Dear reviewer:

Thank you very much for your great help on our manuscript. Many thanks are also to the Associate Editor and the reviewers for their constructive comments and suggestions. They are very important and useful to improve our work and brush up the manuscript. According to all the comments, the paper was thoroughly revised. Meanwhile, some errors and deficiencies have been also revised through our self-check process and proofread service. The key changes are marked with red color. The point-to-point responses to all comments and suggestions from the reviewer are listed in the following. We hope these revisions can satisfy your requirements and meet with your approval, and of course, we are more than happy to improve the paper again according to new comments and suggestions they might come.

Best regards,

Kunlong He and Wei Zhao

Corresponding author: Wei Zhao
E-mail: zhaow@imde.ac.cn

1. about the spatial distribution of the parameters of a, b, and c. These three parameters are used in equations 7 and 8. According to my understanding, they were calibrated at 10 km resolution and then applied to 1 km resolution. So, firstly, are these parameters scale independent? Moreover, are they also temporal-independent?

Ans.: Thanks a lot for your comment. To perform the precipitation downscaling, an important prerequisite is the assumption of spatial invariancy in the precipitation estimation model described in Eq. (6) at coarse and fine scales, which is also the basis of many related downscaling studies for other parameters, such as surface soil moisture and temperature (Hutengs and Vohland, 2016; Mishra et al., 2018; Zhao et al., 2018; Ebrahimy and Azadbakht, 2019). Therefore, these parameters are not scale-independent, the estimated parameters at 10 km resolution scale can be used for the corresponding 100 sub-images units (1 km). Moreover, because we construct models using self-adaptive windows in different local regions on the daily scale, these parameters vary in time and space. Thus, they are also temporal independent. We have clarified the above two points in the revised manuscript.

2. The accuracy of the high-resolution SSM data. The authors are suggested to show the reliability of this new information before downscaling.

Ans.: Thanks a lot for your comment. In fact, the accuracy of the downscaled precipitation results depends on seamless high-resolution soil moisture data. Therefore, SSM is an important variable in the estimation model. The ESA CCI SSM product can only provide coarse-resolution SSM data with unexpected gaps. To obtain daily SSM at a 1-km resolution, the seamless SSM downscaling method proposed by Zhao et al. (2021) is a good choice to achieve this goal. The proposed method was successfully applied to data obtained for the Iberian Peninsula from January 1, 2016 to December 31, 2018. Based on the comparison with the precipitation dataset, the downscaled SSM exhibited strong temporal correlation with rainfall events. Evaluation using the in situ SSM from the REMEDHUS network highlighted the good performance of the downscaled SSM at network level with a correlation coefficient (R) of 0.820. The root-mean-square-error, unbiased root-mean-square error (ubRMSE), and bias were 0.091, 0.033, and 0.085 m^3/m^3, respectively (as shown in table 1). These results confirmed that the proposed method is an efficient and convenient downscaling process that can be successfully used to generate high-resolution SSM data without spatiotemporal gaps. Therefore, based on the seamless, high spatial resolution and high accuracy soil moisture data produced by this method, we believe that it can meet the accuracy requirements of the downscaling process for precipitation. In the revised manuscript, we have added explanations to show the reliability of the high-resolution SSM for the precipitation downscaling.

Table 1

Comparison of the statistical metrics of the ESA CCI SSM and downscaled SSM with the *in situ* SSM at station level on days with ESA CCI SSM values in the study area (N represents the sample number, **significant at the 99% confidence level, bold numbers indicate the best scores, and *italic* numbers indicate the worst scores).

Station ID	Downscaled SSM against *in-situ* SSM					ESA CCI SSM against *in-situ* SSM				
	R	RMSE(m^3/m^3)	*ub*RMSE(m^3/m^3)	Bias(m^3/m^3)	N	R	RMSE(m^3/m^3)	*ub*RMSE(m^3/m^3)	Bias(m^3/m^3)	N
K13	*0.459***	0.098	*0.084*	−0.050	867	*0.456***	0.093	*0.083*	−0.041	811
K10	0.673**	0.159	0.044	0.153	898	0.697**	0.166	0.041	0.160	848
M5	0.814**	0.101	0.034	0.095	898	0.817**	0.100	0.033	0.095	848
N9	0.731**	0.056	0.049	0.028	897	0.713**	0.059	0.050	0.032	818
I6	0.708**	0.192	0.048	0.186	886	0.691**	0.190	0.046	0.185	836
H7	0.694**	*0.199*	0.048	*0.193*	873	0.720**	*0.198*	0.044	*0.193*	826
K9	0.715**	0.130	0.049	0.121	868	0.737**	0.137	0.048	0.128	825
H9	0.673**	0.087	0.077	−0.042	825	0.662**	0.084	0.077	−0.033	777
J14	0.816**	0.106	0.045	0.096	568	0.838**	0.107	0.044	0.098	524
M9	0.749**	0.063	0.043	0.046	898	0.726**	0.069	0.044	0.053	848
F6	0.783**	0.056	0.050	0.026	892	0.810**	0.058	0.047	0.034	865
H13	0.846**	0.071	0.031	0.064	869	0.852**	0.062	0.030	0.054	819
L3	0.596**	0.133	0.048	0.124	873	0.589**	0.131	0.047	0.122	823
J12	0.802**	0.073	0.045	−0.058	896	0.798**	0.072	0.045	−0.057	838
E10	0.650**	0.118	0.057	0.104	895	0.674**	0.116	0.055	0.102	868
O7	0.824**	0.139	0.034	0.135	881	0.807**	0.142	0.033	0.138	803
K4	0.709**	*0.199*	0.044	*0.193*	894	0.701**	0.195	0.043	0.190	844
L7	0.744**	0.053	0.046	0.027	898	0.781**	0.053	0.042	0.032	848
J3	0.771**	0.197	0.042	0.192	898	0.810**	0.194	0.037	0.190	848
F11	0.912**	0.139	0.026	0.136	896	0.897**	0.139	0.026	0.137	790
Average	0.733	0.118	0.047	0.088	868.5	0.739	0.118	0.046	0.091	815.35

3. Validation of precipitation data. Currently, the authors are using pixel-point matching comparison. It is suggested to upscale the point observation of stations to grid scales of 1 km and 10 km. And then comparing the two precipitation data to corresponding ground observation.

Ans.: Very good comment. To date, most studies used rain gauge stations to evaluate the performance of satellite precipitation products and downscaled products because the gauge-based observations are taken as the most accurate precipitation values Using mathematical interpolation method (e.g., Kriging, IDW) to upscale the point observation to grid scales of 10 km and 1 km scales is an effective tool, but these methods may introduce large uncertainties in the upscaled results and lead to poor performance in evaluating the downscaled results (Xiaojun et al., 2021; Zhang et al., 2020). In addition, because the performance of the upscaled results depends on the gauge-based stations density, we will use the upscaled results of rain gauge stations to evaluate the downscaling results in the area of high-density gauge-based stations in future studies (Ma et al., 2017; Chena et al., 2018; Chen et al., 2021; Abdollahipour et al., 2021). About the spatial inconsistency of the point measurement and grid-scale estimation, we have added discussions in the manuscript and it should be paid attention in future comparison.

4. As my speculation, there are more heavy rainfall (big rain rate values) events in high resolution precipitation data. However, it is not shown in the histogram of figures 4 and 7. The authors are suggested to check this issue with rain gauge observations.

Ans.: Thanks a lot for your comment. We have added explanation of this point in the revised manuscript as below: "To assess the GPM products' performance at different precipitation intensity events. The daily precipitation intensity is classified into five categories, and the rainfall thresholds are classified as 0, 10, 20, 40 mm respectively. The performance metrics for the five daily precipitation intensity classes listed in Table 2. In summary, the original and downscaled GPM products performed the best in terms of all performance metrics for the no-rain events, while performed the worst for the violent rain events (> 40 mm d^{-1}). All precipitation products indicated that FAR values continuously performed the worst for the violent rain intensities, which showed that the products are still unable to accurately capture high precipitation values. Due to the reduced FAR values, the CSI value performed the best for no-rain events, followed by light rain ([0, 10) mm d−1), moderate rain ([10, 20) mm d^{-1}), heavy rain, ([20, 40) mm d^{-1}) and violent rain, respectively.

Additionally, the BIAS values showed that all precipitation products overestimated the number of light rain and underestimated moderate rains, heavy rains, and violent rains. Most importantly, the accuracy of the downscaled product was slightly better than the original precipitation product for different rainfall intensity events in terms of CC, RMSE, POD, FAR and CSI values, indicating the reliability of the downscaled products in capturing different rainfall intensity events. ”

Table 2 CC, RMSE, BIAS, POD, FAR and CSI values for the different precipitation intensities for original and downscaled GPM products from 2016 to 2018.

Intensity (mm)	Original						Downscaled					
	CC	RMSE (mm)	BIAS (%)	POD	FAR	CSI	CC	RMSE (mm)	BIAS (%)	POD	FAR	CSI
0	-	1.83	-	0.93	0.34	0.63	-	1.73	-	0.94	0.26	0.70
0-10	0.30	6.39	27.00	0.69	0.65	0.31	0.30	5.98	23.00	0.73	0.60	0.34
10-20	0.15	11.85	-20.00	0.26	0.75	0.15	0.15	11.50	-22.00	0.25	0.74	0.15
20-40	0.15	18.41	-33.00	0.25	0.78	0.13	0.14	18.31	-36.00	0.26	0.77	0.14
>40	0.28	39.53	-47.00	0.23	0.84	0.11	0.28	39.33	-50.00	0.25	0.82	0.12

Abdollahipour, A., Ahmadi, H., and Aminnejad, B.: A review of downscaling methods of satellite-based precipitation estimates, Earth Science Informatics, 1-20, 2021.

Chen, C., Hu, B., and Li, Y.: Easy-to-use spatial random-forest-based downscaling-calibration method for producing precipitation data with high resolution and high accuracy, Hydrol. Earth Syst. Sci., 25, 5667-5682, 10.5194/hess-25-5667-2021, 2021.

Chena, Y., Huanga, J., Shengd, S., Mansaraya, L. R., and Wangh, X.: A new downscaling-integration framework for high-resolution monthly precipitation estimates: Combining rain gauge observations, satellite-derived precipitation data and geographical ancillary data, Remote Sensing of Environment, 214, 154-172, 2018.

Ma, Z., Shi, Z., Zhou, Y., Xu, J., Yu, W., and Yang, Y.: A spatial data mining algorithm for downscaling TMPA 3B43 V7 data over the Qinghai–Tibet Plateau with the effects of systematic anomalies removed, Remote Sensing of Environment, 200, 378-395, 2017.

Xiaojun, G., Peng, C., Xingchang, C., Yong, L., Ju, Z., and Yuqing, S.: Spatial uncertainty of rainfall and its impact on hydrological hazard forecasting in a small semiarid mountainous watershed, Journal of Hydrology, 595, 126049, 2021.

Zhang, L., Ren, D., Nan, Z., Wang, W., Zhao, Y., Zhao, Y., Ma, Q., and Wu, X.: Interpolated or satellite-based precipitation? Implications for hydrological modeling in a meso-scale mountainous watershed on the Qinghai-Tibet Plateau, Journal of Hydrology, 583, 124629, https://doi.org/10.1016/j.jhydrol.2020.124629, 2020.

Zhao, W., Wen, F., Wang, Q., Sanchez, N., and Piles, M.: Seamless downscaling of the ESA CCI soil moisture data at the daily scale with MODIS land products, J. Hydrol., 603, 126930, https://doi.org/10.1016/j.jhydrol.2021.126930, 2021.