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Modeling Dataset Development of Qinghai-Xizang Plateau Soil Moisture (2015–2100)

Song, Q.[1] Liu, Y. X. Y.[2]* Xu, H. Z.[3] Zhang, H. F.[4] Zhu, G. L.[4] Fu, X. P.[4]

1. Beijing Forestry University, Beijing 100101, China;
2. Institute of Geographic Sciences and Natural Resources Research, Chinese Academy of Sciences, Beijing 100101, China;
3. The Second Geological Brigade of the Xizang Autonomous Region Bureau of Geology and Mineral Exploration and Development, Lhasa 850000, China;
4. Monitoring Center for Ecological Environment of Xizang Autonomous Region, Lhasa 850000, China

Abstract: Qinghai-Xizang Plateau plays a crucial role in regional water cycles and ecosystem functioning through its surface soil moisture dynamics. This study developed a surface soil moisture dataset for the Qinghai-Xizang Plateau covering the period from 2015 to 2100 with a spatial resolution of 0.1°×0.1°. First, *in situ* measurements from the MAQU, NAQU, and NGARI networks were used to evaluate the accuracy of 21 CMIP6 soil moisture datasets, along with SMAP and ERA5-Land products, using bias, correlation coefficient (*R*), root mean square error (RMSE), and unbiased RMSE (ubRMSE). Meanwhile, the Enhanced Triple Collocation (ETC) method was employed to obtain random error standard deviation (RESD) and correlation coefficient (CC), based on which 4 Earth system models were selected for data fusion. Second, SMAP and ERA5-Land datasets were fused using differential weighting guided by the ETC evaluation results, and the optimal fusion result was identified. Finally, a Random Forest algorithm was used to integrate multiple sources of explanatory variables for monthly model training, and the model's prediction accuracy was validated against *in situ* observations. The resulting dataset includes: (1) monthly soil moisture data under 4 Shared Socioeconomic Pathways (SSP1-2.6, SSP2-4.5, SSP3-7.0, and SSP5-8.5) from 2015 to 2100 at 0.1° spatial resolution; (2) monthly *in situ* measurements (0–0.1 m depth) from the MAQU, NAQU, and NGARI networks. The dataset is archived in .mdd, .tif, .shp, and .csv formats, consisting of 4,838 data files with data size of 0.99 GB (compressed into 1 file with data size of 315 MB). Results indicate that compared to the original CMIP6 model outputs, the fused product exhibits significantly higher accuracy and lower error, enhancing the characterization of soil moisture dynamics over the Qinghai-Xizang Plateau.

Keywords: Qinghai-Xizang Plateau; surface soil moisture; future multi-scenario; random forest; fusion

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The dataset supporting this paper was published and is accessible through the *Digital Journal of Global Change Data Repository* at: https://doi.org/10.3974/geodb.2025.10.05.V1.

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***Corresponding Author:** Liu, Y. X. Y., Institute of Geographic Sciences and Natural Resources Research, Chinese Academy of Sciences, lyxy@lreis.ac.cn

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1 Introduction

Soil moisture (SM) is a pivotal variable in the terrestrial hydrological cycle and land-atmosphere energy exchange, extensively influencing ecosystem functioning, water resource distribution, agricultural productivity, and climate feedback processes[1,2]. On the Qinghai-Xizang Plateau—a geologically complex and ecologically fragile region often referred to as the "Water Tower of Asia"—the spatiotemporal dynamics of soil moisture not only regulate surface evapotranspiration and permafrost processes but also directly affect regional ecological security and climate change responses[3,4].

Although multiple data sources are available, including remote sensing retrievals, reanalysis datasets, and model simulations, each single source is often limited by inconsistent spatial-temporal coverage, error biases, and lack of physical coherence[5–7]. For instance, the Soil Moisture Active Passive (SMAP) satellite provides high spatial resolution soil moisture products[8], but suffer from short temporal coverage and spatial gaps. In contrast, the ERA5-Land dataset from the European Centre for Medium-Range Weather Forecasts (ECMWF)[9] offers long-term reanalysis data but exhibits spatial heterogeneity in accuracy. Meanwhile, the Coupled Model Intercomparison Project Phase 6 (CMIP6)[10] supplies multi-model, multi-scenario projections of future climate conditions, forming an important basis for long-term soil moisture trend analysis. However, significant discrepancies exist in simulation performance across different CMIP6 models, necessitating a rigorous model selection and fusion process.

In recent years, multi-source data fusion has emerged as an effective strategy for improving the accuracy and spatial consistency of soil moisture predictions. Among available approaches, the Enhanced Triple Collocation (ETC) method enables robust quantification of random errors between datasets[11], while machine learning algorithms such as Random Forest (RF) offer strong nonlinear modeling capacity and scalability, proving effective in soil moisture retrieval and prediction tasks[12].

Furthermore, the Qinghai-Xizang Plateau is particularly sensitive to climate change. Variations in soil moisture directly impact alpine grasslands, permafrost layers, and regional ecological patterns[13]. Hence, access to high-accuracy, long-term soil moisture data that also account for future climate scenarios is essential for advancing regional climate simulations.

To address this need, this study focuses on the Qinghai-Xizang Plateau and develops a fused soil moisture dataset by integrating remote sensing data, reanalysis products, and multi-model CMIP6 soil moisture simulation data. Using *in situ* station observations and the ETC method for accuracy assessment, and training monthly Random Forest models under multiple Shared Socioeconomic Pathway (SSP) scenarios. The final product is a 0.1° spatial resolution surface soil moisture dataset spanning 2015 to 2100, intended to serve as a reliable data foundation for research on climate change, water resources management, and ecosystem dynamics on the Qinghai-Xizang Plateau.

2 Metadata of the Dataset

The metadata of Qinghai-Xizang Plateau soil moisture modeling dataset (2015–2100)[14] is summarized in Table 1. It includes the dataset full name, short name, authors, year of the dataset, temporal resolution, spatial resolution, data format, data size, data files, data publisher, and data sharing policy, etc.

Table 1 Metadata summary of the Qinghai-Xizang Plateau soil moisture modeling dataset (2015–2100)

Items	Description
Dataset full name	Qinghai-Xizang Plateau soil moisture modeling dataset (2015–2100)
Dataset short name	QZP_RF_SoilMoisture_2015-2100
Authors	Song, Q., Beijing Forestry University, songqianxb@bjfu.edu.cn
	Liu, Y. X. Y., Institute of Geographic Sciences and Natural Resources Research, Chinese Academy of Sciences, lyxy@lreis.ac.cn Xu, H. Z., The Second Geological Brigade of the Tibet Autonomous Region Bureau of Geology and Mineral Exploration and Development, 452449161@qq.com Zhang, H. F., Monitoring Center for Ecological Environment of Tibet Autonomous Region, zhf0891@163.com Zhu, G. L., Monitoring Center for Ecological Environment of Tibet Autonomous Region, 17789906283@163.com Fu, X. P., Monitoring Center for Ecological Environment of Tibet Autonomous Region, 359946719@qq.com
Geographical region	Qinghai-Xizang Plateau (approximately 26°N–40°N, 73°E–105°E)
Year	2015–2100
Temporal resolution	Month
Spatial resolution	0.1°×0.1°
Data format	.mdd, .tif, .shp, .csv
Data size	315 MB (compressed)
Data files	(1) Monthly surface soil moisture spatial distribution data from 2015 to 2100 under 4 SSP scenarios: SSP1-2.6, SSP2-4.5, SSP3-7.0, and SSP5-8.5, with a spatial resolution of 0.1°; (2) Monthly *in situ* soil moisture observations (0–0.1 m depth) from 3 networks: MAQU, NAQU, and NGARI
Foundation	National Natural Science Foundation of China (42571539)
Data publisher	Global Change Research Data Publishing & Repository, http://www.geodoi.ac.cn
Address	No. 11A, Datun Road, Chaoyang District, Beijing 100101, China
Data sharing policy	(1) *Data* are openly available and can be free downloaded via the Internet; (2) End users are encouraged to use *Data* subject to citation; (3) Users, who are by definition also value-added service providers, are welcome to redistribute Data subject to written permission from the GCdataPR Editorial Office and the issuance of a *Data* redistribution license; and (4) If *Data* are used to compile new datasets, the "ten percent principal" should be followed such that *Data* records utilized should not surpass 10% of the new dataset contents, while sources should be clearly noted in suitable places in the new dataset[15]
Communication and searchable system	DOI, CSTR, Crossref, DCI, CSCD, CNKI, SciEngine, WDS, GEOSS, PubScholar, CKRSC

3 Methods

3.1 Data Sources

(1) CMIP6 simulation data

This study employed surface (0–10 cm) soil moisture data from 21 Earth system models provided by the CMIP6[16], covering the period from 2015 to 2100 and 4 Shared Socioeconomic Pathways (SSPs): SSP1-2.6 (sustainability pathway), SSP2-4.5 (middle-of-the-road pathway), SSP3-7.0 (regional rivalry pathway), and SSP5-8.5 (fossil-fueled development pathway). The participating models and their originating institutions include: ACCESS-CM2 (Bureau of Meteorology, Australia), BCC-CSM2-MR (China Meteorological Administration, China), CAMS-CSM1-0 (Chinese Academy of Sciences, China), CanESM5-CanOE (Environment and Climate Change Canada, Canada), CESM2 (National Center for Atmospheric Research, USA), CMCC-CM2-SR5 (Euro-Mediterranean Center on Climate Change, Italy), CNRM-CM6-1, CNRM-CM6-1-HR, CNRM-ESM2-1 (Météo- France, France), EC-Earth3-Veg-LR (EC-Earth Consortium, Europe), GFDL-ESM4 (Geophysical Fluid Dynamics Laboratory, USA), IPSL-CM6A-LR (Institute Pierre-Simon Laplace, France), KACE-1-0-G (Korea Institute of Atmospheric Prediction Systems, South Korea), MIROC6, MIROC-ES2L (University of Tokyo and Meteorological Agency, Japan), MPI-ESM1-2-LR (Max Planck Institute for Meteorology, Germany), MRI-ESM2-0 (Meteorological Research Institute, Japan), NorESM2-LM, NorESM2-MM (Norwegian Climate Centre, Norway), TaiESM1 (Academia Sinica, China), UKESM1-0-LL (Met Office Hadley Centre, UK).

(2) Remote sensing and reanalysis data

The Level-3 Soil Moisture Passive Enhanced product[17] from the Soil Moisture Active Passive (SMAP) satellite mission was used, covering the period from March 2015 to April 2025, with a spatial resolution of approximately 0.25°. A-track and D-track data were merged to generate daily and monthly soil moisture time series.

The ERA5-Land reanalysis dataset[18] from the European Centre for Medium-Range Weather Forecasts (ECMWF) provides monthly volumetric soil water content in layer 1 (0–7 cm depth), covering January 2015 to April 2025, at a spatial resolution of 0.1°.

(3) *In situ* data

In situ soil moisture observations were obtained from 3 networks (MAQU, NAQU, and NGARI) within the International Soil Moisture Network (ISMN)[19] on the Qinghai-Xizang Plateau region. The original data are archived in .stm format and contain hourly records.

First, hourly records were aggregated daily: if a depth had more than 6 valid hourly records in a day, the daily average was calculated; if multiple depths within 0–0.1 m were available, their daily averages were further combined into a single soil moisture value for that day; otherwise, the value was treated as missing. Subsequently, daily series were aggregated to monthly values: if a month had at least 6 valid observation days, the monthly average was calculated; otherwise, it was considered missing. The resulting monthly *in situ* soil moisture data were archived in .csv format.

(4) Auxiliary variables

Soil property data were sourced from the Harmonized World Soil Database version 2.0 (HWSD v2.0)[20], including soil bulk density, clay, silt, sand, and gravel content.

Topographic factors were elevation data from the Shuttle Radar Topography Mission (SRTM)[21]. Slope, aspect, and pixel coordinates (latitude and longitude) were calculated based on this dataset.

Climate factors were selected from the Global Climate Data Set Version 2.1 (WorldClim Version 2.1)[22], which provides monthly average values of climate variables such as minimum temperature, average temperature, maximum temperature, precipitation, solar radiation, wind speed, and water vapor pressure (1970–2000).

All data were uniformly resampled to a spatial resolution of 0.1°, with monthly temporal resolution, and converted into GeoTIFF format, facilitating subsequent modeling and prediction.

3.2 Technological Route

Figure 1 illustrates the overall workflow of this study, comprising the following 6 steps:

(1) Standardization of raster data: all dynamic and static variables (including soil moisture, climate factors, terrain factors, etc.) were uniformly converted to GeoTIFF format, with spatial resolution resampled to 0.1° and temporal resolution unified to a monthly scale.

(2) Multi-source soil moisture data accuracy evaluation: using monthly *in situ* measurements as the “true value”, the accuracy of soil moisture data from 21 CMIP6 models, SMAP, and ERA5-Land was evaluated by calculating metrics including bias, correlation coefficient (R), root mean square error (RMSE), and unbiased root mean square error (ubRMSE).

(3) ETC error quantification analysis: the ETC method was applied to perform

unsupervised error analysis on SMAP, ERA5-Land, and CMIP6 model data, generating correlation coefficients (CC) and random error standard deviations (RESD) to assist in model selection and fusion.

(4) Fusion and selection of target variable: based on the ETC assessment results, SMAP and ERA5-Land data were fused using a differentiated weighting method. *In situ* observations were used to assess the performance of different fusion schemes, and the optimal fusion result was selected as the target variable.

(5) Random Forest modeling and prediction: using the optimal SMAP-ERA5 fusion results as the prediction target (*y*), and CMIP6 multi-model data, ETC indicators, climate factors, soil factors, and terrain factors as input variables (*x*), a total of 48 monthly Random Forest models were constructed across 4 SSP scenarios. These models produced a 0.1° resolution, monthly soil moisture dataset for the Qinghai-Xizang Plateau from 2015 to 2100.

(6) Result validation: the model prediction results were re-evaluated against *in situ* measurements using bias, *R*, RMSE, and ubRMSE to assess the reliability and accuracy of

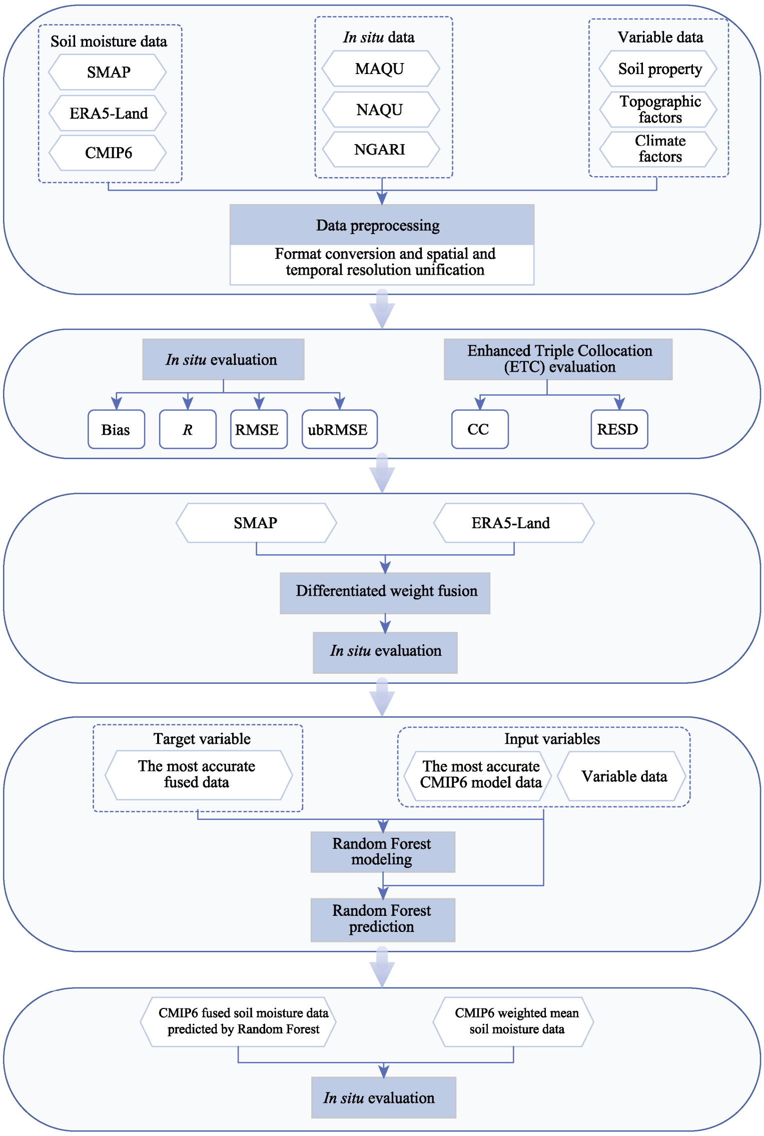

Figure 1 Flowchart of the dataset development

the fusion-based prediction models.

As shown in Figure 2 and Table 2, 4 Earth system models—BCC-CSM2-MR, EC-Earth3-Veg-LR, MPI-ESM1-2-LR, and TaiESM1—were selected for subsequent modeling based on their overall performance. Selection criteria included higher R and lower RMSE from *in situ* validation, as well as higher CC and lower RESD derived from ETC analysis.

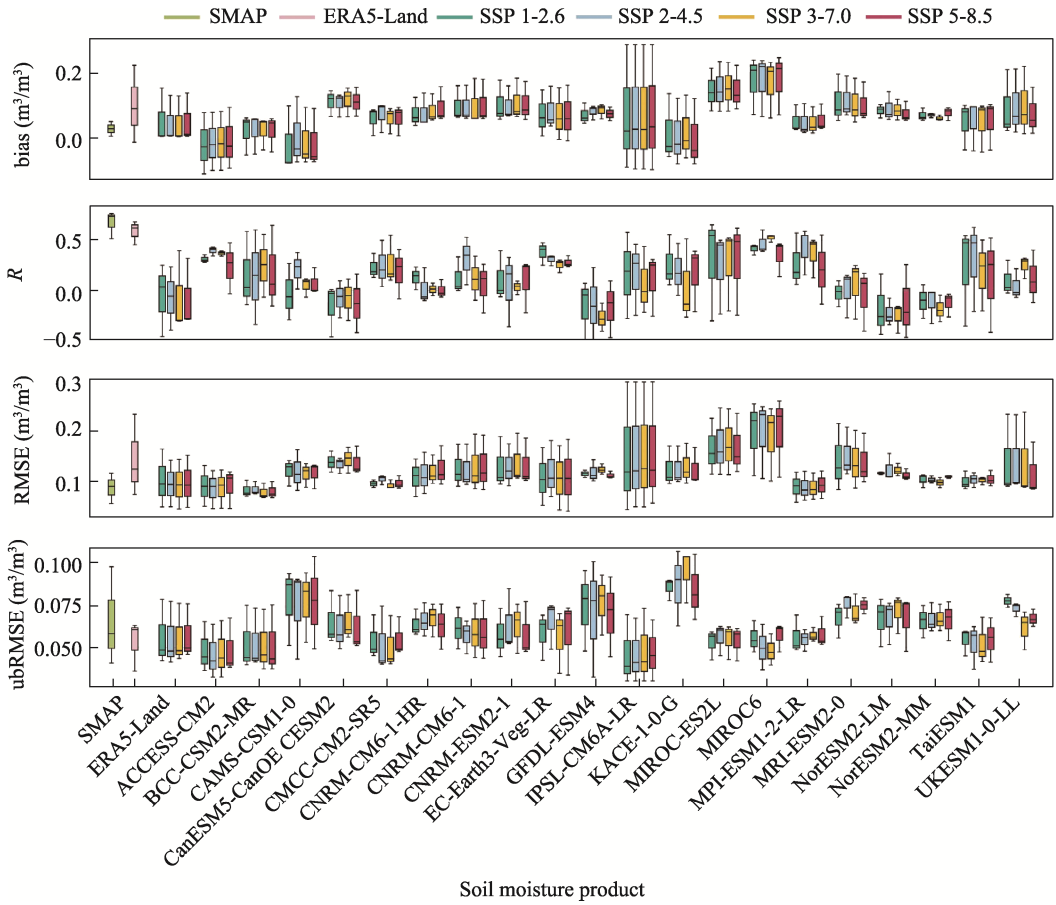

Figure 2 Validation results of various soil moisture products against *in situ* observations

Table 2 Mean ETC evaluation results for each soil moisture product

Soil moisture product	RESD (m^3/m^3)	CC	Soil moisture product	RESD (m^3/m^3)	CC
SMAP	0.06	0.60	ERA5-Land	0.04	0.53
ACCESS-CM2	0.02	0.21	IPSL-CM6A-LR	0.02	0.21
BCC-CSM2-MR	0.02	0.31	KACE-1-0-G	0.07	0.36
CAMS-CSM1-0	0.03	0.38	MIROC-ES2L	0.03	0.40
CanESM5-CanOE	0.06	0.23	MIROC6	0.03	0.33
CESM2	0.03	0.22	MPI-ESM1-2-LR	0.03	0.38
CMCC-CM2-SR5	0.03	0.29	MRI-ESM2-0	0.04	0.20
CNRM-CM6-1-HR	0.03	0.21	NorESM2-LM	0.03	0.27
CNRM-CM6-1	0.03	0.22	NorESM2-MM	0.03	0.21
CNRM-ESM2-1	0.03	0.20	TaiESM1	0.03	0.34
EC-Earth3-Veg-LR	0.04	0.35	UKESM1-0-LL	0.05	0.13
GFDL-ESM4	0.04	0.27			

Based on the ETC evaluation, SMAP and ERA5-Land data were weighted and fused according to different weights. Validation against *in situ* observations indicated that a weighting ratio of 7:3 (SMAP:ERA5-Land) yielded higher correlation and lower error. This fused dataset was ultimately selected as the target variable for the Random Forest modeling.

4 Data Results and Validation

4.1 Dataset Composition

The dataset consists of the following components: (1) Surface soil moisture data for the Qinghai-Xizang Plateau based on 4 SSPs (SSP1-2.6, SSP2-4.5, SSP3-7.0, and SSP5-8.5) from the CMIP6 simulations. The data span from January 2015 to December 2100, with a monthly temporal resolution and a spatial resolution of 0.1°. The unit of measurement is m^3/m^3, with values ranging from 0 to 1. Files are named in the format SSP***_yyyy-mm.tif; (2) *In situ* observational data from 3 monitoring networks: MAQU, NAQU, and NGARI. The dataset is archived in .mdd, .tif, .shp, and .csv formats, comprising a total of 4,838 files with an uncompressed size of approximately 0.99 GB (compressed into 1 file with data size of 315 MB).

4.2 Data Products

Figure 3 illustrates the spatial distribution of surface soil moisture under the 4 SSPs (SSP1-2.6, SSP2-4.5, SSP3-7.0, and SSP5-8.5), as predicted by the multi-source data fusion and Random Forest modeling approach. 4 representative months—January, April, July, and October of 2050—were selected to reflect typical conditions for winter, spring, summer, and autumn, respectively. The results demonstrate that the fused CMIP6 soil moisture data exhibit spatial and temporal patterns that closely align with the seasonal climatic rhythms of the Qinghai-Xizang Plateau. This indicates the model's capability to capture the seasonal variability and spatial heterogeneity of soil moisture across the region, reflecting strong

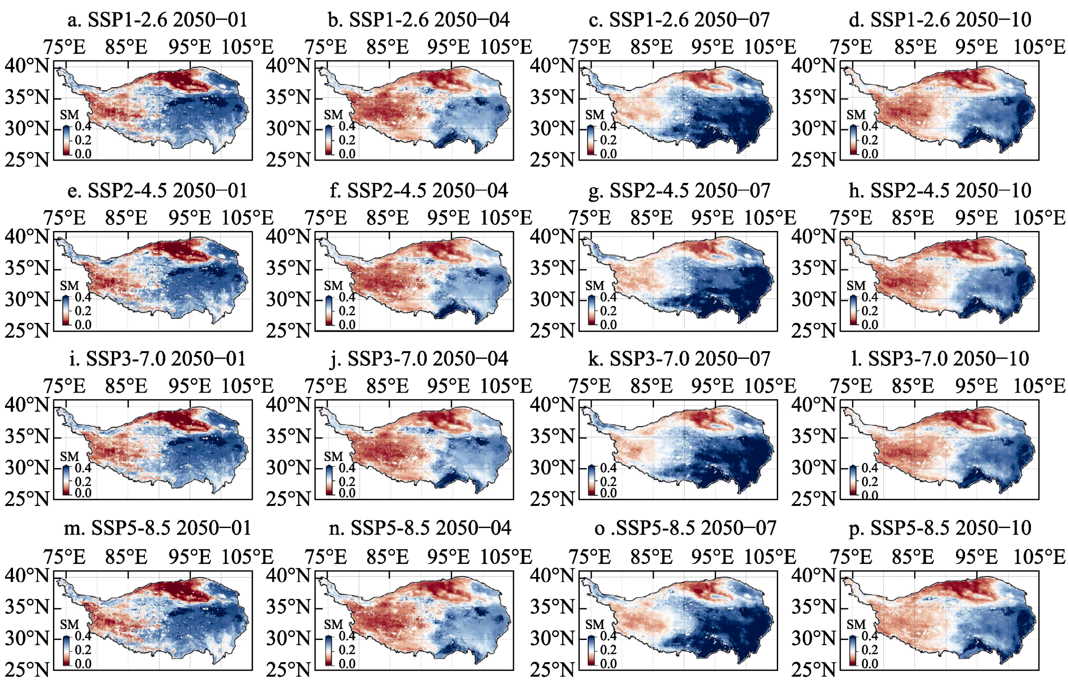

Figure 3 Distribution maps of soil moisture fusion data under four SSPs in Qinghai-Xizang Plateau (2050)

ecological and hydrological sensitivity. To ensure the scientific integrity and practical applicability of the modeled outputs, water body mask data were incorporated during the fusion and modeling processes to exclude rivers, lakes, glaciers, and other non-terrestrial surface areas.

4.3 Data Validation

This study used *in situ* data as a reference for accuracy evaluation, assessing the CMIP6 soil moisture fusion data generated through multi-source fusion and Random Forest methods. The fusion results were compared with the weighted average of 21 original CMIP6 soil moisture datasets. As shown in Table 3, the fusion data outperformed the simple weighted average in all metrics, particularly in terms of the *R* value, demonstrating a stronger fitting capability. This indicates that the constructed fusion data more accurately reflects the spatiotemporal variation of actual surface soil moisture, effectively enhancing the data reliability and applicability. The results further validate the significant advantage of multi-source data fusion combined with Random Forest modeling in improving the accuracy of soil moisture simulation.

Table 3 Accuracy evaluation of CMIP6 soil moisture fusion data predicted by multi-source integration and Random Forest methods

Soil moisture monitoring network	Evaluation indicators	Fused data				Weighted average data			
		SSP 1-2.6	SSP 2-4.5	SSP 3-7.0	SSP 5-8.5	SSP 1-2.6	SSP 2–4.5	SSP 3-7.0	SSP 5-8.5
MAQU	Bias (m^3/m^3)	0.07	0.07	0.07	0.07	0.02	0.02	0.02	0.02
	R	0.56	0.59	0.61	0.58	0.10	0.10	0.07	0.09
	RMSE (m^3/m^3)	0.10	0.10	0.10	0.10	0.11	0.11	0.11	0.11
	ubRMSE (m^3/m^3)	0.06	0.06	0.06	0.06	0.07	0.07	0.07	0.07
NAQU	Bias (m^3/m^3)	0.16	0.16	0.16	0.16	0.07	0.08	0.08	0.08
	R	0.46	0.44	0.49	0.43	0.22	0.26	0.24	0.22
	RMSE (m^3/m^3)	0.17	0.17	0.17	0.17	0.11	0.12	0.11	0.11
	ubRMSE (m^3/m^3)	0.06	0.06	0.06	0.06	0.06	0.06	0.06	0.06
NGARI	Bias (m^3/m^3)	0.00	0.01	0.01	0.01	0.13	0.13	0.13	0.13
	R	0.67	0.66	0.64	0.67	0.02	0.05	0.00	–0.06
	RMSE (m^3/m^3)	0.05	0.05	0.05	0.05	0.15	0.15	0.15	0.14
	ubRMSE (m^3/m^3)	0.03	0.03	0.03	0.03	0.05	0.06	0.05	0.05

5 Discussion and Conclusion

Soil moisture, as an important mediator of land-atmosphere interactions, plays a crucial role in regional climate, water resource allocation, and ecosystem stability. Faced with the dual challenges of increasingly severe climate change and the vulnerability of high-altitude ecosystems, obtaining long-term, multi-scenario, and regional high-resolution surface soil moisture information has become an urgent requirement for hydrological and environmental research. Focusing on the Qinghai-Xizang Plateau, this study selected the 4 best-performing CMIP6 Earth system models based on *in situ* observations and ETC evaluation. Combined with the ETC-derived metrics, SMAP and ERA5-Land products were fused with differentiated weights to construct the target variable for Random Forest modeling. With the assistance of multi-source static and dynamic variables such as climate, topography, and soil properties, monthly Random Forest models were trained, resulting in a surface soil moisture dataset with a spatial resolution of 0.1°, covering the period 2015–2100 under 4 future scenarios. Validation against *in situ* data indicates that the fused dataset significantly outperforms simple weighted averages in terms of correlation and error metrics, demonstrating strong robustness and reliability.

This dataset not only provides data support for future studies on the hydrological cycle and ecological evolution of the Qinghai-Xizang Plateau, but can also be applied to multiple research fields such as ecosystem response, permafrost change monitoring, and high-altitude ecological vulnerability assessment. Additionally, it offers a replicable methodological framework and practical example for multi-scenario, multi-source data-driven geoscience modeling in similar regions.

Author Contributions

Song, Q. processed and analyzed the data and wrote the data paper; Liu, Y. X. Y. designed the overall development of the dataset; Xu, H. Z., Zhang, H. F., Zhu, G. L., and Fu, X. P. collected and organized the data.

Conflicts of Interest

The authors declare no conflicts of interest.

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