Postprint: Utility Assessment of Multi-source Precipitation Data for Small Watershed Hydrologic Simulation

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Abstract

Small watersheds are ideal objects for studying the evolution laws of micro-scale hydrological and water resource systems, the smallest units for calculating river water and sediment yield, and the optimal geographical scale for hydrological and soil erosion research and management. Obtaining precipitation data through remote sensing technology and climate models, and driving distributed hydrological models to simulate and predict hydrological processes, is an inevitable trend in watershed hydrological and water resource research. Using NOAA-CPC-US precipitation as a reference, the accuracy of satellite precipitation products PERSIANN, PERSIANN-CDR, TRMM-3B42V7, GPM-IMERG, radar precipitation StageIV, and climate model ERA5 precipitation products was evaluated across 9 small watersheds in different regions of the United States, and these 7 precipitation products were used to drive the CREST distributed hydrological model to assess the hydrological simulation utility of the 7 precipitation products. The study shows that the agreement between each precipitation product and NOAA-CPC-US precipitation, from highest to lowest, is: StageIV radar precipitation first, followed by PERSIANN-CDR and GPM-IMERG, then PERSIANN and ERA5, and finally TRMM-3B42V7. The precipitation estimation accuracy of each product is slightly lower in small watersheds located in high-latitude regions of northern United States and western mountainous areas, while showing better precipitation accuracy in small watersheds in the central, southern, and eastern United States. In the hydrological simulation utility assessment, the same calibration period was set, the CREST model parameters were calibrated using each of the 7 precipitation products separately, and after obtaining the calibrated parameter sets, the daily runoff processes of the watersheds were simulated for the same validation period. The results show that NOAA-CPC-US and Stage IV radar precipitation perform well in hydrological simulations across various small watersheds; in the northern and western regions of the United States, caution is needed when using PERSIANN, PERSIANN-CDR, GPM- IMERG, and ERA5 precipitation for hydrological simulations. The hydrological simulation performance of TRMM-3B42V7 in small watersheds is unsatisfactory.

Full Text

Evaluating Runoff Simulation of Multi-Source Precipitation Data in Small Watersheds

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Abstract

Small watersheds represent ideal objects for studying the evolution of micro-scale hydrological and water resource systems. They constitute the smallest unit for calculating river water and sediment yield and serve as the optimal geographic scale for hydrology and soil erosion research and management. Using remote sensing technology and climate models to obtain precipitation data that drive distributed hydrological models for simulating and predicting hydrological processes represents an inevitable trend in watershed hydrology and water resources research. This study uses NOAA-CPC-US precipitation data as a reference to evaluate seven precipitation products—PERSIANN, PERSIANN-CDR, TRMM-3B42V7, GPM-IMERG, StageIV, and ERA5—across nine small watersheds in different regions of the United States. The accuracy of these precipitation products was assessed, and they were used to drive the CREST distributed hydrological model to evaluate their hydrological simulation utility. Results indicate that the degree of agreement with NOAA-CPC-US precipitation decreases in the following order: StageIV radar precipitation, followed by PERSIANN-CDR, GPM-IMERG, PERSIANN, ERA5, and TRMM-3B42V7. Precipitation estimation accuracy is slightly lower in small watersheds located in high-latitude northern regions and western mountainous areas of the United States, while better accuracy is observed in central, southern, and eastern regions. In the hydrological simulation utility evaluation, CREST model parameters were calibrated using each of the seven precipitation products during the same calibration period. After obtaining the parameter sets, daily runoff processes were simulated for the same validation period. The results demonstrate that NOAA-CPC-US and StageIV precipitation perform well in hydrological simulations across small watersheds. However, caution is required when using PERSIANN, PERSIANN-CDR, GPM-IMERG, and ERA5 precipitation for hydrological simulations in northern and western U.S. regions, while TRMM-3B42V7 shows unsatisfactory simulation performance.

Keywords: Small watersheds; CREST hydrological model; Multi-source precipitation; Hydrological simulation

1. Introduction

Precipitation constitutes a primary component of the hydrological cycle and serves as the main data input for hydrological model research. It plays a crucial role in studies, monitoring, and forecasting across climate, meteorology, hydrological prediction, and hydrological disaster domains. Surface rain gauge observations offer direct measurements with relatively high accuracy, but their ability to capture the complex spatial distribution of precipitation is limited by station density and spatial arrangement. Ground-based radar can directly detect the spatial distribution of precipitation and track precipitation centers and spatial variations in real time, yet it is susceptible to terrain occlusion and radar beam elevation effects. Although satellite remote sensing precipitation is less accurate than ground observations, it enables large-scale, rapid, and convenient acquisition of continuous precipitation data with certain spatiotemporal precision, partially compensating for deficiencies in ground observations and providing an effective precipitation data source for ungauged or poorly gauged regions. Climate system models can simulate global precipitation, but due to climate complexity, their simulation results still exhibit considerable uncertainty at regional scales, and some climate model precipitation data cannot be directly used for hydrological utility evaluation.

In recent years, rapid development of these three precipitation data acquisition technologies, coupled with the application of machine learning algorithms in precipitation retrieval, has produced numerous precipitation products with varying spatiotemporal resolutions. Many scholars have conducted extensive research on precipitation product accuracy assessment, spatiotemporal precipitation variation, and hydrological simulation utility across different products. Global or large-scale regional runoff simulation and real-time forecasting systems developed based on precipitation products have received positive evaluations in forecasting and reproducing multiple hydrological disaster events. However, previous studies have revealed significant spatial variability in precipitation products, with satellite and radar precipitation products showing varying accuracy across different latitudinal regions. Furthermore, precipitation products with different accuracies lead to differences in runoff simulation precision, indicating that multi-source precipitation products still exhibit considerable uncertainty in hydrological applications across different spatiotemporal scales.

Small watersheds are ideal objects for studying micro-scale hydrological and water resource system evolution. They represent important geographic units for soil erosion control and ecosystem restoration, the smallest unit for calculating river water and sediment yield, and the optimal geographic scale for hydrology and soil erosion research and management. In recent years, scholars have conducted numerous studies on runoff coefficients, surface runoff simulation, and soil water movement at the small watershed scale based on ground observation precipitation. However, the capability of precipitation products with different spatiotemporal resolutions for hydrological simulation and forecasting at the small watershed scale requires further investigation.

Therefore, this study selected nine small watersheds across different geographic regions of the United States, using NOAA-CPC-US gauge-based precipitation reanalysis data as a reference to evaluate the accuracy of satellite precipitation products (PERSIANN, PERSIANN-CDR, TRMM-3B42V7, GPM-IMERG), radar precipitation (StageIV), and climate model precipitation products (ERA5). Combined with the CREST distributed hydrological model, daily runoff processes in each small watershed were simulated to assess the hydrological simulation utility of multi-source precipitation products with different spatiotemporal resolutions at the small watershed scale, thereby providing references for the research and application of these precipitation products in the hydrological sector.

2. Materials and Methods

2.1 Study Area

There is currently no unified definition of small watersheds internationally. Different countries and organizations establish different criteria for delineating small watersheds based on research purposes and perspectives. The small watersheds discussed in this paper are defined according to the U.S. Stream Classification System (USSCE) developed by the Oak Ridge National Laboratory, USA. This system classifies approximately 2.7 million rivers in the United States into eight levels, from largest to smallest: Great River, Large River, Medium River, Small River, Large Creek, Medium Creek, Small Creek, and Headwater Creek. This study selected nine small watersheds from different geographic regions across the continental United States. The rivers in these watersheds belong to the Headwater Creek level in the classification system. Table 1 provides information on the geographic regions, watershed areas, and mean annual flow of these nine watersheds.

2.2 Research Data

This study utilized seven precipitation datasets: NOAA-CPC-US, NCEP-StageIV, PERSIANN, PERSIANN-CDR, TRMM-3B42V7, GPM-IMERG, and

ERA5. The data period spans from 2000 to 2018. The temporal resolution was set to daily scale, and the spatial resolution was unified to 0.0083° × 0.0083°. Since these precipitation products have different native spatiotemporal resolutions, data preprocessing involved converting temporal resolutions finer than daily to daily through accumulation, and unifying spatial resolutions to 0.0083° × 0.0083° using bilinear interpolation.

2.3 Methods

2.3.1 NOAA-CPC-US Precipitation This dataset is a reanalysis precipitation product from the NOAA Climate Prediction Center based on ground observation precipitation. It compiles precipitation information from over ten thousand surface observation stations, implements quality control through comparison with radar, satellite observations, and numerically modeled precipitation, and creates daily precipitation fields through optimal interpolation considering terrain effects, ultimately forming a precipitation product with higher quantitative accuracy and consistency. The spatial resolution is 0.25°, covering the continental United States from 1948 to present. Data are available at https://www.esrl.noaa.gov/psd/data/gridded/data.unified.html.

2.3.2 NCEP-StageIV Radar Precipitation NCEP-StageIV is a radar-based quantitative precipitation estimation product from the U.S. National Weather Service' s National Centers for Environmental Prediction, initiated on January 1, 2002. The data combine precipitation estimates from approximately 140 Doppler next-generation weather radars and measurements from about 5,500 rain gauges across the continental United States. Twelve River Forecast Centers produce data for their respective regions, starting collection every 5-6 minutes and accumulating at hourly time steps. After iterative calculation, review, and manual quality control, regional data are mosaicked to create quantitative precipitation estimates for the continental United States. The data have a spatial resolution of 4 km and temporal resolution of 1 hour, with precipitation units in mm. Detailed characteristics and download links are available at the National Stage IV QPE Product website (www.emc.ncep.noaa.gov/mmb/ylin/pcpanl/stage4/).

2.3.3 PERSIANN Precipitation PERSIANN was developed by the Center for Hydrometeorology and Remote Sensing at the University of California, Irvine. It uses infrared brightness temperature images from geostationary satellites (Metsat-6, Metsat-7, GOES-8, GOES-10, GMS-5) and employs an artificial neural network algorithm to estimate 30-minute rainfall rates, which are then aggregated to 3-hour and daily scales. The spatial resolution is 0.25°, with time coverage from 60°S to 60°N. Data are available at https://chrsdata.eng.uci.edu/.

2.3.4 PERSIANN-CDR Precipitation This dataset provides daily rainfall estimates from 1983 to present, with latitude range 60°S-60°N and spatial resolution 0.25°. Developed by the University of California, Irvine, it is a satellite remote sensing-based precipitation dataset. PERSIANN-CDR is generated through an artificial neural network algorithm on GridSat-B1 infrared satellite data, trained using NCEP StageIV radar precipitation data, and then adjusted using Global Precipitation Climatology Project (GPCP) v2.2 monthly precipitation products. The National Research Council defines this data as a Climate Data Record (CDR) with sufficient length, consistency, and continuity for determining climate variability and change. Data sources and download links are available at https://www.esrl.noaa.gov/psd/data/gridded/data.persiann.html.

2.3.5 TRMM-3B42V7 Satellite Precipitation The Tropical Rainfall Measuring Mission (TRMM) satellite, jointly developed by NASA and JAXA, concluded its observation mission in April 2015 due to fuel depletion and re-entered Earth' s atmosphere over the southern Indian Ocean in June 2015. Following TRMM' s success, the TRMM team continued producing precipitation data products using multiple methods. This study selected TRMM-3B42V7 to evaluate its hydrological utility under current conditions. The product is available on the NASA TRMM satellite data website (https://pmm.nasa.gov/trmm/).

2.3.6 GPM-IMERG Satellite Precipitation The Global Precipitation Measurement (GPM) mission, led by NASA, is the successor to TRMM. Its core observation platform was launched in February 2014, providing global observations of rain and snow within 65°N-S. Compared with TRMM, GPM has expanded coverage to Earth' s poles, higher spatiotemporal resolution, and improved sensor performance for detecting light precipitation. The Integrated Multi-satellitE Retrievals for GPM (IMERG) dataset provides global rainfall estimates at 30-minute and daily scales, calibrated and merged from all microwave, infrared, ground observations, and other sensors using the GPROF2017 algorithm. The spatial resolution is 0.1°, temporal resolution is 30 minutes, with coverage from March 2014 to present and spatial extent 60°S-60°N. Data are available at https://pmm.gsfc.nasa.gov/GPM.

2.3.7 ERA5 Reanalysis Dataset Precipitation ERA5 is the fifth-generation reanalysis dataset from the European Centre for Medium-Range Weather Forecasts (ECMWF), succeeding ERA-Interim and ERA-40. It employs an improved data assimilation system (IFS Cycle 41r2), four-dimensional variational analysis (4D-Var), and radiation variational bias correction, systematically enhancing dataset quality. ERA5 provides global hourly estimates with spatial resolution 0.25° × 0.25°, covering 89.142°S-89.142°N, 180°W-180°E from 1979 to present. This study uses hourly precipitation data downloaded from https://cds.climate.copernicus.eu.

2.3.8 Watershed Runoff, Terrain, and Potential Evapotranspiration Data This study uses watershed boundaries, digital terrain, and runoff data from the U.S. Geological Survey (USGS) and the U.S. Department of Agriculture. Watershed Boundary Dataset V2.2.1 provides watershed boundaries, the USGS 30m digital elevation model (DEM) provides terrain data, and the National Water Information System provides streamflow data. Based on DEM data, ArcGIS analysis tools extract river networks, flow directions, and flow accumulation information. Potential evapotranspiration (PET) data required for distributed hydrological model evaluation are obtained from the Famine Early Warning System (FEWS). Daily global PET is calculated using the Penman-Monteith equation based on climate data from the Global Data Assimilation System, then summed to obtain daily totals. The data have spatial resolution 1.0° × 1.0° and temporal resolution 1 day, available at https://earlywarning.usgs.gov/fews/datadownloads/Global/PET.

2.4 CREST Distributed Hydrological Model

The Coupled Routing and Excess Storage (CREST) model was jointly developed by the Hydrometeorology and Remote Sensing Laboratory (HyDROS) at the University of Oklahoma and NASA' s SERVIR program. It is a distributed hydrological model that divides the entire watershed into grids, uses a variable infiltration capacity curve for grid-by-grid runoff generation, and employs multiple linear reservoirs for grid-by-grid surface and groundwater routing. By coupling runoff generation and routing components, the model simulates runoff processes. The model has demonstrated excellent hydrological simulation and forecasting capabilities at global, large regional, and medium-small scales. CREST requires input data including watershed information (boundaries, DEM, flow direction), precipitation, potential evapotranspiration, outlet discharge, initial conditions, and model parameters. Outputs include soil water content, soil moisture, and surface runoff. For brevity, detailed information on model data preprocessing and parameter ranges is available at the HyDROS model website (http://hydro.ou.edu/research/crest/).

2.5 Statistical Evaluation Metrics

This study selected relative bias (Bias), root mean square error (RMSE), mean absolute error (MAE), and correlation coefficient (CC) to quantitatively evaluate precipitation product accuracy. For hydrological simulation utility, standard deviation (SD), Nash-Sutcliffe efficiency coefficient (NSCE), relative bias (Bias), and correlation coefficient (CC) were used. The formulas are:

$$\text{Bias} = \frac{\sum_{i=1}^{n}(\text{Sim}_i - \text{Obs}_i)}{\sum_{i=1}^{n}\text{Obs}_i}$$

$$\text{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(\text{Sim}_i - \text{Obs}_i)^2}$$

$$\text{MAE} = \frac{1}{n}\sum_{i=1}^{n}|\text{Sim}_i - \text{Obs}_i|$$

$$\text{CC} = \frac{\sum_{i=1}^{n}(\text{Sim}_i - \overline{\text{Sim}})(\text{Obs}_i - \overline{\text{Obs}})}{\sqrt{\sum_{i=1}^{n}(\text{Sim}_i - \overline{\text{Sim}})^2 \sum_{i=1}^{n}(\text{Obs}_i - \overline{\text{Obs}})^2}}$$

$$\text{NSCE} = 1 - \frac{\sum_{i=1}^{n}(\text{Sim}_i - \text{Obs}_i)^2}{\sum_{i=1}^{n}(\text{Obs}_i - \overline{\text{Obs}})^2}$$

where Sim represents multi-source precipitation estimates or CREST-simulated runoff, Obs represents reference precipitation or observed streamflow, n is the number of simulated or observed values, and i is the ith simulated or observed value. For all evaluation metrics, values closer to 0 for Bias, RMSE, and MAE, and closer to 1 for CC and NSCE, represent better performance. Following Moriasi et al., NSCE values are classified into four levels: poor (NSCE < 0.50), satisfactory ($0.50 \leq$ NSCE ≤ 0.65), good ($0.65 <$ NSCE ≤ 0.75), and very good ($0.75 <$ NSCE ≤ 1.00).

3. Results and Analysis

3.1 Precipitation Accuracy Assessment

Since precipitation estimation accuracy significantly affects hydrological simulation utility, this study first evaluates the precipitation accuracy of each product. The NOAA-CPC-US precipitation dataset, which compiles information from over ten thousand ground observation stations with optimal interpolation considering terrain effects and quality control, serves as the reference for evaluating other precipitation products (StageIV, PERSIANN, PERSIANN-CDR, TRMM-3B42V7, GPM-IMERG, ERA5) during the same period.

3.1.1 Grid-Scale Precipitation Accuracy At the grid scale in each small watershed, correlation coefficients between evaluated precipitation products and NOAA-CPC-US precipitation were calculated (Figure 1 [Figure 1: see original paper]). StageIV radar precipitation shows the highest correlation with NOAA-CPC-US, with an average correlation coefficient of 0.85 across nine watersheds, though correlation varies by region. The lowest correlation occurs in the West North Central region. PERSIANN-CDR has the second-highest average correlation coefficient at 0.78, with the lowest correlations in the Northeast and West North Central regions. ERA5 shows an average correlation coefficient of 0.75, with relatively low correlations in the Northwest and Southwest. GPM-IMERG has an average correlation coefficient of 0.71, with lower values in the Northwest and Southwest. PERSIANN shows an average correlation coefficient of 0.68, with lower correlations in the Northeast and West North Central. TRMM-3B42V7 has the lowest average correlation coefficient at 0.65, with particularly low correlations in the Northeast and West North Central regions. All precipitation products show lower correlation coefficients in high-latitude northern areas and western mountainous regions of the United States, while maintaining better correlations in central, southern, and eastern regions. All correlation coefficients pass significance tests at the 95% confidence level.

3.1.2 Accuracy at Different Precipitation Intensity Levels Using international meteorological precipitation intensity classification standards, this study more finely analyzed precipitation accuracy across different intensity levels. Precipitation intensity is divided into six categories based on hourly precipitation: (1) No rain: <1 mm; (2) Light rain: 1 mm $\leq$ precipitation $<$ 2 mm; (3) Moderate rain: 2 mm $\leq$ precipitation $<$ 5 mm; (4) Heavy rain: 5 mm $\leq$ precipitation $<$ 10 mm; (5) Rainstorm: 10 mm $\leq$ precipitation $<$ 20 mm; (6) Downpour: precipitation $\geq$ 20 mm. Statistical analysis of frequency distribution across intensity levels reveals differences in precipitation accuracy among products.

Figure 3 [Figure 3: see original paper] shows the frequency distribution of each precipitation product across different intensity levels. Figure 4 [Figure 4: see original paper] displays frequency errors relative to NOAA-CPC-US precipitation. The occurrence frequencies of different precipitation intensities vary among products, with varying degrees of overestimation and underestimation, though errors do not exceed $±$10%. Generally, most precipitation products underestimate no-rain and light-rain events while overestimating heavy rain and rainstorm events. StageIV radar precipitation demonstrates higher estimation accuracy across all intensity levels than TRMM-3B42V7 satellite precipitation.

Table 2 presents RMSE and MAE values for each precipitation product relative to NOAA-CPC-US across study regions. StageIV shows the smallest average RMSE (5.78 mm) and MAE (2.15 mm). PERSIANN-CDR has average RMSE of 6.52 mm and MAE of 6.39 mm. ERA5 shows average RMSE of 12.14 mm and MAE of 6.90 mm. GPM-IMERG has average RMSE of 23.27 mm and MAE of 53.02 mm. PERSIANN shows average RMSE of 7.06 mm and MAE of 6.52 mm. TRMM-3B42V7 has average RMSE of 6.90 mm and MAE of 7.06 mm. These statistical metrics indicate that StageIV radar precipitation and PERSIANN-CDR maintain relatively high accuracy across different regions and intensity levels.

3.2 Hydrological Simulation Utility Evaluation

Following precipitation accuracy assessment, the seven precipitation products were used to drive the CREST distributed hydrological model to simulate daily runoff processes in nine U.S. small watersheds and evaluate hydrological simulation utility. The simulation scenario was configured with a 2-year model warm-up period (2000-2001), a 10-year calibration period (2002-2011), and a 7-year validation period (2012-2018). CREST model parameters were calibrated using each of the seven precipitation products during the same calibration period.

After obtaining parameter sets, runoff was simulated for the same validation period. NSCE, Bias, and CC statistics were used to evaluate hydrological simulation utility. This scenario design facilitates independent assessment of each precipitation product' s watershed hydrological process simulation capability.

Figure 5 [Figure 5: see original paper] shows standard deviation (SD), RMSE, and CC statistics for daily runoff simulation results in nine watersheds across different U.S. regions. Figure 6 [Figure 6: see original paper] presents NSCE values, and Figure 7 [Figure 7: see original paper] shows relative deviations. Generally, runoff simulation performance during the calibration period is better than during the validation period, with all statistics showing degradation in the validation period.

Based on Moriasi et al., NSCE values are classified into four intervals representing hydrological simulation utility: poor (NSCE < 0.50), satisfactory ($0.50 \leq$ NSCE ≤ 0.65), good ($0.65 <$ NSCE ≤ 0.75), and very good ($0.75 <$ NSCE ≤ 1.00). Table 3 summarizes the performance levels of each precipitation product in runoff simulation for each watershed. NOAA-CPC-US and StageIV precipitation maintain good runoff simulation characteristics across small watersheds in different U.S. geographic regions, with most watersheds achieving "good" or better levels and successfully reproducing daily runoff processes during flood periods. GPM-IMERG and PERSIANN-CDR perform moderately, showing poor simulation effects in northern and western regions. PERSIANN and ERA5 perform relatively poorly, with unsatisfactory hydrological simulation in northern and western U.S. small watersheds. TRMM-3B42V7 shows the poorest performance, with inadequate runoff simulation capability in multiple watersheds, likely due to sensor precision and resolution limitations.

4. Conclusions

Obtaining precipitation estimation data through remote sensing technology to drive hydrological models for simulating and predicting hydrological processes at different scales represents the main trend in watershed hydrology and water resources research. Such data are crucial for forecasting natural disasters including floods, hurricanes, and landslides. Compared with large-scale watersheds, small watersheds are ideal objects for studying micro-scale hydrology, water resources, and water environment, as well as important geographic units for exploring sustainable water resource utilization methods.

In recent years, scholars have conducted numerous global, continental, and large-watershed-scale studies on water resources based on remote sensing precipitation products. However, research and application of remote sensing precipitation estimation data in small watersheds remain insufficient. Therefore, this study used NOAA-CPC-US precipitation as a reference to evaluate the accuracy of StageIV, PERSIANN, PERSIANN-CDR, TRMM-3B42V7, GPM-IMERG, and ERA5 precipitation products. These seven precipitation products were then used to drive the CREST distributed hydrological model to assess their hydrological simulation utility in nine small U.S. watersheds.

The main conclusions are: (1) In precipitation accuracy assessment, the degree of agreement with NOAA-CPC-US precipitation decreases in the order: StageIV radar precipitation, PERSIANN-CDR, GPM-IMERG, PERSIANN, ERA5, and TRMM-3B42V7. Precipitation estimation accuracy is slightly lower in high-latitude northern and western mountainous regions but better in central, southern, and eastern U.S. regions. In terms of capturing different precipitation intensities, TRMM-3B42V7, GPM-IMERG, and PERSIANN-CDR satellite precipitation products underestimate no-rain and light-rain events to varying degrees while overestimating heavy rain and rainstorm events. (2) In hydrological simulation utility evaluation, NOAA-CPC-US and StageIV precipitation perform well in small watershed hydrological simulations. GPM-IMERG and PERSIANN-CDR rank second, while PERSIANN, ERA5, and TRMM-3B42V7 show unsatisfactory simulation performance. These conclusions indicate that StageIV radar precipitation can basically meet the needs of small watershed hydrological simulations in the United States. However, caution is required when using PERSIANN, PERSIANN-CDR, GPM-IMERG, and ERA5 precipitation for small watershed hydrological simulations, particularly in northern and western U.S. regions. TRMM-3B42V7 precipitation data are insufficient to support small watershed hydrological simulations.

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Note: Figure translations are in progress. See original paper for figures.