Applications and Outlook of Soil Moisture Products

Subjects: Remote Sensing
Contributor: Yangxiaoyue Liu , Yaping Yang

Soil moisture (SM), the moisture content in the soil, is a crucial component in the hydrological cycle; it links atmospheric precipitation and underground water and is also an important parameter of energy exchange between the land surface and the atmosphere. Consequently, SM is recognized as an essential element in studies aimed at analyzing and understanding Earth system processes, such as climate change and ecological evolution. Specifically, the available water content, which is essential for vegetation growth, is one of the most important components of soil and has crucial guiding significance for agricultural production. Currently, both ground and spaceborne sensors are used to derive the original SM information. Numerous technologies, such as statistical models, data fusion, machine learning, and assimilation approaches, are widely used to improve SM quality. Additionally, SM datasets with high spatial-temporal resolution are valuable for boosting agricultural production in terms of drought and flood monitoring, crop growth analysis, and yield estimation.

soil moisture | estimation method advances | applications | prospects

1. Applications

Soil moisture (SM) is a sensitive component of the Earth system that interacts with the atmosphere and Earth's surface at every moment. Although the in situ measured SM can precisely reflect the soil water content, the confined extent and point-scale value remarkably restrict its applicability. Moreover, the original remotely sensed SM can hardly provide high-resolution and spatial-temporal continuous SM records because of the inherent limitations of spaceborne microwave sensors. Comparatively, advanced SM products provide unprecedented opportunities for deriving datasets with improved spatial coverage, multi-depth information, high resolution, and extended time sequence from the 1950s to future scenarios. These multi-model improved SM products are broadly applied to advance the understanding of Earth system processes, which mainly include drought monitoring, climate change, hydrology, and ecology.

1.1. Drought Monitoring

Drought is usually induced by a deficiency of precipitation and excess ET, which jointly cause varying degrees of decline in SM. As drought can seriously affect crop growth and yield, agricultural departments have always attached great importance to real-time drought monitoring. Therefore, a wide variety of studies have explored the potential of SM for drought monitoring. First, for regions renowned for their advanced plant product industries, more ground stations could be arranged in cropland when establishing SM networks [1][2][3]. This arrangement style reflects the emphasis attached to cultivation-related drought monitoring by acquiring multi-depth SM recordings in real-time. Second, in regional- or national-scale drought forecasting studies, both in situ measurements and raster SM estimations are employed simultaneously to ensure data accuracy and spatial coverage [4][5][6]. Third, coarse-resolution SM products, retrieved from spaceborne sensors or LSMs, are mainly utilized for depicting large-scale (i.e., continental, global) drought characteristics [7][8]. In these studies, SM and other related auxiliary components, such as vegetation fraction, temperature, and precipitation, were used together in drought applications. These variables are co-converted to representative indices, such as the SM drought index [6], soil water deficit index [5], SM use efficiency [8], perpendicular drought index [7], modified perpendicular drought index [4], and enhanced combined drought index [9], to comprehensively indicate the duration, trend, intensity, and severity of drought conditions.

1.2. Climate Change

The Sixth Assessment Report of the Intergovernmental Panel on Climate Change was released in 2021 [10]. This unequivocally revealed a serious warning of unprecedented warming trends and increasingly frequent extreme weather events. Because every component inside the climate system constantly interacts with each other, the spatial and temporal patterns of SM are derived from the combined actions of all members. Consequently, SM products based on spaceborne sensors and LSMs have been widely used in climate-variability experiments and analyses. Dorigo et al. [11] evaluated the global trend in harmonized multi-satellite surface SM from 1988 to 2010 and found drying and wetting trends in different regions. Qiu et al. [12] compared the performance of satellite- and reanalysis-based SM products. The two types of products exhibit coincident patterns in non-irrigated areas. Moreover, the discrepancy was mainly induced by artificial interference such as irrigation and harvest. On the basis of ECV SM v4.2, Pan et al. [13] conducted seasonal and annual scale analysis, and the results revealed that "wet seasons get wetter, and dry seasons get dryer," proving the gradual extremity tendency. In addition to analyzing the evolutionary features of SM, integrated climate variability studies were carried out in terms of interactions and feedbacks between ET, temperature, precipitation, and SM [14][15][16].

1.3. Hydrology

SM plays an important role in the circulation of land–atmosphere hydrology and energy balance. It could "remember" exceptional signals from the land–atmosphere system and provide effective feedback to other components of the cycle, such as ET, precipitation, underground water, and runoff [17]. The Food and Agriculture Organization of the United Nations Irrigation and Drainage Paper No. 56 on crop Evapotranspiration listed SM availability as a key factor that could influence crop ET estimation [18]. Allam et al. [19] estimated evaporation over the upper Blue Nile Basin and used least-squares data assimilation methods to estimate soil water storage. SM datasets from the ECV, Climate Prediction Center, and Gravity Recovery and Climate Experiment terrestrial water storage were considered essential inputs during the assimilation procedure. The Global Land Evaporation Amsterdam Model v3 uses SM products retrieved from both spaceborne sensors (ECV and SMOS) and LSM (GLDAS Noah) to estimate terrestrial evaporation [20]. Previous studies have suggested a strong coupling between precipitation and SM [21][22]. By inverting the soil–water balance equation, an SM2RAIN algorithm was developed and used to estimate basin- and global-scale precipitation with satisfactory accuracy using in situ and satellite SM observations [23][24]. Swenson et al. [25] detected groundwater variability using in situ measurements in Oklahoma, U.S., and a time series of groundwater anomalies was successfully acquired after removing SM variability in the unsaturated zone. Additionally, remotely sensed SM has been proven capable of efficiently calibrating groundwater-land surface models [26]. Moreover, it is widely acknowledged that the spatial variability of SM and soil properties may have a dominant and complex impact on runoff in terms of changing storm size [27]. Therefore, multi-source SM products are widely utilized in advancing runoff models to help set the initial conditions and reduce prediction uncertainties [28][29].

1.4. Ecology

SM is a crucial regulator of the basic processes in terrestrial ecosystems. Its variability can remarkably impact the operational patterns of terrestrial ecosystems. SM can directly influence photosynthesis and the net primary productivity (NPP) of ecosystems by affecting the occurrence, intensity, and duration of vegetation water stress [30][31]. In addition, both nitrogen and carbon cycles are tightly linked to soil water movement [32]. Therefore, SM plays a significant role in ecosystem processes. Reich et al. [33] explicitly demonstrated the effect of SM on photosynthesis using in situ measurements. The results assumed that low SM may limit photosynthesis in boreal tree species during the growing season, despite warming temperatures. The impact of drought on NPP variability on a global scale was investigated, and a strong positive relationship between available moisture and NPP in arid and seasonally dry regions was demonstrated [34]. The SM balance was calculated using the Carnegie-Ames-Stanford approach and then converted to a water stress factor to express its impact on the NPP. In addition, dozens of global NPP estimation models have treated multi-depth SM (ranging from 0 to 2.5 m) as an important input parameter [35]. Li et al. [32] analyzed SM and other supplementary datasets from 1980 to 2015 in China's dryland derived from TerraClimate [36]. They found that water and soil conservation projects, such as reforestation, evidently increased the net primary production. However, SM continuously decreased, suggesting that the existing ecosystem was unlikely to be sustained. Satellite-derived SM together with related environmental drivers were employed to analyze the evaporation decline in the U.S. from 1961 to 2014, and a significant evaporation decrease of approximately 6% was detected [37].

2. Outlook

Generally, through development for more than half a century, great contributions and advancements have been made in SM acquisition and employment. However, to persistently enhance the performance and applicability of SM products, there is still a long way to go. The researchers propose the following research priorities for future SM estimations.

2.1. Improved Spatial Coverage

Many studies employing SM as a key analysis object used seamless products to ensure complete coverage of the study area. Fortunately, assimilation- and reanalysis-based SM estimations have already overcome this problem in terms of the strength of numerous hydrological models. However, gap regions are prevalent for remotely sensed data. Owing to the limitation of microwave penetration, spaceborne sensors are unable to detect signals in frozen or dense vegetation (≥5 kg/m^2)-covered regions. However, it is crucial to access spatial-temporal continuous SM over forests, which would enhance the understanding of the mechanisms by which forest structure affects soil water conditions. Forests have a significant impact on water movement in nature as well as the regulation of SM, precipitation, evaporation, runoff, and hydrological cycles. Unexpected RFI typically result in exceptional values. Moreover, the rotation difference between the satellite and the Earth could result in a strip-gap region. Hence, it is necessary to explore the capability of gap-filling methods (i.e., classical statistical algorithms and artificial approaches) and determine an adequate method to update the present products on the values of gap regions [38][39]. Data fusion is also an effective approach for improving spatial integrity by blending the quantities of qualified SM information. For example, the multi-source information-merged ECV and SMOPS SM products show an evidently higher coverage percentage than the single sensor-derived ones [40].

2.2. Higher Spatial Resolution

Compared to coarse-resolution SM products, fine-resolution SM products can be more appropriate for landscape scale, watershed scale, and field scale applications; for instance, hydrological simulation over the scale of drainage basins or SM spatial variability analysis on a field scale. Many studies have been conducted on SM downscaling using statistical models, data fusion, assimilation, and machine-learning algorithms. These works obtained good results by integrating high-resolution ancillary data collections from MODIS, Landsat, and Sentinel [41][42][43][44]. Moreover, machine learning approaches have notable advantages in terms of simplicity, efficiency, and competence. It was found that the multi-regression tree-based models could accurately reproduce SM with a downscaled resolution; however, these models did not consider spatial texture features. Comparatively, the advent of deep learning techniques provides an unparalleled opportunity for the simulation of spatially autocorrelated objects, such as SM. Therefore, it would be beneficial to develop a suitable model to estimate SM among the large deep-learning family [45]. In addition, high-resolution land surface observations from well-known optical sensors and SAR could serve as qualified explanatory variables for SM downscaling to hundreds or even dozens of meter grids [46][47].

2.3. Longer Time Span

It can be beneficial to analyze evolutionary trends over decades or even hundreds of years in climate change fields to capture the laws of climate origination and evolution. Thus, it is valuable that the time span of SM datasets can be continuously prolonged. Both satellite-based and assimilated SM products begin when the corresponding observation programs begin. For the sake of continuous acquisition of SM data, on the one hand, observations in existence should be maintained and ensured to work properly; on the other hand, new ground networks and satellites to provide continuous monitoring of SM are indispensable for extending time series. For instance, the National Satellite Meteorological Center of China launched the FY-3E satellite on 5th July 2021, which is dedicated to networking with FY-3C and FY-3D in orbit to observe SM and other meteorological parameters [48]. Additionally, forecasting SM with the help of future scenarios and hydrologic models could also provide access to acquire SM predictions, which may favor the investigation of future climate variations [14][49].

2.4. Higher Temporal Resolution

In addition to pursuing a high spatial resolution, improving the frequency would also be a key research priority for future SM products. Hourly monitoring data can be of great benefit in investigating subtle SM fluctuations induced by artificial irrigation, rainfall, and ET within a day, which is valuable for agricultural and land–atmosphere interaction applications [19][23][24][50]. At present, both in situ measurements and LSMs are capable of providing sub-hourly and sub-daily observations. Additionally, the SMAP publishes three-hourly surface and root zone SM estimates with ~2.5-day latency, which are derived from the assimilation of both ascending and descending brightness temperature data into the catchment LSM [51]. It is suggested that LSM is an effective and promising approach for generating high temporal resolution SM estimates. Furthermore, with an increasing number of satellites launched with different transit moments from each other, it would be promising to acquire observations more and more times per day across the globe [48].

2.5. Shorter Time Latency

It is imperative to access real-time or near-real-time SM recordings to conduct drought monitoring and early flood warning. Croplands also have high timeliness requirements for SM product availability to arrange irrigation or drainage without delay. In situ measurement data can be quickly collected through sensors and the internet. However, in terms of remotely sensed and assimilated products, there is always a latency of dozens of hours. For instance, the SMOPS data latency for 6-h products is 3 h and that for daily products is 6 h. The SMAP data latency for available data products is as follows: (1) Level 1 products, within 12 h of acquisition; (2) Level 2 products, within 24 h of acquisition; (3) Level 3 products, within 50 h of acquisition; and (4) Level 4 products, within 7 days for SM [52]. ERA5 is continuously updated with a latency of approximately 5 days [53]. Consequently, there is an urgent need to accelerate and optimize the processes of data transmission, algorithm operation, and data distribution, which should include, but not be limited to, the improvement of related equipment, techniques, and methodologies.

2.6. Developing Multi-Depth Products

Land surface and root-zone SM recordings are of equal importance for advancing the understanding of Earth's system processes. Furthermore, root-zone SM counts more than top-layer SM in vegetation growth. It is critical to develop multi-depth SM products to comprehensively master the soil wetness profile. In situ measurements can detect multi-depth SM using probes at different depths [1]. Assimilation- and reanalysis-based products can effectively describe soil water movement and then generate root-zone SM estimates to fulfill the requirements of considerably progressing hydrological and agricultural applications [53]. In addition, satellite-based programs have started to produce root-zone values through a data assimilation system. For instance, the SMAP project integrates its own observations with complementary information into an LSM and produces 3 h and 9 km surface (0–5 cm) and root-zone (0–100 cm) SM estimations through both spatial and temporal interpolations and extrapolations [54][55]. The ECV program also initiated a program to develop root-zone SM products using Noah-MP and ISBA LSMs, which are dedicated to linking vegetation phenology and biomass carbon allocation to moisture availability in the soil.

2.7. Higher Data Accuracy

Significant efforts have been devoted to reducing errors to continuously close the gap between SM estimations and real SM conditions. In a previous study, ground probes were periodically calibrated and maintained to ensure their operation under good conditions [1]. AMSR-2 retrieves SM using an X-band signal and applies a neighboring C-band to escape RFI [56]. The SMAP program designed effective L-band SM detection sensors together with advanced anti-RFI devices and improved algorithms to detect and remove harmful interference in the L-band [57][58]. A series of developments in model physics, core dynamics, and data assimilation have been steadily achieved, which have contributed to significant improvements in SM consistency [53]. Despite this progress, there is still considerable room to pursue higher accuracy. Artificial intelligence-driven algorithms display great potential for simulating the SM model. Increasing SM datasets will become available as more ground networks and satellite programs are being planned. A significant benefit can be expected from combining these advanced technologies and datasets.

2.8. Better Model Performance and Interpretability

In recent decades, numerous models have been built and updated to estimate SM, and the overall quality of the corresponding products has been evidently enhanced. Traditional physical models are widely employed in spaceborne and assimilation systems to retrieve SM. These sophisticated and exquisite models are carefully designed and theoretically interpretable [53][59]. In comparison, artificial intelligence-driven approaches, especially the deep learning family, exhibit outstanding capabilities in SM regression and prediction [45][46]. In addition, they have the advantages of being highly efficient, simple, and convenient. However, their inner operational mechanisms are difficult to explain. Consequently, it could be favorable to develop hybrid models by combining physical and artificial intelligence methods, which would be able to exploit the strengths and discard the weaknesses of both methods. The hybrid model is expected to improve both model performance and interpretability.

References

1. Dorigo, W.A.; Wagner, W.; Hohensinn, R.; Hahn, S.; Paulik, C.; Xaver, A.; Gruber, A.; Drusch, M.; Mecklenburg, S.; Oevelen, P.V. The International Soil Moisture Network: A data hosting facility for global in situ soil moisture measurements. Hydrol. Earth Syst. Sci. 2011, 15, 1675–1698.
2. Rossing, W.; Zander, P.; Josien, E.; Groot, J.; Meyer, B.; Knierim, A. Integrative modelling approaches for analysis of impact of multifunctional agriculture: A review for France, Germany and The Netherlands. Agric. Ecosyst. Environ. 2007, 120, 41–57.

3. Van der Veer Martens, B.; Illston, B.G.; Fiebrich, C.A. The Oklahoma Mesonet: A Pilot Study of Environmental Sensor Data Citations. Data Sci. J. 2017, 16, 47.
4. Ghulam, A.; Qin, Q.; Teyip, T.; Li, Z.-L. Modified perpendicular drought index (MPDI): A real-time drought monitoring method. ISPRS J. Photogramm. Remote Sens. 2007, 62, 150–164.
5. Liu, D.; Mishra, A.K.; Yu, Z.; Yang, C.; Konapala, G.; Vu, T. Performance of SMAP, AMSR-E and LAI for weekly agricultural drought forecasting over continental United States. J. Hydrol. 2017, 553, 88–104.
6. Park, S.; Im, J.; Park, S.; Rhee, J. Drought monitoring using high resolution soil moisture through multi-sensor satellite data fusion over the Korean peninsula. Agric. For. Meteorol. 2017, 237–238, 257–269.
7. Sheffield, J.; Wood, E.F. Global Trends and Variability in Soil Moisture and Drought Characteristics, 1950–2000, from Observation-Driven Simulations of the Terrestrial Hydrologic Cycle. J. Clim. 2006, 21, 432–458.
8. Do, N.; Kang, S. Assessing drought vulnerability using soil moisture-based water use efficiency measurements obtained from multi-sensor satellite data in Northeast Asia dryland regions. J. Arid. Environ. 2014, 105, 22–32.
9. Enenkel, M.; Steiner, C.; Mistelbauer, T.; Dorigo, W.; Wagner, W.; See, L.; Atzberger, C.; Schneider, S.; Rogenhofer, E. A Combined Satellite-Derived Drought Indicator to Support Humanitarian Aid Organizations. Remote Sens. 2016, 8, 340.
10. Pedersen, J.S.T.; Santos, F.D.; van Vuuren, D.; Gupta, J.; Coelho, R.E.; Aparício, B.A.; Swart, R. An assessment of the performance of scenarios against historical global emissions for IPCC reports. Glob. Environ. Chang. 2021, 66, 102199.
11. Dorigo, W.; de Jeu, R.; Chung, D.; Parinussa, R.; Liu, Y.; Wagner, W.; Fernández-Prieto, D. Evaluating global trends (1988–2010) in harmonized multi-satellite surface soil moisture. Geophys. Res. Lett. 2012, 39.
12. Qiu, J.; Gao, Q.; Wang, S.; Su, Z. Comparison of temporal trends from multiple soil moisture data sets and precipitation: The implication of irrigation on regional soil moisture trend. Int. J. Appl. Earth Obs. Geoinf. 2016, 48, 17–27.
13. Pan, N.; Wang, S.; Liu, Y.; Zhao, W.; Fu, B. Global Surface Soil Moisture Dynamics in 1979–2016 Observed from ESA CCI SM Dataset. Water 2019, 11, 883.
14. Seneviratne, S.I.; Corti, T.; Davin, E.L.; Hirschi, M.; Jaeger, E.B.; Lehner, I.; Orlowsky, B.; Teuling, A.J. Investigating soil moisture–climate interactions in a changing climate: A review. Earth-Sci. Rev. 2010, 99, 125–161.

15. Rodriguez-Iturbe, I.; D’odorico, P.; Porporato, A.; Ridolfi, L. On the spatial and temporal links between vegetation, climate, and soil moisture. Water Resour. Res. 1999, 35, 3709–3722.
16. Pastor, J.; Post, W. Influence of climate, soil moisture, and succession on forest carbon and nitrogen cycles. Biogeochemistry 1986, 2, 3–27.
17. Li, M.; Wu, P.; Sexton, D.M.; Ma, Z. Potential shifts in climate zones under a future global warming scenario using soil moisture classification. Clim. Dyn. 2021, 56, 2071–2092.
18. Pereira, L.S.; Allen, R.G.; Smith, M.; Raes, D. Crop evapotranspiration estimation with FAO56: Past and future. Agric. Water Manag. 2015, 147, 4–20.
19. Allam, M.M.; Jain Figueroa, A.; McLaughlin, D.B.; Eltahir, E.A. Estimation of evaporation over the upper blue nile basin by combining observations from satellites and river flow gauges. Water Resour. Res. 2016, 52, 644–659.
20. Martens, B.; Miralles, D.G.; Lievens, H.; Van Der Schalie, R.; De Jeu, R.A.; Fernández-Prieto, D.; Beck, H.E.; Dorigo, W.A.; Verhoest, N.E. GLEAM v3: Satellite-based land evaporation and root-zone soil moisture. Geosci. Model Dev. 2017, 10, 1903–1925.
21. Koster, R.D.; Dirmeyer, P.A.; Zhichang, G.; Gordon, B.; Edmond, C.; Peter, C.; Gordon, C.T.; Shinjiro, K.; Eva, K.; David, L. Regions of strong coupling between soil moisture and precipitation. Science 2004, 305, 1138–1140.
22. Koster, R.D.; Suarez, M.J.; Higgins, R.W.; Van den Dool, H.M. Observational evidence that soil moisture variations affect precipitation. Geophys. Res. Lett. 2003, 30.
23. Brocca, L.; Moramarco, T.; Melone, F.; Wagner, W. A new method for rainfall estimation through soil moisture observations. Geophys. Res. Lett. 2013, 40, 853–858.
24. Brocca, L.; Ciabatta, L.; Massari, C.; Moramarco, T.; Hahn, S.; Hasenauer, S.; Kidd, R.; Dorigo, W.; Wagner, W.; Levizzani, V. Soil as a natural rain gauge: Estimating global rainfall from satellite soil moisture data. J. Geophys. Res. Atmos. 2014, 119, 5128–5141.
25. Swenson, S.; Famiglietti, J.; Basara, J.; Wahr, J. Estimating profile soil moisture and groundwater variations using GRACE and Oklahoma Mesonet soil moisture data. Water Resour. Res. 2008, 44.
26. Sutanudjaja, E.; Van Beek, L.; De Jong, S.; Van Geer, F.; Bierkens, M. Calibrating a large-extent high-resolution coupled groundwater-land surface model using soil moisture and discharge data. Water Resour. Res. 2014, 50, 687–705.
27. Merz, B.; Plate, E.J. An analysis of the effects of spatial variability of soil and soil moisture on runoff. Water Resour. Res. 1997, 33, 2909–2922.
28. Brocca, L.; Melone, F.; Moramarco, T.; Wagner, W.; Naeimi, V.; Bartalis, Z.; Hasenauer, S. Improving runoff prediction through the assimilation of the ASCAT soil moisture product. Hydrol.

Earth Syst. Sci. 2010, 14, 1881–1893.

29. Tramblay, Y.; Bouvier, C.; Martin, C.; Didon-Lescot, J.-F.; Todorovik, D.; Domergue, J.-M. Assessment of initial soil moisture conditions for event-based rainfall–runoff modelling. J. Hydrol. 2010, 387, 176–187.
30. Dorigo, W.; Wagner, W.; Albergel, C.; Albrecht, F.; Balsamo, G.; Brocca, L.; Chung, D.; Ertl, M.; Forkel, M.; Gruber, A. ESA CCI Soil Moisture for improved Earth system understanding: State-of-the art and future directions. Remote Sens. Environ. 2017, 203, 185–215.
31. Reichstein, M.; Bahn, M.; Ciais, P.; Frank, D.; Mahecha, M.D.; Seneviratne, S.I.; Zscheischler, J.; Beer, C.; Buchmann, N.; Frank, D.C. Climate extremes and the carbon cycle. Nature 2013, 500, 287–295.
32. Li, C.; Fu, B.; Wang, S.; Stringer, L.C.; Wang, Y.; Li, Z.; Liu, Y.; Zhou, W. Drivers and impacts of changes in China’s drylands. Nat. Rev. Earth Environ. 2021, 2, 858–873.
33. Reich, P.B.; Sendall, K.M.; Stefanski, A.; Rich, R.L.; Hobbie, S.E.; Montgomery, R.A. Effects of climate warming on photosynthesis in boreal tree species depend on soil moisture. Nature 2018, 562, 263–267.
34. Chen, T.; Werf, G.; Jeu, R.d.; Wang, G.; Dolman, A. A global analysis of the impact of drought on net primary productivity. Hydrol. Earth Syst. Sci. 2013, 17, 3885–3894.
35. Churkina, G.; Running, S.W.; Schloss, A.L.; the participants of the Potsdam NPP Model Intercomparison. Comparing global models of terrestrial net primary productivity (NPP): The importance of water availability. Glob. Chang. Biol. 1999, 5, 46–55.
36. Abatzoglou, J.T.; Dobrowski, S.Z.; Parks, S.A.; Hegewisch, K.C. TerraClimate, a high-resolution global dataset of monthly climate and climatic water balance from 1958–2015. Sci. Data 2018, 5, 1–12.
37. Rigden, A.J.; Salvucci, G.D. Stomatal response to humidity and CO 2 implicated in recent decline in US evaporation. Glob. Change Biol. 2017, 23, 1140–1151.
38. Liu, Y.; Yao, L.; Jing, W.; Di, L.; Yang, J.; Li, Y. Comparison of two satellite-based soil moisture reconstruction algorithms: A case study in the state of Oklahoma, USA. J. Hydrol. 2020, 590, 125406.
39. Fang, K.; Shen, C.; Kifer, D.; Yang, X. Prolongation of SMAP to spatiotemporally seamless coverage of continental US using a deep learning neural network. Geophys. Res. Lett. 2017, 44, 11030–11039.
40. Wang, Y.; Leng, P.; Peng, J.; Marzahn, P.; Ludwig, R. Global assessments of two blended microwave soil moisture products CCI and SMOPS with in-situ measurements and reanalysis data. Int. J. Appl. Earth Obs. Geoinf. 2021, 94, 102234.

41. Sadeghi, M.; Babaeian, E.; Tuller, M.; Jones, S. The optical trapezoid model: A novel approach to remote sensing of soil moisture applied to Sentinel-2 and Landsat-8 observations. Remote Sens. Environ. 2017, 198, 52–68.
42. Liu, Y.; Jing, W.; Wang, Q.; Xia, X. Generating high-resolution daily soil moisture by using spatial downscaling techniques: A comparison of six machine learning algorithms. Adv. Water Resour. 2020, 141, 103601.
43. Kim, H.; Lee, S.; Cosh, M.H.; Lakshmi, V.; Kwon, Y.; McCarty, G.W. Assessment and Combination of SMAP and Sentinel-1A/B-Derived Soil Moisture Estimates With Land Surface Model Outputs in the Mid-Atlantic Coastal Plain, USA. IEEE Trans. Geosci. Remote Sens. 2020, 59, 991–1011.
44. Qin, J.; Yang, K.; Lu, N.; Chen, Y.; Zhao, L.; Han, M. Spatial upscaling of in-situ soil moisture measurements based on MODIS-derived apparent thermal inertia. Remote Sens. Environ. 2013, 138, 1–9.
45. Reichstein, M.; Camps-Valls, G.; Stevens, B.; Jung, M.; Denzler, J.; Carvalhais, N. Deep learning and process understanding for data-driven Earth system science. Nature 2019, 566, 10.
46. Peng, J.; Loew, A.; Merlin, O.; Verhoest, N.E.C. A review of spatial downscaling of satellite remotely sensed soil moisture. Rev. Geophys. 2017, 55, 341–366.
47. Xu, C.; Qu, J.J.; Hao, X.; Cosh, M.H.; Prueger, J.H.; Zhu, Z.; Gutenberg, L. Downscaling of Surface Soil Moisture Retrieval by Combining MODIS/Landsat and In Situ Measurements. Remote Sens. 2018, 10, 210.
48. Zhang, P.; Hu, X.; Lu, Q.; Zhu, A.; Lin, M.; Sun, L.; Chen, L.; Xu, N. FY-3E: The First Operational Meteorological Satellite Mission in an Early Morning Orbit; Springer: Berlin/Heidelberg, Germany, 2021.
49. Falloon, P.; Jones, C.D.; Ades, M.; Paul, K.J.G.B.C. Direct soil moisture controls of future global soil carbon changes: An important source of uncertainty. Glob. Biogeochem. Cycles 2011, 25.
50. Mladenova, I.E.; Bolten, J.D.; Crow, W.T.; Sazib, N.; Cosh, M.H.; Tucker, C.J.; Reynolds, C. Evaluating the operational application of SMAP for global agricultural drought monitoring. IEEE J. Sel. Top. Appl. Earth Obs. Remote Sens. 2019, 12, 3387–3397.
51. Reichle, R.H.; Liu, Q.; Ardizzone, J.V.; Crow, W.T.; De Lannoy, G.J.; Dong, J.; Kimball, J.S.; Koster, R.D. The contributions of gauge-based precipitation and SMAP brightness temperature observations to the skill of the SMAP Level-4 soil moisture product. J. Hydrometeorol. 2021, 22, 405–424.
52. He, L.; Chen, J.M.; Mostovoy, G.; Gonsamo, A. Soil Moisture Active Passive Improves Global Soil Moisture Simulation in a Land Surface Scheme and Reveals Strong Irrigation Signals Over Farmlands. Geophys. Res. Lett. 2021, 48, e2021GL092658.

53. Hersbach, H.; Bell, B.; Berrisford, P.; Hirahara, S.; Horányi, A.; Muñoz-Sabater, J.; Nicolas, J.; Peubey, C.; Radu, R.; Schepers, D. The ERA5 global reanalysis. Q. J. R. Meteorol. Soc. 2020, 146, 1999–2049.
54. Entekhabi, D.; Njoku, E.G.; O'Neill, P.E.; Kellogg, K.H.; Crow, W.T.; Edelstein, W.N.; Entin, J.K.; Goodman, S.D.; Jackson, T.J.; Johnson, J.; et al. The Soil Moisture Active Passive (SMAP) Mission. Proc. IEEE 2010, 98, 704–716.
55. Reichle, R.H.; De Lannoy, G.J.M.; Liu, Q.; Ardizzone, J.V.; Colliander, A.; Conaty, A.; Crow, W.; Jackson, T.J.; Jones, L.A.; Kimball, J.S.; et al. Assessment of the SMAP Level-4 Surface and Root-Zone Soil Moisture Product Using In Situ Measurements. J. Hydrometeorol. 2017, 18, 2621–2645.
56. Parinussa, R.M.; Holmes, T.R.H.; Wanders, N.; Dorigo, W.A.; De Jeu, R.A.M. A Preliminary Study toward Consistent Soil Moisture from AMSR2. J. Hydrometeorol. 2013, 16, 932–947.
57. Piepmeier, J.R.; Johnson, J.T.; Mohammed, P.N.; Bradley, D.; Ruf, C.; Aksoy, M.; Garcia, R.; Hudson, D.; Miles, L.; Wong, M. Radio-Frequency Interference Mitigation for the Soil Moisture Active Passive Microwave Radiometer. IEEE Trans. Geosci. Remote Sens. 2014, 52, 761–775.
58. O'Neill, P.; Entekhabi, D.; Njoku, E.; Kellogg, K. The NASA Soil Moisture Active Passive (SMAP) Mission: Overview. In Proceedings of the Geoscience and Remote Sensing Symposium, Honolulu, HI, USA, 25–30 July 2010; pp. 704–716.
59. Hoffmann, L.; Günther, G.; Li, D.; Stein, O.; Wu, X.; Griessbach, S.; Heng, Y.; Konopka, P.; Müller, R.; Vogel, B. From ERA-Interim to ERA5: The considerable impact of ECMWF's next-generation reanalysis on Lagrangian transport simulations. Atmos. Chem. Phys. 2019, 19, 3097–3124.