

# Downscaling Soil Moisture Using Time-Specific Adaptable Machine Learning Models

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**Abstract**  
Soil moisture is a key element in understanding Earth system responses, but accurate observations at the regional to global scales are limited. This study presents a novel machine learning approach to downscale soil moisture from global to regional scales. We use a novel framework to integrate satellite-based soil moisture data with ground-based observations to improve the accuracy of soil moisture estimates at the regional scale.

**Data Validation**  
Figure 2: Data validation results showing the distribution of soil moisture (mm) across the United States. The figure includes a map of the United States with color-coded regions representing different soil moisture levels, and a corresponding line graph showing the distribution of soil moisture over time.

**NASMo-TIAM Dataset**  
The NASMo-TIAM dataset is a novel soil moisture dataset derived from the National Soil Moisture Initiative (NSMI) and the Time-Aware Soil Moisture (TIAM) dataset. It provides high-resolution soil moisture data for the contiguous United States from 2000 to 2020, derived from satellite-based observations and ground-based measurements.

**Workflow and Input Data Collection**  
The workflow involves the collection of input data from various sources, including satellite-based soil moisture data, ground-based observations, and meteorological data. The data is then processed and analyzed using machine learning models to downscale soil moisture to the regional scale.

**Data Availability and Related Publications**  
The dataset is available on the Earth System Research Federation (ESRF) data portal. Related publications include: Llamas, R., & Vargas, R. (2023). Downscaling soil moisture using machine learning models. *Journal of Hydrology*, 615, 108500. Vargas, R., & Llamas, R. (2023). Downscaling soil moisture using machine learning models. *Journal of Hydrology*, 615, 108500.

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## ABSTRACT

Soil moisture is a key element in understanding Earth's systems dynamics. Soil moisture information in a fine-resolution gridded format and on short periods that consider seasonal changes and standardization of input data has not been explored widely. We use Random Forest to downscale coarse-resolution satellite-derived soil moisture estimates (0.25 deg) based on their relationship with a set of static and dynamic covariates used as predictors. We provide surface soil moisture (0-5cm depth) estimates at 250 m of spatial resolution on 16-day periods from mid-2002 to December 2020 at a subcontinental level through the North America Soil Moisture Dataset Derived from Time-Specific Adaptable Machine Learning Models (NASMo-TiAM 250 m). NASMo-TiAM 250 m predictions are evaluated through cross-validation with ESA CCI reference data and independent ground-truth validation using North American Soil Moisture Database (NASMD) records. We found a correlation coefficient and RMSE derived from cross-validation of 0.91 and  $0.03 \text{ m}^3 \text{ m}^{-3}$  respectively. For ground-truth validation, we found an overall correlation of 0.4 and an RMSE of  $0.11 \text{ m}^3 \text{ m}^{-3}$ . Additionally, we observed a correlation of 0.38 and RMSE of  $0.12 \text{ m}^3 \text{ m}^{-3}$  between reference ESA CCI data and NASMD. NASMo-TiAM provides a curated soil moisture dataset and a flexible workflow with the potential for executing alternative machine-learning approaches with different sets of predictors.

# WORKFLOW AND INPUT DATA COLLECTION

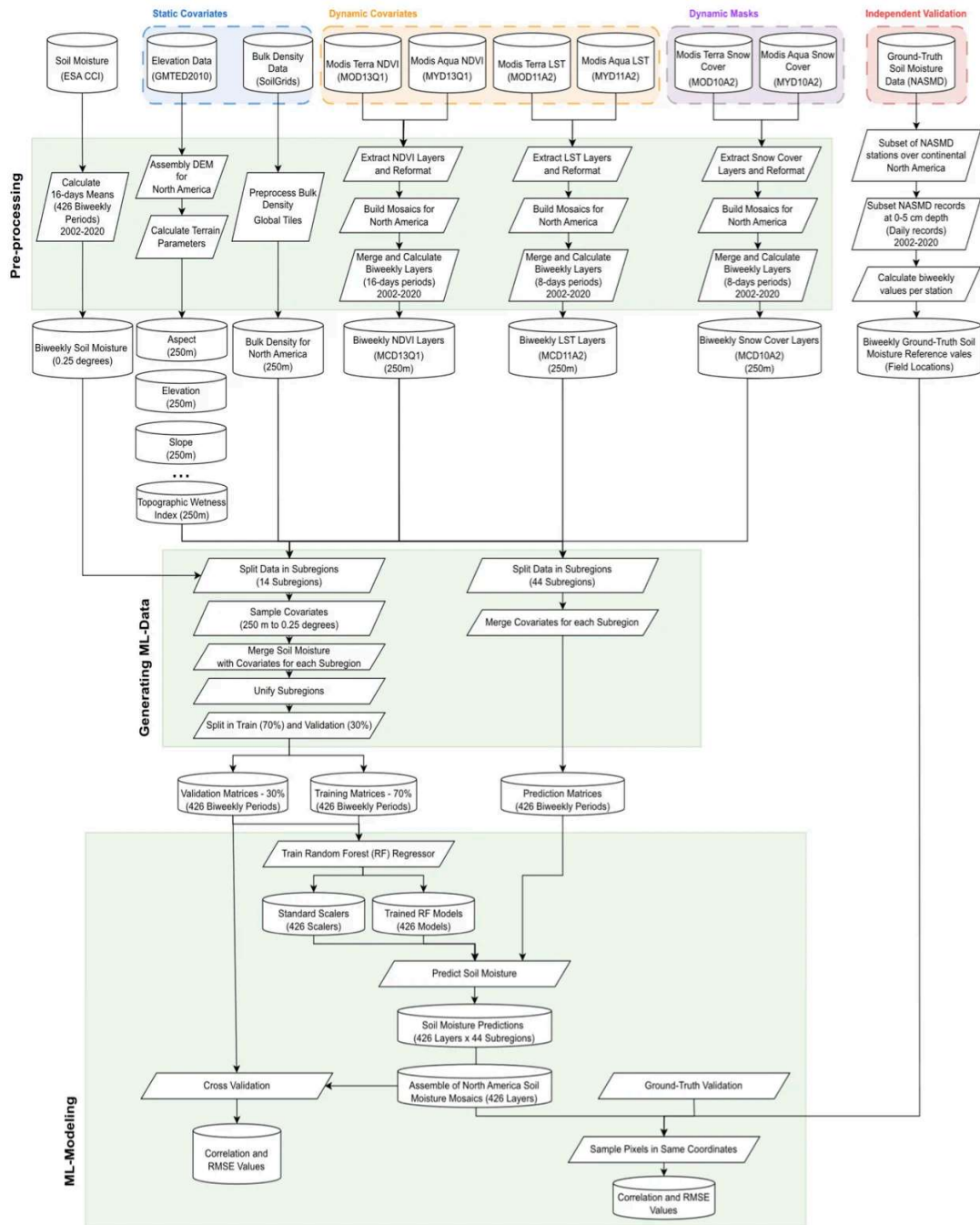


Figure 1 - Workflow for downscaling soil moisture

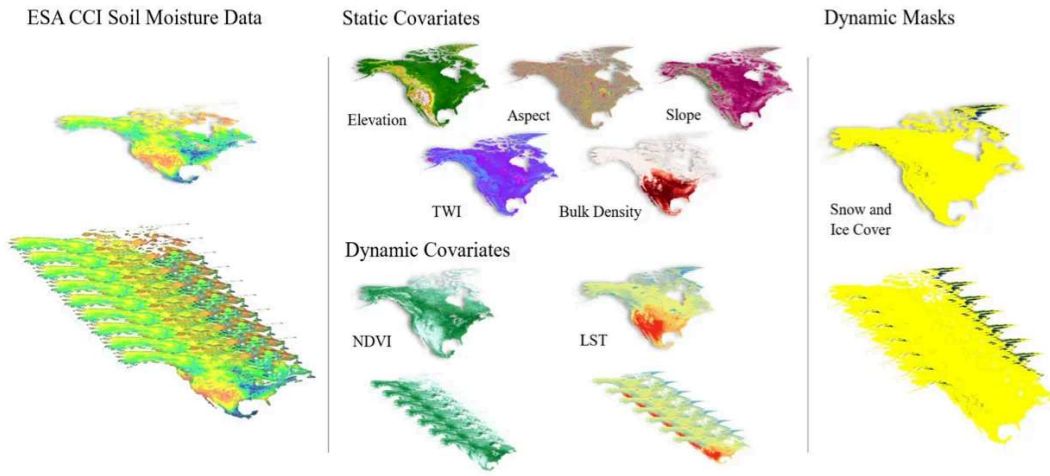


Figure 2 - Input data collection

# DATA VALIDATION

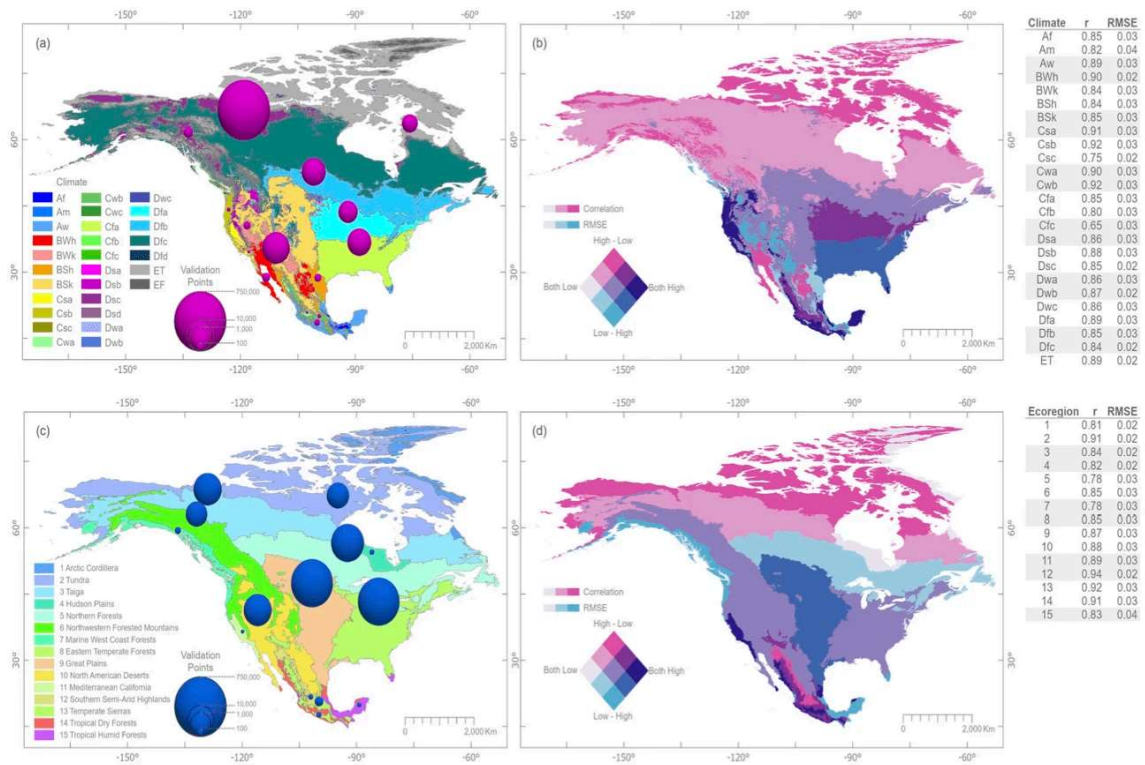


Figure 3 - Cross-validation results between ESA CCI reference data and RF soil moisture predictions at 250 m. (a) Climate zones of North America and the total number of points used for validation along the study time frame (2002-2020); (b) Distribution of correlation and RMSE values per climate zone; (c) Terrestrial ecoregions of North America and the total number of validation points along the study time frame (2002-2020); (d) Distribution of correlation and RMSE values per terrestrial ecoregion.

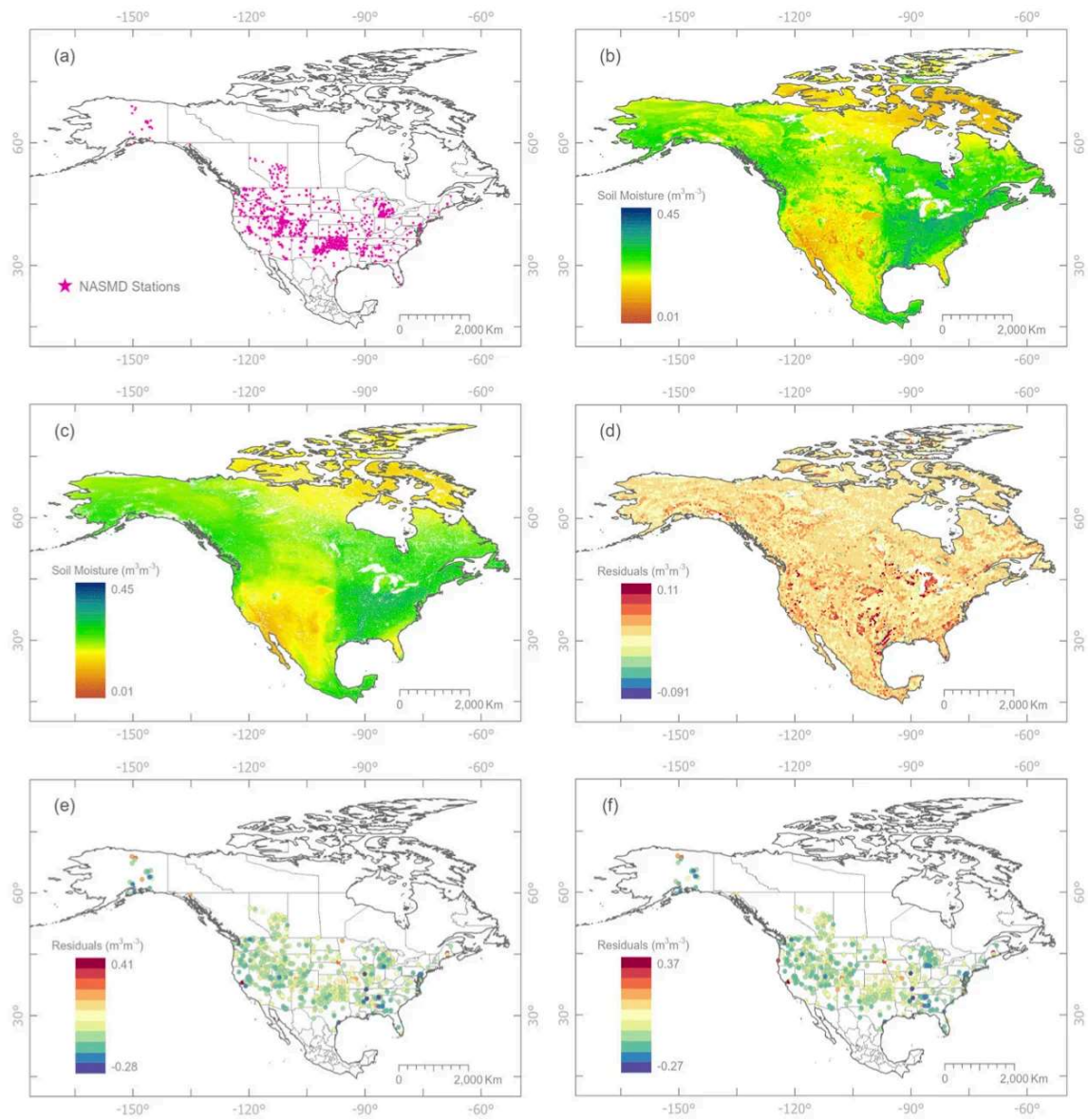


Figure 4 - (a) Distribution of 864 NASMD stations used for ground-truth validation; (b) ESA CCI mean soil moisture values derived from 426 biweekly layers; (c) RF predictions mean soil moisture values derived from 426 biweekly period; (d) Mean cross-validations residuals; (e) Mean residuals for 257 biweekly periods between ESA CCI and NASMD data; (f) Mean residuals for 257 biweekly periods between RF predictions and NASMD data.

## NASMO-TIAM DATASET

NASMo-TIAM (North America Soil Moisture Dataset Derived from Time-Specific Adaptable Machine Learning Models) dataset holds gridded estimates of surface soil moisture (0-5 cm depth) at a spatial resolution of 250 meters over 16-day intervals from mid-2002 to December 2020 for North America. The model employed Random Forests to downscale coarse-resolution soil moisture estimates (0.25 deg) from the European Space Agency Climate Change Initiative (ESA CCI) based on their correlation with a set of static (terrain parameters, bulk density) and dynamic covariates (Normalized Difference Vegetation Index, land surface temperature). NASMo-TIAM 250m predictions were evaluated through cross-validation with ESA CCI reference data and independent ground-truth validation using North American Soil Moisture Database (NASMD) records. The data are provided in cloud optimized GeoTIFF format.

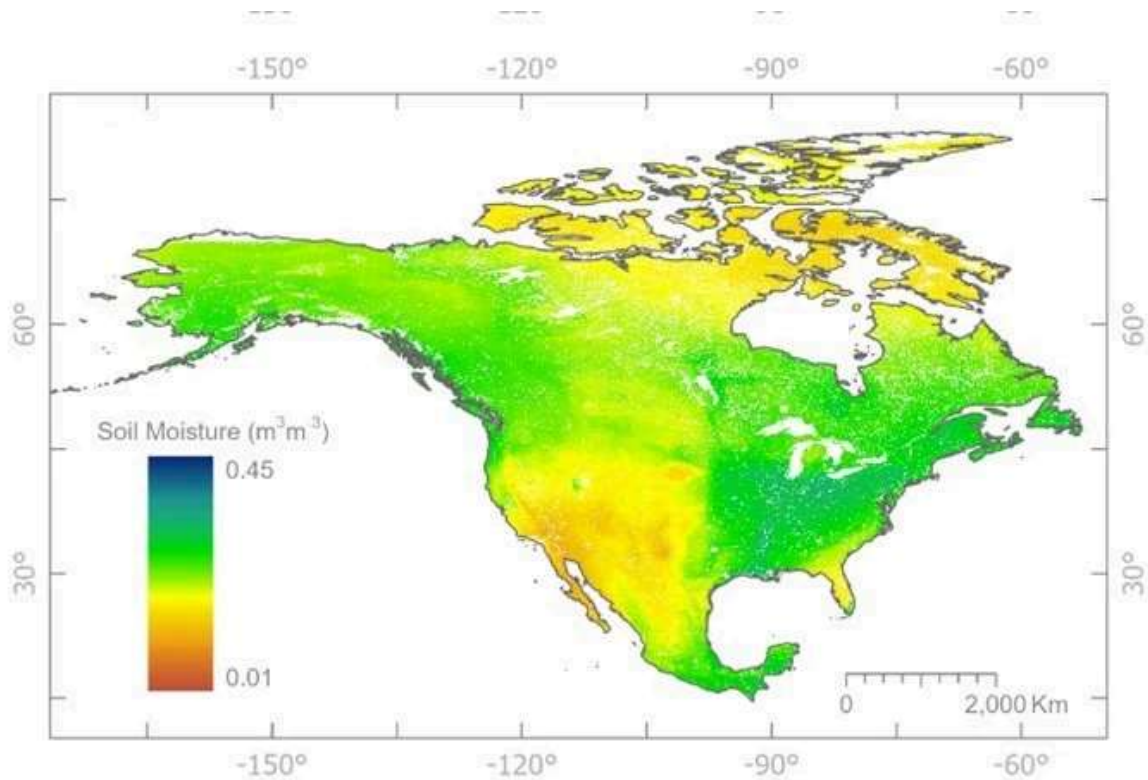


Figure 5 - Soil moisture across North America at 250 meters resolution biweekly.

## DATA AVAILABILITY AND RELATED PUBLICATIONS

### Data availability:

Llamas, R., P. Olaya, M. Taufer, and R. Vargas. 2024. NASMo-TiAM 250m 16-day North America Surface Soil Moisture Dataset. ORNL DAAC, Oak Ridge, Tennessee, USA. <https://doi.org/10.3334/ORNLDAAC/2326>

### Related publications:

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Rorabaugh, D., M. Guevara, R. Llamas, J. Kitson, R. Vargas, and M. Taufer. 2019. SOMOSPIE: A Modular SOil MOisture SPatial Inference Engine Based on Data-Driven Decisions. Pages 1–10 2019 15th International Conference on eScience (eScience). [arxiv.org](http://arxiv.org).

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# TRANSCRIPT

