha factor (days)	0-1	0.004
SMTMP	Snowmelt base temperature ($^{\circ}\text{C}$)	-5-5	2
SMFMX	Melt factor for snow on June 21 ($\text{mm}/^{\circ}\text{C}\text{-day}$)	0-10	10
SFTMP	Snowfall temperature ($^{\circ}\text{C}$)	-5-5	4
SURLAG	Surface runoff lag coefficient	1-24	20
CN2	Initial SCS runoff curve number	35-98	75
SMFMN	Melt factor for snow on December 21 ($\text{mm}/^{\circ}\text{C}\text{-day}$)	0-10	10
CH_K2	Effective hydraulic conductivity in main channel alluvium (mm/hr)	-0.01-500	2
OV_N	Manning's n value	0.01-30	0.5
CH_N2	Manning's n value for the main channel	-0.01-0.3	0.1
GW_DELAY	Groundwater delay (days)	0-500	60
HRU_SLP	Average slope steepness (m/m)	0-0.6	0.3
SOL_Z	Depth from soil surface to bottom of layer (mm)	0-3,000	300

direct influential factors on the hydrological process, particularly in the Hotan River Basin, where the precipitation level is strongly correlated with elevation. The soil parameters (SOL_K) and the initial SCS runoff curve number (CN2) determine the outflow of the surface runoff, lateral flow and shallow aquifers. Average slope steepness (HRU_SLP) is the leading factor in the lateral flow and infiltration runoff. The base flow alpha factor (ALPHA_BF) and groundwater delay (GW_DELAY) were found to greatly affect the groundwater recession process, particularly in the winter.

The CC mentioned above was used to assess the SWAT simulation results during the calibration and validation periods. The Nash–Sutcliffe (NS) efficiency coefficient (Nash & Sutcliffe 1970), total flow error (TFE) and peak flow error (PFE) were also determined (Table 4). The relevant formulas are as follows:

$$NS = 1 - \frac{\sum_{i=0}^n (O_i - S_i)^2}{\sum_{i=0}^n (O_i - \bar{O})^2}; \quad -\infty \leq NS \leq 1 \quad (5)$$

$$TFE = \frac{O_t - S_t}{O_t} \quad (6)$$

$$PFE = \frac{O_p - S_p}{O_p} \quad (7)$$

where O_i and S_i are the observational station's data and the simulated data at time step i , respectively, \bar{O} is the mean value of the observed data, n is the total number of daily time steps, O_t and S_t are the amounts of observational runoff and simulated runoff, respectively, and O_p and S_p are the maximum observed runoff and simulated runoff, respectively.

On a daily time scale, the calibration and validation CC were 0.85 and 0.88, respectively, and the NS reached 0.71

Table 4 | Calibration and validation results of the SWAT model

	Coefficient value	Daily scale	Monthly scale
Calibration period	CORR	0.85	0.95
	NS	0.71	0.90
	TFE	-0.12	-0.11
	PFE	-0.01	-0.12
	CORR	0.88	0.98
Verification period	NS	0.76	0.83
	TFE	-0.26	-0.21
	PFE	-0.12	-0.22

and 0.76, respectively. On a monthly time scale, the calibration and validation CC were 0.95 and 0.98, respectively, and the NS ranged from 0.90 to 0.83. The TFE and PFE of the calibration and validation data were less than 30%. Although the simulated effect of the monthly runoff was better than that of the daily runoff, the absolute values of the indices were still acceptable at daily scales. Figure 4 shows the comparison between the simulated and observed discharge on daily and monthly time scales. The simulated discharge properly represented the peak flow and the trend in the total flow during both the calibration and validation periods. Meanwhile, the SWAT simulated results driven by the raw TRMM rainfall data present lower matching with efficiency coefficient of 0.48 and larger PFE of 40% (Figure 5). At daily scale by row TRMM data, CC and the NS were 0.75 and 0.48, respectively. The PFE reached up to 40%. Therefore, the direct usage of row TRMM data might lead to larger error in the hydrological simulation.

By comparing only the gauge station records with the modelled discharge, the model evaluation may not provide a realistic parameter set. Therefore, additional spatially distributed data were introduced in this study to evaluate the spatial pattern of the model output and spatially evaluate the performance of the SWAT parameters.

RS snow cover data were used as the spatial validation reference to estimate the performance of the RS precipitation and the predictive capacity of the model. Such an evaluation was useful for demonstrating the precision of the modelled snow cover (both in terms of spatial and temporal variations), and a reasonable model of surface runoff and river flows was obtained (Liu *et al.* 2012). As shown in Figure 6, the similarity of results for each month in 2008 present the temporal goodness-of-fit between modelled snow covers with MODIS 10A2 images. Moreover, the spatial similarity is illustrated in Figure 7 at typical time points in different seasons. The following statistic was used to evaluate the similarity of the snow cover areas at the selected time intervals (Liu *et al.* 2012):

$$U_c = \frac{A_{md} \cap A_{rs}}{A_{md} \cup A_{rs}} \quad (8)$$

where A_{md} is the area of snow cover from the hydrological model result, and A_{rs} is the area classified as snow

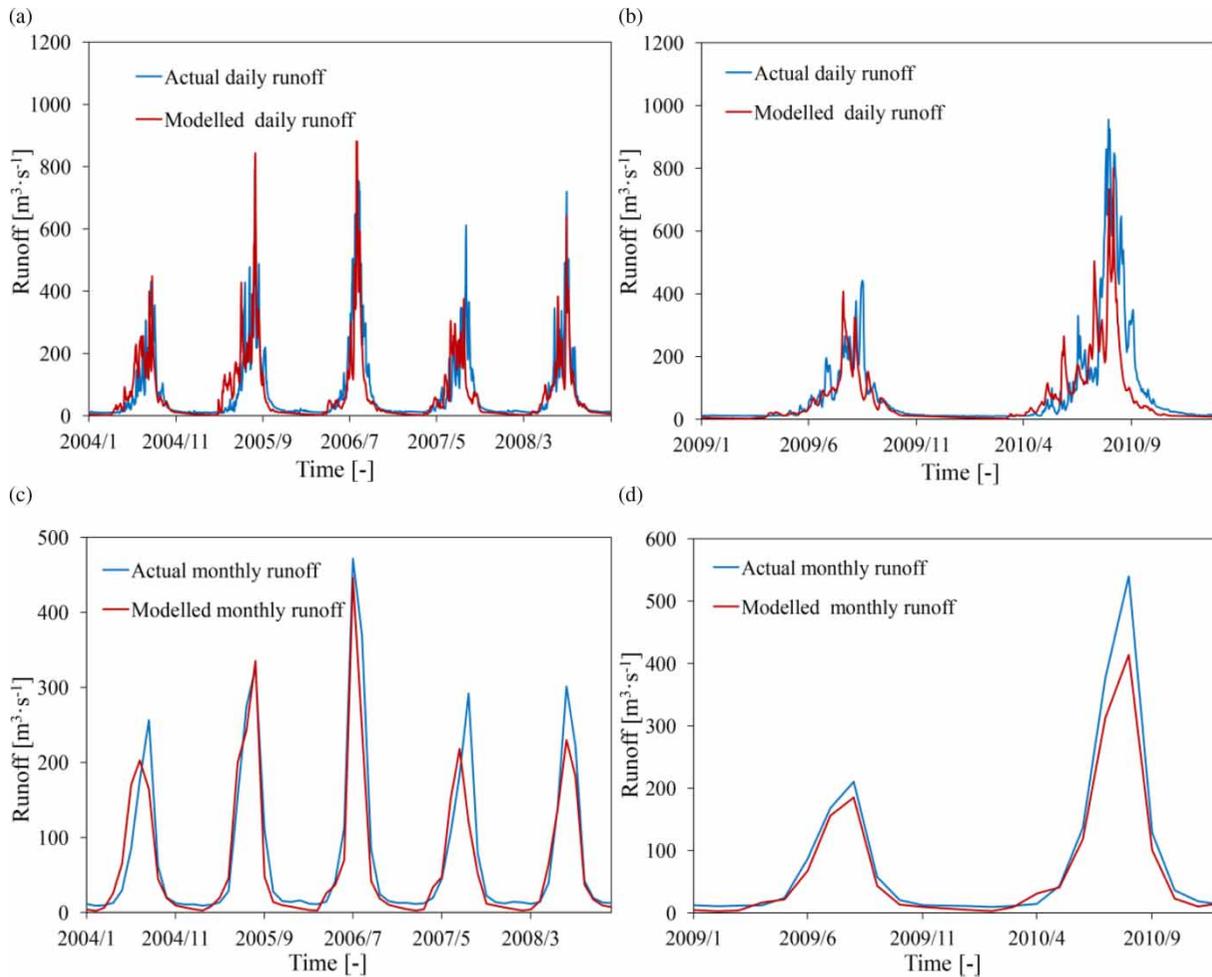


Figure 4 | Calibration and validation results (calibration periods, left column; validation periods, right column) of the SWAT model at daily and monthly scales (daily scale, 1st row; monthly scale, 2nd row) at the TGZLK station.

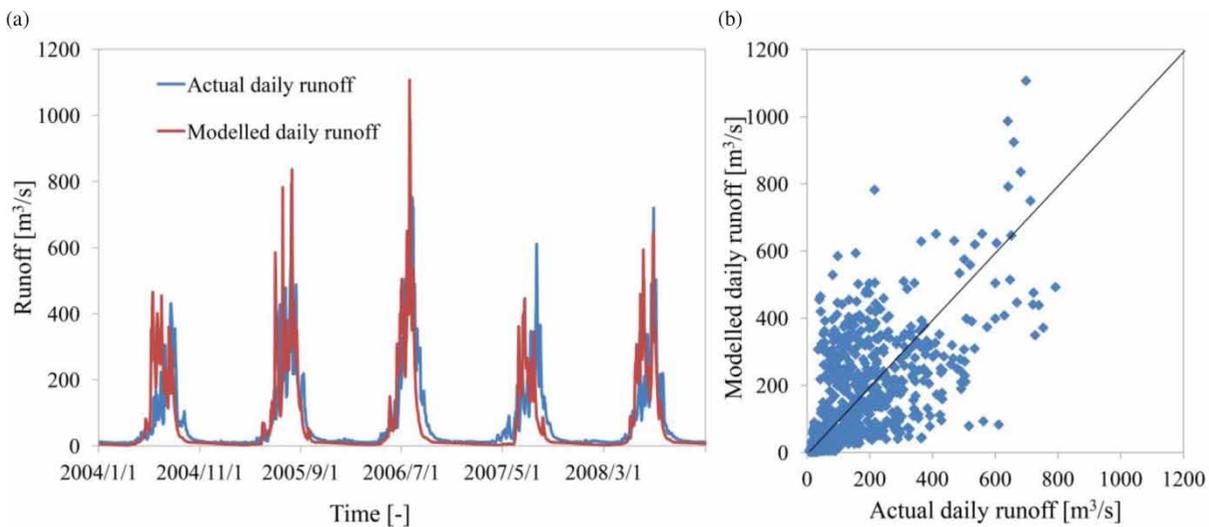


Figure 5 | Calibration results of the SWAT model at daily scales driven by raw TRMM data at the TGZLK station.

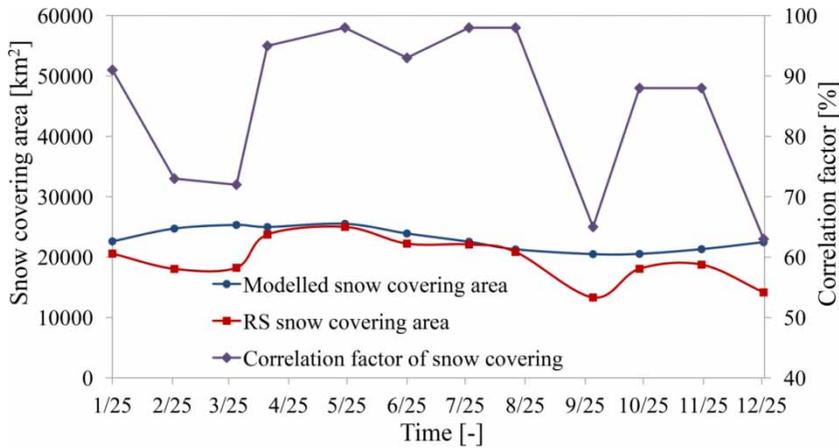


Figure 6 | Snow cover area produced by corrected TRMM input as well as MODIS image and the correlation factor between them.

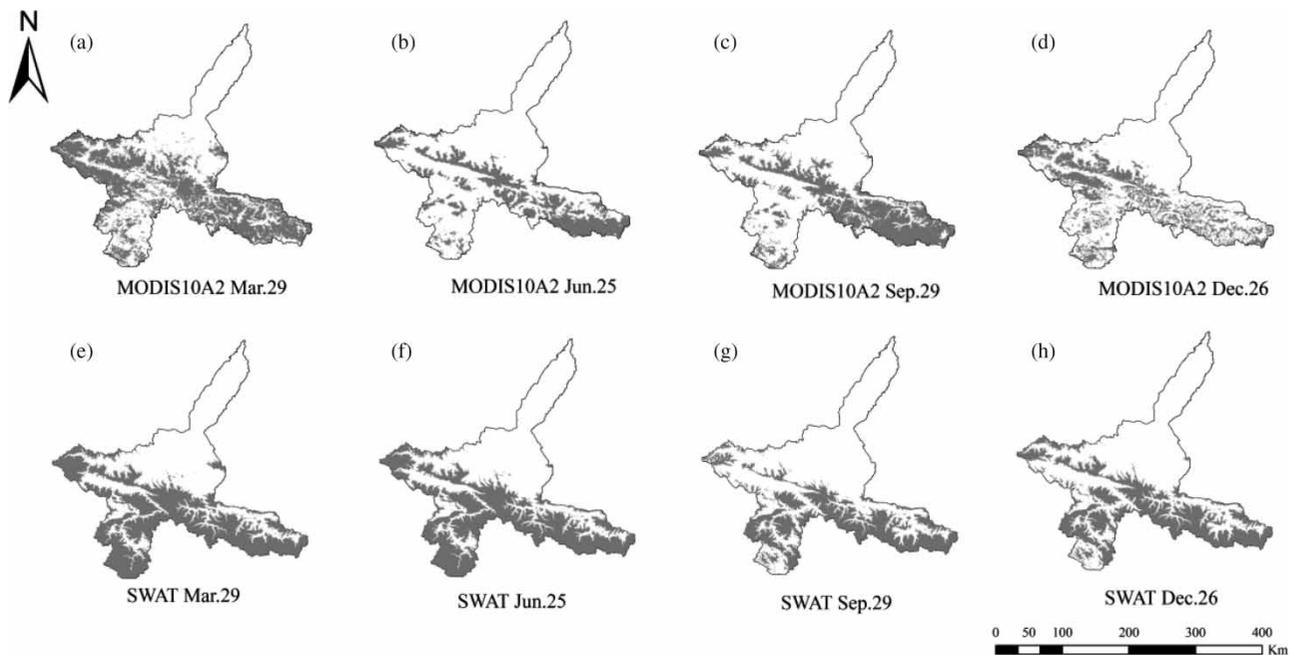


Figure 7 | MODIS 10A2 snow cover image (top row) comparing the SWAT snow cover simulation results (bottom row) for the Hotan River Basin at different time periods in 2008 (the grey areas represent snow, whereas white represents no-snow areas).

cover based on the RS data. In this research, the U_c correlation indicators of the 12 selected time periods ranged from 0.63 to 0.98 in Figure 6, which are 0.71, 0.93, 0.65 and 0.63 in Figure 7. The similarity between the modelled and MODIS snow cover demonstrated that the progression of snowfall, rainfall and snowmelt in the SWAT model reasonably represented the reality of hydrological processes, both spatially and temporally.

CONCLUSIONS AND FUTURE WORK

This article applied the proportional coefficient method to improve the quality of the TRMM rainfall data in the Hotan River Basin and used the corrected TRMM data as direct inputs for the SWAT model. The simulated discharges agreed well with the observations, both at daily and monthly time scales. Although the snow cover results of the SWAT simulation were comparable to the MODIS 10A2 snow

cover images, similar spatial and temporal distributions were observed. Based on the performance of the TRMM rainfall data in this study, the TRMM rainfall data can be used to replace SB data, which partly overcomes the lack of necessary hydrological model input data in remote regions. Meanwhile, the results also indicated the feasibility of proportional coefficient method applied in TRMM data in the research area.

The proportional coefficient method includes a greater number of precipitation gauge stations from outside the study region, where spatial distribution patterns are relatively reliable, and does not directly apply TRMM data. As the ratios between the SB and RS precipitation values were spatially interpolated across the entire study area, all TRMM pixels could undergo correction for further applications. Regarding the geological features of the Hotan River Basin and the available data sets, the proportional coefficient method took full advantage of the *in situ* data and presented feasible methods. However, this method could introduce more spatial distribution information by including more external gauging stations, and its accuracy still relies on the density of the gauging stations in the data processing area. Another notable drawback is that this approach considers only the total amount of precipitation and neglects the frequency correction.

TRMM rainfall data are considered to represent commonly used precipitation data sources because they present spatial heterogeneity and exhibit certain advantages due to their spatial distribution in mountainous areas. In addition, TRMM rainfall data exhibit lower values than the rain gauge data at most stations in the Karakorum-Kunlun Mountains, which is consistent with the research results of Yang & Luo (2013). However, the primary mission and calculation algorithm of the TRMM satellites aim to observe precipitation in the tropics rather than in plateau mountain areas. The accuracy of the data must be examined before their actual application. Moreover, TRMM rainfall data have a relatively low spatial resolution, which also influences the accuracy and restricts the application of these data to the field of hydrology.

As few precipitation gauge stations are located in high-elevation areas, directly validating the corrected TRMM

data is not possible, and hydrological modelling could represent an alternative method of verifying the reliability of the correction approach. When using corrected TRMM data to force the SWAT model, the simulated results showed an advantage over RS precipitation based on the spatial distribution. By comparing the precipitation volume and runoff simulations over 7 years (from 2004 to 2010), the simulated discharge results confirmed that this method can produce reasonable total precipitation and simulated runoff values. When the modelled snow cover patterns were compared with the RS snow cover, similar spatial and temporal distributions were observed. Therefore, the spatial and temporal distributions of the TRMM rainfall data are reasonable. Simultaneously, statistical calculations indicated that the proportion of melting glacier snow in the total discharge was approximately 66.4%, similar to the results presented in previous research (66.8%) (Lv et al. 2010).

Regarding the requirements of the SWAT model, the precipitation inputs must be regulated as potentially restricted stationary data; otherwise, the rich spatial information from the TRMM data will be affected. This work used each TRMM pixel as one station to fully express the spatial variability; therefore, utilizing an empirical parameter, such as PLAPS, could be limited to its minimum value to avoid the uncertainties in the parameter calibration process.

Building upon the success of TRMM, the Global Precipitation Measurement (GPM) mission is committed to extending the possibilities of developing and applying their satellite-based precipitation products. The GPM sensors expand the range of TRMM measurements and provide a new generation of products that provide more accurate transient measurements, particularly for light-intensity precipitation ($<0.5 \text{ mm h}^{-1}$) and falling snow (Joyce et al. 2004; Hou et al. 2014). A comparison of the precision of the TRMM data and the GPM data at the PS station (Figure 8) shows that the GPM data are more precise than the TRMM data, although the effect remains limited (CC and RE are 0.58 and 0.22 for the GPM data and 0.32 and 0.75 for the TRMM data, respectively). In addition, the GPM data must be calibrated before being used in hydrological model simulations of the north-western arid areas of China. However, improving the information used in hydrological applications

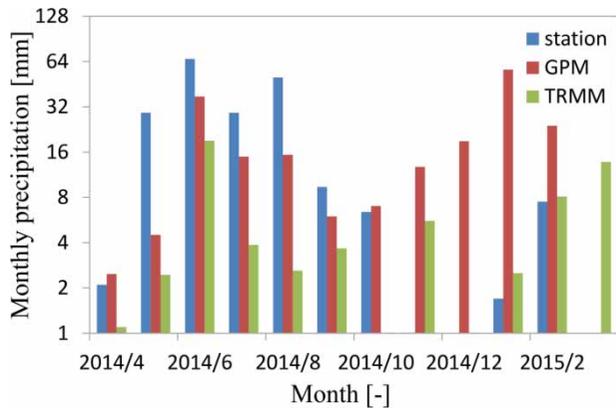


Figure 8 | Monthly precipitation from the rain gauge data, GPM data and TRMM data at PS station (from April 2014 to March 2015).

could lead to improvements in satellite-based rainfall estimation algorithms, RS data correction methods and combined RS data and SB data approaches.

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