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Editorial

Microwave Remote Sensing of Soil Moisture

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1. Introduction

Soil moisture is an important component of the global terrestrial ecosystem and has been recognized as an Essential Climate Variable (ECV) by the Global Climate Observing System (GCOS) [1]. The change in soil moisture content is a critical representation and driving factor of the terrestrial water cycle which has a significant impact on the spatial distribution and intensity of land evapotranspiration, rainfall, and runoff processes, and thus affects a series of important issues related to sustainable development, such as water resources and food security, drought and flood disasters, soil erosion, and ecological degradation [2–4]. Therefore, obtaining accurate spatiotemporal distribution of soil moisture is both necessary and highly interesting.

Microwave remote sensing, in both active and passive forms, is one of the most effective ways to detect soil moisture content on a large scale. Over the past few decades, significant efforts have been made to develop empirical/semi-empirical/theoretical models, retrieval algorithms, downscaling methods, and validation strategies related to the microwave remote sensing of soil moisture [5–12]. Following the turn of the century, a series of microwave-based satellites/sensors have been successfully launched (Figure 1), such as the passive Soil Moisture and Ocean Salinity (SMOS), Advanced Microwave Scanning Radiometer-Earth Observing System (AMSR-E), AMSR2, Fengyun (FY)-3B/C/D, the active Advanced Scatterometer (ASCAT), Sentinel-1, Advanced Land Observing Satellite-2 (ALOS-2), Gaofen-3 (GF-3), and the active-passive Soil Moisture Active Passive (SMAP), and Aquarius. Therefore, satellite soil moisture products have become increasingly abundant, greatly promoting the various application of satellite soil moisture datasets [13–15]. Despite numerous studies and achievements in this field, great challenges remain, such as the spatial resolution, retrieval accuracy, and validation strategies related to satellite soil moisture datasets.

This Special Issue aims to present the most recent scientific advances in the theories, models, algorithms, and products associated with the microwave remote sensing of soil moisture. Ten articles are published in this Special Issue, covering research progress on the following topics: (1) downscaling passive microwave-based soil moisture products, (2) estimating soil moisture from active microwave observations, (3) presenting some new algorithms (freeze–thaw state detection algorithm) and models (soil dielectric models) that are closely related to the microwave remote sensing of soil moisture, (4) evaluating

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microwave-based soil moisture products, (5) reviewing the state-of-the-art techniques and algorithms used to estimate and improve the quality of soil moisture estimations.

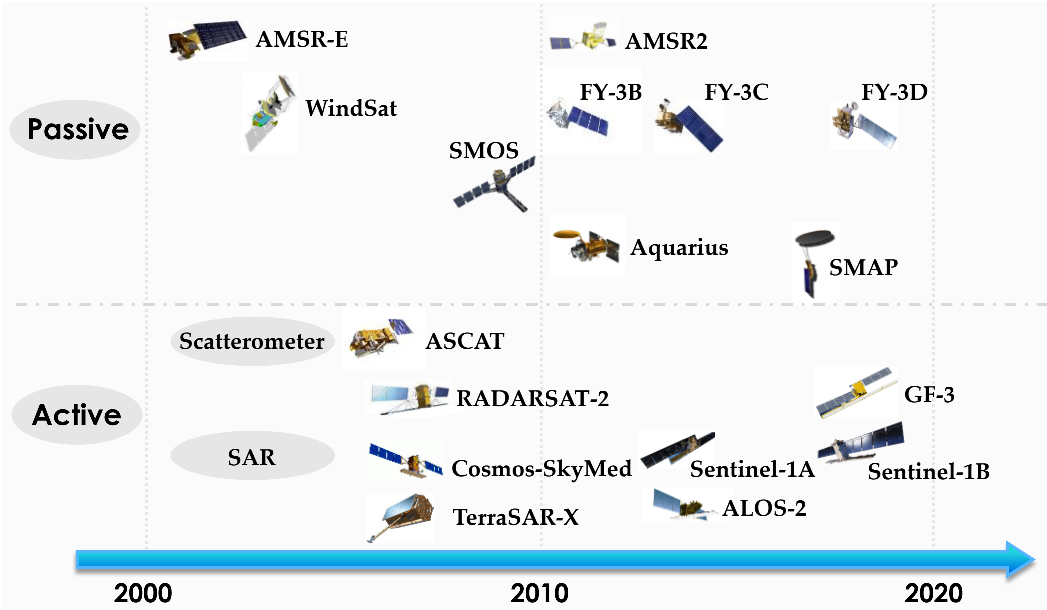

Figure 1. The primary microwave satellites/sensors that have been used to estimate soil moisture since the 2000. Note that both active and passive microwave sensors are mounted on the SMAP and Aquarius missions.

2. Highlights of the Research Articles

Brightness temperature has strong sensitivity to soil moisture [16], making passive microwave remote sensing a valuable tool to estimate soil moisture globally [17]. A number of passive microwave-based soil moisture products, such as SMAP, SMOS, AMSR2, FY-3, are available to the public. However, the coarse spatial resolution of such products (often dozens of kilometers) limits their various applications in the field and at a local scale. Three papers published in this Special Issue address this issue. Zhao et al. [18] evaluated four commonly used auxiliary variables, including NDVI (Normalized Difference Vegetation Index), LST (Land Surface Temperature), TVDI (Temperature Vegetation Dryness Index), and SEE (Soil Evaporative Efficiency), against in situ soil moisture in an arid region of China (Heihe River Basin). They found that SEE was an optimal auxiliary variable for the scaling and mapping of soil moisture, and the combination of multiple auxiliary variables (LST, NDVI, and SEE) was recommended for improving the scaling and mapping accuracy of soil moisture. Llamas et al. [19] proposed a modular spatial inference framework, which was the foundation of a cyberinfrastructure tool named SOil MOisture SPatial Inference Engine (SOMOSPIE), to downscale ESA CCI soil moisture products to 1 km using terrain parameters and examined the skill of two modeling methods, i.e., Kernel-Weighted K-Nearest Neighbor (KKNN) and Random Forest (RF). The results indicated that the SOMOSPIE framework provided a feasible approach to downscaling satellite soil moisture data, and RF performed better in the cross-validation compared to the reference ESA CCI data, but as part of independent validation, KKNN had a slightly higher consistency with ground soil moisture observations. In addition, a soil moisture retrieval and spatiotemporal fusion model (SMRFM) was proposed by Jiang et al. [20] to reduce the dependence of the method on the optical/thermal infrared data. They successfully downscaled the AMSR-E soil moisture from 25 km to 1 km using the MODIS-derived soil moisture and the SMRFM over the Central Tibetan Plateau.

Compared to passive microwave remote sensing, active microwave remote sensing, e.g., the synthetic aperture radar (SAR), can provide soil moisture estimates with much finer spatial resolution but are negatively affected by the geometry of the land surface (e.g., surface roughness and vegetation structure). Therefore, it is still a challenge to obtain SM retrievals with a high accuracy via active microwave measurements. In Dong et al. [21], the response of radar signal to surface parameters was analyzed using the database simulated from the advanced integral equation model (AIEM), and soil moisture was retrieved from Sentinel-1 using empirical models and machine learning methods. It was found the machine learning algorithms performed much better than the empirical models, and the skill of the RF algorithm surpassed that of the other machine learning approaches. Two hybrid methodologies, namely improving a change detection approach with regard to vegetation, and combining a change detection approach with a neural network algorithm, were proposed and tested using Sentinel-1 and Sentinel-2 data in the study by Nativel et al. [22]. Their results indicated that using hybrid algorithms (particularly change detection via a neural network) could improve the accuracy of estimating soil moisture content.

Furthermore, previous studies generally focused on estimating soil moisture in mineral soils since the soil dielectric models used in soil moisture retrieval algorithms were usually mineral-soil-based models. Zhang et al. [23] compared the performance of nine soil dielectric models, four of which incorporate soil organic matter (SOM) in organic soil in Alaska within the framework of the SMAP single-channel algorithm at vertical polarization (SCA-V). Using the SMAP SCA-V algorithm, they reported that the Mironov 2009 and Mironov 2019 models were the best choices for mineral soils (SOM $< 15\%$) and organic soils (SOM $\geq 15\%$), respectively. Meanwhile, there are large uncertainties in soil moisture retrievals when the soil becomes frozen. Thus, soil moisture values are often masked in satellite soil moisture products such as SMAP, SMOS, and AMSR2. In Lv et al. [24], a new freeze–thaw state detection algorithm was developed based on the daily variation of the SMAP H-pol brightness temperature. The physical foundation of the algorithm lied in the fact that the difference in the microwave brightness temperature between 6 a.m. (descending overpass) and 6 p.m. (ascending overpass) was relatively small over frozen soil owing to the large penetration depth, resulting in a higher temperature stability in deeper soils.

Moreover, microwave-based soil moisture products have been extensively evaluated in previous studies using in situ observations. However, most research has ignored the possible vertical mismatch between in situ data and satellite retrievals. Yang et al. [25] investigated the stratification characteristics of in situ soil moisture and assessed SMOS L2, SMOS-IC SMAP L2, SMAP L4 soil moisture products using multilayer in situ data (5, 10, 20, 5.08, 10.16, 20.32 cm) collected from the International Soil Moisture Network (ISMN). They discovered that (1) the differences in soil moisture content between layers were close to or even beyond the 0.04 $m^3\ m^{-3}$ nominal retrieval accuracy of SMOS and SMAP; (2) satellite products showed the highest correlation and the smallest bias with 5/5.08 cm in situ data, and the SMAP L4 product was closest to in situ measurements compared to the other datasets.

In addition, a good summary of the state-of-the-art progress in the microwave remote sensing of soil moisture is of great interest to the soil moisture research community. Two review papers were published in this Special Issue. In Wu and Wen [26], the research progress in observing and simulating L-band microwave emissions, ground soil moisture measurements, and soil moisture retrieval from L-band passive microwave observations over the Third Pole, i.e., the Tibetan Plateau, was summarized. Moreover, Liu and Yang [27] presented a systematic review of the primary methodologies for detecting soil moisture content and the current approaches used to enhance the quality of soil moisture products.

3. Conclusions and Outlook

This Special Issue entitled "Microwave Remote Sensing of Soil Moisture" covers a wide range of research on the satellite detection of soil moisture, including developing retrieval algorithms and downscaling methods, comparing soil dielectric models, freeze–thaw state detection approaches, and satellite soil moisture products. The theories, methods, validations, and applications of satellite soil moisture datasets are reviewed in detail. Notably, there is much room for improvement regarding algorithms and datasets related to the microwave remote sensing of soil moisture and their applications in various disciplines. The selected papers should help the soil moisture research community to better understand the current development status and future trends of microwave remote sensing of soil moisture.

The following aspects could be considered in future research: (1) developing new methods (e.g., upscaling method) for validating satellite soil moisture products, particularly in regions with high spatial heterogeneity; (2) developing new technologies to identify and suppress the influence of radio frequency interference and open water to further improve the quality of microwave signals used for estimating soil moisture; (3) combining active and passive microwave, multi-polarization, and multi-frequency observations to alleviate ill-posed problems, and improve the spatial resolution of soil moisture; (4) developing P-band related theoretical technologies to obtain deeper soil moisture and soil moisture profile information; (5) using bistatic radar (e.g., upcoming Tandem-L) to decouple the effects of soil moisture and other perturbing parameters (e.g., surface roughness) to obtain more reliable soil moisture data with a high spatial resolution.

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References

1. Mason, P.J.; Zillman, J.W.; Simmons, A.; Lindstrom, E.J.; Harrison, D.E.; Dolman, H.; Bojinski, S.; Fischer, A.; Latham, J.; Rasmussen, J.; et al. *Implementation Plan for the Global Observing System for Climate in Support of the UNFCCC (2010 Update)*; Word Meteorological Organization (WMO): Geneva, Switzerland, 2010.
2. Brocca, L.; Zhao, W.; Lu, H. High-resolution observations from space to address new applications in hydrology. *Innovation* **2023**, *4*, 100437. [CrossRef] [PubMed]
3. Yang, H.; Wang, Q.; Zhao, W.; Tong, X.; Atkinson, P.M. Reconstruction of a global 9 km, 8-day SMAP surface soil moisture dataset during 2015–2020 by spatiotemporal fusion. *J. Remote Sens.* **2022**, *2022*, 9871246. [CrossRef]
4. Wang, F.; Harindintwali, J.D.; Wei, K.; Shan, Y.; Mi, Z.; Costello, M.J.; Grunwald, S.; Feng, Z.; Wang, F.; Guo, Y.; et al. Climate change: Strategies for mitigation and adaptation. *Innov. Geosci.* **2023**, *1*, 100015. [CrossRef]
5. Chaubell, M.J.; Yueh, S.H.; Dunbar, R.S.; Colliander, A.; Chen, F.; Chan, S.K.; Entekhabi, D.; Bindlish, R.; O'Neill, P.E.; Asanuma, J.; et al. Improved SMAP dual-channel algorithm for the retrieval of soil moisture. *IEEE Trans. Geosci. Remote Sens.* **2020**, *58*, 3894–3905. [CrossRef]
6. Zeng, J.; Chen, K.S.; Cui, C.; Bai, X. A physically based soil moisture index from passive microwave brightness temperatures for soil moisture variation monitoring. *IEEE Trans. Geosci. Remote Sens.* **2020**, *58*, 2782–2795. [CrossRef]
7. Bauer-Marschallinger, B.; Freeman, V.; Cao, S.; Paulik, C.; Schaufler, S.; Stachl, T.; Modanesi, S.; Massari, C.; Ciabatta, L.; Brocca, L.; et al. Toward global soil moisture monitoring with Sentinel-1: Harnessing assets and overcoming obstacles. *IEEE Trans. Geosci. Remote Sens.* **2019**, *57*, 520–539. [CrossRef]
8. Kim, S.B.; Van Zyl, J.J.; Johnson, J.T.; Moghaddam, M.; Tsang, L.; Colliander, A.; Dunbar, R.S.; Jackson, T.J.; Jaruwatanadilok, S.; West, R.; et al. Surface soil moisture retrieval using the L-band synthetic aperture radar onboard the soil moisture active–passive satellite and evaluation at core validation sites. *IEEE Trans. Geosci. Remote Sens.* **2017**, *55*, 1897–1914. [CrossRef]
9. Ma, C.; Li, X.; Chen, K.S. The discrepancy between backscattering model simulations and radar observations caused by scaling issues: An uncertainty analysis. *IEEE Trans. Geosci. Remote Sens.* **2019**, *57*, 5356–5372. [CrossRef]
10. Peng, J.; Loew, A.; Zhang, S.; Wang, J.; Niesel, J. Spatial downscaling of satellite soil moisture data using a vegetation temperature condition index. *IEEE Trans. Geosci. Remote Sens.* **2015**, *54*, 558–566. [CrossRef]
11. Zhao, W.; Sánchez, N.; Lu, H.; Li, A. A spatial downscaling approach for the SMAP passive surface soil moisture product using random forest regression. *J. Hydrol.* **2018**, *563*, 1009–1024. [CrossRef]
12. Ma, H.; Li, X.; Zeng, J.; Zhang, X.; Dong, J.; Chen, N.; Fan, L.; Sadeghi, M.; Frappart, F.; Liu, X.; et al. An assessment of L-band surface soil moisture products from SMOS and SMAP in the tropical areas. *Remote Sens. Environ.* **2023**, *284*, 113344. [CrossRef]

13. Peng, C.; Zeng, J.; Chen, K.S.; Li, Z.; Ma, H.; Zhang, X.; Shi, P.; Wang, T.; Yi, L.; Bi, H. Global spatiotemporal trend of satellite-based soil moisture and its influencing factors in the early 21st century. *Remote Sens. Environ.* **2023**, *291*, 113569. [CrossRef]
14. Jung, M.; Reichstein, M.; Ciais, P.; Seneviratne, S.I.; Sheffield, J.; Goulden, M.L.; Bonan, G.; Cescatti, A.; Chen, J.; De Jeu, R.; et al. Recent decline in the global land evapotranspiration trend due to limited moisture supply. *Nature* **2010**, *467*, 951–954. [CrossRef]
15. Rigden, A.J.; Mueller, N.D.; Holbrook, N.M.; Pillai, N.; Huybers, P. Combined influence of soil moisture and atmospheric evaporative demand is important for accurately predicting US maize yields. *Nat. Food* **2020**, *1*, 127–133. [CrossRef] [PubMed]
16. Ma, C.; Li, X.; Wang, J.; Wang, C.; Duan, Q.; Wang, W. A comprehensive evaluation of microwave emissivity and brightness temperature sensitivities to soil parameters using qualitative and quantitative sensitivity analyses. *IEEE Trans. Geosci. Remote Sens.* **2017**, *55*, 1025–1038. [CrossRef]
17. Ma, H.; Zeng, J.; Chen, N.; Zhang, X.; Cosh, M.H.; Wang, W. Satellite surface soil moisture from SMAP, SMOS, AMSR2 and ESA CCI: A comprehensive assessment using global ground-based observations. *Remote Sens. Environ.* **2019**, *231*, 111215. [CrossRef]
18. Zhao, Z.; Jin, R.; Kang, J.; Ma, C.; Wang, W. Using of Remote Sensing-Based Auxiliary Variables for Soil Moisture Scaling and Mapping. *Remote Sens.* **2022**, *14*, 3373. [CrossRef]
19. Llamas, R.M.; Valera, L.; Olaya, P.; Taufer, M.; Vargas, R. Downscaling Satellite Soil Moisture Using a Modular Spatial Inference Framework. *Remote Sens.* **2022**, *14*, 3137. [CrossRef]
20. Jiang, H.; Chen, S.; Li, X.; Wu, J.; Zhang, J.; Wu, L. A Novel Method for Long Time Series Passive Microwave Soil Moisture Downscaling over Central Tibet Plateau. *Remote Sens.* **2022**, *14*, 2902. [CrossRef]
21. Dong, L.; Wang, W.; Jin, R.; Xu, F.; Zhang, Y. Surface Soil Moisture Retrieval on Qinghai-Tibetan Plateau Using Sentinel-1 Synthetic Aperture Radar Data and Machine Learning Algorithms. *Remote Sens.* **2023**, *15*, 153. [CrossRef]
22. Nativel, S.; Ayari, E.; Rodriguez-Fernandez, N.; Baghdadi, N.; Madelon, R.; Albergel, C.; Zribi, M. Hybrid methodology using sentinel-1/sentinel-2 for soil moisture estimation. *Remote Sens.* **2022**, *14*, 2434. [CrossRef]
23. Zhang, R.; Chan, S.; Bindlish, R.; Lakshmi, V. A Performance Analysis of Soil Dielectric Models over Organic Soils in Alaska for Passive Microwave Remote Sensing of Soil Moisture. *Remote Sens.* **2023**, *15*, 1658. [CrossRef]
24. Lv, S.; Wen, J.; Simmer, C.; Zeng, Y.; Guo, Y.; Su, Z. A Novel Freeze-Thaw State Detection Algorithm Based on L-Band Passive Microwave Remote Sensing. *Remote Sens.* **2022**, *14*, 4747. [CrossRef]
25. Yang, N.; Xiang, F.; Zhang, H. The Characterization of the Vertical Distribution of Surface Soil Moisture Using ISMN Multilayer In Situ Data and Their Comparison with SMOS and SMAP Soil Moisture Products. *Remote Sens.* **2023**, *15*, 3930. [CrossRef]
26. Wu, X.; Wen, J. Recent Progress on Modeling Land Emission and Retrieving Soil Moisture on the Tibetan Plateau Based on L-Band Passive Microwave Remote Sensing. *Remote Sens.* **2022**, *14*, 4191. [CrossRef]
27. Liu, Y.; Yang, Y. Advances in the Quality of Global Soil Moisture Products: A Review. *Remote Sens.* **2022**, *14*, 3741. [CrossRef]