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SoMoBench: a quasi-global benchmark dataset for data-driven soil moisture modelling with in situ-derived targets

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Abstract. Machine-learning approaches for soil moisture modelling are expanding rapidly, but their comparison remains difficult because studies often use different target data, predictors, preprocessing methods, and evaluation strategies. Here we present SoMoBench, a quasi-global benchmark dataset that provides standardised predictor inputs and soil moisture targets for data-driven modelling. The targets are derived from in situ observations provided by the International Soil Moisture Network and Brazil's CEMADEN network. Sub-daily measurements are aggregated to daily values and assigned to a common 0.25°grid for three nominal soil layers (0–10, 10–30, and 30–50 cm). To reduce site-dependent offsets while retaining observation-derived temporal variability, each station series is adjusted to the mean and standard deviation of collocated ERA5 soil moisture. Target series are constructed only for grid cells containing at least one eligible station, and no spatial interpolation is applied. For each grid cell and layer, the longest station record is used as the primary series, and temporal gaps are filled with validated secondary-station record from the same grid cell when available. The current release spans 2001-2024 and includes 1,445 grid cells with at least one target layer, along with daily ERA5 meteorological predictors for 2000–2024. We characterise the spatial and temporal properties of the targets and illustrate their use with climatology-based and Ridge regression models. The release also includes a Python example notebook and baseline performance results to support reproducibility. SoMoBench is designed as a reusable community resource for observation-informed benchmarking and model intercomparison in soil moisture modelling. The dataset is available for peer review through Zenodo; access information is provided in the Data availability section.

1 Introduction

Soil moisture is a key state variable regulating the exchange of water, energy, and carbon between the land surface and the atmosphere (Seneviratne et al., 2010). Through its role in land–atmosphere coupling, soil moisture influences the occurrence and severity of hydrometeorological extremes, including droughts, floods, and heatwaves (Koster et al., 2004; Seneviratne et al., 2006; Hirschi et al., 2011; Wasko et al., 2020). Despite its importance, accurate representation of soil moisture in process-based models remains challenging because land-surface processes are complex and are often simplified in model formulations (Clark et al., 2017), while key physical parameters related to soil hydraulic and thermal properties are difficult to constrain reli-

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ably (Van Looy et al., 2017; Dai et al., 2019).

Machine-learning (ML) methods are increasingly used for soil moisture modelling tasks, including estimation, forecasting, gap filling, and downscaling (e.g. O and Orth, 2021; Fang and Shen, 2020; O et al., 2022; Zheng et al., 2023; Senanayake et al., 2024). These methods can learn nonlinear relationships among meteorological forcing, land-surface properties, and soil moisture dynamics, offering a flexible complement to conventional process-based modelling (Shen et al., 2018; Reichstein et al., 2019). However, reported model skill depends not only on the ML method itself, but also on choices related to the target dataset, spatial and temporal sampling, predictor set, data preprocessing, and evaluation strategy. As a result, differences among published performances can reflect differences in data preparation and experimental design as much as differences in model capability.

Benchmark datasets can make such comparisons more transparent by providing standardised input data, target variables, and evaluation procedures. Here, a benchmark dataset refers to a standardised input and output resource designed to support ML model development and intercomparison. While benchmark datasets have long been central to ML research, they are also becoming increasingly important in weather forecasting and hydrology, as shown by WeatherBench (Rasp et al., 2020, 2024), CAMELS (Addor et al., 2017), and Caravan (Kratzert et al., 2023). Land-surface benchmarks, including WaterBench-Iowa (Demir et al., 2022), and LandBench (Li et al., 2024), further illustrate the growing demand for standardised model evaluation frameworks.

However, recent benchmarks for land-surface modelling often rely on targets derived from model outputs or reanalysis because these products provide spatially complete and temporally continuous fields. This is useful for emulation and prediction tasks, yet it can make model evaluation partly dependent on reproducing an existing model system. Observation-derived targets provide a complementary perspective by assessing how well data-driven models reproduce measured variability rather than another model output. At the same time, constructing such a dataset from in situ observations introduces additional challenges because soil moisture measurements are point-scale and not immediately comparable across depths, sensors, and networks (Ochsner et al., 2013). A benchmark dataset based on these observations therefore requires careful harmonisation and diagnostic evaluation.

Here we present SoMoBench, a quasi-global benchmark dataset for data-driven soil moisture modelling with targets constructed from in situ observations. The released archive provides daily soil moisture targets for three nominal soil layers (0–10, 10–30, and 30–50 cm) on a 0.25° grid for 2001–2024 and collocated daily ERA5 meteorological forcings for 2000-2024, together with metadata and a Python example notebook demonstrating data loading and baseline modelling. The targets preserve observation-derived temporal dynamics while reducing systematic differences by adjusting the mean and standard deviation

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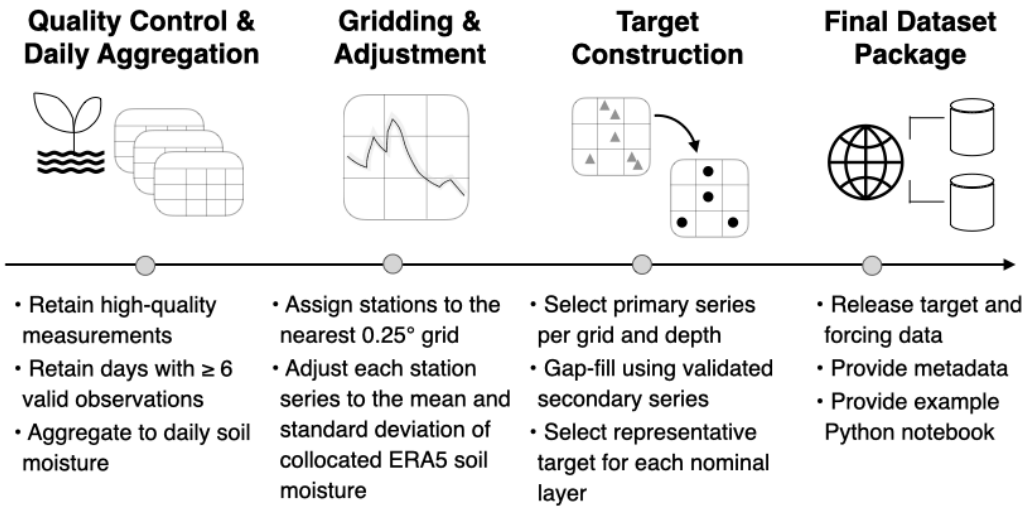


Figure 1. Workflow for constructing SoMoBench. Sub-daily soil moisture measurements from ISMN and CEMADEN are aggregated to daily values, assigned to the nearest grid cell (0.25°) , and adjusted to the local ERA5 soil moisture climatology while retaining their original measurement depths. Candidate target series are then constructed by selecting a primary station record and filling gaps with validated secondary records where available. Finally, one representative target is selected for each nominal soil layer (0–10, 10–30, and 30–50 cm). The released dataset includes target series, meteorological forcing data, metadata, and a Python example notebook.

of each station series to collocated ERA5 soil moisture. This paper describes the data sources and processing workflow, summarises spatial and temporal properties of the targets, and provides baseline modelling results as reference points for future studies.

2 Data and Methods

2.1 Overview of SoMoBench workflow

The SoMoBench workflow converts heterogeneous in situ soil moisture measurements into daily multi-layer target series on a common 0.25° grid (Fig. 1). The workflow consists of quality control and daily aggregation, gridding and climatological adjustment, target construction, and preparation of the released data files. Because the targets are derived from in situ measurements, they are provided only for grid cells and dates with suitable observations rather than as spatially and temporally complete soil moisture fields. The construction procedure is described in detail in Sect. 2.3.

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2.2 Input data sources

In situ soil moisture observations are obtained from the International Soil Moisture Network (ISMN) and Brazil's National Center for Monitoring and Early Warning of Natural Disasters (CEMADEN). For target construction, we use observations from 2001–2024. ISMN provides a global data hosting facility for many regional and national soil moisture networks and includes metadata, sensor information, quality flags, and long-term in situ observations (Dorigo et al., 2011, 2021). Table 1 summarizes the ISMN networks contributing to SoMoBench. CEMADEN provides additional soil moisture observations from Brazil and substantially expands the South American coverage of SoMoBench. We use Version 2 of the publicly available dataset described by Zeri et al. (2020).

Meteorological forcings are obtained from ERA5 reanalysis (Hersbach et al., 2020, 2023). The forcing data are provided as complete daily time series for each target grid cell over 2000-2024, including one year before the target period to support the use of lagged and antecedent meteorological predictors. The provided variables are precipitation, 2 m air temperature, near-surface specific humidity (calculated from dew point temperature and surface pressure), downward shortwave radiation, downward longwave radiation, surface pressure, and 10 m wind speed. Table 2 summarizes the forcing variables provided with the dataset.

Additional descriptors are provided in a metadata file to support filtering, stratified evaluation, and diagnostic analyses. For each target grid cell and layer, the metadata include the grid-cell identifier, coordinates, region, representative measurement depth, record start and end dates, number of valid days, number of contributing stations, and gap-filling fraction. Environmental descriptors in the same file include long-term mean temperature and dryness index derived from ERA5, and mean tree-cover percentage for 2015–2019 derived from the Copernicus Global Land Service Land Cover 100 m Collection 3 product based on PROBA-V observations (Buchhorn et al., 2020b, a)

2.3 Construction of target series

Because ISMN and CEMADEN use different quality-control systems, we use the quality information provided with each dataset. For ISMN, only measurements flagged as good quality are included Dorigo et al. (2013). For CEMADEN, measurements passing the quality control applied by the data provider are used Zeri et al. (2018). A daily value is calculated only on days with at least six valid sub-daily observations. Station records shorter than 90 valid days are discarded.

Each station is assigned to the nearest 0.25° grid cell. At this stage, each station time series remains associated with the measurement depth of the original observation. Measurements reported over a depth interval are assigned to a nominal layer only

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when the entire measurement interval is contained within that layer. Because in situ observations originate from different sensors, calibration methods, and site conditions, their absolute values are not directly comparable across networks, and they may differ even among nearby stations. To reduce these systematic differences, each daily time series is linearly rescaled to match the long-term mean and standard deviation of collocated ERA5 soil moisture over their overlap period during 2001–2024. This approach preserves the temporal dynamics of the in situ measurements while aligning their mean and variability to a common reference scale. The adjustment is motivated by previous studies showing that temporal soil moisture dynamics are generally more spatially coherent than absolute soil moisture values Mittelbach and Seneviratne (2012); Brocca et al. (2014); Nicolai-Shaw et al. (2015). A similar climatological adjustment of in situ soil moisture observations was used in SoMo.ml to support large-scale data-driven soil moisture modelling (O and Orth, 2021).

Following this adjustment, station data within the same grid cell and measurement depth are considered as candidate target series. For each grid cell and measurement depth, the longest available record is selected as the primary series to maximise temporal coverage. Other stations in the same grid cell and depth are used only to fill missing dates and extend coverage beyond the primary record period when they have at least 90 days of overlap with the primary record and a correlation of at least 0.3. Before gap filling, each eligible secondary series is further matched to the mean and standard deviation of the primary series over their overlapping period. This step helps reduce discontinuities when the source station changes over time. When multiple secondary stations are available, they are ranked first by correlation and then by overlap length.

For each grid cell and nominal soil layer, the final representative target is selected from the available candidate depths as the one closest to the nominal layer midpoint. The three nominal layers are 0–10, 10–30, and 30–50 cm, with midpoints of 5, 20, and 40 cm, respectively. Point measurements exactly at 10 or 30 cm are assigned to the shallower layer. If two candidate depths are equally close to the nominal midpoint, the longer record is chosen. Final time series data include an indicator showing whether each value originates from the primary or a secondary station.

2.4 Baseline modelling experiments

We provide simple baseline modelling experiments to demonstrate the practical utility of the data. These experiments are not intended to define state-of-the-art soil moisture models. Instead, they show that the inputs and targets can be used to train and evaluate simple predictive models, and provide reference performance information for future users of SoMoBench. They also illustrate how model performance changes under different predictor configurations.

Each grid cell and layer is modelled independently. Dates with valid target values are ordered chronologically, with the first 80% used for training and the final 20% held out for testing. Performance is evaluated on the held-out period using Pearson correlation and root mean square error (RMSE). This split is deliberately simple, but users can define stricter temporal, spatial,

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or regional splits using the metadata.

We consider four baseline configurations. The first is a monthly climatology baseline that predicts soil moisture using monthly mean target values estimated from the training period only. The second is a Ridge regression model using previous-day meteorological forcing variables. The third is a Ridge regression model that additionally uses antecedent memory features, represented by 7-day accumulated precipitation and 7-day means of the other forcing variables. The fourth is a state-augmented Ridge regression model that includes previous-day soil moisture from overlying layers where available. For Layer 2, this model includes previous-day Layer 1 soil moisture. For Layer 3, it includes previous-day Layer 1 and Layer 2 soil moisture. The state-augmented configuration is not defined for Layer 1. All Ridge models use standardised predictors and a fixed regularisation parameter of α=5.0, implemented in scikit-learn (Pedregosa et al., 2011).

3 Dataset description

The SoMoBench v1.0 archive (O et al., 2026) consists of target time series, meteorological forcing time series, a metadata file, a baseline performance table, and a Python example notebook. The target files contain daily observation-derived soil moisture series for the three nominal layers in CSV format. Each file is indexed by date and includes the soil moisture value and an indicator of whether the value comes from the primary station or from secondary-station gap filling. Both target and forcing data files are named using the grid-cell coordinates, following the format `IDX_{latitude}_{longitude}`. The metadata file describes the grid cells and target records included in the archive. It includes grid-cell identifiers and locations, representative measurement depths, record coverage, contributing networks, and environmental descriptors.

The baseline performance table contains the results of the baseline modelling experiments described in Sect. 2.4. It provides performance metrics at each grid cell and layer for the monthly climatology and Ridge-regression configurations, allowing users to compare new models against the reference results reported in this paper. The Python example notebook demonstrates basic dataset use by running all applicable baseline models for a grid cell selected by the user.

4 Results

4.1 Target coverage and availability

SoMoBench includes 1,445 grid cells with at least one target layer and provides quasi-global coverage across a broad range of hydroclimatic regimes, with particularly dense sampling in North America and Europe (Fig. 2). In addition, the supplementary analysis of environmental diversity shows that SoMoBench includes grid cells ranging from sparsely vegetated to moderately forested regions, and from weakly to strongly seasonal precipitation regimes (Fig. S1). CEMADEN observations expand the

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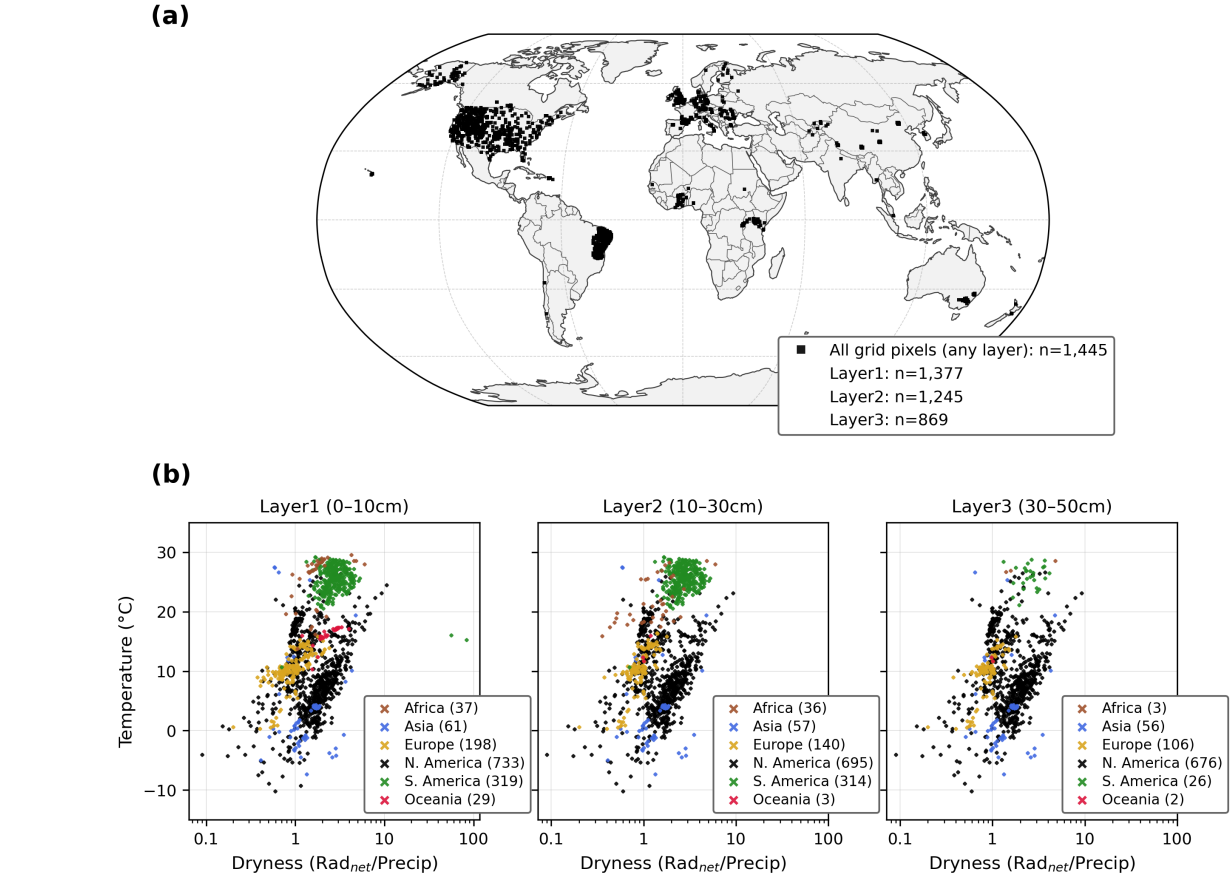


Figure 2. Spatial coverage and hydroclimatic diversity of SoMoBench target grid cells. (a) Global distribution of grid cells with soil moisture targets. The legend reports the number of grid cells available for each layer. (b) Distribution of target grid cells across hydroclimatic regimes, defined by long-term mean dryness and temperature. Dryness is defined as the ratio of long-term mean annual net radiation, converted to equivalent evaporation, to long-term mean annual precipitation Orth and Destouni (2018). Colors denote continental regions. The map is created using the Matplotlib Basemap v1.2.2 toolkit Hunter (2007).

benchmark coverage, particularly for Layers 1 and 2 in South America, where they increase the representation of relatively dry environments. Spatial coverage decreases with depth, and Layer 3 remains the most spatially limited layer.

The spatial distribution of SoMoBench is geographically uneven, as it inherently depends on the availability of in situ observations. This unevenness should be considered when designing train–test subsets or interpreting modelling results, especially for Layer 3, where both spatial coverage and diversity are more limited than in the shallower layers. Nevertheless, the dataset covers a wide range of hydroclimatic and environmental conditions, which is important for data-driven modelling because ML generalisation depends strongly on whether training samples cover diverse conditions O et al. (2020); Gauch et al. (2021). Thus, SoMoBench can support not only general model benchmarking but also targeted experiments that evaluate model trans-

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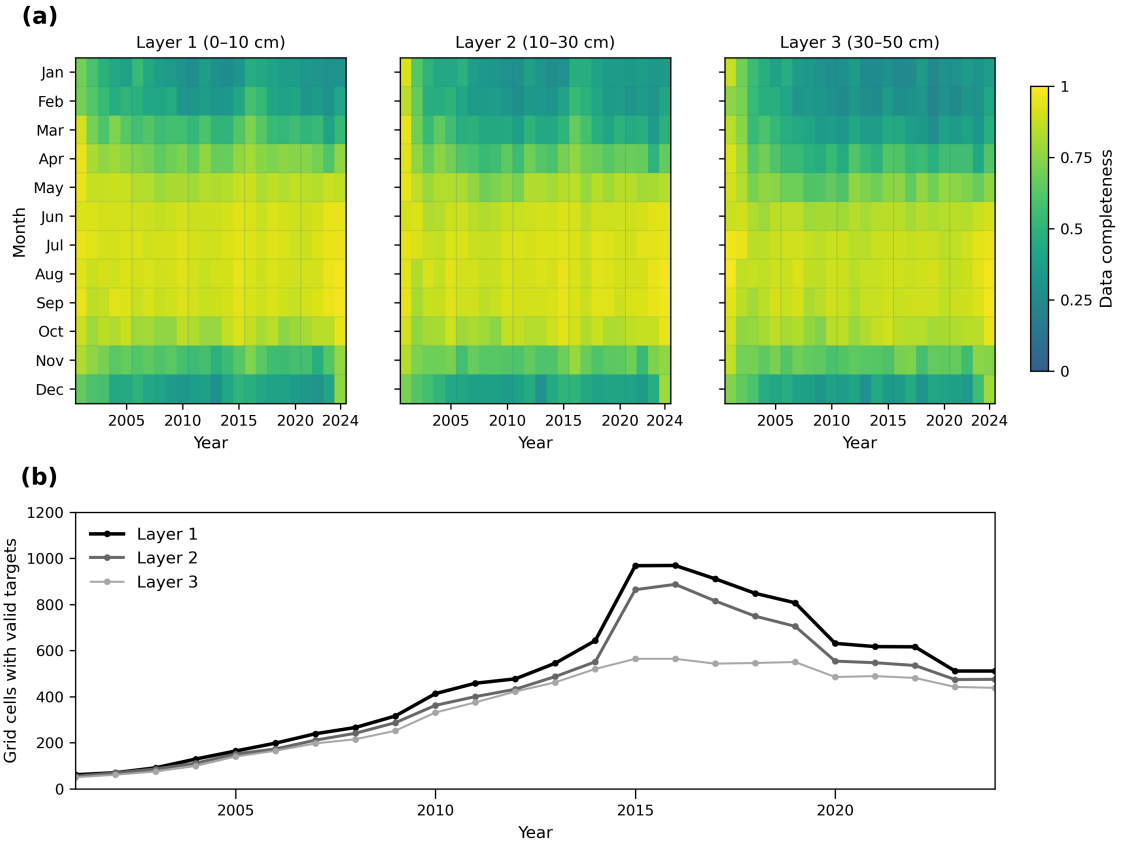


Figure 3. Temporal availability of SoMoBench target data during 2001–2024. (a) Monthly completeness of each layer, calculated as the proportion of days with target values among all possible days within the observation span of each grid cell and layer, where the observation span is defined from the first to the last valid observation. (b) Annual number of grid cells with at least one available target for each layer.

ferability across contrasting regimes. To facilitate such analyses, the released metadata include the long-term temperature and dryness index used in Fig. 2, allowing users to filter, stratify, or interpret benchmark results.

The SoMoBench target record spans 24 years, from 2001 through 2024, and shows clear seasonal and interannual variation in data availability (Fig. 3). Because most target grid cells are located in the Northern Hemisphere, monthly completeness is generally higher during the warm season and lower during the cold season in that hemisphere. The lower cold-season availability partly reflects the ISMN quality-control flags, which already remove many observations affected by frozen soil or other adverse measurement conditions Dorigo et al. (2013, 2021). The released targets do not apply an additional temperature-based freeze mask beyond the source quality control. Instead, the forcing data include near-surface air temperature so that users can define stricter freeze-related filtering criteria if required for their specific application.

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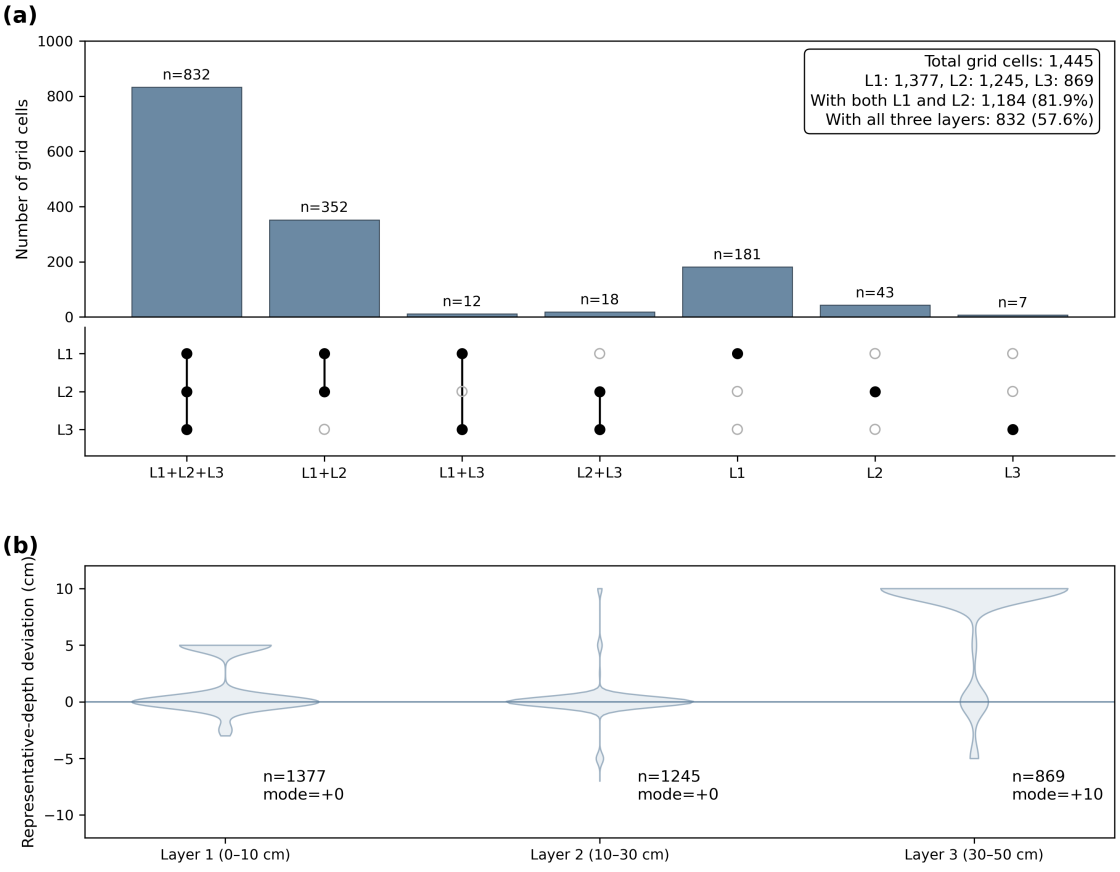


Figure 4. Layer availability and effective measurement depth of SoMoBench targets. (a) Co-location of target layers across grid cells. Bars show the number of grid cells for each layer combination, and the dot matrix indicates whether Layer 1 (L1), Layer 2 (L2), and Layer 3 (L3) are present. (b) Distribution of effective-depth deviations from the nominal mid-depth of each layer, i.e. 5, 20, and 40 cm. Sample size n and modal deviation are reported for each layer.

The annual number of grid cells with at least one available target increases over time, reflecting the expansion of contributing networks and the availability of additional observations. The increase is most pronounced for the shallower layers around 2015-2019, when CEMADEN adds many South American grid cells. Layer 3 does not experience the same expansion and remains more limited throughout the record.

SoMoBench provides substantial multi-layer coverage. The inclusion of deeper target layers enables benchmarking of subsurface soil moisture models, while multiple layers within the same grid cells can support evaluation of vertically coupled soil moisture dynamics and models that use information from multiple soil depths as predictors. Among the 1,445 grid cells with at least one target layer, 832 contain targets for all three layers (Fig. 4a). A further 352 grid cells contain only Layers 1 and 2, while the remaining grid cells provide other two-layer or single-layer combinations. Thus, the dataset supports multi-layer

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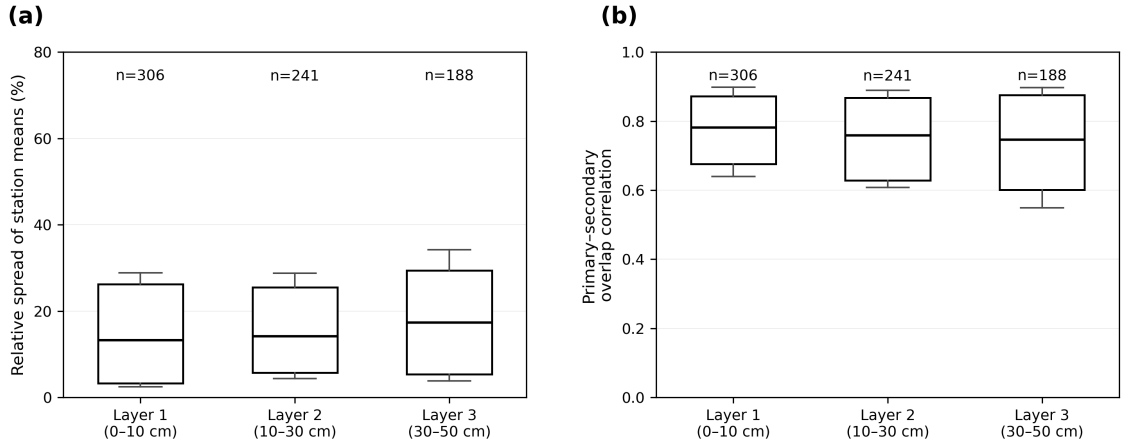


Figure 5. Within-grid consistency of soil moisture measurements used to construct SoMoBench. (a) Relative spread of mean soil moisture among stations within each grid cell and layer before climatological adjustment. The spread is calculated as the standard deviation of the station means divided by their median and expressed as a percentage. (b) Temporal consistency between primary stations and secondary stations used for gap filling. When more than one secondary station contributes to a target, the median correlation is shown. Both panels use only stations that contribute values to the final targets. Sample sizes refer to the number of grid cells with at least one contributing secondary station in each layer. Boxes show the 25th–75th percentiles, horizontal lines show the median, and whiskers show the 20th–80th percentiles.

evaluation across a substantial number of grid cells while retaining single-layer locations that broaden spatial coverage.

Effective measurement depth differs across layers (Fig. 4b). Layers 1 and 2 are generally close to their nominal midpoints of 5 and 20 cm, respectively, whereas Layer 3 has a broader distribution and is often represented by measurements closer to 50 cm than to the nominal 40 cm midpoint. The metadata include the representative depth of each target, which users may use to exclude targets with large depth deviations, include depth deviation as a covariate, or conduct sensitivity analyses with stricter depth matching.

4.2 Technical validation and target uncertainty

We provide a technical validation of the SoMoBench targets using two complementary diagnostics. First, we examine differences in absolute soil moisture levels and temporal consistency among multiple in situ soil moisture time series located within the same grid cell. This analysis examines the premise underlying SoMoBench that temporal soil moisture variability is more spatially coherent within a grid cell than absolute soil moisture levels, and characterises the temporal agreement among secondary stations used for gap filling. Second, we compare the final adjusted targets with collocated ERA5 soil moisture to evaluate the effect of the adjustment and determine the extent to which the targets preserve observation-derived temporal variability.

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Figure 5 illustrates the within-grid consistency of the in situ data used to construct SoMoBench targets. Grid cells with at least one contributing secondary station account for approximately 18% of all target grid cells across the three layers. The relative spread of mean soil moisture among individual stations within the same grid cell is often large before adjustment (Fig. 5a), indicating substantial differences in absolute soil moisture among collocated measurements. These offsets likely reflect differences in sensors, calibration procedures, installation depths, and other site-specific measurement conditions. This result supports the adjustment step to reduce systematic differences among station time series before constructing benchmark targets from multiple observation networks.

In contrast, collocated soil moisture time series generally show coherent temporal variability. The correlations between primary records and secondary records accepted for gap filling are mostly positive and generally high, with median values of 0.78, 0.76, and 0.75 for Layers 1, 2, and 3, respectively (Fig. 5b). Their distribution across hydroclimatic regimes is shown in Fig. S2. We also compare anomaly correlations after removing each station's monthly climatology calculated over the overlap period. Median anomaly correlations are approximately 0.71, 0.65, and 0.60 for Layers 1, 2, and 3, respectively (Fig. S3). This indicates that secondary stations used for gap filling tend to capture similar temporal dynamics to the corresponding primary record, even when their absolute values differ. However, simply averaging all available stations within a grid cell could introduce discontinuities because the set of available stations often changes through time. SoMoBench therefore uses secondary stations only for calibrated gap filling, rather than simple averaging. The released target data include a gap-filling indicator for each daily value, allowing users to exclude gap-filled values or apply stricter filtering criteria if needed.

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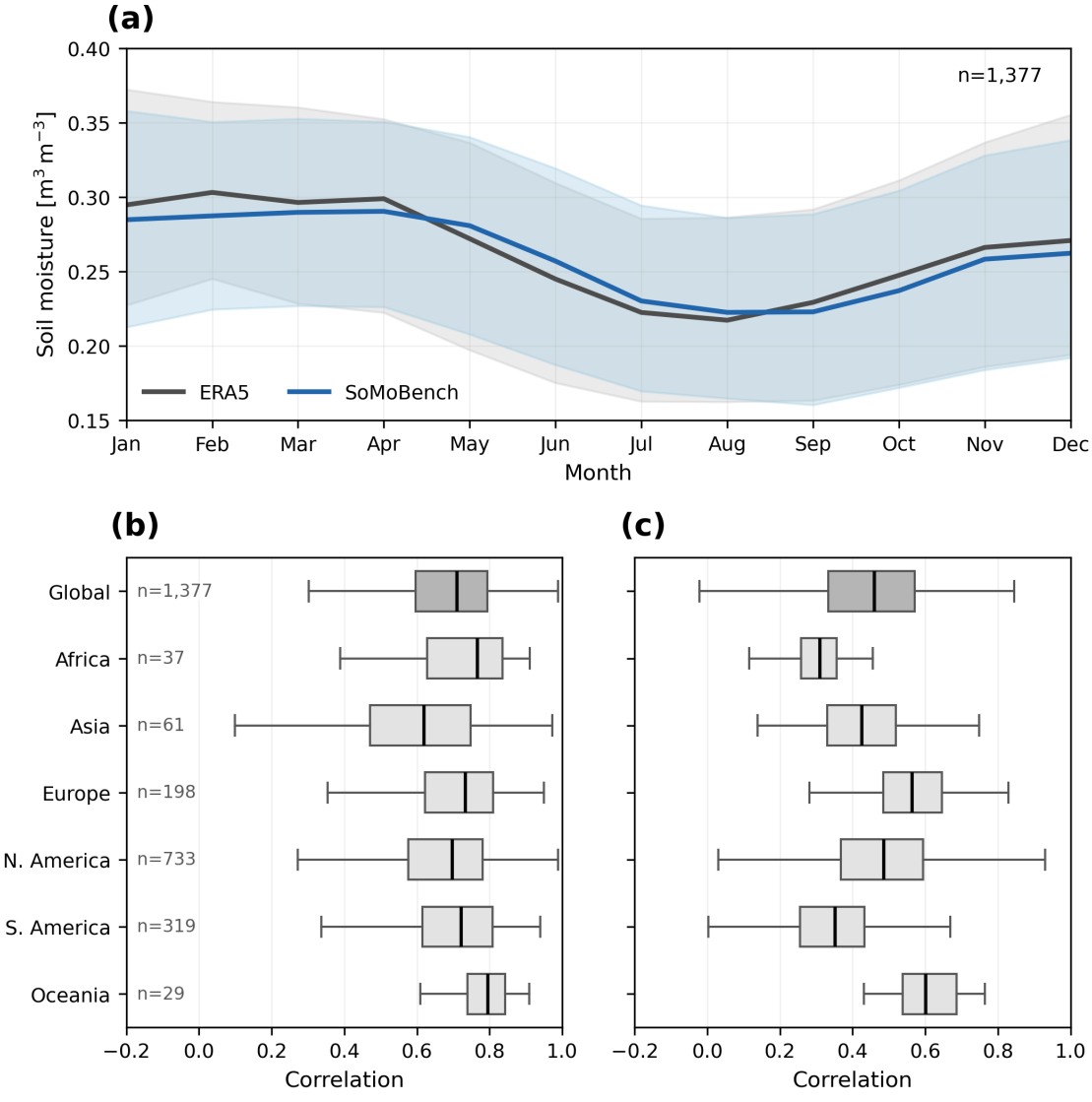


Figure 6. Characterisation of the ERA5-based climatological adjustment for Layer 1 SoMoBench targets. (a) Monthly climatology of SoMoBench and collocated ERA5 soil moisture at matched grid cells. Lines and shading show the median and interquartile range across grid cells. (b) Regional distributions of grid-level correlations between SoMoBench and ERA5 time series. (c) Same as (b), but for daily differences, $\Delta SM = SM(t) - SM(t-1)$.

. Boxes show the interquartile range, centre lines show the median, and whiskers extend to 1.5 times the interquartile range; outliers are omitted.

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Figure 6 evaluates the ERA5-based climatological adjustment for Layer 1. Because the adjustment aligns the long-term mean and standard deviation of each in situ time series to collocated ERA5 soil moisture, the adjusted monthly climatology is expected to resemble ERA5 at matched grid cells (Fig. 6a). This confirms that the targets are placed on a common gridded reference scale, which is especially relevant for applications that compare model performance across grid cells or train models using data pooled across regions. Without such harmonisation, systematic differences among sites and networks could otherwise obscure the soil moisture dynamics that data-driven models are intended to learn.

However, the adjusted targets do not simply reproduce ERA5 temporal variability. Daily correlations between SoMoBench and ERA5 are generally moderate to high but vary across regions (Fig. 6b), while correlations of daily differences are substantially lower (Fig. 6c). Agreement in daily changes becomes weaker at deeper layers (Fig. S4) This contrast indicates that the short-term dynamics of SoMoBench are mainly derived from the in situ measurements. We therefore interpret SoMoBench as an in situ-informed, ERA5-harmonized benchmark dataset whose absolute climatology is largely constrained by the reference reanalysis, while its temporal dynamics remain primarily observation-derived.

4.3 Illustrative soil moisture prediction experiments

Figure 7 presents the baseline modelling experiments introduced in Sect. 2.4. These deliberately simple experiments are intended to demonstrate the use of SoMoBench for model training and evaluation and provide a reproducible reference rather than a comprehensive model intercomparison.

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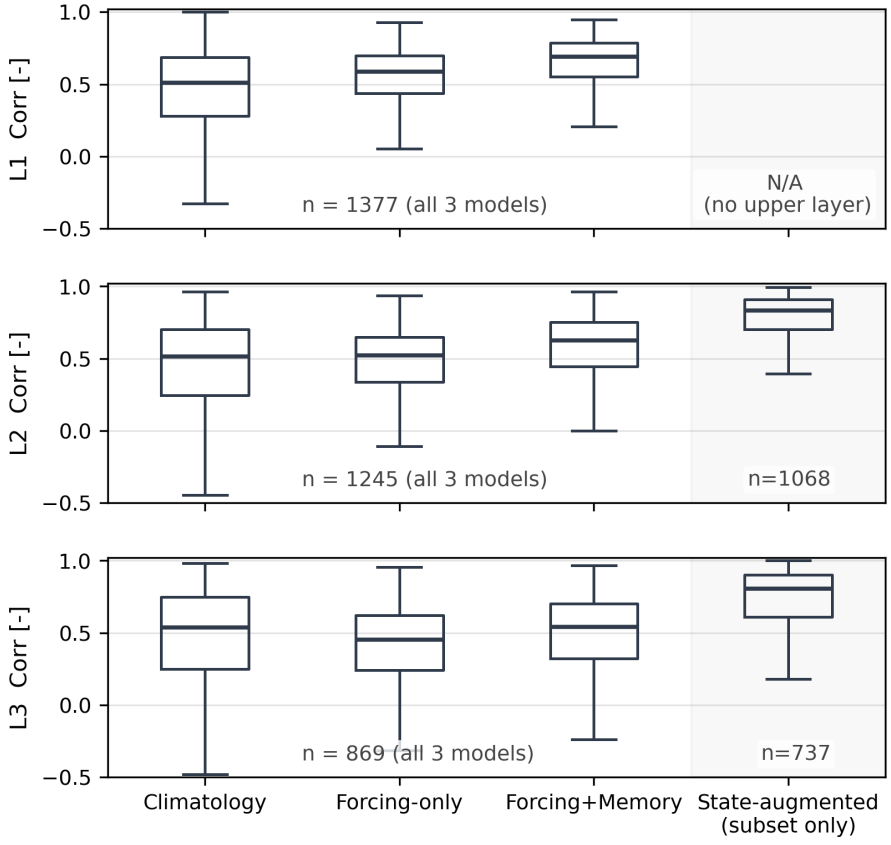


Figure 7. Example application of SoMoBench for soil moisture prediction. Boxplots show Pearson correlations for each grid cell and layer over the held-out test period. Four simple baseline configurations described in Sect. 2.4 are compared: monthly climatology, Ridge regression using previous-day meteorological forcing, Ridge regression using the same predictors together with antecedent memory features, and state-augmented Ridge regression. The state-augmented configuration is not applicable to Layer 1 and is evaluated only for the subset of grid cells and dates with the required overlying-layer target data. Boxes show interquartile ranges, centre lines show medians, and whiskers extend to 1.5 times the interquartile range; outliers are omitted for readability.

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The monthly climatology baseline already shows appreciable predictive skill across all three layers, reflecting the strong seasonal cycle and persistence of soil moisture. For Layer 1, the forcing-only Ridge model improves over climatology, and the addition of memory features provides further gains. This is consistent with the direct response of near-surface soil moisture to recent atmospheric forcing.

For deeper layers, forcing-only models are generally closer to the climatology baseline, while antecedent memory features become more important. This is consistent with the greater persistence of deeper soil moisture and the delayed propagation of atmospheric forcing into the soil profile. The strongest improvements for Layers 2 and 3 are obtained with the state-augmented Ridge model, which additionally uses previous-day soil moisture from the overlying layer. Because this configuration requires the corresponding overlying-layer targets, it is evaluated on smaller subsets, with 1,068 grid cells for Layer 2 and 737 grid cells for Layer 3. Nevertheless, the results illustrate how SoMoBench can be used to quantify the added value of using soil moisture information from overlying layers where multi-layer data are available. The corresponding baseline performance scores are included in the data release to support reproducibility and provide a reference for future model evaluations.

5 Discussion and Conclusions

5.1 Use cases

SoMoBench is designed as a standardised input and output resource that can support data-driven soil moisture modelling. Its main distinction is that the benchmark targets are derived from in situ observations. Existing benchmark resources based on land surface model or reanalysis products are useful, but their target labels inevitably reflect the assumptions of the product from which they are derived. SoMoBench provides a complementary reference by offering in situ-informed targets that preserve temporal information from direct measurements while harmonising the data on a common grid and within consistent nominal depth layers.

The primary purpose of SoMoBench is to provide a common benchmark for developing and evaluating data-driven models, including comparisons among model architectures, memory representations, and data split strategies. The baseline experiments in this paper are intentionally simple, but they provide reproducible reference results for future model assessments. Because the target data are harmonised across many grid cells, SoMoBench can also support large-scale modelling, where multiple sites are used together to train regional or global ML models (Kratzert et al., 2019; O et al., 2022). Building on previous in situ-based global soil moisture modelling efforts such as SoMo.ml (O and Orth, 2021), SoMoBench provides standardised targets and forcings as a reusable benchmark for model development and intercomparison.

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The dataset can also serve as an in situ-informed reference for intercomparison with other soil moisture datasets. Its targets can be used to compare land-surface model outputs, satellite-based products, or ML products trained on other target datasets. Beyond standard model benchmarking, SoMoBench also supports controlled modelling experiments. For example, users can examine transferability between climatically contrasting regions, evaluate regional model transfer, or assess whether specific modelling choices improve predictions under difficult conditions such as dry periods or other extremes. The multi-layer structure also supports experiments on vertical soil moisture dynamics, including the potential benefit of using shallow layer information to predict deeper layer soil moisture.

5.2 Limitations and target uncertainty

The dataset covers diverse hydroclimatic and environmental conditions, but its spatial distribution remains geographically uneven. Very cold or dry regions are underrepresented, and data availability is lower during cold seasons, which should be considered when interpreting modelling performance. Layer 3 has lower spatial coverage and more limited temporal availability than the shallower layers. Point-to-grid representativeness also cannot be fully resolved, even after climatological adjustment. The targets are derived from point measurements and may not fully represent sub-grid variability in soil texture, vegetation, or land management. In addition, because the adjustment uses ERA5 long-term mean and standard deviation, the long-term statistics of the targets depend partly on that reference product.

The targets and meteorological predictors come from different data sources. Although the observation-informed targets provide a complementary reference to reanalysis-derived labels, observational uncertainty and reanalysis errors may limit agreement between predictions and targets. Nonetheless, the baseline results in Fig. 7 show that the provided predictors contain information relevant to the target variability and can support informative and reproducible model comparisons. The current release focuses on a common ERA5-based predictor set rather than an exhaustive collection of possible inputs. Users may supplement it with predictors from other datasets or with additional variables, such as Earth observation products and static attributes. Future versions may include predictors from additional datasets, a broader range of variables, and higher spatial and temporal resolutions.

Uncertainty in the target data also remains difficult to quantify comprehensively. In principle, multiple colocated stations within a grid cell could be used to estimate target uncertainty or construct ensemble targets. However, most grid cells have only a small number of colocated sensors, and their records often have limited temporal overlap. We therefore do not provide an ensemble uncertainty estimate in the current release. Instead, SoMoBench provides diagnostic information on within-grid consistency (Fig. 5), metadata on the number of contributing stations and an indicator of whether each target value comes from the primary or a secondary station. These fields allow users to filter or stratify the data according to their uncertainty criteria. Users requiring stricter criteria can define subsets of grid cells, exclude gap-filled values, or apply additional filters using the

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released metadata.

As ML approaches become increasingly common in Earth system modelling, benchmark datasets are becoming important for reproducible model development and evaluation. While such resources are now widely used in atmospheric and hydrological modelling, comparable benchmarks for land-surface variables, and especially soil moisture, remain limited. SoMoBench addresses this gap by providing a shared benchmark designed specifically for data-driven soil moisture modelling. By providing standardised inputs and in situ-informed targets, the dataset supports further advances in data-driven soil moisture modelling.

6 Code availability

The code used to reproduce the figures and baseline modelling experiments presented in this paper is available at https://github.com/osungmin/somobench/.

7 Data availability

The SoMoBench v1.0 dataset (O et al., 2026) is available for peer review through the following temporary Zenodo review link:

https://zenodo.org/records/21534022?preview=1&token=eyJhbGciOiJIUzUxMiJ9.eyJpZCI6IjE1MzUwOTAzLTk4YmYtNDEwMC1hZjNmLTliZWFlMjhjZmY1NyIsImRhdGEiOnt9LCJyYW5kb20iOiJmZjBjMmRlMjY0ZDc5YWFlOWYwODk4ZjU3YzA5NTVmZiJ9.y2NazeUb8afGyhqZE2rRaO3wfQedZHGcPSGzPpOBQR02Rm8WB_SMkh8devXY8jh1RIZmOb8yD2HxgSgOfry6Ag

The archive includes daily soil moisture target time series, meteorological forcing time series, metadata, baseline performance results, and a Python example notebook. The CC BY 4.0 licence applies only to the processed SoMoBench products; it does not apply to the original input datasets. The original input datasets are available from the International Soil Moisture Network (https://ismn.earth/), the CEMADEN soil moisture dataset (https://data.mendeley.com/datasets/xrk5rfcpvg/2), and ERA5 reanalysis (https://cds.climate.copernicus.eu/).

Author contributions. S. O. conceived the study, conducted the analysis, and prepared the original draft. R. O. and W. D. provided feedback on the study design and contributed to the interpretation of the results. All authors reviewed and approved the final manuscript.

Competing interests. The authors declare that they have no conflict of interest.

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Preprint. Discussion started: 12 November 2026
© Author(s) 2026. CC BY 4.0 License.



References

Addor, N., Newman, A. J., Mizukami, N., and Clark, M. P.: The CAMELS data set: catchment attributes and meteorology for large-sample studies, Hydrology and Earth System Sciences, 21, 5293–5313, https://doi.org/10.5194/hess-21-5293-2017, 2017.

Al Bitar, A., Leroux, D., Kerr, Y. H., Merlin, O., Richaume, P., Sahoo, A., and Wood, E. F.: Evaluation of SMOS Soil Moisture Products Over Continental U.S. Using the SCAN/SNOTEL Network, IEEE Transactions on Geoscience and Remote Sensing, 50, 1572–1586, https://doi.org/10.1109/TGRS.2012.2186581, 2012.

Al-Yaari, A., Dayau, S., Chipeaux, C., Aluome, C., Kruszewski, A., Loustau, D., and Wigneron, J.-P.: The AQUI Soil Moisture Network for Satellite Microwave Remote Sensing Validation in South-Western France, Remote Sensing, 10, 1839, https://doi.org/10.3390/rs10111839, 2018.

Alday, J. G., Camarero, J. J., Revilla, J., and de Dios, V. R.: Similar diurnal, seasonal and annual rhythms in radial root expansion across two coexisting Mediterranean oak species, Tree Physiology, 40, 956–968, https://doi.org/10.1093/treephys/tpaa041, 2020.

Ardö, J.: A 10-Year Dataset of Basic Meteorology and Soil Properties in Central Sudan, Dataset Papers in Geosciences, 2013, 1–6, https://doi.org/10.7167/2013/297973, associated data set: https://doi.org/10.7167/2013/297973/dataset, 2013.

Baldocchi, D., Falge, E., Gu, L., Olson, R., Hollinger, D., Running, S., Anthoni, P., Bernhofer, C., Davis, K., Evans, R., Fuentes, J., Goldstein, A., Katul, G., Law, B., Lee, X., Malhi, Y., Meyers, T., Munger, W., Oechel, W., Paw U, K. T., Pilegaard, K., Schmid, H. P., Valentini, R., Verma, S., Vesala, T., Wilson, K., and Wofsy, S.: FLUXNET: A New Tool to Study the Temporal and Spatial Variability of Ecosystem-Scale Carbon Dioxide, Water Vapor, and Energy Flux Densities, Bulletin of the American Meteorological Society, 82, 2415–2434, https://doi.org/10.1175/1520-0477(2001)082<2415:FANTTS>2.3.CO;2, 2001.

Bell, J. E., Palecki, M. A., Baker, C. B., Collins, W. G., Lawrimore, J. H., Leeper, R. D., Hall, M. E., Kochendorfer, J., Meyers, T. P., Wilson, T., and Diamond, H. J.: U.S. Climate Reference Network Soil Moisture and Temperature Observations, Journal of Hydrometeorology, 14, 977–988, https://doi.org/10.1175/JHM-D-12-0146.1, 2013.

Beyrich, F. and Adam, W.: Site and Data Report for the Lindenberg Reference Site in CEOP – Phase I, Berichte des Deutschen Wetterdienstes 230, Deutscher Wetterdienst, Offenbach am Main, Germany, https://www.cen.uni-hamburg.de/en/icdc/data/atmosphere/docs-atmo/dwd230-ceop-report.pdf, last access: 23 July 2026; ISBN 978-3-88148-422-0, 2007.

Biddoccu, M., Ferraris, S., Opsi, F., and Cavallo, E.: Long-term monitoring of soil management effects on runoff and soil erosion in sloping vineyards in Alto Monferrato (North-West Italy), Soil and Tillage Research, 155, 176–189, https://doi.org/10.1016/j.still.2015.07.005, 2016.

Bircher, S., Skou, N., Jensen, K. H., Walker, J. P., and Rasmussen, L.: A soil moisture and temperature network for SMOS validation in western Denmark, Hydrology and Earth System Sciences, 16, 1445–1463, https://doi.org/10.5194/hess-16-1445-2012, 2012.

Blöschl, G., Blaschke, A. P., Broer, M., Bucher, C., Carr, G., Chen, X., Eder, A., Exner-Kittridge, M., Farnleitner, A., Flores-Orozco, A., Haas, P., Hogan, P., Kazemi Amiri, A., Oismüller, M., Parajka, J., Silasari, R., Stadler, P., Strauss, P., Vreugdenhil, M., Wagner, W., and Zessner, M.: The Hydrological Open Air Laboratory (HOAL) in Petzenkirchen: a hypothesis-driven observatory, Hydrology and Earth System Sciences, 20, 227–255, https://doi.org/10.5194/hess-20-227-2016, 2016.

Bogena, H. R., Montzka, C., Huisman, J. A., Graf, A., Schmidt, M., Stockinger, M., von Hebel, C., Hendricks Franssen, H.-J., van der Kruk, J., Tappe, W., Lücke, A., Baatz, R., Bol, R., Groh, J., Pütz, T., Jakobi, J., Kunkel, R., Sorg, J., and Vereecken, H.: The TERENO-Rur

https://doi.org/10.5194/essd-2026-620
Preprint. Discussion started: 12 November 2026
© Author(s) 2026. CC BY 4.0 License.



Hydrological Observatory: A Multiscale Multi-Compartment Research Platform for the Advancement of Hydrological Science, Vadose Zone Journal, 17, 1–22, https://doi.org/10.2136/vzj2018.03.0055, 2018.

Brocca, L., Melone, F., Moramarco, T., and Morbidelli, R.: Antecedent wetness conditions based on ERS scatterometer data, Journal of Hydrology, 364, 73–87, https://doi.org/10.1016/j.jhydrol.2008.10.007, 2009.

Brocca, L., Hasenauer, S., Lacava, T., Melone, F., Moramarco, T., Wagner, W., Dorigo, W., Matgen, P., Martínez-Fernández, J., Llorens, P., Latron, J., Martin, C., and Bittelli, M.: Soil moisture estimation through ASCAT and AMSR-E sensors: An intercomparison and validation study across Europe, Remote Sensing of Environment, 115, 3390–3408, https://doi.org/10.1016/j.rse.2011.08.003, 2011.

Brocca, L., Zucco, G., Mittelbach, H., Moramarco, T., and Seneviratne, S. I.: Absolute versus temporal anomaly and percent of saturation soil moisture spatial variability for six networks worldwide, Water Resources Research, 50, 5560–5576, https://doi.org/10.1002/2014WR015684, 2014.

Buchhorn, M., Lesiv, M., Tsendbazar, N.-E., Herold, M., Bertels, L., and Smets, B.: Copernicus Global Land Cover Layers–Collection 2, Remote Sensing, 12, 1044, https://doi.org/10.3390/rs12061044, 2020a.

Buchhorn, M., Smets, B., Bertels, L., De Roo, B., Lesiv, M., Tsendbazar, N.-E., Herold, M., and Fritz, S.: Land Cover 2015–2019 (raster 100 m), global, yearly – version 3, VITO [data set], version 3, https://doi.org/10.2909/c6377c6e-76cc-4d03-8330-628a03693042, 2020b.

Caldwell, T. G., Bongiovanni, T., Cosh, M. H., Jackson, T. J., Colliander, A., Abolt, C., Casteel, R., Larson, T., Scanlon, B., and Young, M. H.: The Texas Soil Observation Network: A Comprehensive Soil Moisture Dataset for Remote Sensing and Land Surface Model Validation, Vadose Zone Journal, 18, 190 034, https://doi.org/10.2136/vzj2019.04.0034, 2019.

Calvet, J.-C., Fritz, N., Froissard, F., Suquia, D., Petitpa, A., and Piguet, B.: In situ soil moisture observations for the CAL/VAL of SMOS: the SMOSMANIA network, in: 2007 IEEE International Geoscience and Remote Sensing Symposium, pp. 1196–1199, IEEE, https://doi.org/10.1109/IGARSS.2007.4423019, 2007.

Clark, M. P., Bierkens, M. F. P., Samaniego, L., Woods, R. A., Uijlenhoet, R., Bennett, K. E., Pauwels, V. R. N., Cai, X., Wood, A. W., and Peters-Lidard, C. D.: The evolution of process-based hydrologic models: historical challenges and the collective quest for physical realism, Hydrology and Earth System Sciences, 21, 3427–3440, https://doi.org/10.5194/hess-21-3427-2017, 2017.

Cook, D. R.: Soil Water and Temperature System (SWATS) Instrument Handbook, Technical Report DOE/SC-ARM-TR-063, Atmospheric Radiation Measurement Climate Research Facility, Richland, Washington, USA, https://doi.org/10.2172/1251383, 2016.

Cooper, H. M., Bennett, E., Blake, J., Blyth, E., Boorman, D., Cooper, E., Evans, J., Fry, M., Jenkins, A., Morrison, R., Rylett, D., Stanley, S., Szczykulska, M., Trill, E., Antoniou, V., Askquith-Ellis, A., Ball, L., Brooks, M., Clarke, M. A., Cowan, N., Cumming, A., Farrand, P., Hitt, O., Lord, W., Scarlett, P., Swain, O., Thornton, J., Warwick, A., and Winterbourn, B.: COSMOS-UK: national soil moisture and hydrometeorology data for environmental science research, Earth System Science Data, 13, 1737–1757, https://doi.org/10.5194/essd-13-1737-2021, 2021.

Dąbrowska-Zielińska, K., Musiał, J., Malińska, A., Budzyńska, M., Gurdak, R., Kiryła, W., Bartold, M., and Grzybowski, P.: Soil Moisture in the Biebrza Wetlands Retrieved from Sentinel-1 Imagery, Remote Sensing, 10, 1979, https://doi.org/10.3390/rs10121979, 2018.

Dai, Y., Xin, Q., Wei, N., Zhang, Y., Shangguan, W., Yuan, H., Zhang, S., Liu, S., and Lu, X.: A Global High-Resolution Data Set of Soil Hydraulic and Thermal Properties for Land Surface Modeling, Journal of Advances in Modeling Earth Systems, 11, 2996–3023, https://doi.org/10.1029/2019MS001784, 2019.

https://doi.org/10.5194/essd-2026-620
Preprint. Discussion started: 12 November 2026
© Author(s) 2026. CC BY 4.0 License.



dall'Amico, J. T., Schlenz, F., Loew, A., Mauser, W., Kainulainen, J., Balling, J. E., and Bouzinac, C.: The SMOS Validation Campaign 2010 in the Upper Danube Catchment: A Data Set for Studies of Soil Moisture, Brightness Temperature, and Their Spatial Variability Over a Heterogeneous Land Surface, IEEE Transactions on Geoscience and Remote Sensing, 51, 364–377, https://doi.org/10.1109/TGRS.2012.2196523, 2013.

Demir, I., Xiang, Z., Demiray, B., and Sit, M.: WaterBench-Iowa: a large-scale benchmark dataset for data-driven streamflow forecasting, Earth System Science Data, 14, 5605–5616, https://doi.org/10.5194/essd-14-5605-2022, 2022.

Dorigo, W., Himmelbauer, I., Aberer, D., Schremmer, L., Petrakovic, I., Zappa, L., Preimesberger, W., Xaver, A., Annor, F., Ardö, J., Baldocchi, D., Bitelli, M., Blöschl, G., Bogena, H., Brocca, L., Calvet, J.-C., Camarero, J. J., Capello, G., Choi, M., Cosh, M. C., Van De Giesen, N., Hajdu, I., Ikonen, J., Jensen, K. H., Kanniah, K. D., De Kat, I., Kirchengast, G., Kumar Rai, P., Kyrouac, J., Larson, K., Liu, S., Loew, A., Moghaddam, M., Martínez Fernández, J., Mattar Bader, C., Morbidelli, R., Musial, J. P., Osenga, E., Palecki, M. A., Pellarin, T., Petropoulos, G. P., Pfeil, I., Powers, J., Robock, A., Rüdiger, C., Rummel, U., Strobel, M., Su, Z., Sullivan, R., Tagesson, T., Varlagin, A., Vreugdenhil, M., Walker, J., Wen, J., Wenger, F., Wigneron, J. P., Woods, M., Yang, K., Zeng, Y., Zhang, X., Zreda, M., Dietrich, S., Gruber, A., Van Oevelen, P., Wagner, W., Scipal, K., Drusch, M., and Sabia, R.: The International Soil Moisture Network: serving Earth system science for over a decade, Hydrology and Earth System Sciences, 25, 5749–5804, https://doi.org/10.5194/hess-25-5749-2021, 2021.

Dorigo, W. A., Wagner, W., Hohensinn, R., Hahn, S., Paulik, C., Xaver, A., Gruber, A., Drusch, M., Mecklenburg, S., Van Oevelen, P., Robock, A., and Jackson, T.: The International Soil Moisture Network: a data hosting facility for global in situ soil moisture measurements, Hydrology and Earth System Sciences, 15, 1675–1698, https://doi.org/10.5194/hess-15-1675-2011, 2011.

Dorigo, W. A., Xaver, A., Vreugdenhil, M., Gruber, A., Hegyiová, A., Sanchis-Dufau, A. D., Zamojski, D., Cordes, C., Wagner, W., and Drusch, M.: Global Automated Quality Control of In Situ Soil Moisture Data from the International Soil Moisture Network, Vadose Zone Journal, 12, 1–21, https://doi.org/10.2136/vzj2012.0097, 2013.

Fang, K. and Shen, C.: Near-Real-Time Forecast of Satellite-Based Soil Moisture Using Long Short-Term Memory with an Adaptive Data Integration Kernel, Journal of Hydrometeorology, 21, 399–413, https://doi.org/10.1175/JHM-D-19-0169.1, 2020.

Gauch, M., Mai, J., and Lin, J.: The proper care and feeding of CAMELS: How limited training data affects streamflow prediction, Environmental Modelling & Software, 135, 104 926, https://doi.org/10.1016/j.envsoft.2020.104926, 2021.

Hajdu, I., Yule, I., Bretherton, M., Singh, R., and Hedley, C.: Field performance assessment and calibration of multi-depth AquaCheck capacitance-based soil moisture probes under permanent pasture for hill country soils, Agricultural Water Management, 217, 332–345, https://doi.org/10.1016/j.agwat.2019.03.002, 2019.

Hersbach, H., Bell, B., Berrisford, P., Hirahara, S., Horányi, A., Muñoz-Sabater, J., Nicolas, J., Peubey, C., Radu, R., Schepers, D., Simmons, A., Soci, C., Abdalla, S., Abellan, X., Balsamo, G., Bechtold, P., Biavati, G., Bidlot, J., Bonavita, M., De Chiara, G., Dahlgren, P., Dee, D., Diamantakis, M., Dragani, R., Flemming, J., Forbes, R., Fuentes, M., Geer, A., Haimberger, L., Healy, S., Hogan, R. J., Hólm, E., Janisková, M., Keeley, S., Laloyaux, P., Lopez, P., Lupu, C., Radnoti, G., de Rosnay, P., Rozum, I., Vamborg, F., Villaume, S., and Thépaut, J.-N.: The ERA5 global reanalysis, Quarterly Journal of the Royal Meteorological Society, 146, 1999–2049, https://doi.org/10.1002/qj.3803, 2020.

https://doi.org/10.5194/essd-2026-620
Preprint. Discussion started: 12 November 2026
© Author(s) 2026. CC BY 4.0 License.



Hersbach, H., Bell, B., Berrisford, P., Biavati, G., Horányi, A., Muñoz Sabater, J., Nicolas, J., Peubey, C., Radu, R., Rozum, I., Schepers, D., Simmons, A., Soci, C., Dee, D., and Thépaut, J.-N.: ERA5 hourly data on single levels from 1940 to present, Copernicus Climate Change Service (C3S) Climate Data Store (CDS) [data set], https://doi.org/10.24381/cds.adbb2d47, 2023.

Hirschi, M., Seneviratne, S. I., Alexandrov, V., Boberg, F., Boroneant, C., Christensen, O. B., Formayer, H., Orlowsky, B., and Stepanek, P.: Observational evidence for soil-moisture impact on hot extremes in southeastern Europe, Nature Geoscience, 4, 17–21, https://doi.org/10.1038/ngeo1032, 2011.

Hollinger, S. E. and Isard, S. A.: A Soil Moisture Climatology of Illinois, Journal of Climate, 7, 822–833, https://doi.org/10.1175/1520-0442(1994)007<0822:ASMCOI>2.0.CO;2, 1994.

Hunter, J. D.: Matplotlib: A 2D Graphics Environment, Computing in Science & Engineering, 9, 90–95, https://doi.org/10.1109/MCSE.2007.55, 2007.

Ikonen, J., Smolander, T., Rautiainen, K., Cohen, J., Lemmetyinen, J., Salminen, M., and Pulliainen, J.: Spatially Distributed Evaluation of ESA CCI Soil Moisture Products in a Northern Boreal Forest Environment, Geosciences, 8, 51, https://doi.org/10.3390/geosciences8020051, 2018.

Jackson, T. J., Cosh, M. H., Bindlish, R., Starks, P. J., Bosch, D. D., Seyfried, M., Goodrich, D. C., Moran, M. S., and Du, J.: Validation of Advanced Microwave Scanning Radiometer Soil Moisture Products, IEEE Transactions on Geoscience and Remote Sensing, 48, 4256–4272, https://doi.org/10.1109/TGRS.2010.2051035, 2010.

Jin, R., Li, X., Yan, B., Li, X., Luo, W., Ma, M., Guo, J., Kang, J., Zhu, Z., and Zhao, T.: A Nested Ecohydrological Wireless Sensor Network for Capturing the Surface Heterogeneity in the Midstream Areas of the Heihe River Basin, China, IEEE Geoscience and Remote Sensing Letters, 11, 2015–2019, https://doi.org/10.1109/LGRS.2014.2319085, 2014.

Kang, C.-Y., Kanniah, K. D., and Kerr, Y. H.: Calibration of SMOS Soil Moisture Retrieval Algorithm: A Case of Tropical Site in Malaysia, IEEE Transactions on Geoscience and Remote Sensing, 57, 3827–3839, https://doi.org/10.1109/TGRS.2018.2888535, 2019.

Kirchengast, G., Kabas, T., Leuprecht, A., Bichler, C., and Truhetz, H.: WegenerNet: A Pioneering High-Resolution Network for Monitoring Weather and Climate, Bulletin of the American Meteorological Society, 95, 227–242, https://doi.org/10.1175/BAMS-D-11-00161.1, 2014.

Koster, R. D., Dirmeyer, P. A., Guo, Z., Bonan, G., Chan, E., Cox, P., Gordon, C. T., Kanae, S., Kowalczyk, E., Lawrence, D., Liu, P., Lu, C.-H., Malyshev, S., McAvaney, B., Mitchell, K., Mocko, D., Oki, T., Oleson, K., Pitman, A., Sud, Y. C., Taylor, C. M., Verseghy, D., Vasic, R., Xue, Y., and Yamada, T.: Regions of Strong Coupling Between Soil Moisture and Precipitation, Science, 305, 1138–1140, https://doi.org/10.1126/science.1100217, 2004.

Kratzert, F., Klotz, D., Shalev, G., Klambauer, G., Hochreiter, S., and Nearing, G.: Towards learning universal, regional, and local hydrological behaviors via machine learning applied to large-sample datasets, Hydrology and Earth System Sciences, 23, 5089–5110, https://doi.org/10.5194/hess-23-5089-2019, 2019.

Kratzert, F., Nearing, G., Addor, N., Erickson, T., Gauch, M., Gilon, O., Gudmundsson, L., Hassidim, A., Klotz, D., Nevo, S., Shalev, G., and Matias, Y.: Caravan – A global community dataset for large-sample hydrology, Scientific Data, 10, 61, https://doi.org/10.1038/s41597-023-01975-w, 2023.

https://doi.org/10.5194/essd-2026-620
Preprint. Discussion started: 12 November 2026
© Author(s) 2026. CC BY 4.0 License.



Lebel, T., Cappelaere, B., Galle, S., Hanan, N., Kergoat, L., Levis, S., Vieux, B., Descroix, L., Gosset, M., Mougin, E., Peugeot, C., and Seguis, L.: AMMA-CATCH studies in the Sahelian region of West Africa: An overview, Journal of Hydrology, 375, 3–13, https://doi.org/10.1016/j.jhydrol.2009.03.020, 2009.

Li, B., Wang, C., Gu, X., Zhou, X., Ma, M., Li, L., Feng, Z., Ding, T., Li, X., Jiang, T., Li, X., and Zheng, X.: Accuracy calibration and evaluation of capacitance-based soil moisture sensors for a variety of soil properties, Agricultural Water Management, 273, 107 913, https://doi.org/10.1016/j.agwat.2022.107913, 2022.

Li, Q., Zhang, C., Shangguan, W., Wei, Z., Yuan, H., Zhu, J., Li, X., Li, L., Li, G., Liu, P., and Dai, Y.: LandBench 1.0: A benchmark dataset and evaluation metrics for data-driven land surface variables prediction, Expert Systems with Applications, 243, 122 917, https://doi.org/10.1016/j.eswa.2023.122917, 2024.

Marczewski, W., Slominski, J., Slominska, E., Usowicz, B., Usowicz, J., Romanov, S., Maryskevych, O., Nastula, J., and Zawadzki, J.: Strategies for validating and directions for employing SMOS data, in the Cal-Val project SWEX (3275) for wetlands, Hydrology and Earth System Sciences Discussions, 7, 7007–7057, https://doi.org/10.5194/hessd-7-7007-2010, 2010.

Mattar, C., Santamaría-Artigas, A., Durán-Alarcón, C., Olivera-Guerra, L., Fuster, R., and Borvarán, D.: The LAB-Net Soil Moisture Network: Application to Thermal Remote Sensing and Surface Energy Balance, Data, 1, 6, https://doi.org/10.3390/data1010006, 2016.

Mittelbach, H. and Seneviratne, S. I.: A new perspective on the spatio-temporal variability of soil moisture: temporal dynamics versus time-invariant contributions, Hydrology and Earth System Sciences, 16, 2169–2179, https://doi.org/10.5194/hess-16-2169-2012, 2012.

Moghaddam, M., Entekhabi, D., Goykhman, Y., Li, K., Liu, M., Mahajan, A., Nayyar, A., Shuman, D. I., and Teneketzis, D.: A Wireless Soil Moisture Smart Sensor Web Using Physics-Based Optimal Control: Concept and Initial Demonstrations, IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing, 3, 522–535, https://doi.org/10.1109/JSTARS.2010.2052918, 2010.

Morbidelli, R., Saltalippi, C., Flammini, A., Rossi, E., and Corradini, C.: Soil water content vertical profiles under natural conditions: matching of experiments and simulations by a conceptual model, Hydrological Processes, 28, 4732–4742, https://doi.org/10.1002/hyp.9973, 2014.

Nguyen, H. H., Kim, H., and Choi, M.: Evaluation of the soil water content using cosmic-ray neutron probe in a heterogeneous monsoon climate-dominated region, Advances in Water Resources, 108, 125–138, https://doi.org/10.1016/j.advwatres.2017.07.020, 2017.

Nicolai-Shaw, N., Hirschi, M., Mittelbach, H., and Seneviratne, S. I.: Spatial representativeness of soil moisture using in situ, remote sensing, and land reanalysis data, Journal of Geophysical Research: Atmospheres, 120, 9955–9964, https://doi.org/10.1002/2015JD023305, 2015.

O, S. and Orth, R.: Global soil moisture data derived through machine learning trained with in-situ measurements, Scientific Data, 8, 170, https://doi.org/10.1038/s41597-021-00964-1, 2021.

O, S., Dutra, E., and Orth, R.: Robustness of Process-Based versus Data-Driven Modeling in Changing Climatic Conditions, Journal of Hydrometeorology, 21, 1929–1944, https://doi.org/10.1175/JHM-D-20-0072.1, 2020.

O, S., Orth, R., Weber, U., and Park, S. K.: High-resolution European daily soil moisture derived with machine learning (2003–2020), Scientific Data, 9, 701, https://doi.org/10.1038/s41597-022-01785-6, 2022.

O, S., Orth, R., and Dorigo, W.: SoMoBench: a quasi-global benchmark dataset for data-driven soil moisture modelling with in situ-derived targets, https://doi.org/data in review, 2026.

https://doi.org/10.5194/essd-2026-620
Preprint. Discussion started: 12 November 2026
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Ochsner, T. E., Cosh, M. H., Cuenca, R. H., Dorigo, W. A., Draper, C. S., Hagimoto, Y., Kerr, Y. H., Larson, K. M., Njoku, E. G., Small, E. E., and Zreda, M.: State of the Art in Large-Scale Soil Moisture Monitoring, Soil Science Society of America Journal, 77, 1888–1919, https://doi.org/10.2136/sssaj2013.03.0093, 2013.

Ojo, E. R., Bullock, P., L'Heureux, J., Powers, J., McNairn, H., and Pacheco, A.: Calibration and Evaluation of a Frequency Domain Reflectometry Sensor for Real-Time Soil Moisture Monitoring, Vadose Zone Journal, 14, vzj2014.08.0114, https://doi.org/10.2136/vzj2014.08.0114, 2015.

Orth, R. and Destouni, G.: Drought reduces blue-water fluxes more strongly than green-water fluxes in Europe, Nature Communications, 9, 3602, https://doi.org/10.1038/s41467-018-06013-7, 2018.

Osenga, E. C., Arnott, J. C., Endsley, K. A., and Katzenberger, J. W.: Bioclimatic and soil moisture monitoring across elevation in a mountain watershed: Opportunities for research and resource management, Water Resources Research, 55, 2493–2503, https://doi.org/10.1029/2018WR023653, 2019.

Pedregosa, F., Varoquaux, G., Gramfort, A., Michel, V., Thirion, B., Grisel, O., Blondel, M., Prettenhofer, P., Weiss, R., Dubourg, V., Vanderplas, J., Passos, A., Cournapeau, D., Brucher, M., Perrot, M., and Duchesnay, É.: Scikit-learn: Machine Learning in Python, Journal of Machine Learning Research, 12, 2825–2830, https://jmlr.org/papers/v12/pedregosa11a.html, last access: 23 July 2026, 2011.

Petropoulos, G. P. and McCalmont, J. P.: An Operational In Situ Soil Moisture and Soil Temperature Monitoring Network for West Wales, UK: The WSMN Network, Sensors, 17, 1481, https://doi.org/10.3390/s17071481, 2017.

Ralph, F. M., Wilson, A., Alden, K., Ellis, J., Cooper, E., Paulsson, P., Kawzenuk, B., and Yao, Y.: Center for Western Weather and Water Extremes (CW3E) Surface Meteorological Observational Dataset, UC San Diego Library Digital Collections [data set], https://doi.org/10.6075/J0SX6DDH, 2022.

Rasp, S., Dueben, P. D., Scher, S., Weyn, J. A., Mouatadid, S., and Thuerey, N.: WeatherBench: A Benchmark Data Set for Data-Driven Weather Forecasting, Journal of Advances in Modeling Earth Systems, 12, e2020MS002 203, https://doi.org/10.1029/2020MS002203, 2020.

Rasp, S., Hoyer, S., Merose, A., Langmore, I., Battaglia, P., Russell, T., Sanchez-Gonzalez, A., Yang, V., Carver, R., Agrawal, S., Chantry, M., Ben Bouallegue, Z., Dueben, P., Bromberg, C., Sisk, J., Barrington, L., Bell, A., and Sha, F.: WeatherBench 2: A Benchmark for the Next Generation of Data-Driven Global Weather Models, Journal of Advances in Modeling Earth Systems, 16, e2023MS004 019, https://doi.org/10.1029/2023MS004019, 2024.

Reichstein, M., Camps-Valls, G., Stevens, B., Jung, M., Denzler, J., Carvalhais, N., and Prabhat: Deep learning and process understanding for data-driven Earth system science, Nature, 566, 195–204, https://doi.org/10.1038/s41586-019-0912-1, 2019.

Rüdiger, C., Hancock, G., Hemakumara, H. M., Jacobs, B., Kalma, J. D., Martinez, C., Thyer, M., Walker, J. P., Wells, T., and Willgoose, G. R.: Goulburn River experimental catchment data set, Water Resources Research, 43, W10 403, https://doi.org/10.1029/2006WR005837, 2007.

Sánchez, N., Martínez-Fernández, J., Scaini, A., and Pérez-Gutiérrez, C.: Validation of the SMOS L2 Soil Moisture Data in the REMEDHUS Network (Spain), IEEE Transactions on Geoscience and Remote Sensing, 50, 1602–1611, https://doi.org/10.1109/TGRS.2012.2186971, 2012.

https://doi.org/10.5194/essd-2026-620
Preprint. Discussion started: 12 November 2026
© Author(s) 2026. CC BY 4.0 License.



Schaefer, G. L., Cosh, M. H., and Jackson, T. J.: The USDA Natural Resources Conservation Service Soil Climate Analysis Network (SCAN), Journal of Atmospheric and Oceanic Technology, 24, 2073–2077, https://doi.org/10.1175/2007JTECHA930.1, 2007.

Senanayake, I. P., Pathira Arachchilage, K. R. L., Yeo, I.-Y., Khaki, M., Han, S.-C., and Dahlhaus, P. G.: Spatial Downscaling of Satellite-Based Soil Moisture Products Using Machine Learning Techniques: A Review, Remote Sensing, 16, 2067, https://doi.org/10.3390/rs16122067, 2024.

Seneviratne, S. I., Lüthi, D., Litschi, M., and Schär, C.: Land–atmosphere coupling and climate change in Europe, Nature, 443, 205–209, https://doi.org/10.1038/nature05095, 2006.

Seneviratne, S. I., Corti, T., Davin, E. L., Hirschi, M., Jaeger, E. B., Lehner, I., Orlowsky, B., and Teuling, A. J.: Investigating soil moisture–climate interactions in a changing climate: A review, Earth-Science Reviews, 99, 125–161, https://doi.org/10.1016/j.earscirev.2010.02.004, 2010.

Shen, C., Laloy, E., Elshorbagy, A., Albert, A., Bales, J., Chang, F.-J., Ganguly, S., Hsu, K.-L., Kifer, D., Fang, Z., Fang, K., Li, D., Li, X., and Tsai, W.-P.: HESS Opinions: Incubating deep-learning-powered hydrologic science advances as a community, Hydrology and Earth System Sciences, 22, 5639–5656, https://doi.org/10.5194/hess-22-5639-2018, 2018.

Smith, A. B., Walker, J. P., Western, A. W., Young, R. I., Ellett, K. M., Pipunic, R. C., Grayson, R. B., Siriwardena, L., Chiew, F. H. S., and Richter, H.: The Murrumbidgee soil moisture monitoring network data set, Water Resources Research, 48, W07 701, https://doi.org/10.1029/2012WR011976, 2012.

Su, Z., Wen, J., Dente, L., van der Velde, R., Wang, L., Ma, Y., Yang, K., and Hu, Z.: The Tibetan Plateau observatory of plateau scale soil moisture and soil temperature (Tibet-Obs) for quantifying uncertainties in coarse resolution satellite and model products, Hydrology and Earth System Sciences, 15, 2303–2316, https://doi.org/10.5194/hess-15-2303-2011, 2011.

Tagesson, T., Fensholt, R., Guiro, I., Rasmussen, M. O., Huber, S., Mbow, C., Garcia, M., Horion, S., Sandholt, I., Holm-Rasmussen, B., Göttsche, F.-M., Ridler, M., Boke-Olén, N., Olsen, J. L., Ehammer, A., Madsen, M., Olesen, F., and Ardö, J.: Ecosystem properties of semiarid savanna grassland in West Africa and its relationship with environmental variability, Global Change Biology, 21, 250–264, https://doi.org/10.1111/gcb.12734, 2015.

Van Cleve, K., Chapin, F. S., and Ruess, R.: Bonanza Creek Long Term Ecological Research Project Climate Database, University of Alaska Fairbanks [data set], https://www.lter.uaf.edu/, last access: 23 July 2026, 2015.

van de Giesen, N., Hut, R., and Selker, J.: The Trans-African Hydro-Meteorological Observatory (TAHMO), WIREs Water, 1, 341–348, https://doi.org/10.1002/wat2.1034, 2014.

van der Velde, R., Benninga, H.-J. F., Retsios, B., Vermunt, P. C., and Salama, M. S.: Twelve years of profile soil moisture and temperature measurements in Twente, the Netherlands, Earth System Science Data, 15, 1889–1910, https://doi.org/10.5194/essd-15-1889-2023, 2023.

Van Looy, K., Bouma, J., Herbst, M., Koestel, J., Minasny, B., Mishra, U., Montzka, C., Nemes, A., Pachepsky, Y. A., Padarian, J., Schaap, M. G., Tóth, B., Verhoef, A., Vanderborght, J., Van Der Ploeg, M. J., Weihermüller, L., Zacharias, S., Zhang, Y., and Vereecken, H.: Pedotransfer Functions in Earth System Science: Challenges and Perspectives, Reviews of Geophysics, 55, 1199–1256, https://doi.org/10.1002/2017RG000581, 2017.

Wasko, C., Nathan, R., and Peel, M. C.: Changes in Antecedent Soil Moisture Modulate Flood Seasonality in a Changing Climate, Water Resources Research, 56, e2019WR026 300, https://doi.org/10.1029/2019WR026300, 2020.

https://doi.org/10.5194/essd-2026-620
Preprint. Discussion started: 12 November 2026
© Author(s) 2026. CC BY 4.0 License.



Woods, M., Cobley, A., and GROW Consortium: GROW Soil Moisture Data, University of Dundee [data set], https://doi.org/10.15132/10000156, 2020.

Yang, K., Qin, J., Zhao, L., Chen, Y., Tang, W., Han, M., Zhu, L., Chen, Z., Lv, N., Ding, B., Wu, H., and Lin, C.: A Multiscale Soil Moisture and Freeze–Thaw Monitoring Network on the Third Pole, Bulletin of the American Meteorological Society, 94, 1907–1916, https://doi.org/10.1175/BAMS-D-12-00203.1, 2013.

Zech, C., Schöne, T., Illigner, J., Stolarczuk, N., Queißer, T., Köppl, M., Thoss, H., Zubovich, A., Sharshebaev, A., Zakhidov, K., Toshpulatov, K., Tillayev, Y., Olimov, S., Paiman, Z., Unger-Shayesteh, K., Gafurov, A., and Moldobekov, B.: Hydrometeorological data from ROMPS network in Central Asia, GFZ Data Services [data set], https://doi.org/10.5880/GFZ.1.2.2020.002, 2020.

Zeri, M., Alvalá, R. C. S., Carneiro, R., Cunha-Zeri, G., Costa, J. M., Rossato Spatafora, L., Urbano, D., Vall-Llossera, M., and Marengo, J.: Tools for Communicating Agricultural Drought over the Brazilian Semiarid Using the Soil Moisture Index, Water, 10, 1421, https://doi.org/10.3390/w10101421, 2018.

Zeri, M., Costa, J. M., Urbano, D., Cuartas, L. A., Ivo, A., Marengo, J., and Alvalá, R. C. S.: A soil moisture dataset over the Brazilian semiarid region, Mendeley Data [data set], version 2, https://doi.org/10.17632/xrk5rfcpvg.2, 2020.

Zhao, T., Shi, J., Lv, L., Xu, H., Chen, D., Cui, Q., Jackson, T. J., Yan, G., Jia, L., Chen, L., Zhao, K., Zheng, X., Zhao, L., Zheng, C., Ji, D., Xiong, C., Wang, T., Li, R., Pan, J., Wen, J., Yu, C., Zheng, Y., Jiang, L., Chai, L., Lu, H., Yao, P., Ma, J., Lv, H., Wu, J., Zhao, W., Yang, N., Guo, P., Li, Y., Hu, L., Geng, D., and Zhang, Z.: Soil moisture experiment in the Luan River supporting new satellite mission opportunities, Remote Sensing of Environment, 240, 111 680, https://doi.org/10.1016/j.rse.2020.111680, 2020.

Zheng, C., Jia, L., and Zhao, T.: A 21-year dataset (2000–2020) of gap-free global daily surface soil moisture at 1-km grid resolution, Scientific Data, 10, 139, https://doi.org/10.1038/s41597-023-01991-w, 2023.

Zreda, M., Shuttleworth, W. J., Zeng, X., Zweck, C., Desilets, D., Franz, T., and Rosolem, R.: COSMOS: the COsmic-ray Soil Moisture Observing System, Hydrology and Earth System Sciences, 16, 4079–4099, https://doi.org/10.5194/hess-16-4079-2012, 2012.

https://doi.org/10.5194/essd-2026-620
Preprint. Discussion started: 12 November 2026
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Table 1. ISMN networks contributing observations to the final SoMoBench targets. The number of contributing stations is calculated across all three target layers; stations contributing to multiple layers are counted only once.

Network	Region(s)	Stations (n)	Reference
AMMA-CATCH	Africa	7	Lebel et al. (2009)
ARM	North America	33	Cook (2016)
BDF-Saxony	Europe	4	–
BFG-Nw	Europe	1	–
BIEBRZA-S-1	Europe	9	Dąbrowska-Zielińska et al. (2018)
BNZ-LTER	North America	9	Van Cleve et al. (2015)
Berlin	Europe	18	–
CALABRIA	Europe	5	Brocca et al. (2011)
CAMPANIA	Europe	2	Brocca et al. (2011)
COSMOS	Africa, Europe, North America	7	Zreda et al. (2012)
COSMOS-UK	Europe	48	Cooper et al. (2021)
CTP-SMTMN	Asia	39	Yang et al. (2013)
CW3E	North America	20	Ralph et al. (2022)
DAHRA	Africa	1	Tagesson et al. (2015)
DWD	Europe	19	–
FLUXNET-AMERIFLUX	North America	7	Baldocchi et al. (2001)
FMI	Europe	11	Ikonen et al. (2018)
FR-Aqui	Europe	4	Al-Yaari et al. (2018)
GROW	Europe	32	Woods et al. (2020)
GTK	Europe	6	–
HOAL	Europe	15	Blöschl et al. (2016)
HOBE	Europe	20	Bircher et al. (2012)
HSC-SEOLMACHEON	Asia	1	–
HYDROL-NET-PERUGIA	Europe	2	Morbidelli et al. (2014)
HiWATER-EHWSN	Asia	1	Jin et al. (2014)
ICN	North America	1	Hollinger and Isard (1994)
IIT-KANPUR	Asia	1	–
IPE	Europe	2	Alday et al. (2020)
KIHS-CMC	Asia	5	–
KIHS-SMC	Asia	2	–

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Table 1 continued.

Network	Region(s)	Stations (n)	Reference
LAB-net	South America	3	Mattar et al. (2016)
LABFLUX	Europe	4	–
MAQU	Asia	23	Su et al. (2011)
METEROBS	Europe	1	–
MOL-RAO	Europe	2	Beyrich and Adam (2007)
MySMNet	Asia	1	Kang et al. (2019)
NAQU	Asia	8	Su et al. (2011)
NGARI	Asia	16	Su et al. (2011)
NVE	Europe	1	–
OZNET	Oceania	35	Smith et al. (2012)
PTSMN	Oceania	4	Hajdu et al. (2019)
REMEDHUS	Europe	14	Sánchez et al. (2012)
RISMA	North America	23	Ojo et al. (2015)
ROMPS	Asia	9	Zech et al. (2020)
RSMN	Europe	20	–
RU-ADDFerti	Europe	3	–
Ru-CFR	Europe	2	–
SASMAS	Oceania	9	Rüdiger et al. (2007)
SCAN	North America	220	Schaefer et al. (2007)
SD-DEM	Africa	1	Ardö (2013)
SKKU	Asia	5	Nguyen et al. (2017)
SMN-SDR	Asia	24	Zhao et al. (2020)
SMOSMANIA	Europe	22	Calvet et al. (2007)
SNOTEL	North America	473	Al Bitar et al. (2012)
SOILSCAPE	North America, Oceania	72	Moghaddam et al. (2010)
SONTE-China	Asia	12	Li et al. (2022)
STEMS	Europe	10	Biddoccu et al. (2016)
SWEX-POLAND	Europe	5	Marczewski et al. (2010)
TAHMO	Africa	65	van de Giesen et al. (2014)
TERENO	Europe	5	Bogena et al. (2018)
TWENTE	Europe	30	van der Velde et al. (2023)
TxSON	North America	9	Caldwell et al. (2019)

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Table 1 continued.

Network	Region(s)	Stations (n)	Reference
UDC-SMOS	Europe	11	dall'Amico et al. (2013)
UMBRIA	Europe	12	Brocca et al. (2009)
UMSUOL	Europe	1	–
USCRN	North America	115	Bell et al. (2013)
VAS	Europe	2	Jackson et al. (2010)
VDS	Asia	4	–
WATERLINE	Europe	2	–
WEGENERNET	Europe	10	Kirchengast et al. (2014)
WSMN	Europe	2	Petropoulos and McCalmont (2017)
XMS-CAT	Europe	19	–
iRON	North America	7	Osenga et al. (2019)

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Table 2. Meteorological forcing variables included in SoMoBench. Forcings are distributed as complete daily time series for 2000–2024 at target grid cells.

Variable	Description	Units
`tp`	Total precipitation	$\mathrm{mm\,d^{-1}}$
`t2m`	Near-surface air temperature at 2 m	K
`qair`	Near-surface specific humidity	$\mathrm{kg\,kg^{-1}}$
`ssrd`	Surface downward shortwave radiation	$\mathrm{W\,m^{-2}}$
`strd`	Surface downward longwave radiation	$\mathrm{W\,m^{-2}}$
`sp`	Surface pressure	Pa
`ws`	Magnitude of the daily-mean 10 m wind vector	$\mathrm{m\,s^{-1}}$