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Dear Editor and Anonymous Referee #2,

On behalf of my co-authors, we thank you for the constructive comments and suggestions, which significantly improved the manuscript (**NO. ESSD-2022-217**) entitled “Global soil moisture storage capacity at 0.5° resolution for geoscientific modelling”.

The manuscript has been revised based on the comments from editors and reviewers. A point-by-point response to the reviews with referencing to the lines of the manuscript is attached to this letter. All the changes are marked in blue in the reply.

Thank you very much for handling our manuscript. We hope that you will find it to your satisfaction and we look forward to hearing from you in the near future.

Sincerely Yours

Pan Liu

Pan Liu
On behalf of all co-authors

Response to Reviewer #2

Specific comments

1. Line 99: There are 113 years in total. However, the authors only indicated 111 years. How about the other two years? How do you select the years for calibration and for validation?

Response:

Thank you. The other two years are used for warm-up. The warm-up is an adjustment process for the model to reach an optimal state. The sentences have been revised as follows:

Monthly measurements cover the year from 1902 to 2014 in the global grids. The data for the **first 3 years** is used for warm-up, 80 years for calibration, and the remaining 30 years for validation.

2. Line 319: What is CCN?

Response:

Sorry for the mistake. CNN represents convolutional neural networks. The sentence has been revised as follows:

The model parameter SMSC among the three monthly water balance models is the same in the proposed dataset constructed by **CNN**.

3. Line 391: "Secondly, there are also errors in the measurement data of the observation station, which leads to the uncertainty of the input data." What kind of errors?

Response:

We appreciate your comments. The sentence has been revised as follows:

Secondly, the errors also come from the observation uncertainty of the input data. Every stage of hydrological modelling acquires some uncertainty. This uncertainty can be broadly grouped into input forecast uncertainty and hydrological model uncertainty. The input forecast uncertainty implies uncertainty due to input data such as precipitation, temperature and other metrological inputs to the model (Singh and Dutta, 2017).

Singh, S.K. and Dutta, S., 2017. Observational uncertainty in hydrological modelling using data depth. Glob. Nest J, 19: 489-497.

4. Line 641:Table 1 Please introduce the accuracy level of every data used in this study.

Response:

Thank you very much.

The Climatic Research Unit Timeseries dataset (CRU TS) is a widely used climate dataset on a 0.5° latitude by 0.5° longitude grid over all land domains of the world except Antarctica. It is derived by the interpolation of monthly climate anomalies from extensive networks of weather station observations. CRU TS has good high-frequency agreement with CRUTEM4.6 (correlation coefficient, $R = 0.99$ globally), UDEL ($R = 0.97$ globally) and JRA-55 ($R = 0.99$ globally, 1958-2017 only) (Harris et al., 2020).

The Global Streamflow Characteristics Dataset (GSCD) consists of global maps of 17 streamflow characteristics, providing information about runoff behavior for the entire land surface including ungauged regions. It was constructed by streamflow observations from a highly heterogeneous set of 3394 catchments (<10,000 km^2) worldwide. The maps were compared to equivalent maps derived from the simulated daily runoff of four macroscale hydrological models (Beck et al., 2015).

Soil and vegetation dataset is provided by high-resolution estimates within a global 30 arc-second (~1 km) grid using the best available data for topography, climate, and geology as input (Pelletier et al., 2016).

Topography dataset contains elevation-based parameters at 0.5° spatial resolutions that were developed to support a wide variety of global modeling activities. It is the highest resolution database of global coverage of standard elevation-based derivatives (Verdin et al., 2011).

The Global Runoff Data Centre (GRDC) is built to provide a global observed hydrological data set to complement a specific set of atmospheric data in the framework of the First Global GARP Experiment (FGGE). Today the database comprises discharge data of well over 10,000 gauging stations from all over the world .

The global grid runoff depth database (GRUN) dataset contains a gridded global reconstruction of monthly runoff timeseries. On average GRUN shows higher predictive skills than a collection of the global hydrological models, especially with respect to the reproduction of the seasonality, dynamics and anomalies of runoff (Ghiggi et al., 2019).

Therefore, the spatial and temporal resolution of the input information has been added in Table 1 as follows:

Table 1. Research data and sources.

Data type	Data	Spatial resolution	Temporal resolution	Data/product sources
Meteorology	Precipitation Potential evaporation Near-surface temperature	0.5 degree	1901 - 2018 Monthly	Cru TS 4.03 monthly high-resolution grid data https://data.ceda.ac.uk/badc/cru/data/cru_ts/cru_ts_4.03
Soil and vegetation	Soil thickness	0.5 degree	Static	Global 1km grid soil, weathering layer, and sedimentary layer thickness published by ORNL in 2016 https://daac.ornl.gov/SOILS/guides/Global_Soil_Regolith_Sediment.html
	Root zone depth			Global root zone depth products released by Stockholm university in 2016 http://dx.doi.org/10.5194/hess-20-1459-2016-supplement
	Soil type			Upper and lower global soil type data released by USDA https://www.nrcs.usda.gov/wps/portal/nrcs/detail/soils/use/
	Types of land use			AVHRR land-use types issued by NOAA
Topography	Slope Altitude Composite terrain index CTI	0.5 degree	Static	GMT global 0.5-degree terrain data released by ISLSCP in 2010 https://daac.ornl.gov/cgi-bin/dsviewer.pl?ds_id=1007
Runoff characteristic	Average flow Runoff coefficient Baseflow coefficient 1% flood discharge	0.5 degree	Static	GSCD global runoff data set released by GloH2O in 2015 http://www.gloh2o.org/gscd/
Runoff	Runoff of catchment stations	Stations	1991 - 2010 Monthly	GRDC global runoff data center (Including data from more than 10000 stations around the world) https://www.bafg.de/GRDC/EN/Home/homepage_node.html
	Grid runoff	0.5 degree	1902 - 2014 Monthly	GRUN global grid runoff depth database released by the Federal Institute of technology https://doi.org/10.6084/m9.figshare.9228176

Harris, I., Osborn, T.J., Jones, P. and Lister, D., 2020. Version 4 of the CRU TS monthly high-resolution gridded multivariate climate dataset. Scientific Data, 7(1): 1-18.

Beck, H.E., de Roo, A. and van Dijk, A.I.J.M., 2015. Global Maps of Streamflow Characteristics Based on Observations from Several Thousand Catchments*. Journal of Hydrometeorology, 16(4): 1478-1501.

Pelletier, J.D. et al., 2016. A gridded global data set of soil, intact regolith, and sedimentary deposit thicknesses for regional and global land surface modeling. Journal of Advances in Modeling Earth Systems, 8(1): 41-65.

Verdin, K.L. et al., 2011. ISLSCP II HYDRO1k elevation-derived products.

Ghiggi, G., Humphrey, V., Seneviratne, S.I. and Gudmundsson, L., 2019. GRUN: an observation-based global gridded runoff dataset from 1902 to 2014. Earth System Science Data, 11(4): 1655-1674.

5. Line 645: Table 3 Why do you only test the performance of image window at 5×5 and 10×10?

Response:

Thank you for the comments.

The selection of the image window is a trade-off between the level of accuracy and the speed of computing. The image window at 5×5 corresponds to the influence of a 2.5° square (approximately 250 km) on the center point, while 10×10 corresponds to the influence of a 5° square (approximately 500 km). It is generally within this distance that the spatial variables are similar, and it is meaningless in farther distance. Additionally, we added the results for the smaller image window(3×3). The results show that the recognition network is poor if the image window is too small. The computational burden from the increase in image windows is no longer as cost-effective as the increase in the correlation coefficient for the image window from 5×5 to 10×10.

Table 3. Results of construction model of global soil moisture storage capacity (SMSC) parameters.

Image window	Time interval	Loss function	Evaluating indicator	
		MSE	MAE	R^2
3×3	Training set	0.0116	0.0752	0.7256
	Test set	0.0252	0.0964	0.4867
5×5	Training set	0.0032	0.0411	0.8932
	Test set	0.0170	0.0666	0.5935
10×10	Training set	0.0021	0.0341	0.9139
	Test set	0.0061	0.0510	0.7597

6. Line 695: Figure 2 The legends of (a) and (b) do not match the color of the content.

Response:

Thank you. The legends of (a) and (b) have been modified as follows:

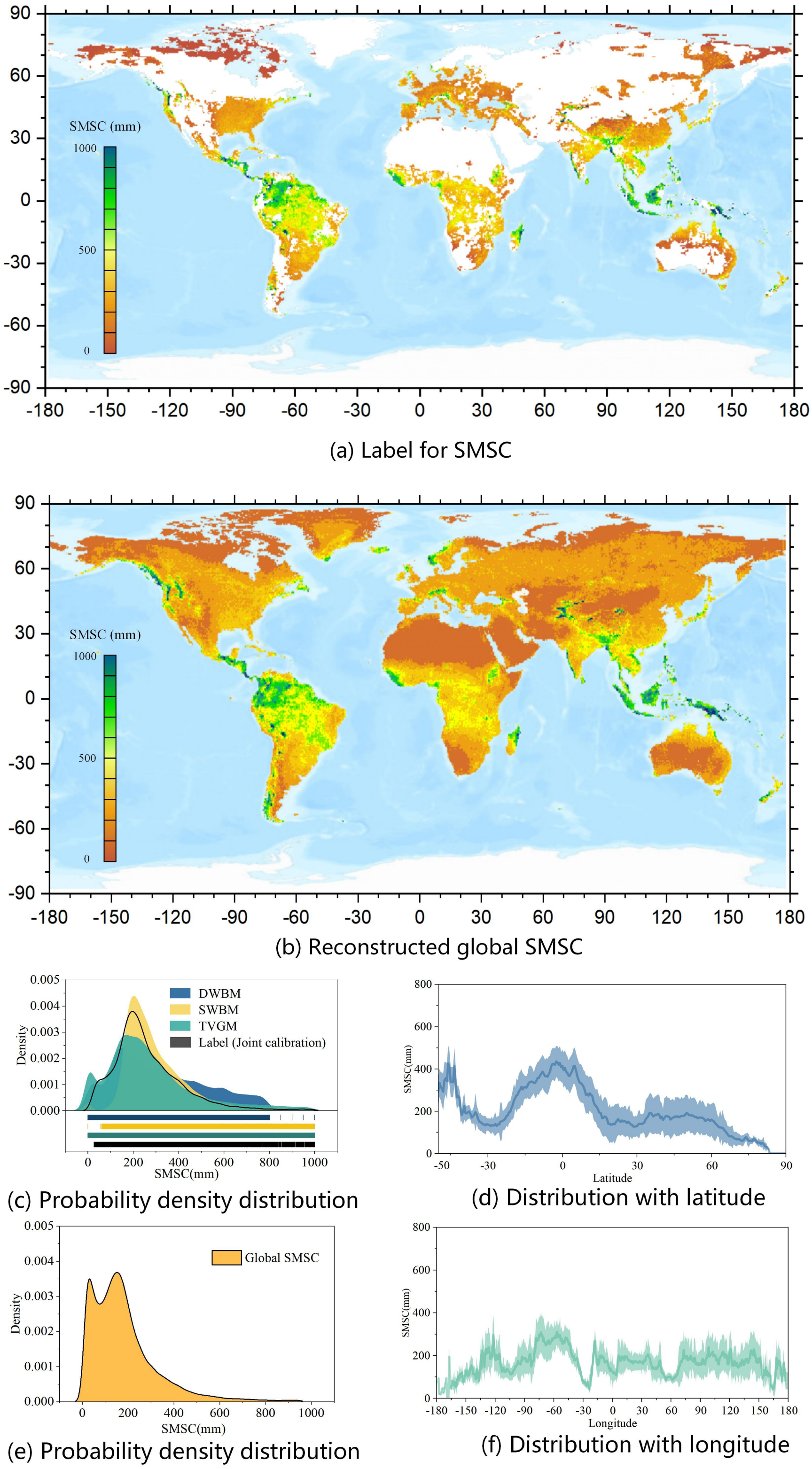

Figure 1. Spatial distribution of labels and construction results for global soil moisture storage capacity (SMSC) parameters. (a) The spatial distribution of the label for deep learning of jointly calibrated SMSC values. (b) The spatial distribution of the constructed global SMSC parameters. (c) The probability density distribution of SMSC parameters calibrated in the labeling area. (e) The probability density distribution of constructed global SMSC parameters. (d) and (f) The distribution of variations of global SMSC with latitude and longitude.

7. Line 701: Figure 3 What are the other parameter datasets?

Response:

Thanks for your suggestion.

Other parameter datasets represent the estimations of global root zone parameters from previous studies. They are root zone storage capacity at 0.5° resolution (SR_CRU, Figure 3a) from Wang-Erlandsson et al. (2016) and rooting depth at 1.0° resolution (SR, Figure 3c) from Schenk et al. (2009).

The captions of Figure 3 have been revised to avoid confusions as follows:

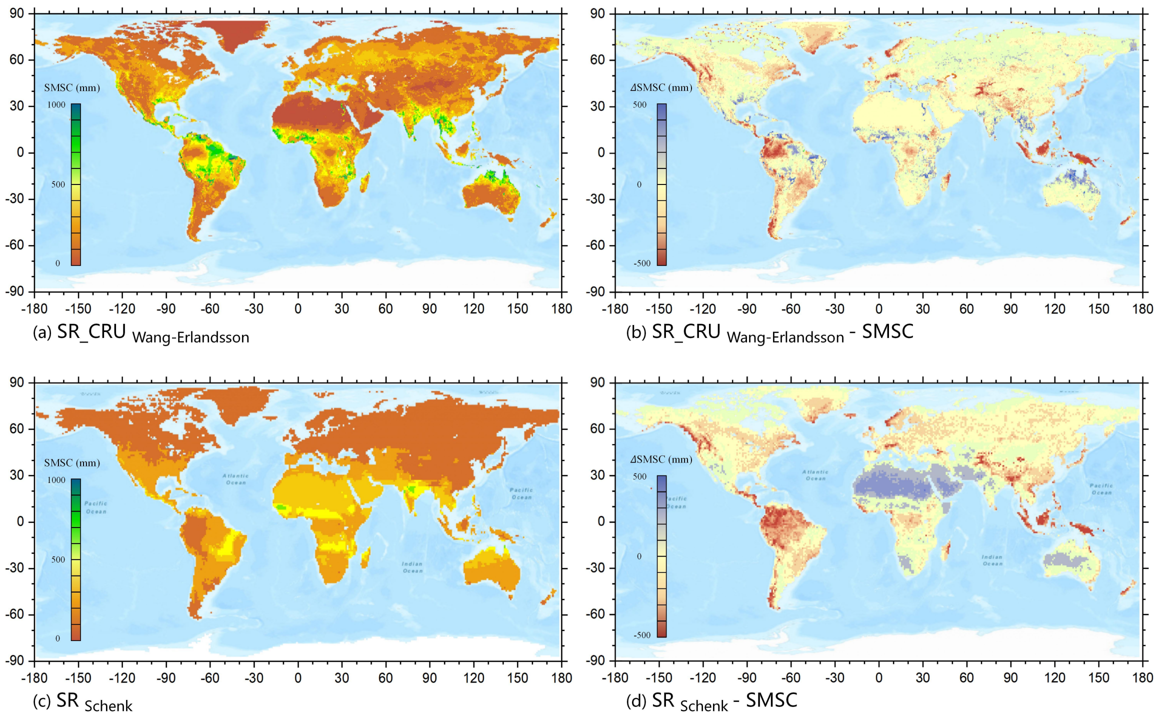

Figure 3. Spatial distribution of other parameter datasets and the differences with global soil moisture storage capacity (SMSC) parameters. (a) The spatial distribution of root zone storage capacity at 0.5° resolution by Wang-Erlandsson et al. (2016). (c) The spatial distribution of rooting depth at 0.5° resolution by Schenk et al. (2009). (b) and (d) The differences between global SMSC parameters and global root zone parameters from the previous studies.

Schenk H. J., Jackson R. B., Hall F. G., Collatz G. J., Meeson B. W., Los S. O., Brown De Colstoun E., Landis D. R. Islscp ii ecosystem rooting depths. ORNL DAAC, 2009.

Wang-Erlandsson, L., Bastiaanssen, W. G., Gao, H., Jägermeyr, J., Senay, G. B., Van Dijk, A. I., Guerschman, J. P., Keys, P. W., Gordon, L. J., and Savenije, H. H.: Global root zone storage capacity from satellite-based evaporation, Hydrology and Earth System Sciences, 20, 1459-1481, 10.5194/hess-20-1459-2016, 2016.

8. Line 701: Figure 3 The legends of (a) and (c) do not match the color of the content.

Response:

Thanks for your suggestion. The legends of (a) and (c) have been modified as follows:

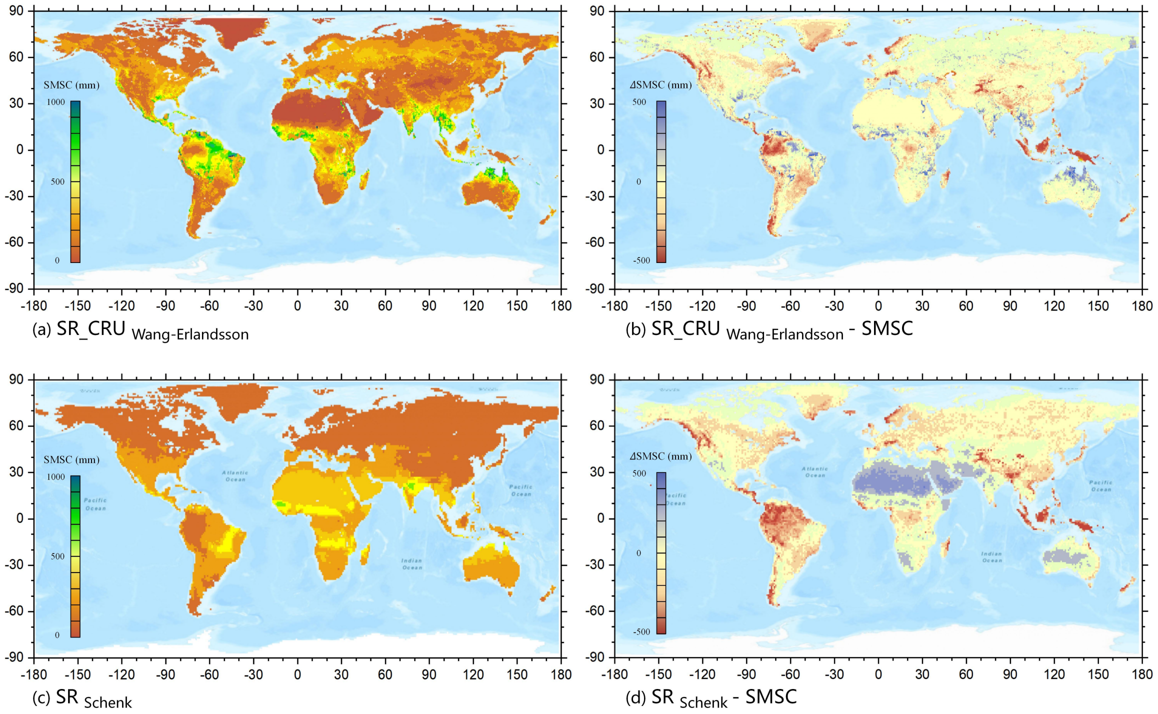

Figure 3. Spatial distribution of other parameter datasets and the differences with global soil moisture storage capacity (SMSC) parameters. (a) The spatial distribution of root zone storage capacity at 0.5° resolution by Wang-Erlandsson et al. (2016). (c) The spatial distribution of rooting depth at 0.5° resolution by Schenk et al. (2009). (b) and (d) The differences between global SMSC parameters and global root zone parameters from the previous studies.

9. Line 710: Figure 5 The R^2 of streamflow versus three simulated streamflow should be displayed in this figure.

Response:

We appreciate your comments. Figure 5 has been revised as follows:

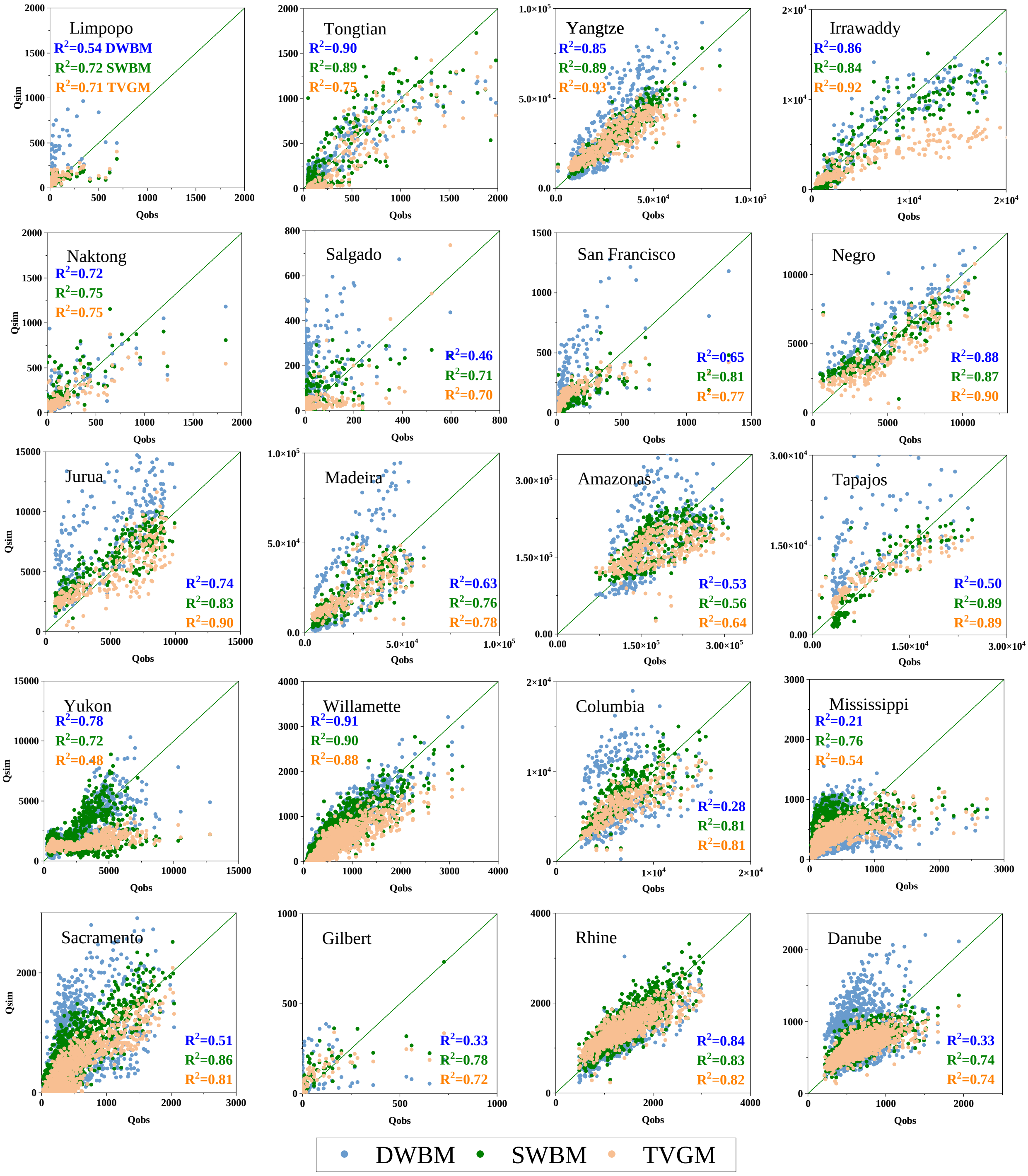

Figure 5. Monthly observed streamflow versus simulated streamflow for three monthly water balance models in typical catchments. Blue dots represent Dynamic Water Balance Model (DWBM). Green dots represent Snowbelt-based Water Balance Model (SWBM). Orange dots represent Time-variant Gain Model (TVGM)

10. Line 722: Figure 7 How to calculate weights of permutation importance? Why can the spatial correlation be presented by the weights of permutation importance?

Response:

Thanks for your valuable suggestions.

The evaluation of the permutation importance is to observe how much each feature contributes, and then compare the contributions between features by the average value. For a fitted predictive model, permutation importance can compute the reference score of the model on the dataset. The importance i_j for each feature f_j defined as:

$$i_j = s - \frac{1}{K}\sum_{k=1}^{K} s_{k,j}$$

where s is the reference score of the model, and k is each repetition in input factors.

The accuracy classifier s is the spatial correlation coefficient (R^2), that is the reason why the spatial correlation can be presented by the weights of permutation importance. The permutation importance are applied in previous studies of deep learning for spatial analysis (Su et al., 2022; Li and Choi, 2021; Sheng et al., 2021).

Li G, Choi Y. HPC cluster-based user-defined data integration platform for deep learning in geoscience applications[J]. Computers & Geosciences, 2021,155:104868.

Sheng Y, Kong Q, Beroza G C. Network analysis of earthquake ground motion spatial correlation: a case study with the San Jacinto seismic nodal array[J]. Geophysical Journal International, 2021,225(3):1704-1713.

Su Y, Li N, Yang H, Wang F, Sun C, Zhen Z, Zou Z, Ge X. A Feature Importance Analysis Based Solar Irradiance Mapping Model Using Multi-channel Satellite Remote Sensing Data: 2022 IEEE/IAS 58th Industrial and Commercial Power Systems Technical Conference (I&CPS), 2022. IEEE.