Synergizing active and passive microwave observations for enhanced soil moisture mapping

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Dear Editor,

Soil moisture (SM) is widely recognized as an essential variable in water-carbon coupling of terrestrial ecosystems, playing a significant role in various domains including drought monitoring, crop yield estimation, and carbon uptake,[1] and is highlighted as an Essential Climate Variable by World Meteorological Organization. Compared to *in situ* observations with limited spatial coverage, active and passive microwave satellite observations have emerged as the most promising technologies for large-scale SM mapping, benefiting from their stronger penetration capabilities through vegetation and clouds than those of optical and thermal satellites.

Both active and passive microwave observations have been shown to complement each other in SM mapping.[2] However, most existing efforts on SM retrieval have focused on using a single observation mode, either passive or active (e.g., passive mode including SMAP (Soil Moisture Active Passive), SMOS (Soil Moisture and Ocean Salinity), and AMSR2 (Advanced Microwave Scanning Radiometer 2), or active mode including ASCAT (Advanced Scatterometer) and Sentinel-1) rather than integrating both types of observation from multiple passive/active sensors. The latter has been proven to further improve the accuracy and spatial/temporal resolution of SM inversion. This letter presents a synthesis of the enhancements, limitations, and future directions for SM mapping by blending active and passive microwave observations, illustrated with selected examples (Figure 1).

ACTIVE AND PASSIVE MICROWAVE FUSION APPROACHES FOR SM ESTIMATION

The synergy of active and passive microwave observations for SM mapping mainly involves combining coarse-resolution passive microwave data with active microwave data at higher (e.g., synthetic aperture radar) or similar (scatterometer) spatial scales. The former relies on the high-resolution properties of radar backscatter (i.e., σ) and on its generally assumed linear correlation with passive brightness temperature (TB) which is significantly influenced by SM dynamics, to derive high-resolution SM. However, typically these approaches do not fully leverage the complementary nature of active and passive microwave signals across varying surface conditions. Here, we highlight the benefit of integrating active and passive microwave observations at the same or similar spatial scales, as this has been shown to significantly improve SM estimation across varying vegetation densities compared to using a single sensor.[3] The benefits of integrating these observations for SM inversion stem from the distinct response mechanisms of active and passive measurements to SM, which provide complementary information. Though passive microwaves primarily respond to the changes in dielectric properties which are dominated by SM and canopy water, it is also notably affected by surface temperature (i.e., canopy and soil temperature). In contrast, active microwaves are more susceptible to vegetation structure and surface roughness features, but not to surface temperature. The different sensitivities of passive and active observations to surface characteristics allow for improved SM mapping across different surface conditions when they are combined. This is done along three main approaches (Figure 1A): (1) physical-based integration of active and passive observations, (2) machine learning to integrate active and passive observations and ancillary information, and (3) statistical blending of single-sensor from multiple active and passive satellite missions.

Current approaches to physics-based integration typically involve merging radiative transfer models for TB with scattering models for σ within a unified inversion framework.[3] These methods necessitate collocated active and passive observations and rely on accurate representation of vegetation conditions, including canopy water content (CWC) and temperature. The primary benefit lies in the complementary sensitivities of TB and σ to SM, which enhance the robustness of SM retrievals. These complementary sensitivities also provide additional observational constraints that help alleviate the ill-posed nature of the inversion. Regularization is achieved by constraining vegetation-related parameters using ancillary data or physically plausible ranges. However, current studies based on that approach face limitations due to uncertainties in forward models, including model structural simplifications, parameter uncertainties (e.g., surface roughness and vegetation properties), and scale mismatches with satellite observations, challenges in accurately parameterizing vegetation at large scales, and the need for precise temporal and geometric alignment between sensors.

Machine learning integration approaches merge active σ and passive TB by building nonlinear relationships among multi-frequency and multi-angular signals with SM.[4] These methods typically require extensive, quality-controlled training datasets, and a wide range of auxiliary variables to implicitly account for factors like vegetation and temperature, which are explicitly modeled in physical-based approaches. Though machine learning enhances flexibility without complex physical modeling, its effectiveness is limited by the representativeness of the training data concerning diverse biome/climate conditions, and the constraints of physical interpretability.

Regarding the integration of multiple sensors, existing approaches focus on producing long-term SM records by merging different active and passive single-satellite retrievals through systematic rescaling and error-based weighting. This strategy is at the basis of the ESA CCI (European Space Agency Climate Change Initiative) and Copernicus Climate Change Service (C3S) SM products,[5] which establishes a common SM climatology across sensors by applying techniques such as cumulative distribution function (CDF) matching and triple-collocation (TC) derived error estimates along with the least squares method, to enhance temporal coherence and minimize inter-sensor biases. The main strengths include not only extended temporal coverage but also the elimination of the necessity for simultaneous observations from multiple sensors, but their performance is still constrained by the quality of parent SM retrievals, the used SM climatology, and the fusion strategy.

OBSTACLES TO MAKING PROGRESS

Despite substantial advances in active and passive combination for SM mapping, several obstacles continue to hinder the accuracy, robustness, and scalability of current methods (Figure 1B).

(1) Insufficient parameterization of surface and vegetation conditions. In all three approaches, uncertainties in vegetation status regarding water and temperature are recognized as major sources of retrieval uncertainty. For example, some microwave SM retrieval algorithms use optical vegetation indices such as NDVI (Normalized Difference Vegetation Index) to estimate vegetation water content based on empirical modeling, but these indices do not well represent the actual vegetation water status in diverse biomes. In most SM retrieval algorithms, canopy temperature is assumed to equal soil

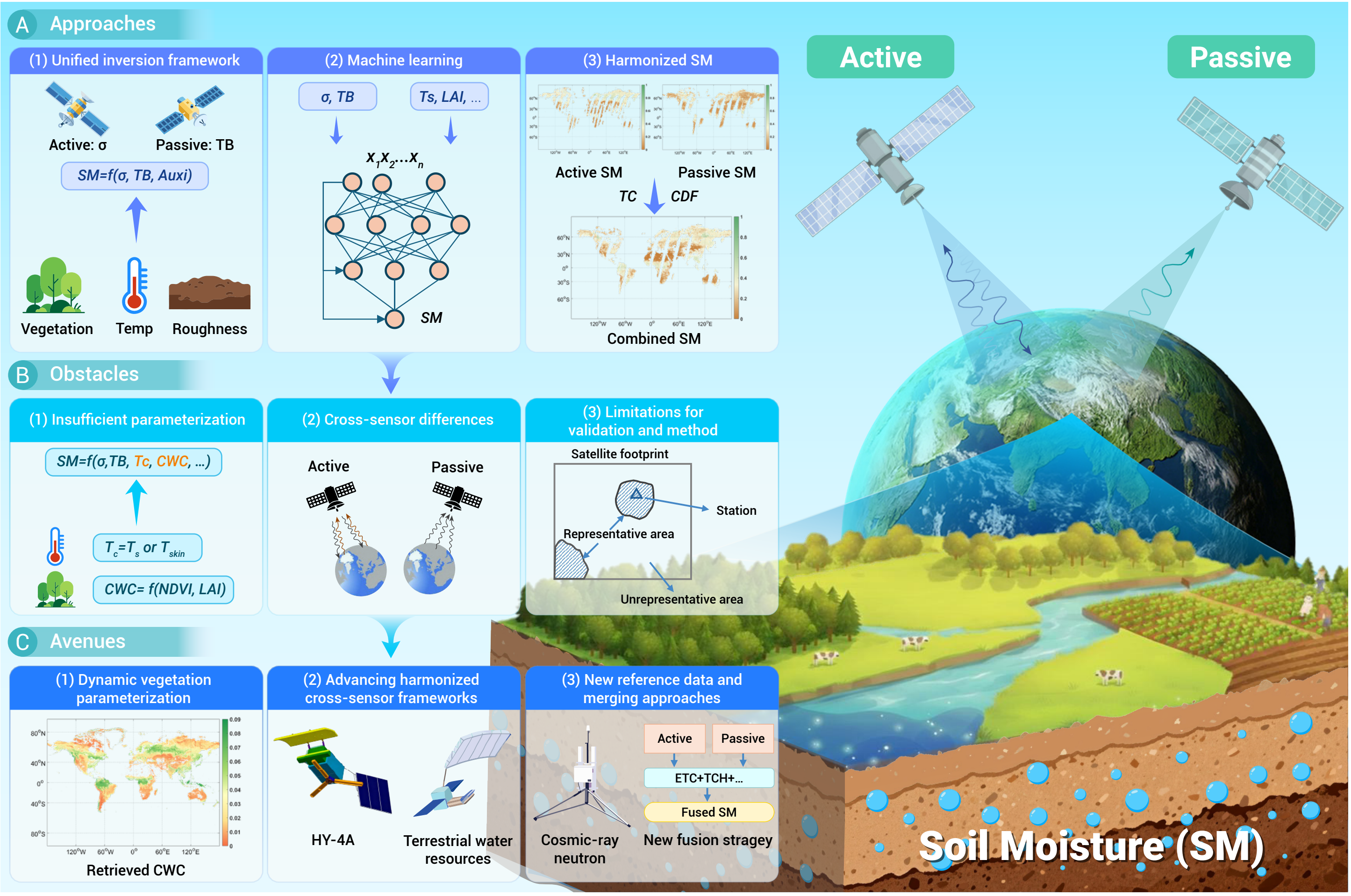

Figure 1. Integration of active and passive microwave observations for SM mapping.

temperature, which will introduce uncertainties as there may be significant differences between the two parameters particularly during the day.

(2) Cross-sensor differences that reduce consistency in the integrations. Active and passive microwave sensors on diverse satellites often differ in incident angle, temporal sampling, frequency/wavelength, and the temporal continuity of their platforms due to the evolving satellite constellation. These differences further result in discrepancies in sensor response and error structure for SM retrieval. The SMAP mission aimed to address these limitations in active-passive integration for SM mapping, but the radar sensor unfortunately ceased operations just three months after its launch in 2015.

(3) Limitations in reference data and statistical merging. There exists a spatial mismatch between point-based *in situ* measurements and pixel-based satellite SM, limiting the calibration of physical models and reducing the representativeness of training datasets for machine learning approaches. Blended products face the same constraint when evaluating long-term consistency. In addition, statistical merging methods such as TC rely on assumptions such as error independence which are not always met in practice. As a result, merged products may inherit residual errors from the input datasets.

FUTURE AVENUES

Future advancements in SM mapping through the integration of active and passive microwave measurements will focus on dynamic parameterization, advancing harmonizations, and new reference data and fusion methods (Figure 1C):

(1) Dynamic vegetation parameterization. Recent advancements in satellite derived global CWC and canopy temperature products have enabled more accurate dynamic parameterization of vegetation in both physical and machine learning integration models. Additionally, microwave vegetation properties (e.g., vegetation optical depth as the proxy of canopy water) are also more suitable for microwave models than optical indices. Machine learning techniques can also be integrated into physical models to improve parameter optimization. Such hybrid approaches can enhance the physical consistency of SM inversion under varying ground conditions.

(2) Advancing harmonized cross-sensor frameworks. Future missions that integrate passive radiometers and active radars can deal with the issue of cross sensor differences. For example, both the newly launched Chinese oceanographic satellite HY-4A (launched in November 2024) and the upcoming Terrestrial Water Resources satellite feature active and passive microwave sensors on a single platform. Such platforms will provide truly co-located active-passive observations and reduce cross-sensor inconsistencies.

(3) New reference data and merging approaches. New source SM data can complement existing *in situ* networks to support more comprehensive validations on active-passive derived SM products, such as cosmic-ray neutron sensing by providing improved spatial representativeness to satellite footprints, particularly in heterogeneous regions. Additionally, as an emerging SM detection technique, GNSS-R (Global Navigation Satellite System Reflectometry) offers a viable option for integration due to its complementary nature in active-passive fusion. For the fusion strategy, various mathematical methods, such as Extended TC (ETC), Three-Cornered Hat (TCH), and double instrumental variable (IVd), can be integrated to achieve improved fusion weights. Meanwhile, newly developed techniques that synergize machine learning and interpolation methods can be employed to address missing values that do not conform to the assumptions of these mathematical methods, resulting in seamless fusion weights and enhanced quality of the merged SM products.

SUMMARY AND OUTLOOKS

This letter highly summarized the recent progress, challenges, and future directions for SM mapping by integrating active and passive microwave observations. Future improvements could involve the inclusion of newly developed operational vegetation canopy water and temperature products into the parameterization, utilizing hybrid physical and machine learning approaches, introducing new reference data, and employing new fusion strategies. Such efforts are expected to improve SM mapping via active and passive microwave measurements, thereby enhancing support for eco-hydrology applications in terrestrial ecosystems.

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AUTHOR CONTRIBUTIONS

All authors contributed to the manuscript and approved the final version.

DECLARATION OF INTERESTS

The authors declare no competing interests.