COMMENTARY

High-resolution soil moisture mapping through passive microwave remote sensing downscaling

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Soil moisture (SM) is a crucial geophysical parameter that connects the global terrestrial water, energy, and carbon cycles. Remote sensing, as a valuable tool for earth monitoring, provides an efficient way to capture large-scale SM information. Among various remote sensing techniques, microwave remote sensing, particularly passive microwave remote sensing, is capable of all-day and all-weather observation, penetrating short vegetation and shallow soil layers, and also sensitive to soil permittivity, making it the most effective means of large-scale SM mapping.[1] Passive microwave sensors primarily receive natural radiation from the ground objects. However, due to the weak radiation energy from land surface, they require large antenna sizes, resulting in observations with coarse spatial resolution (dozens of kilometers) which are difficult to meet the demand for fine-scale SM in many fields, such as agricultural management. To address this limitation, spatial downscaling technology has gradually become a key focus in the study of passive microwave remote sensing of SM. The core of spatial downscaling methods is to improve the spatial resolution of passive microwave SM data, which typically has a coarse spatial resolution of around 25 - 50 km. Current downscaling methods can enhance this resolution to a finer scale, often reaching resolutions between 0.5 and 5 km. By leveraging the rich spatial details of high-resolution downscaling factors, researchers have been able to improve the spatial resolution of passive microwave SM data to better support applications that require fine-scale SM information. This paper introduces the three most common downscaling strategies including empirical methods, semi-empirical methods, and physical methods, then discusses the challenges in spatial downscaling of passive microwave SM data, and finally provides prospects for its future development (Figure 1).

SATELLITE SM DOWNSCALING METHODS

Over the past few decades, various SM downscaling (also known as SM disaggregation) methods have been proposed, aiming to convert SM data

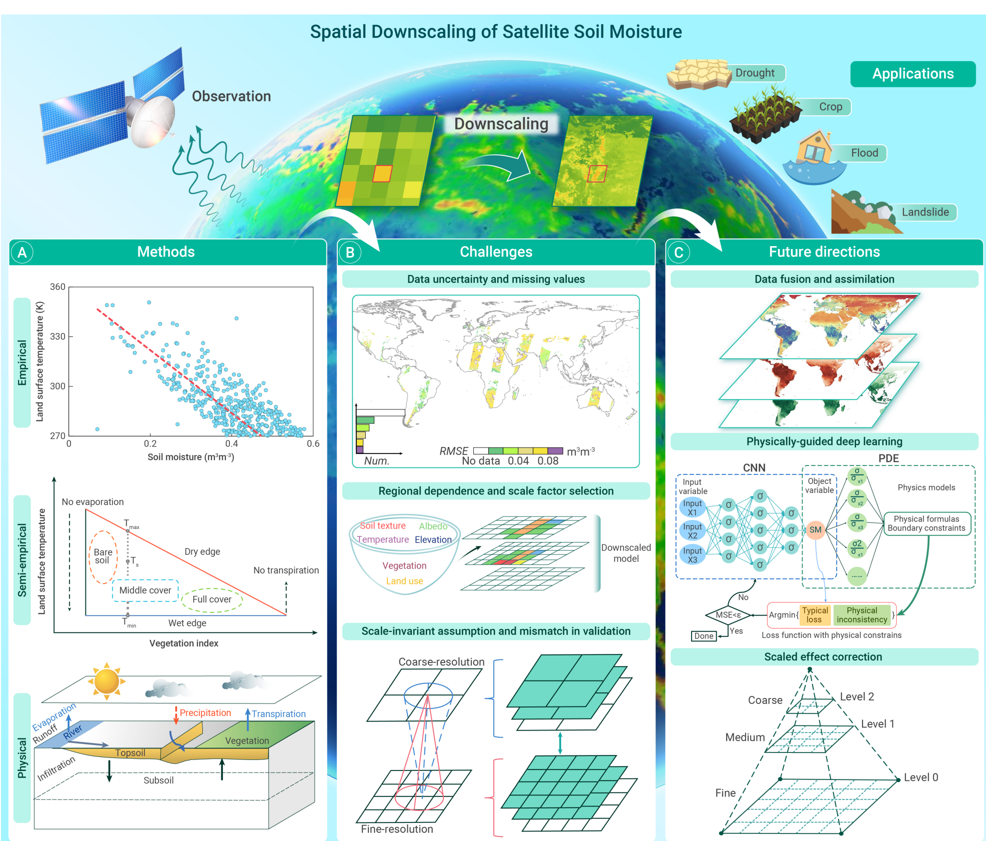

Figure 1. Spatial downscaling of passive microwave SM data: (A) downscaling methods, (B) challenges, and (C) future directions.

from coarse resolution to fine resolution for a more detailed description of surface moisture conditions.[2] These methods typically assume a scale-invariant relationship between SM and auxiliary parameters from coarse scale to fine scale. First, the relationship is established at a coarse resolution and subsequently applied to fine-resolution auxiliary parameters to obtain high-resolution SM. These auxiliary parameters are collectively termed scale factors. Based on the approach of establishing the relationship between passive microwave SM and scale factors, spatial downscaling methods can be roughly divided into three categories: empirical methods, semi-empirical methods, and physical methods (Figure 1A).[3]

Empirical methods use statistical correlations to describe the relationship between SM and scale factors based on existing observational data and prior knowledge for the establishment of downscaling models. Common empirical downscaling models include polynomial regression, geographically weighted regression, and machine learning algorithms such as random forests and neural networks.

Although empirical methods are highly operable, they lack clear physical mechanisms, making it difficult to understand the interactions between various scale factors and SM. Semi-empirical methods, such as the triangle method and the evaporative fraction approach, start from a physical background and empirically simplify physical model parameters using simulated or experimental data. These methods offer a compromise between the complexity of physical methods and the simplicity of empirical methods. Although they reduce the computational burden compared to physical methods, they still face challenges in parameter selection and simplification, which can introduce uncertainties in the downscaling results. Physical methods, such as the land surface process models, assimilate passive microwave SM into these models by introducing high-resolution downscaling factors to produce high-resolution SM outputs. However, uncertainties in model structure and parameters can limit the accuracy of these methods.

Across all these methods, the choice of scale factors is crucial. Frequently used scale factors include land surface temperature (LST), vegetation indices such as normalized difference vegetation index (NDVI) and enhanced vegetation index (EVI), surface albedo, soil properties (e.g., texture), and terrain attributes like slope and aspect. Optical remote sensing products, especially those from MODIS and Landsat, provide high-resolution LST and vegetation indices, which are widely used in downscaling methods.

CHALLENGES OF CURRENT METHODS

Despite significant progress in spatial downscaling of passive microwave SM, several challenges remain (Figure 1B):

(1) Data uncertainty and missing values. The accuracy of the original passive microwave SM products and scale factor data directly impacts downscaling results. Improving retrieval algorithms for these datasets is essential for more precise downscaled SM. Additionally, issues such as satellite orbit gaps and quality control of retrieval algorithms result in missing values in passive microwave SM products. Scale factors obtained from optical remote sensing data are often affected by cloud cover, resulting in data gaps. These gaps, along with other limitations, make obtaining high-resolution and continuous SM data challenging.

(2) Regional dependence of methods and selection of scale factors. Most satellite SM downscaling methods are designed for specific land surfaces and climate conditions, displaying significant regional dependency that hinders their global applications. Another key factor affecting the accuracy of downscaled SM is the selection of scale factors with most downscaling methods relying on high-resolution optical/thermal infrared data inputs, such as surface temperature, vegetation indices, and surface albedo. However, different downscaling methods exhibit varying sensitivities to the uncertainty of these input data, which not only increases the difficulty of constructing the downscaling relationship models, but also limits the application of these methods on a global scale.

(3) Scale-invariant assumption and spatial mismatch in validation. Current satellite SM downscaling methods often assume that the relationship between SM and scale factors remains unchanged at both the original (coarse-scale) and target (fine-scale) resolutions. However, this assumption may not hold due to spatial heterogeneity and nonlinear effects during the downscaling process. Validation of downscaled SM is further complicated by the spatial mismatch between pixel-based downscaled data and point-based ground measurements. This scale gap poses challenges for evaluating the reliability of downscaled SM.

FUTURE DIRECTIONS

Future directions for spatial downscaling of passive microwave SM will focus on enhancing the universality, accuracy, and understanding of the physical mechanisms underlying these methods (Figure 1C):

(1) Optimizing multi-source data fusion and assimilation technology. To address the issue of data uncertainty and missing values, future research will focus on optimizing multi-source data fusion, combining passive microwave, active microwave, optical, and thermal infrared datasets. These fusion techniques, along with advanced assimilation approaches such as ensemble Kalman filter, and four-dimensional variational assimilation, are expected to enhance the accuracy and spatiotemporal continuity of downscaled SM.[4]

(2) Developing physically-guided machine learning methods. Enhancing the universality of downscaling methods requires developing models that are adaptable to various land surfaces and climates. Physically-guided machine learning techniques, which automatically select and optimize relevant scale factors, offer potential to improve the robustness of downscaling methods in diverse environments. Moreover, introducing regional awareness and super-resolution techniques with physical constraints can reduce reliance on region-specific data, expanding the applicability of downscaling methods globally.

(3) Correcting scale effects in downscaling methods. To address the limitation of scale-invariant assumptions, it is essential to develop cross-scale models that account for spatial heterogeneity and nonlinearity. Investigating the interactions between SM and scale factors at various scales will help establish cross-scale physical-statistical hybrid models. Considering scale effects through multi-scale data fusion and non-linear scale transformation functions can more accurately describe SM variations at different spatial resolutions. A practical solution for validation is to develop advanced upscaling methods to upscale the spatial scale of ground SM to that of downscaled SM, ensuring more reliable evaluation of the downscaling methods.

Additionally, improving the fusion of ground point SM data with satellite/airborne remote sensing data is crucial. A promising approach is the recently developed Generate high Resolution, Accurate, Seamless data using Point-Surface fusion (GRASPS) method, which enhances the spatial and temporal resolution of SM data by combining point-based ground measurements with grid-based satellite observations.[5]

SUMMARY AND OUTLOOKS

This study presents the current status, challenges, and future directions of spatial downscaling of passive microwave SM data. Future efforts in this field will focus on optimizing multi-source data fusion and assimilation techniques, developing physically-guided machine learning methods as well as new downscaling methods that take into account scale effects. These developments are expected to enhance the accuracy and universality of satellite SM downscaling methods, thus better serving various fields such as agriculture, forestry, meteorology, hydrology, among others.

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DECLARATION OF INTERESTS

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