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Temporal and Spatial Variation Characteristics of Soil Moisture in Spring in the Arid Regions of Northwest China in the Past 60s years

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Abstract

Soil moisture (SM) is one of the important parameters in the process of land-atmosphere interactions. The spatial-temporal distribution of SM plays a significant role in weather and climate research. In this study, based on the monthly SM datasets from GLDAS (Global Land Surface Data Assimilation System), the temporal and spatial changes of shallow SM are discussed, and the applicability of five domestic models from Coupled Model Intercomparison Project 6 (CMIP6) is also evaluated in the Northwest China. The results show that: 1) The shallow SM (0 - 10 cm) in spring in Northwest China was generally low during 1948-2015, and the low value areas were mainly located in the Tarim Basin in Xinjiang and the Gobi and desert areas in western Inner Mongolia. In most parts of Northwest China, SM had an increasing trend in spring, this implies it became wetter in recent 60 years; 2) There are larger difference between the five models for simulating SM. Except for BCC-ESM1, all the four models (including BCC-CSM2-MR, FGOALS-f3-L, FGOALS-g3, TaiESM1) can basically simulate the spatial distribution and trend of SM in spring, all the spatial correlation coefficients between the four models and GLDAS data pass the 99% significant level; 3) After multi-ensemble mean, the simulation performance can be obviously improved, the spatial correlation can reach about 0.55 in spring, the spatial trend is much closer to the GLDAS.

Keywords

Soil Moisture, GLDAS, CMIP6, Temporal-Spatial Characteristics

1. Introduction

Soil moisture (SM) is closely related to many disciplines such as climatology and ecology, especially in the climatology, it is an important land surface parameter, its effect on temperature on land is higher than that of sea temperature. It not only controls the land surface energy and water budget, but also leads to the changes of local temperature and wind field, which can cause the changes of atmospheric circulation and have effect on climate (He et al., 2017). SM is also the direct source of water in natural ecosystems, which affects the growth and development of crops and plants (Liu et al., 2018). So SM has always been a research hotspot of scientists at home and abroad.

Many scholars have made relevant studies on SM in northwest of China. Su et al. (2016) studied the temporal and spatial characteristic of SM at the depth of 10 cm in the Tarim basin, they found that SM displayed an increasing trend, Chen et al. (2021) indicated that SM also increased in Gansu, Ningxia and other regions, Wang et al. (2020) suggested SM had an increasing trend at the depth of 10 cm during the period of 1961-2016. However, the observation method of SM is fixed-point observation, which requires a lot of manpower and therefore has a high cost (Ruosteenoja, et al., 2018), so the observation stations are fewer. At present, SM is mainly through satellite and remote sensing monitoring. Satellite monitoring has good spatial coverage, but the quality of satellite data is poor in the regions where vegetation, frost and snow are abundant, whereas remote sensing monitoring can only monitor SM at the surface level. Due to geographical environment and other factors, the SM observation data is scare, with the development of numerical models, the observation data can be replaced by other relevant data in the study. However, due to the differences in the use of models, data assimilation methods and SM calculation methods, the accuracy of the data still needs to be verified. Global Land Surface Data Assimilation System (GLDAS) includes four land surface process models which are Noah, Catchment, VIC and Mosaic, Deng et al. (2018) evaluated the SM products of the four models, they found the Noah product had good performance in the Tibetan Plateau. Li et al. (2019) indicated the SM from Noah025 had different accuracy in different soil depths in the arid region of Northwest China, it displayed the well performance at the depth of 0 - 10 cm.

The northwest arid region is one of the three major natural geographical regions in China (Qin, 2011), there is less precipitation in these regions, the annual precipitation mount is about 200 mm, but the radiation is strong and evapotranspiration is large. Hence, water shortages is one of reasons that affect the economic development of the northwest region, the government and the scientific community have pay great attention to and studied the northwest arid region. The terrain conditions in the regions are very complex and diverse, it causes a certain difficulty for monitoring the soil moisture. Therefore, in this paper surface SM from GLDAS_Noah025 is used to study the temporal-spatial characteristic of SM, and then the five model performance will be verified, compared with the GLDAS data.

2. Data and Methods

2.1. Data

To understand the spatial-temporal change of SM in the arid region of northwest China, the monthly SM data from GLDAS (Global Land Data Assimilation System) is employed, The time series cover the period 1948-2015 at a resolution of $0.25 \times 0.25^{\circ}$. Hereafter, we refer to the GLDAS data set as the observation.

To evaluate the performance of models from CMIP6, we examined five domestic models participating in CMIP6 with monthly SM output from the historical stimulation (Eyring et al., 2016), output from run1 of each model are used (e.g., r1i1p1). Basic information of the models is given in **Table 1**.

Because the spatial resolution of observation and simulation is different, then they are regridded (bilinear interpolation) to a $1^{\circ} \times 1^{\circ}$ latitude-longitude grid for the analysis.

2.2. Methods

In this paper, two statistical methods are used to discuss the variation of SM.

1) Correlation Coefficient:

$$r = \frac{\sum_{i=1}^{n}\left(X_i - \bar{X}\right)^2\left(Y_i - \bar{Y}\right)^2}{\sqrt{\sum_{i=1}^{n}\left(X_i - \bar{X}\right)^2}\sqrt{\sum_{i=1}^{n}\left(Y_i - \bar{Y}\right)^2}}$$

where r represents the correlation coefficient between X and Y, X and Y are observation and simulation, respectively.

2) Regression analysis:

$$Y = b + at,$$

where a represents the linear trend of factor Y with time t.

3. Results

3.1. The Spatial Distribution of SM

Figure 1 displayed the observed spatial distribution of SM at the shallow depth in the arid region of northwestern China in spring (**Figure 1(a)**) and autumn (**Figure 1(b)**). It can be seen that SM was generally lower at shallow layer, it was related to the climate factors. There was lower precipitation mount and bigger radiation in the arid region of northwestern China, the change of precipitation had main effect on the change of SM, furthermore, the bigger radiation would cause the temperature to increase, this increased water loss by evaporation (Yao et al., 2018). There was strong similarity between the distribution of SM at shallow layer in spring and autumn, the low value area was mainly distributed in the Tarim Basin in Xinjiang and the Gobi region

Table 1. Models information used in this study.

Number	Model	Institution-Country	Resolution
1	BCC-CSM2-MR	Beijing Climate Center-China	320 × 160
2	BCC-ESM1	Beijing Climate Center-China	128 × 64
3	FGOALS-f3-L	Chinese Academy of Sciences-China	288 × 192
4	FGOALS-g3	Chinese Academy of Sciences-China	180 × 80
5	TaiESM1	Taiwan-China	288 × 192

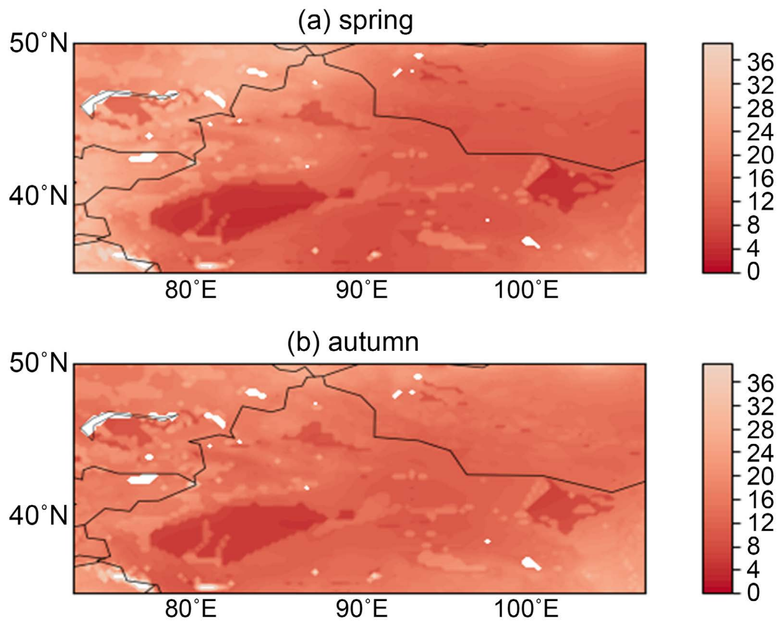

Figure 1. The spatial distribution of observed SM in spring (a) and autumn (b) in the Northwest arid areas of China (unit: kg/m^2).

of western Inner Mongolia, this is consistent with the previous study (Li et al., 2011).

3.2. The Temporal Variation of SM

Figure 2 suggested the interannual variation of SM at shallow layer in the Northwest arid areas of China during the period of 1950-2010. The SM changed greatly, which was related to the precipitation, temperature and wind speed (Ding et al., 2018), furthermore, strong solar radiation also could cause SM a greater change range. In general, both the SM in spring and autumn indicated an increasing trend from 1950 to 2010, especially in spring , the increased trend was about 0.28 kg/m^2/10a, which was higher than that in autumn. Figure 3 illustrated the spatial distribution of trend of SM, it can be seen that SM at shallow layer displayed an increasing trend in spring and autumn in most part of Northwest arid areas of China, especially in the north. While there was a declined trend in southern part of the north and a few regions in the east. It is consistent with the result from Wang et al. (2020), they found that both the

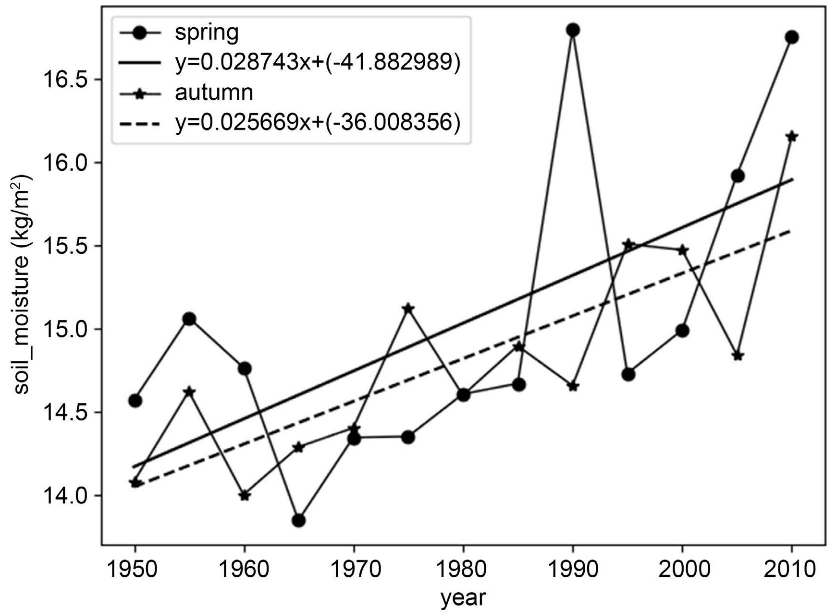

Figure 2. The interannual variation of SM in spring and autumn in the Northwest arid areas of China (unit: kg/m^2).

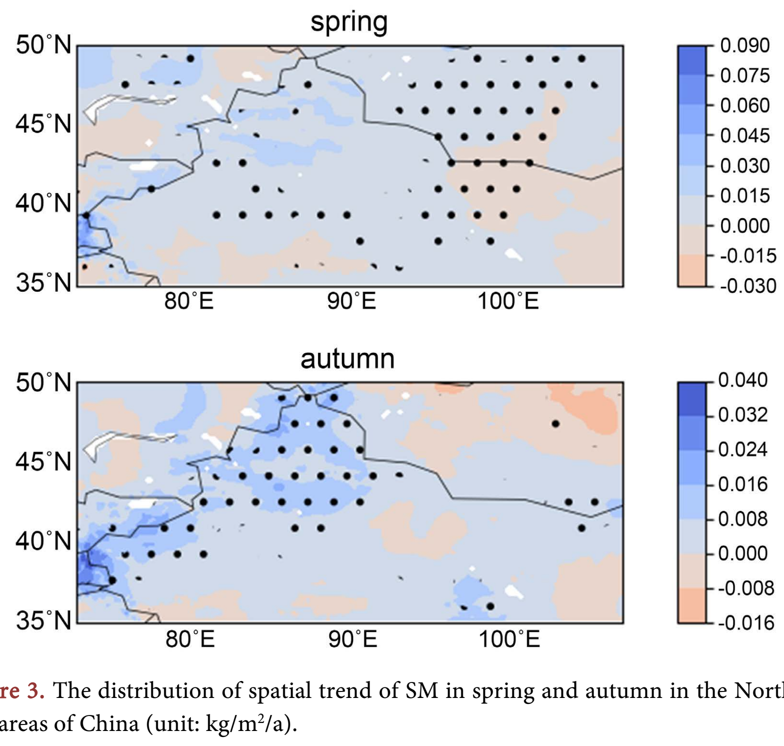

Figure 3. The distribution of spatial trend of SM in spring and autumn in the Northwest arid areas of China (unit: $kg/m^2/a$).

precipitation and the SM at 0 - 10 cm depth shown an increasing trend during 1961 to 2016 in the Northwest China. On the one hand, this may be due to the increased precipitation in the Northwest China, on the other hand, it is related to the improvement of vegetation condition, Li et al. (2009) demonstrated that the vegetation coverage had an increasing trend in Xinjiang, this will contribute to the increase of SM.

3.3. The Performance of Models from CMIP6

Figure 4 given the spatial distribution of SM in spring in the arid region of northwest China from five domestic models of CMIP6. Compared with the observation (GLDAS), the simulated SM had lower value in spring, except for BCC-ESM1, both the observation and simulation displayed a similar spatial distribution, with a zonal distribution from southwest to northeast, the low value areas were mainly located in the Tarim Basin. However, BCC-ESM1 had a lower value region located in the north. In general, most of domestic models all can simulate the spatial distribution of SM in spring and autumn (figure not shown).

In order to further understand the spatial simulation performance of CMIP6 models, Table 2 indicated the spatial correlation coefficient between the observed and simulated SM in spring and autumn. Except for BCC-ESM1, other models' simulation had better correlation with observation in spring, the correlation passed 99% significant level, especially FGOALS-f3-L, the correlation can reach about 0.65. There was consistent result in autumn. However, there are some differences between different models, in order to improve the simulation performance, the correlation between the multi-model ensemble mean and observation are also calculated, the correlation can reach about 0.55 and 0.66 in spring and autumn, respectively. To sum up, multi-model ensemble mean can improve the simulation performance.

Figure 5 indicated the spatial trend distribution of SM from observation and simulation. BCC-CSM2-MR displayed that SM had an increasing trend in most parts of the arid region of Northwest China, especially in the northern parts

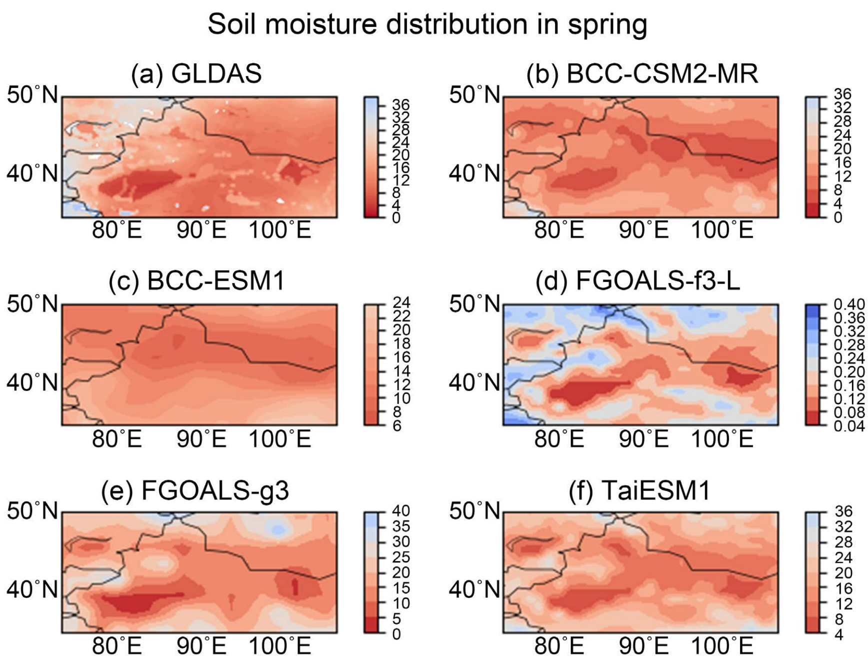

Figure 4. The distribution of SM in spring in the Northwest arid areas of China (unit: kg/m^2).

Table 2. The spatial correlation between the observation and simulation in the spring and autumn.

model	spring	autumn
BCC-CSM2-MR	0.44*	0.58*
BCC-ESM1	0.13*	0.40*
FGOALS-f3-L	0.65*	0.60*
FGOALS-g3	0.53*	0.58*
TaiESM1	0.51*	0.63*
Ensemble-mean	0.55*	0.66*

Note: * indicated the correlation passes 99% significant level.

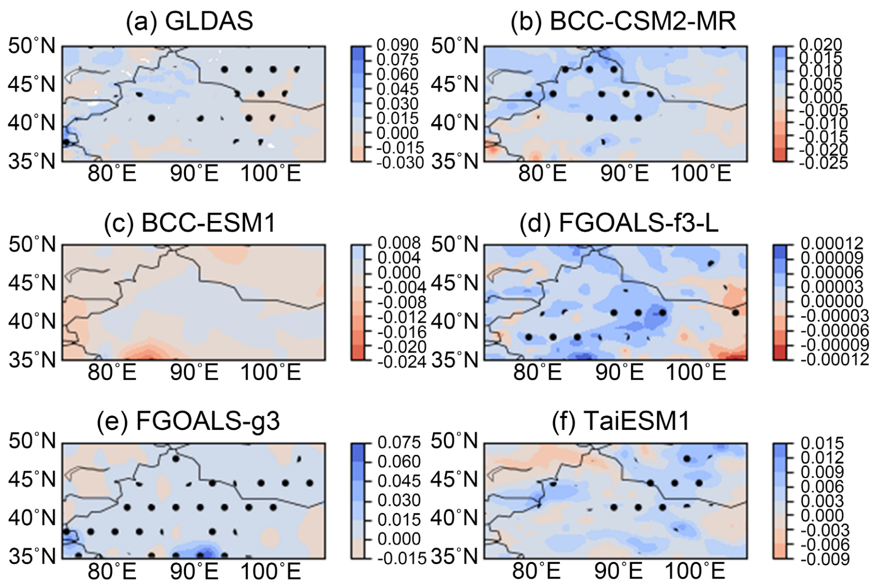

Figure 5. The distribution of trend of SM in spring in the Northwest arid areas of China (unit: $kg/m^2/a$).

of Xinjiang, the increasing trend was more significant, however, SM had a declined trend in a small part of western Xinjiang, Western Inner Mongolia, Gansu and Ningxia, the trend passed the 95% significant level in north Xinjiang. BCC-ESM1 indicated that SM had an increasing trend in the northern part of the arid region of Northwest China, where the SM value was lower. FGOALS-f3-L illustrated that SM increased in the west, and decreased in the east, this implies that it was wetter in the west and dried in the east. FGOALS-g3 model illustrated that SM had an increasing trend ($P > 95\%$) in most parts, while in few part in the east SM had a decreasing trend. TaiESM1 model suggested that SM had an increasing trend in most parts of Xinjiang, and a decreasing trend in Gansu and western Inner Mongolia. In general, except for BCC-ESM1, other models can basically depict the spatial change of SM, especially BCC-CSM2-MR, which was closer to the observation, but the intensity of increasing was weaker than that of the observation.

The interannual variation of SM from the observation and five models were shown in **Figure 6**. Compared with the observation, FGOALS-f3-L, B CC-ESM1 and BCC-CSM2-MR obviously underestimated the SM, while for FGOALS-g3 and TaiESM1 it might be just the opposite. It can be seen that there are big differences among the models. However, overall the performance of TaiESM1 was the best, it can well simulate the variation tendency.

Although individual model can well simulate the spatial distribution or interannual variation, different models still have big difference, in order to improve the simulation performance, **Figure 7** given the spatial distribution of trend after multi-model ensemble mean, it can be seen that it is closer to the observation (**Figure 7**). So the multi-model ensemble mean can improve the stimulation performance.

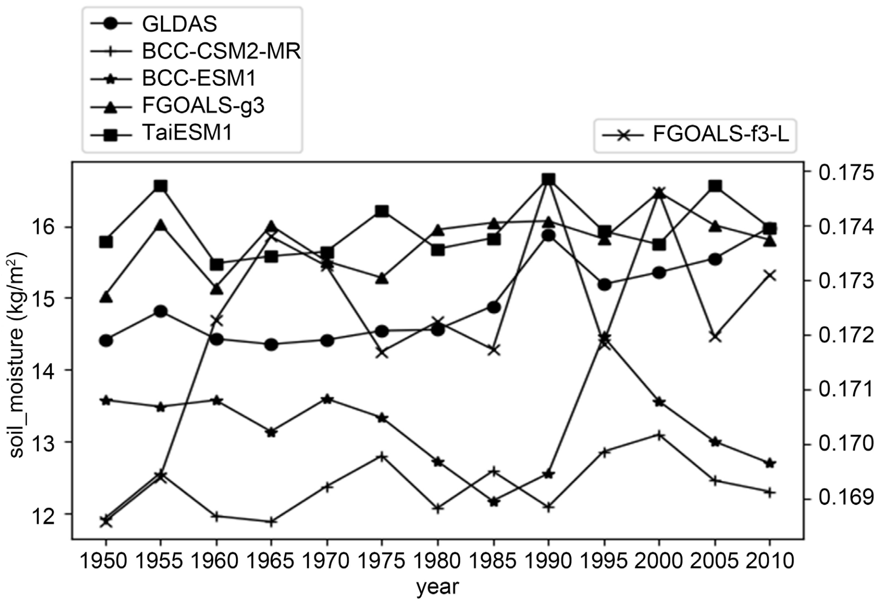

Figure 6. The interannual variation of SM in spring in the Northwest arid areas of China (unit: kg/m²).

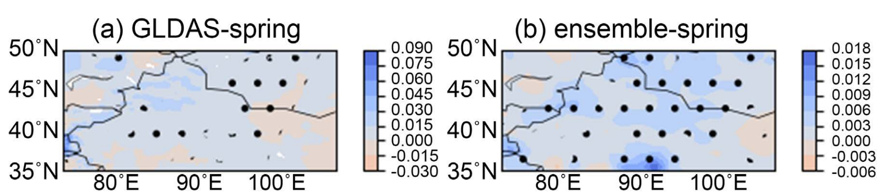

Figure 7. The spatial distribution of SM's trend from multi-model ensemble mean in spring in the Northwest arid areas of China (unit: kg/m²/a).

4. Conclusion

1) From 1948 to 2015 SM was basically low, and the regions with low SM mainly located in the Tarim Basin in Xinjiang, the gobi and desert in western Inner Mongolia, it displayed an increasing trend in most regions in the arid region of northwest China. SM had a larger fluctuation during 1985-1995, it in-

creased obviously during 1985-1990, and decreased rapidly during 1990-1995, overall SM had an increasing trend in the arid region of northwest China in spring and autumn, especially in spring, the increasing trend is more significant than that in autumn. This implies that it became wetter at the shallow layer in the arid region of northwest China.

2) Except for BCC-ESM1, all the four models (including BCC-CSM2-MR, FGOALS-f3-L, FGOALS-g3, TaiESM1) can basically simulate the spatial distribution of SM in spring, all the spatial correlation coefficients between the four models and observation pass the 99% significant level, although the correlation between the FGOALS-f3-L's simulation and observation was the highest, it was about 0.65, the SM value was obviously underestimated, compared with the observation. Based on the spatial distribution and the correlation coefficient, the simulation from TaiESM1 is closer to the observation.

3) In most parts of the arid region of northwest China, SM had an increasing trend, except for BCC-ESM1, all the four models (including BCC-CSM2-MR, FGOALS-f3-L, FGOALS-g3, TaiESM1) can well simulate the spatial change. Based on the distribution and intensity of SM, the performance of BCC-CSM2-MR model is relatively better.

4) In terms of the temporal variation, SM had an increasing trend, the rate was about 0.28 $kg\cdot m^{-2}\cdot(10a)^{-1}$ in spring. Two models (including FGOALS-g3 and TaiESM1) not only can well simulate the change trend of SM, but also are relatively closer to the observation. The performance of BC-CSM2-MR, BCC-ESM1 and FGOALS-f3-L models is weak, they obviously underestimate the SM. In general, TaiESM1 can well reflect the interannual variation of SM.

5) From the spatial distribution and interannual variation, there are big differences among the five domestic models, after multi-model ensemble mean, the simulation performance can be improved.

Although the performance can be improved after ensemble mean, but the biases still exist. Therefore, it is necessary to consider the systematic biases when assessing the SM change in the arid region of northwest China.

Conflicts of Interest

The authors declare no conflicts of interest regarding the publication of this paper.

References

Chen, T., Gu, Z., Dai, H., & Ma, P. (2021). Applicability Evaluation of Soil Moisture from CMIP6 in Tibetan Plateau. *Plateau and Mountain Meteorology Research, 41,* 41-48. (In Chinese)

Deng, M., Meng, X., Ma, Y., & An, Y. (2018). Analysis on Soil Moisture Characteristics of Tibetan Plateau Based on GLDAS. *Journal of Arid Meteorology, 36,* 595-602. (In Chinese) https://doi.org/10.11755/j.issn.1006-7639(2018)-04-0595

Ding, X., Lai, X., Fan, G. Z. et al. (2018). Analysis on the Applicability of Reanalysis Soil Temperature and Moisture Datasets over Qinghai-Tibetan Plateau. *Plateau Meteorol-*

ogy, 37, 626-641. (In Chinese)

Eyring, V., Bony, S., Meehl, G. A., et al. (2016). Overview of the Coupled Model Intercomparison Project Phase 6 (CMIP6) Experiment Design and Organization. *Geoscientific Model Development, 9*, 1937-1958. https://doi.org/10.5194/gmd-9-1937-2016

He, Y., Wen. J., Huang, Y. et al. (2017). Spatio-Temporal Characteristics of Soil Moisture Simulated over the Source Region of the Yellow River. *Plateau Meteorology, 36,* 129-137. (In Chinese) https://doi.org/7522/j.issn.1000-0534.2015.001117

Li, M. X., Ma, Z. G., & Niu, G. Y. (2011). Modeling Spatial and Temporal Variations in Soil Moisture in China. *Chinese Science Bulletin, 56,* 1809-1820. (In Chinese) https://doi.org/10.1007/s11434-011-4493-0

Li, X., Shao, M., Zhao, C., & Jia, X. (2019). Spatial Variability of Soil Water Content and Related Factors across the Hexi Corrodor of China. *Journal of Arid Land, 11,* 123-134. (In Chinese) https://doi.org/10.1007/s40333-018-0123-x

Li, X., Shi, Q., Guo, J. et al. (2009). The Response of the NDVI to Climate Variability in Northwest Arid Area of China form 1981-2001. *Journal of Arid Land Resources and Environment, 23,* 12-16. (In Chinese)

Liu, H., Wang, F., & Zhang, T. (2018). Evaluation Applicability of CLDAS and GLDAS Soil Moisture for the Loes Plateau. *Agricultural Research in the Arid Areas, 36,* 270-277. (In Chinese) https://doi.org/10.7606/j.issn.1000-7601.2018.05.38

Qin, D. (2011). Review and Introduction of the Natural Geography of Arid Areas in China. *Acta Geographica Sinica, 66,* 1005. (In Chinese)

Ruosteenoja, K., Markkanen, T., Venäläinen, A., Räisänen, P., & Peltola, H. (2018). Seasonal Soil Moisture and Drought Occurrence in Europe in CMIP5 Projections for the 21st Century. *Climate Dynamics, 50,* 1177-1192. https://doi.org/10.1007/s00382-017-3671-4

Su, B., Wang, A., Wang, G., Wang, Y., & Jiang, T. (2016). Spatiotemporal Variations of Soil Moisture in the Tarim River Basin, China. *International Journal of Applied Earth Observation and Geoinformation, 48,* 122-130. https://doi.org/10.1016/j.jag.2015.06.012

Wang, A., Miao, Y., & Chen, Y. (2020). Interdecadal Variation of Land Water Budget in Northwest China from 1961 to 2016. *Transactions of Atmospheric Sciences, 43,* 953-966. (In Chinese) https://doi.org/10.13878/j.cnki.dqkxxb.20201112001

Yao, J. Q., Zhao, Y., Chen, Y. N. et al. (2018). Multi-Scale Assessments of Droughts: A Case Study in Xinjiang, China. *Science of the Total Environment, 630,* 444-452. https://doi.org/10.1016/j.scitotenv.2018.02.200