

Water Resources Research

REVIEW ARTICLE

10.1029/2024WR037929

Special Collection:

A Continuing Special Collection for Translational Water Research: Looking for Theory-Practice Synthesis for Actionable Outcomes

Key Points:

- Recent high-resolution (3–500 m, daily–weekly) remote sensing soil moisture and evapotranspiration products summarized
- Limitations of data and retrieval algorithms of soil moisture and evapotranspiration and their couplings reviewed
- Ten different application areas of soil moisture and evapotranspiration products discussed illustrating diverse stakeholder needs

Correspondence to:

J. Huang, V. Sehgal and J. B. Fisher,
jhuang426@wisc.edu;
vsehgal@agcenter.lsu.edu;
joshbfisher@gmail.com

Citation:

Huang, J., Sehgal, V., Alvarez, L. V., Brocca, L., Cai, S., Cheng, R., et al. (2025). Remotely sensed high-resolution soil moisture and evapotranspiration: Bridging the gap between science and society. *Water Resources Research*, 61, e2024WR037929. <https://doi.org/10.1029/2024WR037929>

Received 10 MAY 2024

Accepted 19 APR 2025

Corrected 12 JUN 2025

This article was corrected on 12 JUN 2025. See the end of the full text for details.

Author Contributions:

Conceptualization: Jingyi Huang, Vinit Sehgal, Luca Brocca, K. Arthur Endsley, Yilin Fang, Gerbrand Koren, Jiafu Mao, Mingjie Shi, Joshua B. Fisher

© 2025. The Author(s).

This is an open access article under the terms of the [Creative Commons Attribution License](#), which permits use, distribution and reproduction in any medium, provided the original work is properly cited.

Remotely Sensed High-Resolution Soil Moisture and Evapotranspiration: Bridging the Gap Between Science and Society

Jingyi Huang¹ , Vinit Sehgal² , Laura V. Alvarez³ , Luca Brocca⁴ , Shuohao Cai¹, Rui Cheng⁵ , Xinghua Cheng⁶ , Jinyang Du⁷ , Bassil El Masri⁸ , K. Arthur Endsley⁷ , Yilin Fang⁹ , Jie Hu¹ , Mahesh Jampani¹⁰ , Md Golam Kibria¹¹, Gerbrand Koren¹² , Lingcheng Li¹³ , Laibao Liu^{14,15} , Jiafu Mao¹⁶ , Hernan A. Moreno³ , Angela Rigden¹⁷ , Mingjie Shi¹³ , Xiaoying Shi¹⁶, Yaoping Wang¹⁶ , Xi Zhang¹⁸, and Joshua B. Fisher^{19,20} 

¹Department of Soil and Environmental Sciences, University of Wisconsin-Madison, Madison, WI, USA, ²School of Plant, Environmental and Soil Sciences, Louisiana State University, Baton Rouge, LA, USA, ³Department of Earth, Environmental and Resource Sciences, University of Texas at El Paso, El Paso, TX, USA, ⁴National Research Council, Research Institute for Geo-Hydrological Protection, Perugia, Italy, ⁵Kravis Department of Integrated Sciences, Claremont McKenna College, Claremont, CA, USA, ⁶Department of Natural Resources and the Environment, University of Connecticut, Storrs, CT, USA, ⁷W.A. Franke College of Forestry & Conservation, Numerical Terradynamic Simulation Group, The University of Montana, Missoula, MT, USA, ⁸Department of Earth and Environmental Sciences, Murray State University, Murray, KY, USA, ⁹Energy and Environment Division, Pacific Northwest National Laboratory, Richland, WA, USA, ¹⁰International Water Management Institute (IWMI-CGIAR), Colombo, Sri Lanka, ¹¹Department of Engineering Sciences, Morehead State University, Morehead, KY, USA, ¹²Copernicus Institute of Sustainable Development, Utrecht University, Utrecht, The Netherlands, ¹³Atmospheric, Climate, and Earth Sciences Division, Pacific Northwest National Laboratory, Richland, WA, USA, ¹⁴Department of Geography, The University of Hong Kong, Hong Kong, China, ¹⁵Institute for Climate and Carbon Neutrality, The University of Hong Kong, Hong Kong, China, ¹⁶Environmental Sciences Division and Climate Change Science Institute, Oak Ridge National Laboratory, Oak Ridge, TN, USA, ¹⁷Department of Earth System Science, University of California, Irvine, CA, USA, ¹⁸Department of Biosystems Engineering & Soil Science, University of Tennessee, Knoxville, TN, USA, ¹⁹Schmid College of Science and Technology, Chapman University, Orange, CA, USA, ²⁰Hydrosat USA, Washington, DC, USA

Abstract This paper reviews the current state of high-resolution remotely sensed soil moisture (SM) and evapotranspiration (ET) products and modeling, and the coupling relationship between SM and ET. SM downscaling approaches for satellite passive microwave products leverage advances in artificial intelligence and high-resolution remote sensing using visible, near-infrared, thermal-infrared, and synthetic aperture radar sensors. Remotely sensed ET continues to advance in spatiotemporal resolutions from MODIS to ECOSTRESS to Hydrosat and beyond. These advances enable a new understanding of bio-geo-physical controls and coupled feedback mechanisms between SM and ET reflecting the land cover and land use at field scale (3–30 m, daily). Still, the state-of-the-science products have their challenges and limitations, which we detail across data, retrieval algorithms, and applications. We describe the roles of these data in advancing 10 application areas: drought assessment, food security, precision agriculture, soil salinization, wildfire modeling, dust monitoring, flood forecasting, urban water, energy, and ecosystem management, ecohydrology, and biodiversity conservation. We discuss that future scientific advancement should focus on developing open-access, high-resolution (3–30 m), sub-daily SM and ET products, enabling the evaluation of hydrological processes at finer scales and revolutionizing the societal applications in data-limited regions of the world, especially the Global South for socio-economic development.

Plain Language Summary This paper reviews the recent high-resolution remotely sensed soil moisture (SM) and evapotranspiration (ET) products and modeling, and how SM and ET are interacted with each other. High-resolution SM products were produced via downscaling satellite passive microwave products using artificial intelligence and high-resolution remote sensing visible, near-infrared, thermal-infrared, and synthetic aperture radar sensors. High-resolution ET products were developed from MODIS to ECOSTRESS to Hydrosat and beyond. These advances enable a new understanding of bio-geo-physical controls and feedback mechanisms between SM and ET reflecting land cover and land use at field scale (3–30 m, daily). There are challenges and limitations regarding the data, retrieval algorithms, and applications. We describe the roles of these data in advancing 10 application areas: drought assessment, food security, precision agriculture, soil

Data curation: Jingyi Huang, Vinit Sehgal, Luca Brocca, Yaoping Wang, Joshua B. Fisher
Funding acquisition: Jingyi Huang, Vinit Sehgal, Jiafu Mao, Joshua B. Fisher
Methodology: Jingyi Huang, Vinit Sehgal, Luca Brocca, Joshua B. Fisher
Writing – original draft: Jingyi Huang, Vinit Sehgal, Laura V. Alvarez, Luca Brocca, Shuohao Cai, Rui Cheng, Xinghua Cheng, Jinyang Du, Bassil El Masri, K. Arthur Endsley, Yilin Fang, Jie Hu, Mahesh Jampani, Md Golam Kibria, Gerbrand Koren, Lingcheng Li, Laibao Liu, Jiafu Mao, Hernan A. Moreno, Angela Rigden, Mingjie Shi, Xiaoying Shi, Yaoping Wang, Xi Zhang, Joshua B. Fisher
Writing – review & editing: Jingyi Huang, Vinit Sehgal, Laura V. Alvarez, Luca Brocca, Shuohao Cai, Rui Cheng, Xinghua Cheng, Jinyang Du, Bassil El Masri, K. Arthur Endsley, Yilin Fang, Jie Hu, Mahesh Jampani, Md Golam Kibria, Gerbrand Koren, Lingcheng Li, Laibao Liu, Jiafu Mao, Hernan A. Moreno, Angela Rigden, Mingjie Shi, Xiaoying Shi, Yaoping Wang, Xi Zhang, Joshua B. Fisher

salinization, wildfire modeling, dust monitoring, flood forecasting, urban water, energy, and ecosystem management, ecohydrology, and biodiversity conservation. Future work should focus on developing open-access, high-resolution (3–30 m), sub-daily SM and ET products, enabling the evaluation of hydrological processes at finer scales and revolutionizing the societal applications in data-limited regions of the world, especially the Global South for socio-economic development.

1. Introduction

Soil moisture (SM) refers to the amount of water stored within the pore spaces of soil and serves as an important source of water for the atmosphere mainly through evapotranspiration (ET) (Entekhabi et al., 2010; Karthikeyan et al., 2017; Seneviratne et al., 2010). Surface SM (e.g., 0–10 cm) plays a crucial role in regulating bare soil evaporation and infiltration. Meanwhile, rootzone SM (e.g., 0–1 m) is directly linked to soil water potential, determining the water accessible for uptake by plant roots and thus transpiration (Brust et al., 2021; Seneviratne et al., 2010). Here, we use the conventional term “evapotranspiration” or “ET” throughout the paper and refer to the sum of evaporation from soil and intercepted precipitation and plant transpiration instead of the generic term “evaporation” (Miralles et al., 2020).

The transient storage of water in soil and its atmospheric transfer flux as ET within the soil-plant-atmosphere continuum are key environmental variables in the terrestrial ecosystem (Felton et al., 2025; Fisher et al., 2017). The coupling between SM and ET regulates the terrestrial water, carbon, and energy cycles (Kannenberg et al., 2023), where SM is directly related to multiple parts of ET. When contributions to ET from vegetated and non-vegetated (soil) surfaces are considered separately, SM controls the rate at which evaporated water from soil enters the surrounding air (Baldocchi et al., 2022; Sadeghi et al., 2020); SM also directly influences the transpiration of vegetation not only in the form of plant available water but also, in interaction with rooting depth, soil hydraulic properties, and plant hydraulic traits (Li, Yang, et al., 2021; Purdy et al., 2018).

Given their important roles in the soil-plant-atmosphere continuum, accurate and timely knowledge of SM and ET in space and time is vital to water resources management, weather forecasting, and disaster management (Anderson et al., 2016; Orth & Seneviratne, 2014). Because of the tradeoff between spatial and temporal resolution for Earth-observing satellites, traditional monitoring and modeling approaches have struggled to capture the spatial and temporal heterogeneity in SM and ET simultaneously at high resolutions (Fisher et al., 2017). Consequently, the utilization and application of extant coarse-resolution SM and ET products are generally limited to a select group of end-users.

Advances in remote sensing platforms and computational algorithms have enabled the development of moderate-to-high spatial (3 m–3 km) and temporal (daily to weekly) resolution products of SM and ET from the field to global scales. These recently developed data sets offer users (ranging from farmers and water resources managers to researchers and policymakers) unprecedented opportunities to use accurate and timely estimates of SM and ET and make informed decisions as well as improve our understanding of the environmental dynamics of terrestrial ecosystems (Brocca et al., 2024). Although several recent reviews have evaluated the advances in remote sensing-based SM (Li, Leng, et al., 2021; Peng et al., 2021) and ET (Chen & Liu, 2020; García-Santos et al., 2022; Pan et al., 2020) products or retrieval algorithms, the recent development of high-resolution SM and ET products is a result of novel input data and retrieval algorithms which have not been comprehensively covered in these reviews; also, few reviews have focused on the synergy between high-resolution SM and ET products. Still, there remains a large “valley of death” between these data advances and integration into decision-making systems, but through interdisciplinary design thinking, this gap can be bridged (Purdy et al., 2019). Here, we define high-resolution products as products that have spatial resolutions between 30 m and 3 km for SM products and 3–500 m for ET products and temporal resolutions from daily to weekly.

The goals of this review are: (a) from the data producer's perspective, to provide a summary of the recently developed high-resolution remote sensing-based SM and ET products, focusing on the challenges and limitations in data and retrieval algorithms and (b) from the user's perspective, to discuss the roles of these new SM and ET products in advancing 10 application areas and highlight the user's need for future research in SM and ET modeling.

2. An Overview of 30 m to 3 km and Weekly/Sub-Weekly SM Products

2.1. Brief Summary of Retrieving Algorithms and Existing Products

Unlike existing remote sensing SM retrieval algorithms, high-resolution SM retrieval relies on algorithms that leverage remote sensing platforms with high spatial and/or temporal resolutions, such as optical, near-infrared (NIR), thermal infrared (TIR), and microwave sensors (Li, Leng, et al., 2021). Compared to the optical and NIR/TIR wavelengths, the microwave band is most suitable for SM retrieval because of its direct physical linkage with SM—water responds directly to microwave wavelengths—as well as the microwave's ability to penetrate the topsoil and through some clouds and canopies (Babaeian et al., 2019; Peng et al., 2021). Microwave remote sensing-based SM retrieval approaches can be grouped into five types (Karthikeyan et al., 2017): (a) physical, (b) semi-empirical, (c) empirical, (d) vegetation contribution-based, and (e) change-detection-based models. But, microwave remote sensing tends to be coarse-resolution, so additional data sets are needed for downscaling. For detailed information and a comprehensive review of various downscaling methods (e.g., geostatistical, process model-based, machine learning-based) for high-resolution SM product development, please refer to Peng et al. (2017), Abdollahipour et al. (2022), and Senanayake et al. (2024). In Section 2, we focus on examples of high-resolution SM products, associated retrieval algorithms, and input data.

For enhancing the spatial and temporal resolutions of satellite SM products, strategies typically involve either advanced data processing techniques leveraging overlapping passive microwave footprint observations or incorporating higher-resolution information from sources like active microwave/Synthetic Aperture Radar (SAR) observations, optical-infrared (IR) remote sensing, in situ observations, or land surface model simulations. Cross-scale relationships among observations, retrievals, or simulations may be based on physically based and/or machine- or deep-learning methods. Such downscaled products of SM (mostly SMAP coarse-resolution SM), like those derived from Planet (Du, Chen, et al., 2022; Du, Kimbll, et al., 2022; Planet, 2023), Landsat-8 and Sentinel-2 (Sadeghi et al., 2017), MODIS (Colliander et al., 2017), Sentinel-1 (Bauer-Marschallinger, Freeman, et al., 2018; Bauer-Marschallinger, Paulik, et al., 2018; Das et al., 2019) satellites, offer spatial resolutions from a few meters to hundreds of meters and temporal resolutions ranging from daily to weekly; yet, there are tradeoffs among resolution, frequency, and accuracy (Table 1). Temporal interpolation techniques have been used to overcome the cloud-induced missing values and low frequency of vegetation index retrievals in optical remote sensing imagery (Song et al., 2022). Different from traditional machine learning models (e.g., Random Forest), advanced deep learning techniques (e.g., ResNet Models, Regression Neural Network) can provide feasible spatial patterns and details (Kolassa et al., 2018; Yuan et al., 2020; Zhao et al., 2022) without explicit parameterization of physical relationships, offering great opportunities to synthesize multi-source SM data retrieved by various methods.

One example of retrieving SM at high spatial and temporal resolution is the SMAP-HydroBlocks (SMAP-HB) data-model approach. The modeled surface SM data set at 30-m spatial resolution and sub-daily temporal resolution is based on a scalable scheme, which combines high-resolution land surface modeling, radiative transfer modeling, machine learning, SMAP satellite microwave data, and in situ observations. SMAP-HB fuses HydroBlocks-Tau-Omega Radiative Transfer Model output at 30-m resolution and SMAP L3 brightness temperature observations at 36 km resolution using a cluster-based merging scheme (Vergopolan et al., 2020). SMAP-HB, in addition to its higher resolution, provides performance similar to that of SMAP L4 and enhanced-resolution SMAP L3 SM products, based on a validation using observations from in situ sensors at 1,191 sites over CONUS. Thus, the data product can be broadly used to understand SM conditions at a high resolution and to estimate the susceptibility to wildfires, landslides, flooding, and waterlogging conditions (Vergopolan et al., 2021). Still, it is not yet clear how well such a modeled product can be used for precision agriculture (e.g., irrigation management) at the field scale.

2.2. Challenges and Research Gaps

Despite advancements, challenges persist in achieving high accuracy and precision, together with high spatial resolution and short latency, in SM retrieval. Typical coarse-resolution SM products like SMAP have a global root-mean-square-error (RMSE) of less than $0.04 \text{ m}^3 \text{ m}^{-3}$, which is relatively easy to achieve at a coarse (e.g., 9-km/36-km) pixel size. However, fine-resolution SM products may suffer from decreased precision or inability to capture spatial variability from input coarse-resolution satellite microwave measurements (e.g., RMSE of $0.07 \text{ m}^3 \text{ m}^{-3}$ for the 30-m SMAP-HB, Vergopolan et al., 2021) due to the inherent spatial heterogeneity of soil

Table 1
Examples of High-Resolution (30 m–3 km and Weekly/Sub-Weekly) Soil Moisture Products and Algorithms and Example Applications (Refer to Section 5)

Examples	Sensors/Products	Algorithms	Spatial resolution	Temporal resolution	Spatial coverage	Temporal coverage	Example applications
Bauer-Marschallinger, Freeman, et al. (2018)	Sentinel-1	Change detection	1 km	3–12 days	Global	2014–2017	5.1, 5.2, 5.3, 5.5, 5.7, 5.10
Bauer-Marschallinger, Paulik, et al. (2018)	ASCAT + Sentinel-1	Temporal filtering	1 km	Daily	Global	2014–2017	5.1, 5.3, 5.5, 5.7, 5.10
Merlin et al. (2013)	SMOS + MODIS/ASTER/Landsat	Evaporation-based disaggregation (“DISPATCH”)	100 m, 3 km	Daily	Small region	2011	5.3
Song et al. (2022)	AMSR-E/AMSR-2 + MODIS	Improved DISPATCH	1 km	Daily	China	2003–2019	5.1
Planet (2023)	SMAP + AMSR-E/AMSR-2 + Sentinel-2	Land Parameter Retrieval Model with disaggregation	100 m – 1 km	Daily	Global	2017–present	5.1, 5.2, 5.3, 5.4, 5.5, 5.9, 5.10
Das et al. (2019)	SMAP + Sentinel-1	SMAP active-passive algorithm	1–3 km	12 days	Global	2015–present	5.1, 5.2, 5.3, 5.4, 5.5, 5.6, 5.7, 5.9, 5.10
Fang et al. (2022)	SMAP + MODIS + AVHRR	Thermal inertia theory	1 km	Daily	Global	2015–2020	5.1, 5.5
Lakshmi and Fang (2023)	SMAP + MODIS	Downscaling based on land surface temperature	1 km	Daily	Global	2015–2022	5.1
Du, Chen, et al. (2022)	SMAP + Planet	Machine learning	3 m	Daily	Regional	2021	5.3
Du et al. (2024)	SMAP + + Landsat	Machine learning	30 m	Daily	Regional	2017–2019	5.1, 5.2, 5.3
Huang et al. (2022)	ERA5_Land + MODIS + Landsat + SMAP + in situ	Machine learning	30 m	Daily	Field sites	2017	5.1, 5.3
Abowarda et al. (2021)	ESA CCI + SMAP L4 + CLDAS + MODIS + Landsat	Machine learning	30 m	Daily	Watershed	2016	5.1, 5.3
Ning et al. (2023)	ERA5_Land + SMAP + SMOS + ESA CCI + NLDAS	Machine learning	30 m	Daily	CONUS	2016	5.1
Peng et al. (2024)	SMAP + MODIS + Sentinel-1 + Landsat	Machine learning	30–500 m	Daily	CONUS	2016–present	5.1, 5.3
Huang et al. (2020)	SMAP + Sentinel-1 + SRTM + Soil	Machine learning	100 m	12 days	Global	2016–2020	5.1, 5.3, 5.9, 5.10
Long et al. (2019)	SMAP + MODIS + CLDAS + ESA CCI	Machine learning	1 km	Daily	Regional	2015–2016	5.1
Wang, Li, et al. (2023)	GLDAS + CRU + MODIS + SRTM + Crop types + Estimated irrigation	Machine learning	1 km	monthly	Watershed	2011–2013	5.1, 5.9
Wernicke et al. (2024)	SMAP + CYGNSS	Downscaling SMAP TB using CYGNSS	3 km	Daily	Global	2017–2023	5.1, 5.3, 5.10
Zhang et al. (2023)	ERA5_Land + GLASS	Machine learning	1 km	Daily	Global	2000–2020	5.1
Zheng et al. (2023)	ERA5_Land + ESA-CCI	Machine learning	1 km	Daily	Global	2000–2020	5.1
Shi et al. (2024)	ERA5_Land + in situ	Machine learning	1 km	Daily	CONUS	2000–present	5.1
Han et al. (2023)	ERA5_Land + MODIS	Physics-informed machine learning	1 km	Daily	Global	2000–2020	5.1
Vergopolan et al. (2021)	SMAP	Data assimilation with land surface models	30 m	Daily	CONUS	2015–2019	5.1, 5.3, 5.9

texture and hydraulic properties, heterogeneous rainfall and/or irrigation distribution, evaporation and plant water uptake, as well as topographic differences that affect surface and subsurface runoff (Robinson et al., 2008). Besides, the increased bias in the fine-solution SM products can result from the inaccurate parameterization of land surface parameters in land surface models (Chaney et al., 2016) or inaccurate parameterization of soil and vegetation dielectric properties or surface roughness in radiative transfer models (e.g., Jackson, 1993; Njoku & Li, 1999; O'Neill et al., 2018) used to retrieve SM at the fine spatial resolutions. Recent development of comprehensive global 1 km land surface parameters incorporating the latest data sets of land use, vegetation, soil and topography has shown promise in better representing this spatial heterogeneity (Li et al., 2024). Bridging the gap between coarse and fine spatial and temporal resolutions remains a critical challenge, limiting the seamless integration of data across different resolutions.

Other issues related to the influence of vegetation cover on sensor signal penetration depth, the impact of surface roughness, and the need for ancillary data for algorithm calibration pose ongoing research challenges. Due to these interference factors, retrieving SM in regions other than bare or agricultural fields (with low canopy cover), such as forests (Andreadis et al., 2022) and wetlands (Dabrowska-Zielinska et al., 2018), remains a major measurement gap and consequent active research area. Many hydrological and agricultural applications also require accurate estimation of rootzone SM (Carranza et al., 2021). However, acquiring accurate rootzone SM is still a challenging task due to the limited remote sensing information in deeper soil layers. Regardless of the effects of vegetation cover on signal, spaceborne sensors can only detect a few millimeters (optical and thermal sensors) to centimeters (microwave sensors) (Li, Leng, et al., 2021). Generally, rootzone SM is estimated using physical/process-based models (e.g., Noah-MP, Niu et al., 2011; SMAP L4; Reichle et al., 2017) by building connections between surface and rootzone SM, but more efforts are needed to produce quality-consistent products across soil layers, time and space.

Shallow penetration depth of microwave sensors is a critical limitation in retrieving rootzone SM using existing algorithms and sensors. Anomalies in the surface soil moisture are indicative of persistent soil moisture anomalies in the rootzone due to strong interconnection through advective and diffusive soil hydrologic processes, except in arid regions where hydrologic decoupling between surface and root zone is prevalent (Ford et al., 2014; Hirschi et al., 2014; Sehgal & Sridhar, 2019). Studies have demonstrated that root water uptake in plants preferentially favors upper soil profiles (Dong et al., 2022; Feldman et al., 2023, 2024). Hence, temporal dynamics in the surface SM typically constitute the larger fraction of variability in the rootzone SM, terrestrial water, and energy coupling (Dong & Crow, 2018; Dong et al., 2022; Manfreda et al., 2014; Sehgal et al., 2024). For this reason, several studies have successfully demonstrated the application of surface SM in studying ecosystem processes and their response to climatic stressors including flash droughts and heatwaves (Sehgal et al., 2021b). In addition, machine learning-based methods show promise in mapping SM profiles by integrating multi-source remote sensing data, which have been applied to monitoring underground waste disposal (Jarchow et al., 2024) and flash drought forecast (Du et al., 2024).

2.3. Limitations and Opportunities of Input Data

The accuracy of high-resolution SM products is contingent on the quality of the input data. While remote sensing provides valuable insights into estimating surface SM under sparse vegetation cover, the nature of sensor measurements in different electromagnetic spectrum domains limits the satellite observations of SM in certain conditions. When optical, NIR, or TIR sensors are used in developing SM products, they are limited by cloud cover and weather conditions. As for microwave measurements, they are affected by radio frequency interference (affecting passive microwave SM retrieval in urban areas, Piepmeier et al., 2013) or surface roughness (limiting the use of radar signals in rough terrains and mountainous areas, Hornbuckle et al., 2017; Zheng et al., 2018). Microwave satellite measurements are also observed at different wavelengths, polarizations, and incidence angles and have, therefore, a varying sensitivity to SM (Ulaby et al., 2014). Furthermore, the penetration depth of remote sensing is very poor, which leads to an incomplete description of variation in water availability and water stress in the root zone (Srivastava, 2017).

In situ observations of SM also pose uncertainties (e.g., the spatial scale mismatch issue between observations and remotely sensed data) that hinder the evaluation of remotely sensed and downscaled SM products (Peng et al., 2017). Regional SM products produced from in situ sensor networks often have a high temporal resolution (hourly to sub-daily), but they suffer from limited spatial coverage (Ochsner et al., 2019). Most of these networks

are distributed in grassland or forest soils, or situated in the global north (Cosh et al., 2021; Ochsner et al., 2013), limiting their applications to managed land (e.g., cropland); and such data are absent in countries where limited access to water resources under drought poses serious risks to food security. The advent of emerging technologies, including cosmic-ray neutron rovers (Andreasen et al., 2017; Heidebüchel et al., 2016), unmanned aerial vehicles (Akbar et al., 2021; Ge et al., 2019; Houtz et al., 2023; Ye et al., 2024), GNSS-R-based CYGNSS missions (Chew & Small, 2018; Clarizia et al., 2019; Kim & Lakshmi, 2018), and low-cost wireless sensor networks (Akbar et al., 2021; Bogena et al., 2007; Briciu-Burghina et al., 2022; Jamroen et al., 2020), presents exciting opportunities to enhance the input data quality, quantity, and spatial and temporal resolutions of input data sets for these models.

2.4. Limitations and Opportunities of Retrieval Algorithms

The design of SM retrieval algorithms must account for the inherent complexities of soil-vegetation-atmosphere interactions. Current algorithms often under-represent land cover changes, do not apply to rough terrain, and rely on accurate ancillary maps of land surface parameters (e.g., soil and vegetation characteristics). The retrieval quality of each satellite SM product is also affected by numerous spatially and temporally variable factors, that is, climatic, topographic, and land cover conditions, instrument characteristics, and the retrieval algorithm structure (Crow et al., 2012; Molero et al., 2018; Ochsner et al., 2013). Different satellite retrieval products can use similar ancillary information, such as temperature and/or vegetation information, in a radiative transfer model, resulting in correlated errors (Gruber et al., 2016). Data validation should be a continuous process throughout the lifetime of different satellite missions (Gruber et al., 2020).

Accurate absolute SM values are needed for hydrological, agricultural, and ecosystem applications (Peng et al., 2021). However, current SM values in land surface models and satellite data are more accurate in temporal dynamics than absolute values (Dai et al., 2019; Koster et al., 2009). SM in land surface models could differ in several orders of absolute value because of their highly dependent model settings and more accurate soil property maps are needed to constrain the absolute values (Dai et al., 2019; Koster et al., 2009). One recent study of the monthly timescale in a large, agriculture-dominated water basin found that crop type and estimated irrigation were important predictors of temporal SM dynamics (Wang, Li, et al., 2023). However, most studies at high temporal resolution and large spatial extents do not appear to report application-specific predictor importance. More attention to driving relationships and model selection could improve both data-oriented studies and the capacity of human-Earth system global models (e.g., Global Change Assessment Model—Calvin et al., 2017) in the future. Additionally, remote sensing products are not capable of characterizing SM diurnal cycle because satellites usually have a revisit time of a few days. For example, SMAP (Liu et al., 2021) and SMOS (Kerr et al., 2012) provide global SM estimates every 2–3 days. Recent research has investigated the potential to overcome these limitations through ML approaches and the fusion/assimilating of diverse data sets to enhance their robustness across different environmental conditions. As shown in Table 1, most of the current remote sensing products are surface SM. It has become an ongoing research task to investigate the potential to assimilate surface SM retrieval from remote sensing platforms into land surface models to estimate rootzone SM (e.g., Vergopolan et al., 2021) and evaluate the performance of different land surface models and data-assimilation algorithms using in situ SM measurements collected within the soil surface (e.g., Cosh et al., 2021; Ochsner et al., 2019).

3. Overview of High-Resolution 3 m to 1 km and Daily to Weekly ET Products

High-resolution ET products include a suite of algorithms that integrate satellite-based observations, meteorological data, and/or land surface models. Notable products, such as MODIS and ECOSTRESS, provide estimates at fine spatial and/or temporal resolutions and offer valuable insights into the dynamic processes governing water, carbon, and energy fluxes within ecosystems. While a variety of approaches have been adopted to estimate ET at 3 m to 1 km scale and daily to-weekly time steps, models in widespread use today tend to be based fundamentally on Penman-Monteith or Priestley-Taylor methods, or estimate latent heat flux (ET) as a residual of the surface energy balance (Zhang et al., 2016). Similar to SM downscaling, spatial downscaling approaches have also been used to develop high-resolution ET products. For detailed information of the physics-based versus data-driven statistical/machine learning downscaling methods, please refer to Hong et al. (2011), Ke et al. (2016, 2017), and Mahour et al. (2017). In Section 3, we focus on examples of high-resolution ET products, associated retrieval algorithms, and input data.

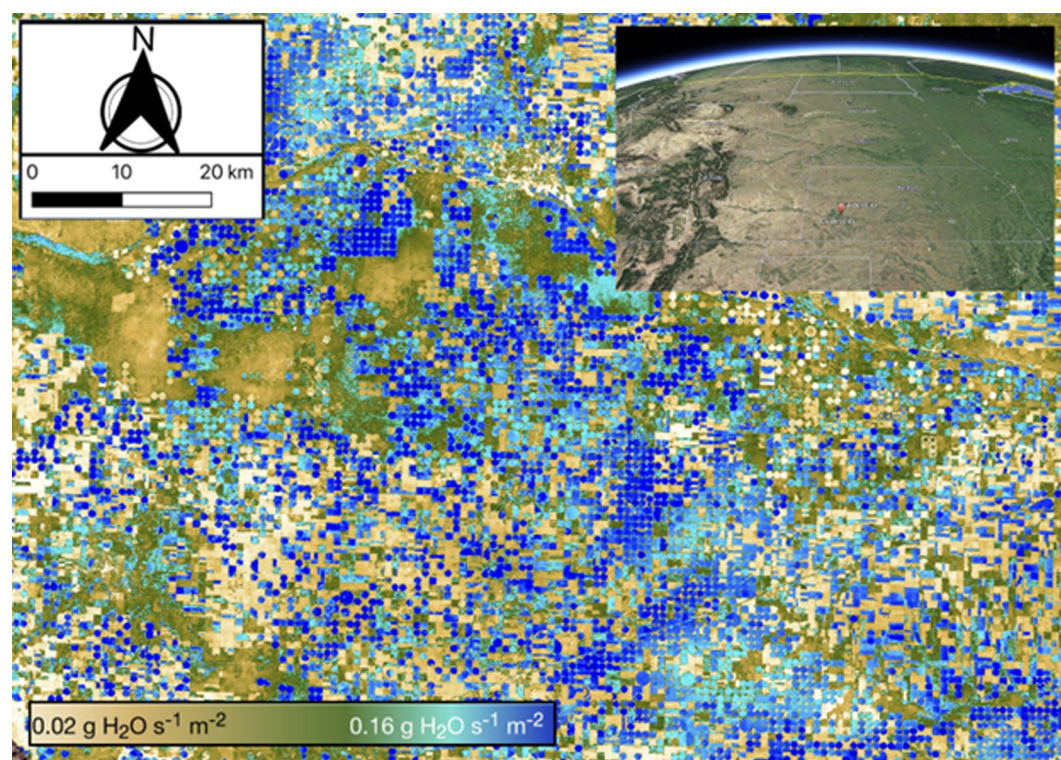


Figure 1. ECOSTRESS produces high-resolution (70 m) evapotranspiration (ET) data, enabling differentiation of water use throughout the landscape, such as among and within the pivot irrigation agricultural fields of Garden City, Kansas, USA. Dark blues represent high ET, and beige colors represent low ET.

3.1. Brief Summary of ET Retrieval Algorithms and Existing Remote Sensing Products

The most widely used remotely sensed ET product is MODIS (MOD16), which uses a modified Penman-Monteith approach forced by surface reflectance and climate re-analysis data (Mu et al., 2011). The MODIS standard ET product, since inception in the year 2000, has transitioned to a VIIRS (Visible Infrared Imaging Radiometer Suite) standard product (Endsley & Zhao, 2023) due to the planned termination of MODIS in December 2025. This product is available at 500 m every 8 days, globally. There have been many attempts to improve MOD16, such as an explicit SM constraint on evaporation (Brust et al., 2021), inspired by similar Penman-Monteith models like ETLook (Pelgrum et al., 2010) that use satellite microwave data, though the MOD16 operational product remains the same.

Building on the success of the MODIS standard ET product, and satisfying the demand for even higher resolution, the ECOSTRESS operational product (Fisher et al., 2020) is now seeing wider use than MOD16 (Figure 1). The global ECOSTRESS product uses the PT-JPL retrieval algorithm (Fisher et al., 2008), driven by ECOSTRESS land surface temperature, surface reflectance fused from Landsat and Sentinel-2, and meteorology (version 1 from MODIS: Famiglietti et al., 2018; version 2 from climate re-analysis). ECOSTRESS includes an additional ET product for the US-only, using the DisALEXI/ALEXI model (Cawse-Nicholson, Anderson, et al., 2021). ECOSTRESS data are available at 70 m every 1–5 days, globally between 52°S–52°N. PT-JPL will continue to provide the ET product for NASA's upcoming SBG mission aiming for 60 m resolution every 3 days (Cawse-Nicholson, Townsend, et al., 2021).

Both PT-JPL and DisALEXI/ALEXI are also included in the OpenET production system, along with the eeMETRIC, SIMS, SSEBop, and geeSEBAL algorithms (Melton et al., 2022). OpenET runs all models at 30 m using Landsat data with daily weather interpolation for much of the US. While each model has its strengths and weaknesses, OpenET has emerged as the leader in ET data accuracy through its statistical ensemble of the models (Volk et al., 2024). Merging ET model ensembles is an active area of research (Jung et al., 2019; Mao et al., 2015; Shang et al., 2021; Xu et al., 2019; Yao et al., 2014, 2017). As shown in Table 2, there are some other global

remote sensing-derived ET products in active use, including GLEAM (Martens et al., 2017; Miralles et al., 2011), BESS (Ryu et al., 2011), GLASS (Xie, Yao, et al., 2022), SEBS (Su, 2002), and WaPOR (Pelgrum et al., 2010). These approaches range from the foundational Priestley-Taylor and Penman-Monteith algorithms to more complex representations of canopy structure and biochemistry. Users and developers of these products continue to refine the resolutions, accuracies, and applications. Finally, one of the most widely used ET algorithms for field-scale applications is the foundational SEBAL model (Bastiaanssen et al., 1998), a surface-energy balance approach based on the near-surface temperature gradient within a satellite image scene. SEBAL is used in the Hydrosat IrriWatch product in over 60 countries by hundreds of users from farmers and agronomists to consultants and software developers (Fisher, 2022; McGlinchy et al., 2023).

3.2. Challenges and Research Gaps

The key challenge in ET data production is simultaneous high spatial and high temporal resolution (Fisher et al., 2017). This is a fundamental trade-off in remote sensing. From an engineering perspective, when the instrument is close to, or zoomed-in, on the Earth, it provides high spatial resolution, but it takes a long time to cover the whole Earth repeatedly; alternatively, the instrument is far from Earth, or zoomed-out, allowing fast repeat coverage, but coarse spatial resolution. This is why we have had high spatial resolution from Landsat (~100 m) every 16 days, or frequent coverage from MODIS (daily) but with much coarser resolution than field-scale (~1 km). Geostationary options provide sub-daily temporal resolutions but even coarser spatial resolutions than MODIS (>3 km). ECOSTRESS, on board the International Space Station, provides a compromise among these anchor options with a 70-m resolution every 1–5 days (Fisher et al., 2020). Still, none of these provide the requisite <100 m daily resolutions demanded by a myriad of societal applications (Fisher et al., 2017). Even the planned flagship missions of Surface Biology and Geology (SBG), Thermal infraRed Imaging Satellite for High-resolution Natural resource Assessment (TRISHNA), and Land Surface Temperature Monitoring (LSTM) do not achieve this goal and hinge on precarious synergy among missions and agencies to move us toward the goal, at least for a short time (Cawse-Nicholson, Anderson, et al., 2021). Active research has involved spatiotemporal fusion to move us toward that goal, but large uncertainties are introduced in the inherent interpolations and physically disconnected downscaling approaches (Anderson et al., 2021; Aragon et al., 2023; Desai et al., 2021; Gao et al., 2006; Mao et al., 2021; McGlinchy et al., 2023; Wen et al., 2022).

The only way to achieve daily, high spatial resolution TIR and VNIR measurements for ET data is by having a significant increase in the number of high-resolution TIR satellites. Cost has traditionally prohibited this dream from becoming a reality. Landsat costs on the order of US\$1B, for example, primarily due to engineering mass, volume, and energy requirements particularly associated with the cryocooler (Loomis et al., 2015; NASA, 2018). Telescoping a geostationary option would cost similarly, if not greater. As such, the spatiotemporal requirements for improved, global ET monitoring remain elusive. Yet, upcoming satellite platforms may provide the answer. Hydrosat has innovated through these engineering limitations to remove the cryocooler resulting in significant cost reductions and enabling a new generation constellation of satellites (Fisher, 2022). Instead of having one Landsat every 16 days, the Hydrosat constellation will provide 16 satellites every day at 50 m TIR and 20 m VNIR resolutions (Figure 2). The first launch of the Hydrosat constellation was August 2024 with the second launch following in 2025, and the rest of the constellation thereafter.

3.3. Limitations and Opportunities of Input Data

Due to the complexity of the ET process as a dynamic balance between plant, atmosphere, energy, and water, ET retrieval algorithms necessarily must include information on all four areas (Baldocchi et al., 2022; Fisher et al., 2017; but see also Armanios & Fisher, 2014; Shi et al., 2022). Specifically, ET algorithms are driven by land surface temperature (LST), vegetation greenness, and meteorology such as air temperature, humidity/vapor pressure deficit, and net radiation. Any deviation, uncertainty, scale mismatch, and/or temporal offset among any of these forcing variables will propagate as uncertainty into the final ET product (Badgley et al., 2015; Polhamus et al., 2013) (Figure 3). Some of these inputs are highly heterogeneous in space, such as LST and greenness, necessitating high spatial resolution (Aragon et al., 2018). Others are highly variable in time, such as LST and meteorology, necessitating high temporal resolution (Farella et al., 2022). Additional considerations such as soil heat flux are replete with their sources of error that propagate into the final ET calculations (Purdy et al., 2016). Furthermore, many ET applications would benefit from low latency of data availability, yet ET production latency is dependent on the lowest common denominator, that is, which input data source is the slowest.

Table 2
Examples of High-Resolution (3–500 m and Daily to Weekly) ET Products and Algorithms and Example Applications (Refer to Section 5)

References	Sensors/Products	Algorithms	Spatial resolution	Temporal resolution	Coverage	Example applications
Aragon et al. (2018)	Planet	PT-JPL	3 m	Daily	Local	5.3
Bastiaanssen et al. (1998), Fisher (2022), McGlinchy et al. (2023)	Hydrosat IrriWatch	SEBAL	10–50 m	Daily	Global, on demand	5.1., 5.2, 5.3, 5.5, 5.10
Melton et al. (2022)	Landsat (OpenET)	PT-JPL, DisALEXI/ALEXI, eeMETRIC, SIMS, SSEBop, and geeSEBAL	30 m	8-day with daily interpolation	Western USA	5.1. 5.2, 5.3, 5.5, 5.8, 5.9
Fisher et al. (2008, 2020)	ECOSTRESS	PT-JPL	70 m	1–5 days	Global, between 52°S and 52°N	5.1, 5.2, 5.3, 5.4, 5.5, 5.8, 5.9, 5.10
Cawse-Nicholson, Anderson, et al. (2021)	ECOSTRESS	DisALEXI/ALEXI	70 m	1–5 days	CONUS	5.1, 5.2, 5.3, 5.5
Mu et al. (2011)	MODIS	MOD16	500 m	8-day	Global	5.1, 5.2, 5.3, 5.4, 5.5, 5.6, 5.7, 5.8, 5.9, 5.10
Miralles et al. (2011)	MODIS	GLEAM	500 m	8-day	Global	5.1., 5.2, 5.3, 5.5, 5.10
Ryu et al. (2011)	MODIS	BESS	500 m	8-day	Global	5.1., 5.2
Xie, Yao, et al. (2022)	MODIS	GLASS	500 m	8-day	Global	5.1., 5.2
Su (2002)	MODIS	SEBS	500 m	8-day	Global	5.1., 5.2, 5.5
Pelgrum et al. (2010)	MODIS	WaPOR	500 m	8-day	Global	5.1, 5.2, 5.5
Zhang et al. (2019)	MODIS	PML-2	500 m	8-day	Global	5.1, 5.2, 5.5, 5.9

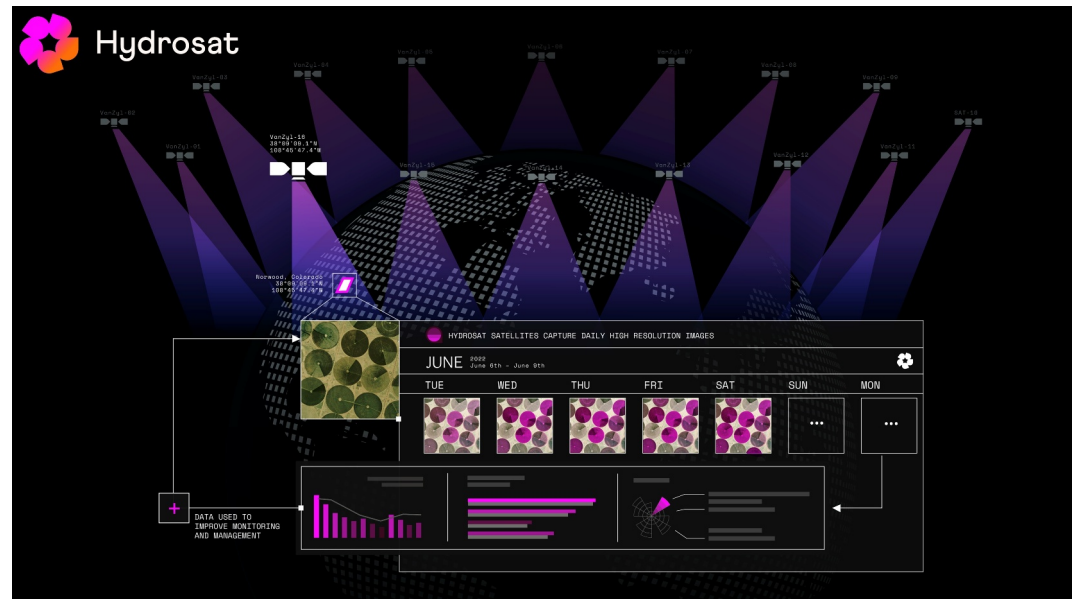


Figure 2. The Hydrosat constellation includes 16 satellites, which allow high resolution (50 m thermal infrared; 10 m visible-to-near-infrared) global imaging every day, particularly useful for applications such as agriculture and ecosystem management.

3.4. Limitations and Opportunities of Retrieval Algorithms

In the 2000s, simultaneous development of ET algorithms emerged that fused early work on ET process-modeling with available remotely sensed data (Fisher et al., 2005; Jiménez et al., 2011, 2018; McCabe et al., 2013; Michel et al., 2016; Miralles et al., 2016; Mu et al., 2011; Mueller et al., 2011). These algorithms were mostly based on Penman-Monteith or Priestley-Taylor foundations for direct ET calculation, or surface energy balance for ET as the residual, as introduced in Section 3.1 (Fisher et al., 2011). Note that when discussing energy-based ET

calculation, technically, it is the latent heat flux (LE) that is calculated, which is not the same as ET but can be readily converted; here, we use these terms interchangeably. All these ET models lack some specificity of environmental processes or drivers (e.g., detailed aerodynamic or stomatal resistances, Shuttleworth & Wallace, 1985). As such, all models make assumptions on how to derive the mechanistic ET process. In so doing, human contextual biases are introduced that equip some models to perform better than others in some situations and vice versa, but no model performs best everywhere and all the time (Volk et al., 2024). Some models partition ET into two or three sources (i.e., soil evaporation, canopy transpiration, interception evaporation), though few data exist to straightforwardly evaluate this partitioning (Stoy et al., 2019; Talsma, Good, Jimenez, et al., 2018; Talsma, Good, Miralles, et al., 2018). Nevertheless, ET model development has generally stabilized since the 2000s with new models mostly being derivatives or calibrations of this foundational set. Given this backdrop, OpenET led the fusion of these models into an ensemble product that generally outperforms all individual models (Melton et al., 2022; Volk et al., 2023, 2024).

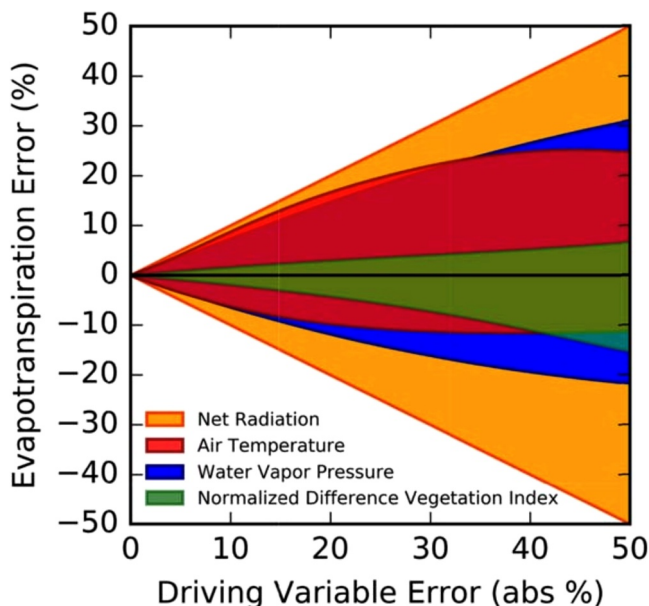


Figure 3. Errors in input data and algorithms propagate non-linearly through to errors in the final evapotranspiration retrieval. Figure from: Fisher et al. (2017).

4. Interactions Between SM and ET

4.1. Bivariate Relationship Between SM-ET or SM-Evaporative Fraction

Despite the advances and limitations in SM and ET modeling (Figure 4), recent studies have combined SM and ET products to understand their



Figure 4. Summary of limitations and opportunities of high-resolution soil moisture (SM) and evapotranspiration (ET) products.

interactions. Mesoscale coupling between SM and evaporative fraction (EF) directly impacts the global water cycle, land carbon cycle, and surface energy balance and is a key process of land atmospheric feedback when SM-EF coupling is strong (Liu, Gudmundsson, et al., 2020; Sehgal & Mohanty, 2024; Seneviratne et al., 2010). The emergent patterns of SM-EF coupling also contain signatures of the effective hydraulic behavior of the remote-sensing pixel, which can help model and predict the water retention characteristics of the landscape. ET and SM are tied together by plants, where ET and hydraulic redistribution affect SM dynamics, and the moisture transported by roots is closely related to gradients of water potential in soil and plants (Li, Yang, et al., 2021).

There is a well-documented framework for SM-EF coupling, originally developed by Budyko (1956, 1974) and highlighted in Seneviratne et al. (2010). In the SM-limited regime, SM is below the critical point, and SM-EF coupling is strong. Once SM falls below the critical point, SM decreases EF until SM reaches the wilting point. In the energy-limited regime, the SM level is above the critical point. EF variation is independent of SM and mainly limited by available energy for ET. We note that increased ET can also deplete soil water through root water uptake and even initiate or exacerbate droughts (Seneviratne et al., 2012; Wang et al., 2019; Zhao et al., 2022). SM-EF coupling is largely responsible for SM impacts on the climate system. In the SM-limited regime, SM depletions during drought conditions reduce terrestrial evaporative cooling as the ratio of sensible- to latent heat flux increases, thus inducing changes in near-surface air temperature (Hirschi et al., 2011; Lei et al., 2018; Zeppetello et al., 2019). These meteorological connections are critical in further accentuating the severity of droughts due to decreasing moist static energy in the atmospheric boundary layer, which further reduces precipitation likelihood (Alessi et al., 2022; Guillod et al., 2015). In contrast, while critical in drought recovery mechanisms, the energy-limited regime can restrict convective precipitation development by lowering the atmospheric boundary layer (Taylor et al., 2012). The energy-limited phase of SM-EF coupling is governed by the loss of SM via gravity drainage or ET at potential/near-potential rates, accompanied by a reduction in the near-surface temperatures. An enhanced understanding of sap flow dynamics, vegetation optical depth, and the relationships between these two metrics across vegetation types is essential to unraveling the interactions between SM and ET, especially under drought stress conditions (De Cáceres et al., 2021; Fisher et al., 2007; Rao et al., 2019; Sapfluxnet, 2024). In a warmer world, SM-EF coupling is also expected not to be constant, given the underlying processes influenced by climate change. For instance, many regions, such as the Amazon and the Mediterranean, are projected to experience accentuated SM drying (Cook et al., 2020), suggesting a potentially greater shift from an energy-limited regime to an SM-limited regime in these regions.

Despite the criticality of terrestrial water-energy coupling in development, propagation of droughts, and the recovery thereof, current understanding of these mesoscale processes is critically limited by synchronous observations of SM and ET at consistent spatial and temporal scales. Also, there are still large uncertainties in the

representation of SM-climate interactions in models, especially during climate extremes (Liu et al., 2023; Miralles et al., 2019). This hinders the improvement in the understanding of the relationship between SM/ET and drought impacts on different vegetation types and land ecosystems. While recent studies on understanding terrestrial water-energy-carbon coupling (Feldman et al., 2019; Koster et al., 2024; Liu, Zhu, et al., 2020; Sehgal et al., 2021) rely on remotely sensed products from SMAP/SMOS and EF estimates from MODIS or other contemporary data sets, high-resolution, near-real-time monitoring of the dynamic shifts in terrestrial water-energy coupling processes remain largely elusive.

There is increasing evidence highlighting the role of SM and ET in regulating methane (CH_4) fluxes from the soil and tree stems (Gauci et al., 2024; Pangala et al., 2015, 2017). For instance, wetland stem CH_4 fluxes increased with an increase in SM (Jeffrey et al., 2023; Pangala et al., 2014; Pitz et al., 2018). Moreover, the diffusion of soil CH_4 through the tree stem was found to be driven by transpiration (sap flow) (Covey & Megonigal, 2019; Megonigal et al., 2020; Takahashi et al., 2022). Thus, the availability of high-resolution SM and ET data is crucial to advance the current research focused on understanding the spatial and temporal variability of stem CH_4 fluxes (Gauci et al., 2024).

4.2. How to Integrate SM Into ET Models

Integrating high-resolution SM data into ET models is crucial for capturing the dynamic feedback between SM availability and vegetation water use. Remotely sensed SM has often been used for detecting ET regime transitions (Mbabazi et al., 2024) but not so much integrated into biophysical models estimating ET (Dong et al., 2022). Existing modeling efforts have been made to integrate SM into ET at a coarse resolution via coupled hydrological and land surface models (e.g., GLEAM, HOLAPS, CLASS) and have demonstrated promising outcomes (Hobeichi et al., 2020; Loew et al., 2016). One additional challenge is the estimation of independent components of ET (evaporation, E, and transpiration, T) as they appear to be controlled by different but partially overlapping mechanisms, including the available evaporative energy (e.g., net radiation) and variable-depth SM. E occurs from the shallowest layers of soil and wetted surfaces exposed to the atmosphere, but T seems to respond more directly to the deeper moisture (Kemp et al., 1997; Reynolds et al., 2000). Moreover, the redistribution of SM from the dryer to wetter soil layers by roots brings more complexity to the target (Lee et al., 2005). E and T are related to important biogeochemical processes like photosynthesis and subsequent plant carbon sequestration during T.

Almost all the aforementioned remotely sensed ET algorithms were developed before the availability of remotely sensed SM; as such, they were developed without explicit incorporation of SM using proxies or other indicators related to SM. For example, Fisher et al. (2008) developed a complementary relationship between soil water control and the overlying humidity and vapor pressure deficit that assumes that wet soil leads to wet overlying air. Mu et al. (2011), also searching for an SM constraint for MOD16, took the Fisher et al. (2008) relationship directly and integrated it into their algorithm as well. Moreover, when remotely sensed SM did eventually become available, many of the models continued to exclude these data due to the coarse resolution of the SM not applicable for most of the field-scale applications.

Nonetheless, some of these ET algorithms did develop options for including SM. PT-JPL developed an SM integration using SMAP, replacing the moisture proxy functions for direct SM (Purdy et al., 2018). Specifically, SM directly constrains both the soil evaporation component and the plant transpiration component in the PT-JPLsm version (Figure 5). For soil evaporation, SM is incorporated relative to the soil-plant wilting point and the soil field capacity, not unlike implementation approaches in DisALEXI/ALEXI (Anderson et al., 2007) and GLEAM (Martens et al., 2017; Miralles et al., 2011). For plant transpiration, SM is used to constrain the plant moisture stress function of PT-JPL, relative to canopy height and its sensitivity to soil water availability. The updated PT-JPLsm model was evaluated at 14 eddy flux sites with COSMOS measurements and was found to reduce ET bias and RMSE by 20%–30%, primarily in water-limited conditions and regions.

The SM-integrated version of PT-JPL was also incorporated into the second collection of ECOSTRESS ET data production. In ECOSTRESS, SM is ingested from reanalysis (GEOS-FP) at coarse resolution, then downscaled to the native ECOSTRESS 70 m resolution using remotely sensed LST and NDVI following Colliander et al. (2017). Other approaches have used the modeling logic of PT-JPL to integrate soil moisture into ET modeling, such as combined active and passive microwave-based soil moisture from the European Space Agency's Climate Change Initiative (Dorigo et al., 2017; Yao et al., 2019). The 70 m downscaled SM produced within the ECOSTRESS ET

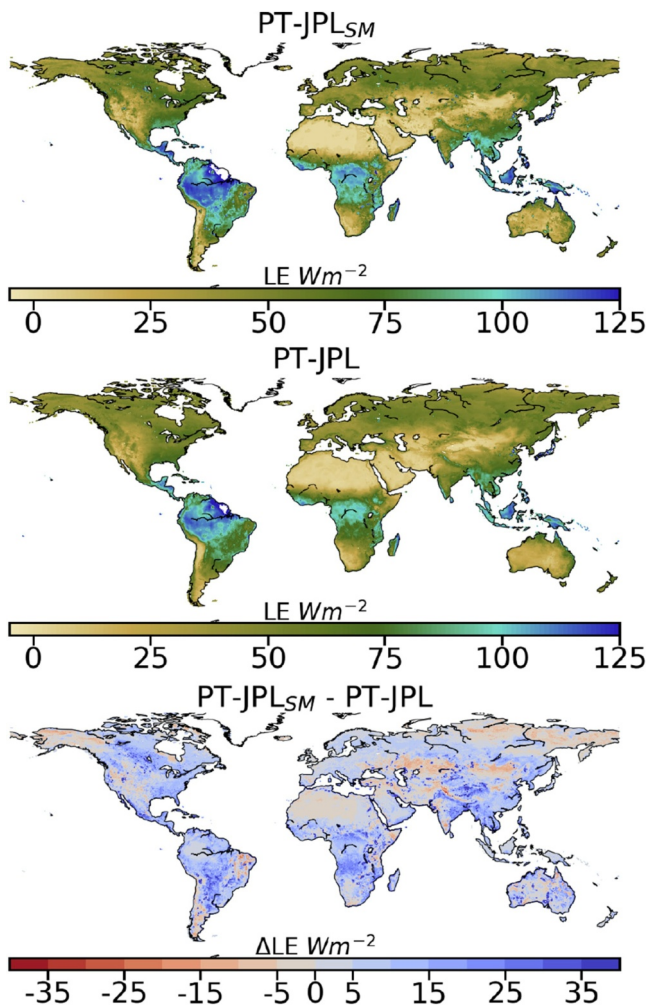


Figure 5. While ET can be produced globally without SM (top), the inclusion of SM (middle) improves accuracy in some areas (bottom). Figure from: Purdy et al. (2018).

data production software is also being distributed to the community for evaluation, making it the highest spatial resolution operational SM data available. This SM data is yet to be evaluated at the time of this writing; we encourage readers to be among the first to conduct such an evaluation, connecting with the PT-JPL developers.

The correct integration of SM into models appears to be via this distinction between shallow versus deep rootzone processes, as they seem to predominantly control E and T separately. Some options could be either estimating T via rootzone SM and E from shallow SM estimates or vice versa (estimating soil shallow and rootzone moisture from E and T, respectively). Some studies also considered evaporation from intercepted precipitation (Kim, Park, et al., 2023). Although there has been some progress in estimating the partitioning through field measurements (Kool et al., 2014; Wang et al., 2010; Williams et al., 2004; Yezpey et al., 2005), eddy covariance correlation-based approaches (Nelson et al., 2018; Scanlon & Kustas, 2010) and mathematical models (Burt et al., 2005; Farahani et al., 2007; Nelson et al., 2018; Rana & Katerji, 2000; Shuttleworth & Wallace, 2009; Tanny, 2013; Zhao et al., 2019; Zhou et al., 2016), large gaps persist in describing the main controls on the partitioning including the role of SM, vegetation density and activity, and atmospheric demand as well as scaling up from site to ecosystem estimations. Concerning vegetation, water use efficiency (WUE) is highly under-explored as it ties water use per unit of carbon fixed into the plant bodies (Anderson et al., 2018; Cooley et al., 2022; Scanlon & Kustas, 2012).

5. Applications and Challenges of Using SM and ET Products in Decision-Making

In this section, we summarize the applications of high-resolution SM and ET products in ten decision-making areas. Note that the example applications listed in Tables 1 and 2 are for demonstration only because the potential and full capacity of these new products for water resources management have not been fully explored. Specifically, we are currently in the midst of technology development on high-resolution SM and ET products, with only the first few integrations of SM and ET together from the technology perspective. So, the applications of these remotely sensed high-resolution SM and ET products often lag behind but will eventually catch up as the technology matures. In

theory, any application that uses ET will benefit from an SM-infused-ET, and any application that uses SM alone could also benefit from a complementary analysis of ET as well.

5.1. Drought Assessment and Mitigation Strategies

Long-term and spatiotemporal-continuous SM and ET products are important in drought studies, especially in mining the spatiotemporal patterns of droughts and their long-term trends (Cai et al., 2021; Sheffield et al., 2009). For example, the Run Theory (Guerrero-Salazar & Yevjevich, 1975), which is widely used to extract drought events, relies on the long-term SM series. It has been used to study the development of drought events, including the movement of drought centroids (Lloyd-Hughes, 2012; Xu et al., 2015). The spatial and temporal granularity of SM and ET data sets enables more precise monitoring of SM deficits and vegetation stress, facilitating early warning systems for drought events (Anderson et al., 2016; Otkin et al., 2014).

Flash droughts are characterized by rapid intensification of drought to severe levels over a large area (Christian et al., 2019; Osman et al., 2022; Otkin et al., 2018) and are associated with large-scale agricultural losses (Jencso et al., 2019; Jin et al., 2019) and expansive wildfires (Christian et al., 2020). As the frequency and intensity of flash droughts are on the rise (Touma et al., 2015; Yuan et al., 2019), accompanied by a global decrease in the drought recovery period (Schwalm et al., 2017), they pose a new challenge for seasonal and sub-seasonal climate predictions (Pendergrass et al., 2020). Hence, near-real-time identification and early warning of flash droughts

have implications for global food and water security. While flash droughts can be triggered by heatwave or precipitation-deficit (Christian et al., 2019; Otkin et al., 2017), the hydrological signature of flash drought stress on terrestrial ecosystems can be monitored through a rapid decrease of SM (Liu, Zhu, et al., 2020; Mo & Lettenmaier, 2015, 2016) or anomalous variability in ET. Flash droughts have impacted North America and Europe (O & Park, 2023), but the phenomenon is spreading to other regions (Yuan et al., 2023).

While the use of SMAP/SMOS observations for monitoring flash droughts holds promise due to its accuracy and global coverage, challenges exist in the implementation of existing products in real/near-real-time drought monitoring due to temporal gaps and low revisit frequency. Similarly, current global observations for ET are limited by a relatively coarse temporal resolution (8–16 days). Furthermore, a detailed assessment of the drought stress propagation in the vadose zone within the context of vegetation and atmospheric feedback remains to be explored. Land-atmosphere feedback processes can accentuate or modulate the initiation and propagation of drought conditions at the regional scale. While the constraints and critical thresholds of the terrestrial water and energy cycles are relatively well studied within the context of field-scale ecohydrology, large-scale studies of the SM-ET relationship would help to better understand the constraints on feedbacks and potential resilience of terrestrial ecosystems to drought conditions (Mishra et al., 2023). However, recent studies in the mesoscale patterns of soil moisture drydowns and terrestrial water-energy coupling have enabled the use of satellite-based SM in near-real-time flash drought monitoring. For example, Sehgal et al. (2021b) developed the Flash Drought Stress Index for monitoring emergent flash droughts at a global scale, which forms the basis of an operational platform called FLASH (Flash Drought Assessment using SMAP Hydrology) for operational drought assessment. Sehgal et al. (2024) demonstrated that studying the coupling dynamics of SM-ET using SMAP and MODIS can help identify emerging flash droughts at a regional scale. Similarly, evaporative stress is strongly associated with the development of flash droughts (Nguyen et al., 2019; Parker et al., 2021), especially during heatwaves.

Drought mechanisms, impact, and mitigation strategies can vary widely across hydroclimates, ecosystems, and cropping regions. The recent development of regional drought mitigation strategies with a focus on high-resolution ET monitoring has advanced drought mitigation efforts in the western and Southwestern US. One example of direct incorporation of high-resolution ET into decision-making comes from the State of New Mexico, USA (Fisher et al., 2023). In collaboration with the New Mexico Office of the State Engineer, the State drought assessors (i.e., the State Climatologist and NOAA National Weather Service), and key wildfire assessment scientists, this project undertook the extensive effort of crossing the “valley of death” from data to applications. The applications included: (a) detailed and frequent information on drought related to vegetation; (b) historical assessments of agricultural consumptive use; and (c) forest stress for wildfire modeling. The work entailed co-development of UI/UX and desired data output characteristics, technical transition of software from research institutions (i.e., NASA JPL) to state-accessible systems (i.e., AWS), training and educational systems developed by product designers, and impact assessment. Multiple elements are required to ensure successful application transitions, and the training and logistical scheduling/coordination of disparate people, permits, and approvals are non-trivial bottlenecks that must be patiently overcome. Success is often considered binary—the system/product either works completely as intended or it is not used (Figure 6).

5.2. Food Security Prediction Systems

Droughts and heatwaves, and subsequent food crashes, are increasing in frequency, magnitude, and intensity with climate change while populations continue to rise (Krishnamurthy et al., 2020; Tripathy et al., 2023). Notably, famine early warning systems miss many food crises—under certain conditions, more than 50% of food crisis transitions are completely missed resulting in millions of lives at stake (Choularton & Krishnamurthy, 2019). While ET is essential for daily agricultural management, Krishnamurthy et al. (2022) found that SM from SMAP, when combined with Tipping Point Theory, provides an unprecedented lead time of 3–6 months in predicting food crises. Not to be understated, they found that their model, the Soil Moisture Auto-Regressive Threshold (SMART) captured every single food crisis ($n = 212$), and recovery, within the satellite SM record ($r^2 = 0.83$). This breakthrough is a significant advancement that has the potential to save millions of lives (Figure 7).

The significance of remotely sensed SM in predicting food crises aligns with recent findings that highlight its added value in resolving water stress in crop yield models. Proctor et al. (2022), for example, found that incorporating remotely sensed coarse spatial resolution SM (ESA-CCI) into statistical crop yield models significantly improves model performance relative to those relying on precipitation as a proxy of water

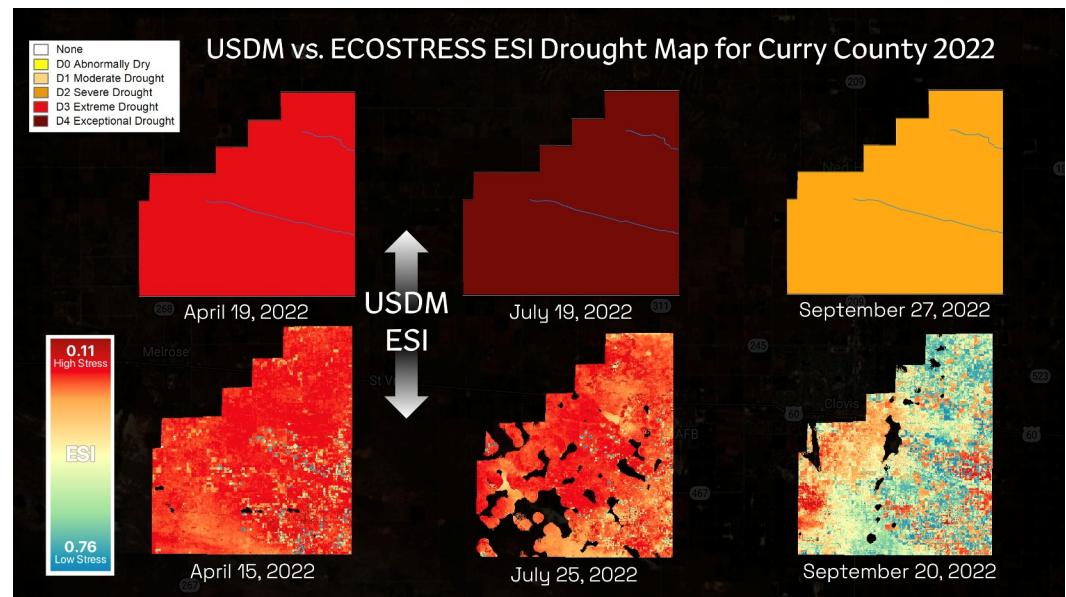


Figure 6. Integrating high-resolution ET-based drought data (i.e., Evaporative Stress Index, ESI) into statewide drought assessment allows state climatologists to improve their understanding of how drought impacts different land covers, people, and sectors throughout the state. Here, we show an example from a project in New Mexico, USA, working in conjunction with the state climatologist and drought task force of the Office of the State Engineer.

availability. Specifically, empirical models with remotely sensed SM explained 30%–120% more of the inter-annual yield variations than those using precipitation when applied to national-level yields across the globe for staple crops (maize, soybeans, millet, and sorghum). Consistent results have also been found at the sub-national scale, for example, for maize in India (Modanesi et al., 2020) and the Midwestern US (Rigden et al., 2020). Empirical crop yield models using remotely sensed SM also led to better separation resolving crop heat and water stress (Proctor et al., 2022). This separation between heat and water stress is critical when leveraging empirical approaches to predict crop yield responses to climate change due to the non-stationary relationship between

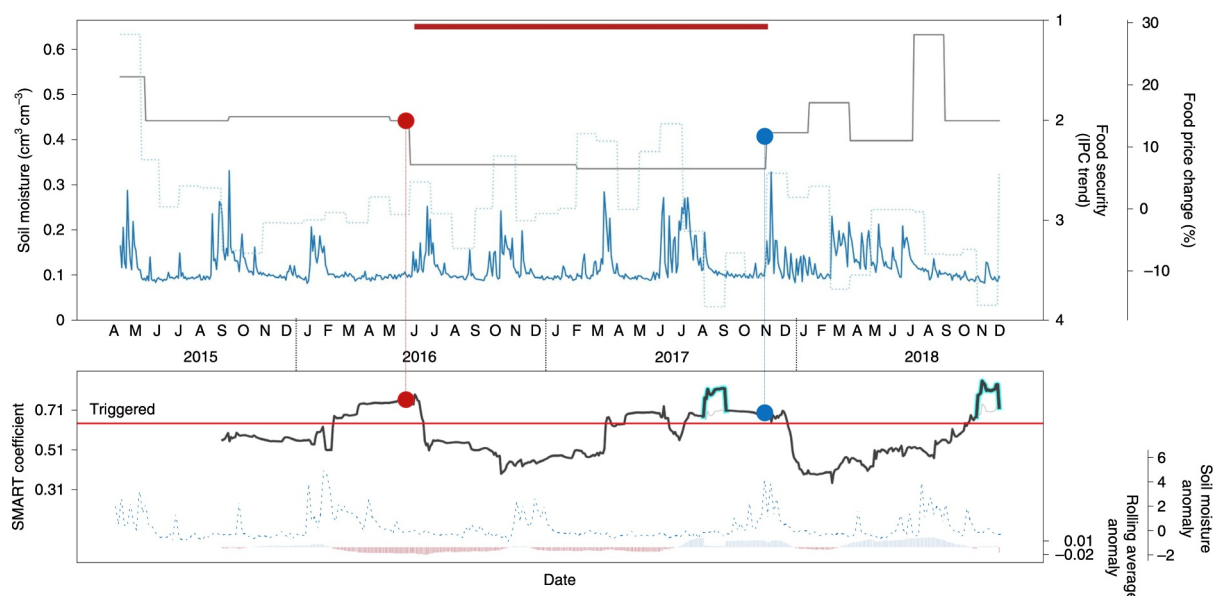


Figure 7. The Soil Moisture Auto-Regressive Threshold (SMART) system integrates SMAP SM with tipping point metrics, enabling it to predict every food crash (and recovery) 3–6 months before it occurs. Figure from: Krishnamurthy et al. (2022).

temperature and SM (Lesk et al., 2022; Rigden et al., 2020). ET has also helped with food-security monitoring (Hobbins et al., 2023). Together, SM-based forecasting and ET-based real-time management complement each other to address the short- and long-term problems.

5.3. Precision Agriculture and Agricultural Water Management

In the vast expanse of agricultural lands across the United States, optimizing crop growth and yield is essential for ensuring food security and economic stability. A crucial factor influencing crop productivity is the availability of SM, directly impacting crop development, health, and productivity. The moisture availability for rainfed farmlands is primarily influenced by the seasonal pattern of rainfall (intensity and frequency) and its interactions with the soil-plant-atmosphere continuum (Eeswaran et al., 2021; Franzluebbers et al., 2011; Saadi et al., 2022), which makes rainfed agricultural system more vulnerable to the impacts of climate variability and extremes (e.g., the devastating drought happened in 2012 and 2023). SM status works as an early warning indicator, informing producers to take essential actions to keep field-scale soil water content at appropriate level to mitigate the impacts of emergent climatic events on crop yields. Compared with rainfed farming systems, irrigation farmlands continue to expand through the cropping region and have grown to more than 23 million hectares in 2017 (~4% increase from 2012) (Kim, Kumar, & Kam, 2023). Irrigated agriculture is the largest consumer of water in the United States (Ruess et al., 2023). Monitoring SM status is important for developing irrigation strategies to increase water use efficiency by applying water at appropriate times, locations, and quantities, especially in arid and semiarid agroecosystems. For example, in Kentucky, it is recommended to turn on the irrigation when the soil volumetric water content is depleted by 40% of the plant-available water content (Knott et al., 2022).

Soil water storage dynamics and actual water availability (defined as the range from field capacity to permanent wilting point) for crops are a function of SM and ET (Babaeian & Tuller, 2023; Tuller et al., 2023). Due to the complicated interactions among multiple factors such as topography, soil types/properties, and local crop growth, SM and ET dynamics can vary considerably within a field. Agricultural management practices largely depend on an accurate and timely characterization of spatiotemporal rootzone SM/ET dynamics. Monitoring SM and understanding ET rates are pivotal for decision support in agricultural management. SM and ET mapping within crop fields can be derived from ground instrumentation, such as in situ sensor networks. However, the implementation of sensors is labor-, time- and cost-consuming at the field scale and the results are influenced by the design of the network (i.e., the distribution of the sensors in the agricultural field) (Petropoulos et al., 2018).

Alternatively, remote sensing approaches have shown great potential for providing estimates of spatial and temporal estimates of SM/ET for agronomic applications (Huang et al., 2019; Zipper & Loheide, 2014). Integration of remote sensing data into decision support systems and crop models provides producers and policy-makers with actionable insights for optimizing irrigation schedules, improving water use efficiency, mitigating water-related conflicts, and estimating irrigation water use (Brombacher et al., 2022; Crosby & Wang, 2021; Dari et al., 2023; Talib et al., 2024). For instance, in the arid and semiarid regions of the southwestern United States, where water scarcity is a pressing issue, remote sensing technologies have been instrumental in optimizing irrigation scheduling and improving water use efficiency in crop production (French et al., 2018; Singh & Das, 2022; Taghvaeian et al., 2018). By estimating SM levels and ET rates, producers can optimize irrigation applications to match crop water requirements, thereby reducing water consumption and minimizing environmental impact. Similarly, in the Midwest Corn Belt, where intensive corn and soybean production dominates, remote sensing-based monitoring of SM and ET has facilitated precision agriculture practices and enhanced crop yield predictions (Cammalleri et al., 2014; Ines et al., 2013; Zhao et al., 2021). Furthermore, by integrating satellite-derived data with ground-based observations and weather forecasts, producers can make informed decisions regarding planting/harvesting dates and water and nutrient management, leading to increased yields, profitability and enhanced environmental quality. This can be optimized such that T exceeds the water loss through E. To ensure proper agricultural water management, monitoring through in situ or remote is key (e.g., Berger et al., 2022).

Despite the numerous benefits of remote sensing approaches and significant advances that have been made, remote sensing products in relation to SM and ET have not been widely adopted by the end users (i.e., producers). Most available remote sensing data sets are at a resolution of 1 km or coarser, which is significantly larger than most actual farmlands and cannot represent the spatial dynamic of field-scale SM (Fisher et al., 2017; Ochsner et al., 2013; Petropoulos et al., 2015). To address this issue many researchers are working to produce fine-

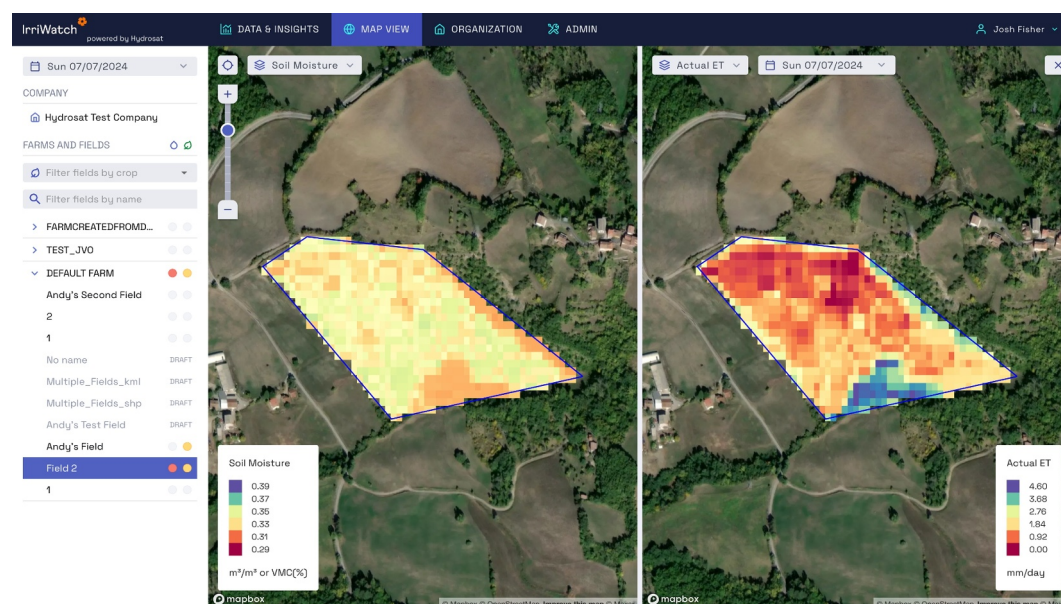


Figure 8. Hydrosat's IrriWatch remote sensing-based platform provides farmers with operational management tools for irrigation and crop management.

resolution maps for field-scale applications by using spatial downscaling techniques (Petroopoulos et al., 2018). More recently, the fusion of multi-sensor observations to improve the spatial and temporal resolutions of SM/ET products has been popular. For instance, Hydrosat's IrriWatch is now used by hundreds of farmers, agronomists, consultants, and decision-makers in over 60 countries (at the time of writing), covering over a hundred different crop types and over 2M ha of land (<https://www.hydrosat.com/>; <https://irriwatch.com/>). IrriWatch uses a combination of Landsat, ECOSTRESS, VIIRS, and Sentinel 1/2/3 among other inputs to create an extensive suite of data products and analytics tailored to its many disparate types of users (Bastiaanssen et al., 1998). IrriWatch is incorporating the new Hydrosat constellation of 20–50 m daily data to refine the resolutions and accuracies even further (Fisher, 2022). In addition to farmers, Hydrosat's users include food and seed businesses, irrigation suppliers, agriculture software companies, banks and insurance, and governmental organizations (Fisher, 2022). Hydrosat answers operational questions such as: (a) how much water does each field need?; (b) how can variable rate irrigation be operationalized?; (c) can spatial data layers integrate into existing farm management systems?; (d) can my bulk product yield be forecasted?; and, (e) what is the duration of the gate/valve opening? Lessons learned from IrriWatch are that use cases are extremely diverse and nuanced, requiring extensive human operator attention; a one-size-fits-all approach would limit applications (Figure 8).

5.4. Soil Salinization Management

Soil salinity elevates the osmotic potential in the vicinity of plant roots, leading to reduced water uptake by the roots and an accumulation of undesirable ions within the plants (Talat, 2020). This has a comparable impact on plant growth to that of drought. The level of salinity in soils is becoming too high for traditional crops and is anticipated to worsen even more due to climatic changes. The dryland areas of South America, southern and western Australia, Mexico, southwest United States, and South Africa are identified as the salinization hotspots (Hassani et al., 2021; Wang, Gao, et al., 2023). Besides primary or dryland salinity, irrigation salinity or secondary salinity are a significant threat to local agricultural production (Butcher et al., 2016). Visible seawater intrusion is converting farmland into marshes (Mondal et al., 2023; Figure 9). Understanding its broader implications on soil health and ecosystem dynamics has become imperative.

The relationship between soil salinity and SM and ET data is crucial for understanding the impact of salinity on water availability for vegetation. These empirical relationships can inform soil salinity management strategies and help identify areas prone to salinity-induced water stress. One of the most commonly used approaches in implementing scientific salinity management is using SM sensors (Taghvaeian et al., 2020). The irrigation

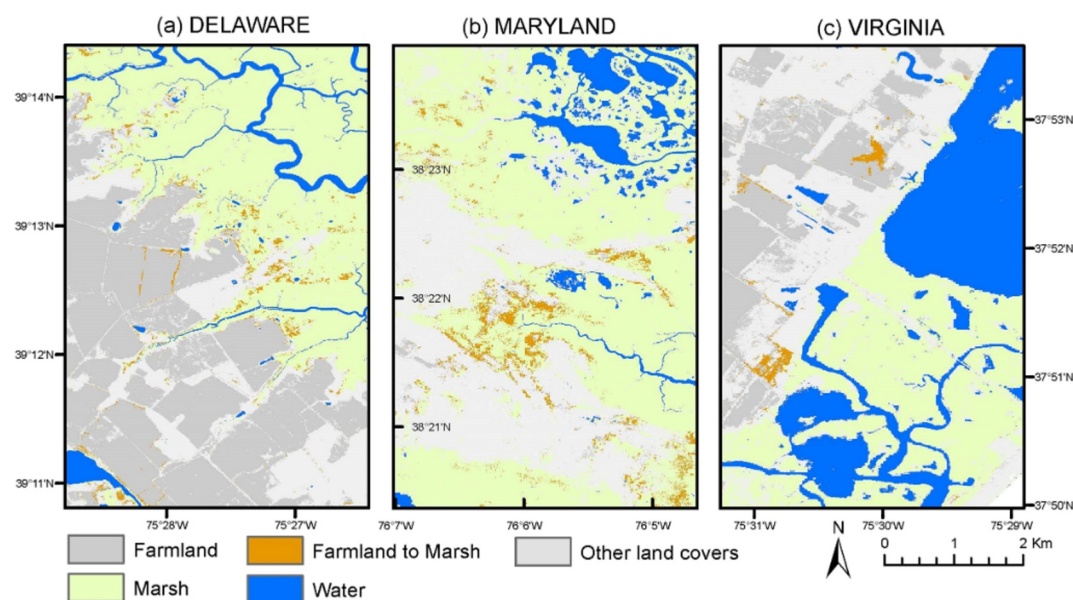


Figure 9. Over 8,000 ha of farmlands were converted to marsh between 2011 and 2017 due to soil salinization. Credit: Mondal et al., 2023.

scheduling and irrigation approaches (drip vs. flood) are crucial in managing SM and salinity levels, especially in arid regions relying on irrigation (Ren et al., 2019; Wang, Gao, et al., 2023). Direct use of remote sensing SM as an indicator for irrigation scheduling needs further investigation. For example, the estimation of SM from optical remote sensing data products may result in large bias and uncertainty at times affected by the irrigation process, where the highly variable moisture and salinity content play significant roles in determining the spectral behavior across wavelengths from Visible to SWIR (Du, Chen, et al., 2022; Du, Kimbll, et al., 2022).

Our literature review revealed no direct reference to explicit ET products with respect to soil salinization management except for small-scale field studies. However, remote sensing products related to plant growth provide indirect evidence of soil salinity stress affecting vegetation ET. For instance, vegetation water content detected through remote sensing offers insights into soil salinity stress (Wen et al., 2020), which subsequently impacts the ET of vegetation. This gap in the literature underscores a need for future research to develop explicit ET products that account for soil salinity conditions. For example, integrating with groundwater and soil salinity, satellite-based ET from Landsat images has been shown to have the potential to be an efficient method of estimating ET (Aboelsoud et al., 2023). Developing such products could provide valuable insights into the impacts of soil salinization on vegetation ET, ultimately informing management strategies for mitigating these effects.

5.5. Wildfire Forecasting and Modeling

SM influence on the likelihood, size, and seasonality of wildfires is well-documented. O et al. (2020) identified strong negative associations between anomalous SM before the fire season and the area burned. Krueger et al. (2015) observed that larger fires occurred at lower SM levels than smaller fires, underscoring the critical role of SM in wildfire danger assessments. Similarly, Krueger et al. (2016) described how below-average SM coincided with high wildfire occurrence in both growing and dormant seasons, indicating the need for season-specific fire management strategies.

Incorporating SM information into predictive wildfire models has also shown promising results. Farahmand et al. (2020) highlighted the significance of hydrological information, including SM, in extending the forecast ability into the months preceding wildfire activity. This is further supported by Sazib et al. (2021), who found a strong association between fire activity and SM anomalies, demonstrating that remote-sensing-based SM products could predict fire activity with a 1–2 months lead time. Krueger et al. (2022) also conducted a comprehensive review of the potential for integrating in situ, remotely sensed, and modeled SM information into fire danger rating systems. Their findings suggest that such integration could enhance predictions of fuel moisture (the

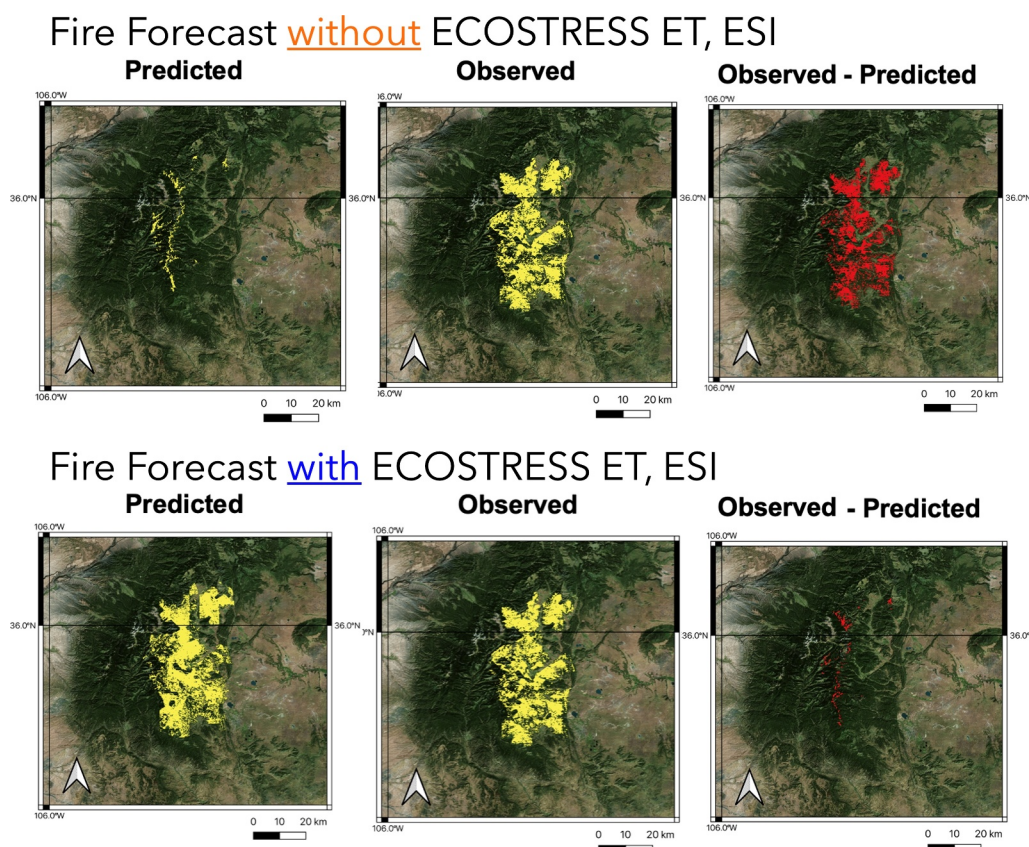


Figure 10. Wildfire presence and burn severity are better predicted when incorporating information on ET and evaporative stress than without. Here, an example is shown using ECOSTRESS data in New Mexico, USA. Red regions indicate the differences between predicted and observed burn severity.

amount of water in a fuel, such as vegetation, expressed as a percentage of the fuel's dry weight), provide earlier warnings of wildfire danger, and improve forecasts of wildfire occurrence and size.

Despite these advancements, significant challenges in understanding and predicting the SM-wildfire relationships remain. Wildfires are influenced by a complex interplay of various environmental factors, with SM being just one component of this intricate puzzle. Developing comprehensive diagnostic systems and process-oriented models that can accurately integrate and weigh these factors is crucial for reliable wildfire prediction and management (Krueger et al., 2022; Littell et al., 2016; Yu et al., 2020, 2022). Additionally, integrating multi-source SM and wildfire data into existing fire behavior models presents a complex challenge. Future research should focus on localized studies and the development of frameworks that better consider inputs and uncertainties from multi-source data sets and algorithms, accounting for the integrated interactions between SM, vegetation, climate, and human disturbances (Xie, Qi, et al., 2022; Zacharakis & Tsihrintzis, 2023).

ET improves wildfire predictions of presence and burn severity. Specifically, products of ET such as Evaporative Stress Index (ET/PET) and Water Use Efficiency (WUE) from ECOSTRESS significantly improved wildfire predictions across major wildfire regions of the world, including Australia, California (Pascolini-Campbell et al., 2022; Zhu et al., 2024), Oregon (Amici et al., 2022), and New Mexico (Joshi et al., 2024). Not only does such information provide direct indicators of plant stress related to wildfire susceptibility, but high-resolution measurements from missions such as ECOSTRESS give wildfire managers data at actionable scales for wildfire control and treatments (Poulos et al., 2021; Wilder & Kinoshita, 2022). The power of this data is only recently emerging both in the scientific literature and in the wildfire applications communities; some evidence points to potential universality in wildfire prediction using these data (Figure 10). Future research is needed for improved representation of fuel characteristics in responses to meteorological conditions and SM and dynamic modeling of moisture content in different vegetation types with high-resolution SM or ET products.

5.6. Dust Formation Monitoring

SM plays a significant role in the formation and emission of dust, especially in arid and semi-arid regions (Ishizuka et al., 2008). At the global scale, about 2,100 Tg/year of dust enters the atmosphere (Ginoux et al., 2001). Major sources of dust are in the moisture-limited regimes, including the Middle East, Central Asia, and the west coast of North Africa, through wind erosion (Prospero et al., 2002). The amount and composition of dust and aerosol affect the radiative forcing, cloud properties, and precipitation, and consequently impact the Earth's climate and biogeochemistry (Scanza et al., 2015). Dust monitoring is, therefore, crucial to the coupling relationship between SM and climate.

Once a dry layer of soil at the surface is formed, dust emission could be attributed to natural processes (e.g., wind erosion) for 75% and human activities (e.g., tillage) for 25% globally (Ginoux et al., 2012). Specifically, tillage-caused dust emissions are the combined result of moisture distribution along the soil profile and tillage intensity (Funk et al., 2008). After precipitation events, water in the soil decreases dust emissions due to increased wind erosion threshold velocity (Cornelis et al., 2004; Pierre et al., 2012). Under a clean atmosphere, energy scattering processes are reduced, and ET can reach its maximum values provided surface water and aerodynamic conditions are met. However, significant amounts of dust in the air can affect the thermal distribution across the lower troposphere by enhancing thermal inversions, thus temporarily reducing and delaying vertical convective fluxes, including ET (Soleimani Sardoo et al., 2022). Meanwhile, strong and heterogeneous mesoscale convective systems tend to form due to an increase of condensation nuclei when moisture conditions in the atmosphere are favorable (Chen et al., 2020).

Remote sensing of SM and ET plays a crucial role in understanding and mitigating dust formation, particularly in arid and semi-arid regions where dry soils are highly susceptible to wind erosion (Nicholson et al., 1998). Satellites like NASA's SMAP provide global SM data, enabling the identification of dry regions prone to dust generation (Entekhabi et al., 2010). SMAP's high-resolution SM maps have been extensively used to monitor drought conditions, which are closely linked to increased dust activity. Models such as METRIC (Mapping EvapoTranspiration at high Resolution with Internalized Calibration) utilize satellite imagery to estimate ET rates, offering valuable insights into regions where SM is rapidly depleting, thus increasing the likelihood of dust emission (Allen et al., 2007). This integrated approach has been demonstrated to improve drought monitoring and enhance the accuracy of dust storm predictions, as evidenced by studies that combine these data sets to assess and predict environmental risks (Anderson et al., 2012). Research in the Sahel region of Africa has shown that satellite-derived SM data can help predict dust outbreaks, with persistently low SM serving as a key indicator (Marticorena et al., 2017).

With the upcoming changes in temperature and precipitation across the globe, including in agricultural areas, hotter and drier conditions could lead to higher dust emissions that can alter (for days or months) the radiation budget, vertical mixing, and transport of moisture, thus altering the SM and ET regimes (Huang et al., 2014). Satellite-based SM data sets (e.g., SMOS, AMSR2) have been utilized to represent surface conditions and improve the estimation of dust emission (Kim et al., 2017). However, the net impact of dust on the hydrological cycle is still unclear and dependent on local conditions (Kok et al., 2023). General circulation models need to better simulate the interactions between dust, atmospheric humidity, radiative budget, and precipitation processes to better understand threshold values and the spatio-temporal scopes of these processes (e.g., regional to continental scale and hours to months), particularly under the changing global atmospheric conditions.

5.7. Flood Monitoring and Forecasting

The utilization of high-resolution SM products can play a crucial role in advancing streamflow forecasting and flood modeling by incorporating antecedent SM conditions and vegetation water uptake (Wang, Wyatt, & Ochsner, 2023; Wyatt et al., 2020). Assessing pre-storm SM conditions can potentially enhance flood forecasting systems, given their substantial impact on flood peaks during storm events (Chen et al., 2014; Massari et al., 2014). The SM content dictates the water storage capacity in the unsaturated zone and influences percolation to the saturated zone, thereby shaping the precipitation needed to trigger overland flow. It is imperative to acknowledge that assimilating the remotely sensed SM can significantly alter the parametrization of hydrological models (e.g., Schmugge et al., 2002; Wanders et al., 2014), consequently affecting the potential benefits derived from incorporating observations of other hydrological variables.

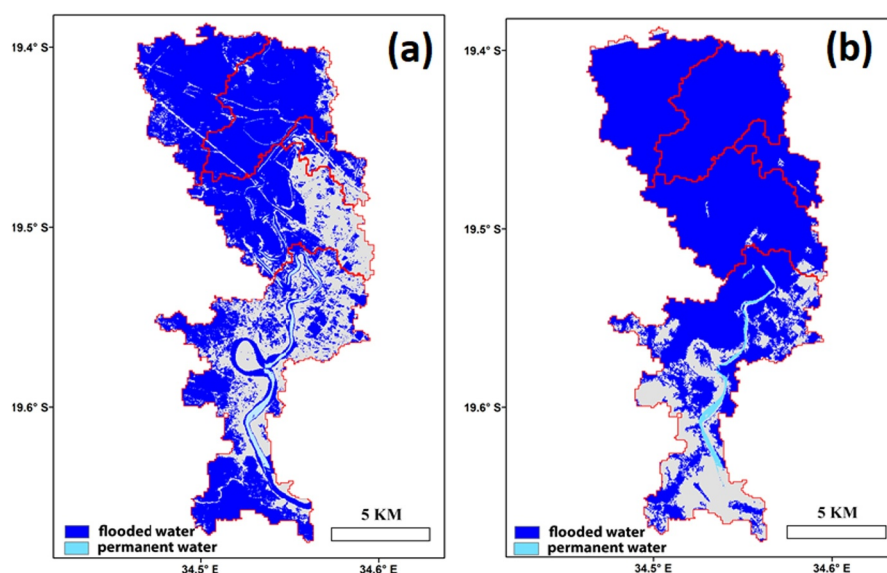


Figure 11. Inundation maps of selected catchments in southeast Africa during the Cyclone Idai event on 19 March 2019, produced using (a) a machine learning-based approach where SMAP SM and fractional water are the two most important features for 1-day forecast, and (b) Sentinel-1 SAR observations provided by NASA Advanced Rapid Imaging and Analysis (ARIA) program. Based on: Du et al. (2021).

In addition to physically based flood modeling, SM observations also directly support machine-learning-based flood inundation forecasting, as evidenced by the case study for assessing flood risks in southeast Africa during the 2019 Cyclone Idai event (Du et al., 2021; Figure 11). The SMAP SM and fractional water of the target catchments were found as the two most important features in the 1-day forecasts, underscoring the critical role of background surface wetness levels in determining the impact of imminent precipitation on short-term inundation changes (Du et al., 2021). In general, active and passive microwave remote sensing provides a unique capability to obtain observations of SM at global and regional scales that help satisfy the science and application needs of hydrology for flood monitoring and modeling (Njoku & Entekhabi, 1996; Schmugge et al., 2002). Challenges encountered include accurately representing soil hydraulic properties, integrating local topography into models, accounting for land use changes in flood risk assessments, and selecting an appropriate model-satellite integration method, such as data assimilation. The integration of high-resolution SM products not only enhances streamflow forecasting and flood modeling by considering pre-storm SM conditions but also underscores the complexities and challenges associated with assimilating remotely sensed data into hydrological models. The integration also offers a detailed delineation of surface wetness heterogeneity, potentially enabling household-level flood inundation forecasts within data-driven flood forecasting frameworks. However, while satellite retrievals of SM are directly used in drought and precision agriculture studies discussed before, direct use of satellite SM for operational flood forecasting is critically limited by the lack of high spatiotemporal resolution (e.g., hourly/sub-daily and sub-kilometer) satellite retrievals (Azimi et al., 2020; Uddin et al., 2019). This gap in literature and technology is evident in Figure 14 (Figure 12).

5.8. Urban Water, Energy, and Ecosystem Management

Urban ET accounts for 38% of annual water loss in temperate cities, escalating to 81% during summer (Grimmond & Oke, 1986). Latent heat flux through ET is a non-negligible term in the urban energy balance, amounting to 13%–67% of the sensible heat flux depending on the timing and location (Jacobs et al., 2015; Ward et al., 2016). Accurate estimations of urban SM and ET, especially over green infrastructure, are central to use cases like irrigation scheduling, urban heat island mitigation, and urban forestry (e.g., Nouri et al., 2013; Wan et al., 2021; Yu et al., 2024). The information also improves scientific understanding of urban processes, for example, the evaporative versus shading cooling effect of vegetation (e.g., Figure 12 from Schwaab et al., 2021; Yu et al., 2024), and the resilience of different urban vegetation types to extreme events (Miller et al., 2020).

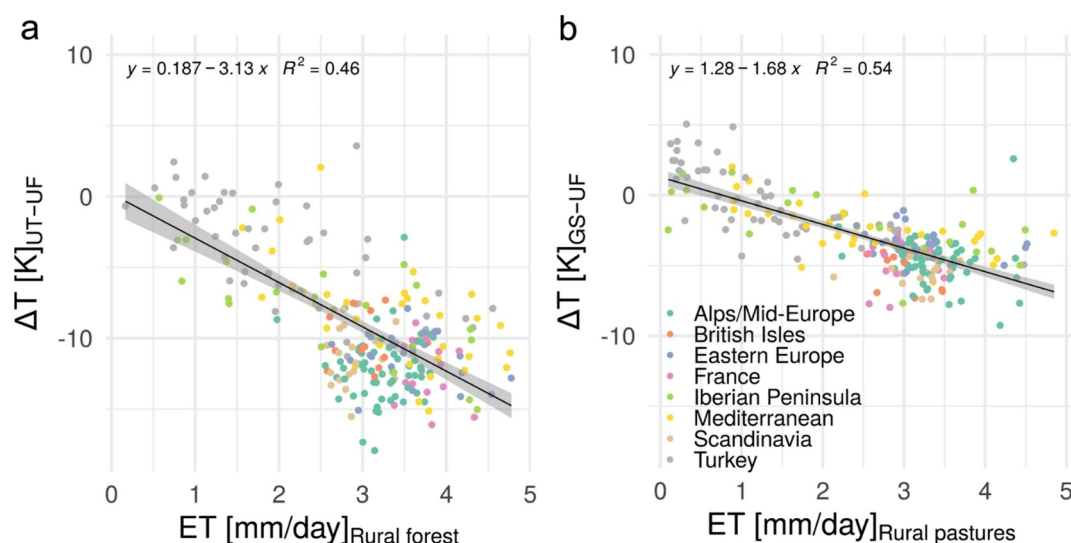


Figure 12. (a) Scatterplot of temperature differences between urban trees (UT) and urban fabric (UF) plotted against (ET) estimated for rural forests. (b) Scatterplot of temperature differences between treeless urban green spaces (GS) and urban fabric (UF) plotted against ET estimated for rural pastures. Each dot represents a city. All cities in a specific region are shown in the same color. Based on Schwaab et al. (2021).

There are two ongoing challenges in bridging remote sensing with urban SM and ET estimation and applications. One is that urban vegetation patches (a few meters for street trees, tens of meters for lawns, and a few hundred meters to a few kilometers for urban parks) are too small compared to the resolutions of state-of-the-art operational SM and ET products (Tables 1 and 2). The other is that retrieval algorithms are not well-developed for the heterogeneous urban environment. Studies have begun to tackle those challenges at the individual city level. For example, an early improvement on the SEBAL algorithm found it necessary to add the anthropogenic heat flux to correctly model urban ET; the study targeted multi-year annual ET using MODIS (500 m–1 km) inputs (Cong et al., 2017). The later uSEBAL ET algorithm, which considers urban land cover and anthropogenic heat flux, supports the earlier finding by showing statistically significant improvements against the original SEBA (Faridatul et al., 2020). The study targeted daily, 30 m resolution using 16 cloud-free days in the Landsat inputs, but the validation was only against pan evaporation (Faridatul et al., 2020). The TRU model improves upon the single and two-source energy balance models (e.g., TSEB, SEBAL) by considering three sources for urban ET (soil surfaces, vegetation, and impervious area) (Chen et al., 2022). The study targeted 30 m resolution and 63 cloud-free days in the Landsat inputs spanning 3 years and showed RMSE of 40.2 W/m² when compared against eddy covariance observed latent heat fluxes. Developments on the SCOPE model, which considers radiative transfer through soil, leaf, and canopy in addition to energy balance, have focused on post-processing algorithms that can correct for the effect of relative vegetated and impervious fractions (Rocha et al., 2022; Yu et al., 2024). The post-processed hourly ET showed RMSE of 37.55–56.50 W/m² and R^2 of 0.47–0.82 when compared against eddy covariance data during an entire year (Rocha et al., 2022) and a 3-day heat wave (Yu et al., 2024). The best spatial resolution of SCOPE-estimated urban ET is 100 m, using resampled Sentinel-2 and GEDI inputs (Yu et al., 2024). Combining multi-source geospatial data (Sentinel-2, Urban Atlas building height, municipal vegetation height map), eddy covariance observations, and machine learning, city-wide hourly ET has been estimated at 10 m resolution at R^2 of 0.56–0.76, and root mean square error of 0.0171–0.0289 mm (Vulova et al., 2023). Fewer studies focused on urban SM. The methods are either jointly with ET estimation (e.g., Jiang & Weng, 2017) or depend on existing products (e.g., Ahlmer et al., 2018).

While the above studies demonstrate the feasibility of estimating urban ET using remote sensing, the estimation of ET at <30 m resolution, the estimation of urban SM, and the scaling up from individual cities to multiple cities over a large region or the globe, remain open challenges. Multi-source data fusion and advanced machine learning approaches may be worth future methodological explorations (e.g., Qin et al., 2022; Vulova et al., 2023). Successfully tackling those challenges will reduce the need for decision-makers to conduct expensive ground observations and increase the availability and accuracy of urban planning tools. It will also alleviate the current data

limitation on a large-scale understanding of urban-rural ecosystem contrasts (e.g., Schwaab et al., 2021; Wang et al., 2024) and contribute to better modeling of urban land surface-atmosphere feedback (e.g., Cao et al., 2016).

5.9. Ecohydrology and Biodiversity Conservation

SM and ET variations are important indicators for the dynamics of ecosystems; ET is the number one climatic predictor of biodiversity (Fisher et al., 2011) and spatial variation in SM availability can determine niche partitioning (Silvertown et al., 2015). Here, we contrast cropland and grassland ecosystems with forest ecosystems. In general, forest ecosystems have deeper rooting depths, accessing deep SM compared to crops and grassland. These deeper roots can sustain ET during drought periods where SM declines in the upper soil layers (Buitink et al., 2020). The performance of satellite SM products (e.g., SMAP) also differs. For example, in croplands and grasslands, SM retrievals are generally better than in forested ecosystems (Chan et al., 2018; Feng et al., 2022), mainly due to scattering or attenuation from dense vegetation, though SM retrievals from L-band are improving (Colliander et al., 2020). In croplands the onset of field irrigation as well as the ability to differentiate between irrigated and non-irrigated fields is predicted well by SMAP SM retrievals (Lawston et al., 2017; Mladenova et al., 2017). By comparison, monitoring ET from space is more challenging in croplands than that in forests and grasslands due to management practices (e.g., irrigation, fertilization) introducing uncertainty (Wu et al., 2022; Zhang et al., 2021). However, satellite ET data sets can track the diurnal and seasonal cycle of cropland ET, and higher-resolution ET derived from Cubesats data (~3 m resolution) have the potential to improve cropland ET monitoring (Aragon et al., 2021).

Satellite-based SM and ET data are crucial for calculating basin-scale water balances and modeling. They offer valuable insights into the amount of water stored in the rootzone and transferred from the land to the atmosphere. Integrating SM and ET parameters into hydrological models improves water balance predictions and reduces uncertainties in overall estimations, improving decision-making in a variety of areas including irrigation scheduling and water resource allocations. Moreover, satellite-based SM data can help estimate potential groundwater recharge by identifying areas where the soil has a high moisture content, suggesting that excess water might percolate down to recharge the local or regional aquifers. For example, assimilated water storage derived from GRACE and SM derived from SMOS support improved water balance at the regional scale (Tian et al., 2017). Several studies have emphasized the enhanced estimations of regional or river basin-scale water balances that can be achieved using SM and ET products (Falalakis & Gemitzi, 2020; Fereidoon et al., 2019; Jiang et al., 2020; Koster et al., 2018; Liu et al., 2018; López López et al., 2017; Moreira et al., 2019). While GRACE data is reliable for regional-scale groundwater storage estimations, it is often overlooked for SM estimations (Abiy & Melesse, 2017). However, data assimilation of GRACE with SM and ET products, along with improved integrated modeling frameworks, can yield better water balance estimations (Magotra et al., 2024; Pascolini-Campbell et al., 2020, 2021; Tangdamrongsub et al., 2020; Zhang et al., 2022). In addition, estimated ET rates can convey the amount of water available for infiltration and recharge, which could be promising in water-scarce regions (Mbabazi et al., 2024). Integrating satellite-based SM and ET data into basin-scale water balance and aquifer management can be strengthened by model ensembles and data assimilation to provide high-resolution data sets.

Under projected climate change and intensified anthropogenic activities, invasive species can alter regional vegetation-climate feedbacks if they exhibit high resource competitiveness. Here, SM can be the key to a mechanistic process understanding of the invasive species establishment (Westerband et al., 2020). For example, Hawaii faces an urgent challenge of exotic species invasion and native species extinction due to the historic isolation of the islands (Sax & Gaines, 2008). Therefore, SM has become a powerful tool to evaluate the impact of invasive species and the effectiveness of native species restoration strategies in Hawaii (Enoki & Drake, 2017; Kagawa et al., 2009; Perkins et al., 2014; Thaxton et al., 2012). However, SM in Hawaii is highly heterogeneous in space because of steep volcano slopes, prevailing trade winds, and heterogeneous soil age due to frequent volcanic activities. Existing studies often rely on field measurements of SM at a regional scale, which fails to develop effective measurements of island-wide species invasion risks (Enoki & Drake, 2017; Kagawa et al., 2009; Perkins et al., 2014; Thaxton et al., 2012). Spatial mapping of native/invasive species primarily focuses on vegetation canopy (Asner, Jones, et al., 2008; Asner, Knapp, et al., 2008; Pejchar et al., 2020). To advance the effective conservation and restoration of native species for tropical high-elevation islands like Hawaii, high resolution SM data sets and observational platforms (Table 1), will play an important role (Boelman et al., 2007; Povak et al., 2017).

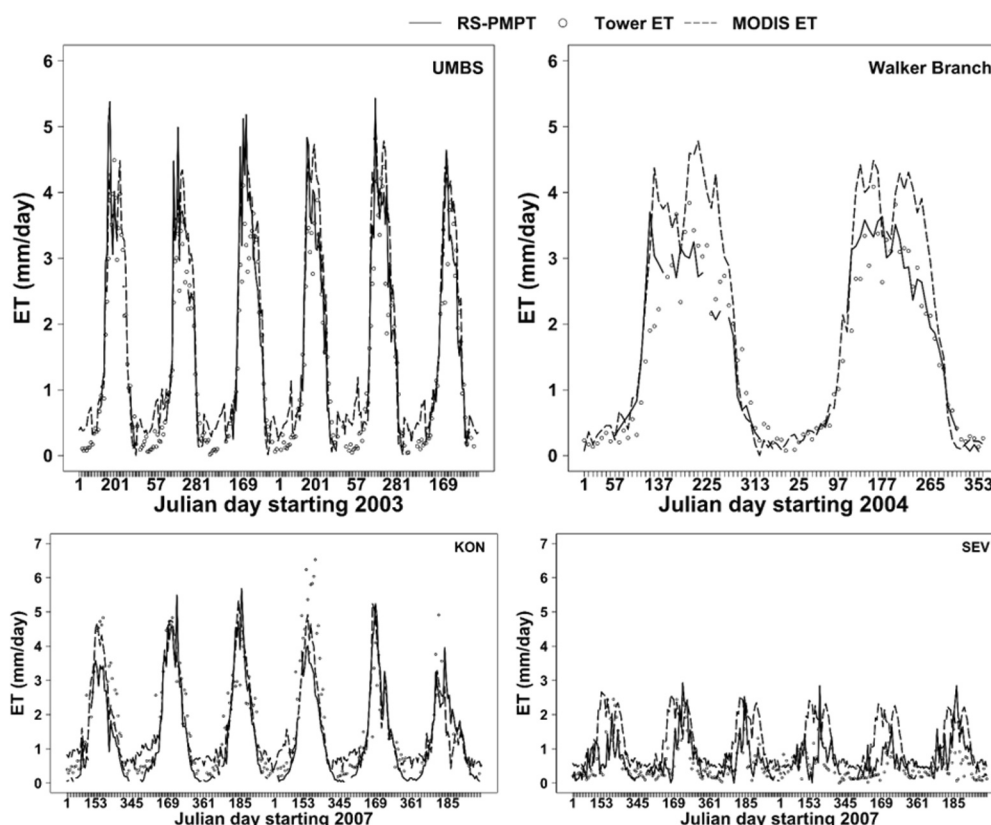


Figure 13. Seasonal time series of daily ET for the deciduous forest (top panels) and grassland sites (bottom panels) either at the eddy flux tower (open circle) or predicted by the RS-ET model (black line) and modified from El Masri et al. (2019).

Long-term, high-resolution ET data are also important for monitoring the terrestrial ecosystem's water and carbon cycle and understanding the terrestrial ecosystems' response to climate change (Ajur & Al-Ghamdi, 2021; Zhan et al., 2021). For instance, MODIS ET has been used to estimate trends in ET at the regional (Hobeichi et al., 2021) and watershed scales (Parajuli et al., 2022). The spatial and temporal ET data have enabled the studies of global hydrological change to understand the terrestrial ecosystem water use efficiency (WUE) trends and variability with time (Tang et al., 2014) that can facilitate management practices aimed at adaptation to global hydrological change. The spatial and temporal variability of remote sensing-derived ET and WUE enables the contrast of the differences in ET and WUE between grassland and forested ecosystems (Cooley et al., 2022; El Masri et al., 2019; Figure 13).

5.10. Challenges and Opportunities in the Global South

Considering the infrastructure gaps, satellite-based SM and ET products provide critical data that would otherwise be unavailable in regions with limited ground-based monitoring infrastructure (Myeni et al., 2019; Ndehedehe et al., 2018). Despite the recent improvements, SM and ET estimations in the Global South have relatively few in situ or validation points (Fereidoon et al., 2019; Fisher et al., 2009; Jung et al., 2019; Melo et al., 2021; Myeni et al., 2019). The estimated product or model results often face the question of reliability, and it has been more challenging to create accurate remote sensing products than in the global north. One validation approach is to use water balance-based ET instead of eddy flux towers (Weerasinghe et al., 2020); the application is valuable for yield forecasting for local farmers and insurance companies (Benami et al., 2021), and hydrological modeling (Dembélé et al., 2020).

The lack of sufficient technical expertise in many developing countries is also a major factor that often limits the effective use of satellite-based SM and ET products. Even with greater limitations, the current available SM and ET products in the global south significantly enhance water management, yield forecasting, and disaster preparedness in the Global South (Abiy & Melesse, 2017; Fereidoon et al., 2019; Moreira et al., 2019). Spatial and

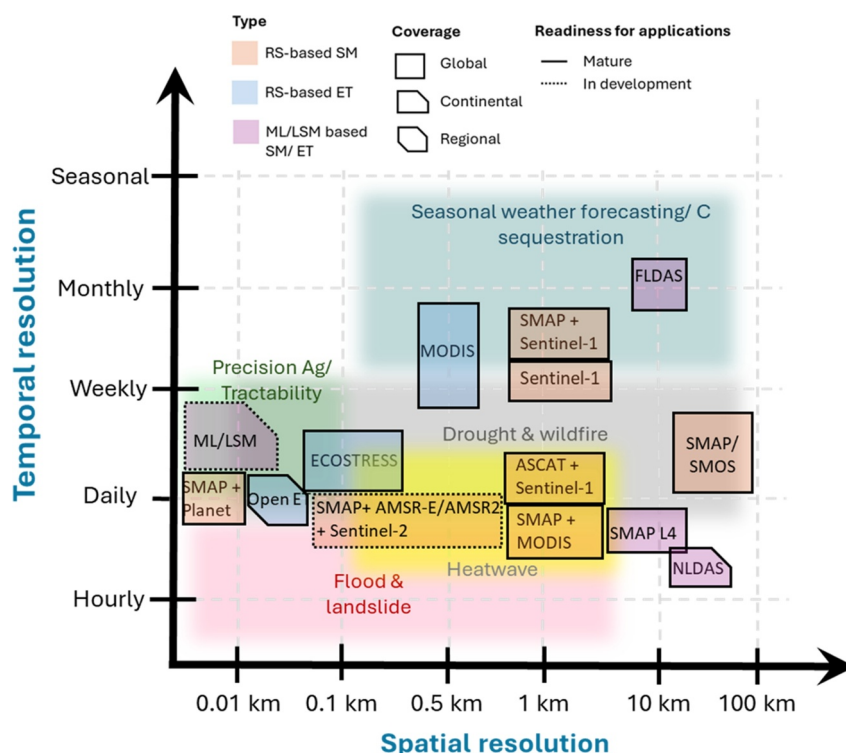


Figure 14. Summary of spatial and temporal resolutions, spatial coverage, and applications of various soil moisture (SM) and evapotranspiration (ET) products.

temporal resolution constraints of satellite data may not always meet the specific needs of local applications, limiting the accuracy and reliability of satellite-derived information. SMAP and GRACE missions have provided detailed insights into SM and water storage dynamics, which are critical for effective water resource management in data-scarce environments. Integrating satellite data with ground-based observations and local knowledge can improve the accuracy and relevance of management decisions, making them more effective and sustainable in the long run. A multi-faceted approach is needed to address the challenges in the Global South and harness the full potential of satellite-based SM and ET products.

6. Summary and Future Perspectives

SM and ET are key environmental variables that play critical roles in the water, carbon, and energy cycling of ecosystems. The emergence of numerous satellite SM and ET products over the past decades has helped advance the understanding of fundamental life-sustaining environmental processes. Here, we review the state-of-the-science of retrieval, modeling, bio-geo-physical controls, and coupled feedback mechanisms between SM and ET from regional to global scales. We provide a survey of the available remotely sensed and simulated SM and ET products, including details on the key aspects of their modeling/retrieval algorithms and spatiotemporal resolution and limitations. We provide a comprehensive review of diverse applications of SM and ET data sets, such as ecosystem services, weather and climate modeling/forecasting, agricultural water management, and mitigating risks of hydroclimatic extremes such as flash droughts, wildfires, floods, and severe dust monitoring, among others.

Despite several pathbreaking advancements in retrieving and modeling these key hydrological variables over the last decade, the general trajectory of such advancements has now exceeded those in data processing, storage, and computing capabilities. We identify several underlying limitations that prohibit seamless monitoring and modeling capabilities of SM and ET at field-scale and sub-daily resolution with the extent ranging from regional to continental scale (Figure 14). Several of these challenges pertain to the underlying remote-sensing principles in ET and SM retrieval (hyperspectral vs. microwave sensors) that determine the spatial and temporal resolution of the retrieval (spatial and temporal resolution of the sensor) and spatial coverage (effect of cloud coverage, radio-frequency-interference, high vegetation water content, etc.). Measurement of rootzone SM needs low-

Acknowledgments

J. Huang was supported by the USDA Agriculture and Food Research Initiative Foundational Program (Grant 2023-67021-40007) and Marvin T. Beatty Professorship in Soil Science from the University of Wisconsin-Madison. V. Sehgal is funded in parts by the Louisiana Agricultural Experiment Station, the Hatch Program of USDA-NIFA, and USDA-NRCS grant (NR247217XXXXG001). J. B. Fisher was supported in part by NASA's ECOSTRESS Science and Applications Team (ESAT) (80NSSC23K0309) and NASA's Earth Science Applications: Water Resources (WATER) (80NSSC22K0936) programs. B. El Masri was supported by NASA Kentucky EPSCoR under NASA award No: 80NSSC20M0047 and NASA EPSCoR FY22 R3 under NASA award No: 80NSSC22M0247, DOE (Environmental System Science: DE-SC0022228), and NSF (MRI: 2215877 and EPSCoR Fellowship: 2327374). J. Mao, Y. Wang, and X. Shi were supported by the Reducing Uncertainties in Biogeochemical Interactions through Synthesis and Computing Scientific Focus Area (RUBISCO SFA) project funded through the Earth and Environmental Systems Sciences Division of the Biological and Environmental Research Office in the US Department of Energy (DOE) Office of Science. Oak Ridge National Laboratory (ORNL) is supported by the Office of Science of the DOE under Contract No. DE-AC05-00OR22725. This research is also an outcome of the Soil Moisture Working Group supported by ORNL RUBISCO SFA. L. Brocca was supported by the European Union "Open Earth Monitor Cyberinfrastructure" project (grant agreement No. 101059548), the Italian Department of Civil Protection, and the European Space Agency project DTE Hydrology Evolution (Grant ESA 4000136272/21/I539 EF—CCN N. 1). L. V. Alvarez was supported by the National Science Foundation (NSF) CAREER award 2239550 and the National Oceanic and Atmospheric Administration (NOAA) Cooperative Science Center Educational Partnership Program with Minority Serving Institutions (MSI) award NA22SEC4810016, and the Army Research Office (ARO) Cooperative Agreement Numbers W911NF-24-1-0296 and W911NF-23-2-0046. H. A. Moreno was funded by the National Oceanic and Atmospheric Administration (NOAA) Cooperative Science Center Educational Partnership Program with Minority Serving Institutions (MSI) award NA22SEC4810016. B. El Masri was supported by NASA Kentucky under NASA award No: 80NSSC20M0047, NASA Kentucky R3 award, DOE (Environmental System Science: DE-SC0022228), and NSF (NSF EPSCoR Fellowship: 2327374). The views and conclusions contained in this document are

frequency microwave sensor operation (<500 MHz) to penetrate below the surface soil profile—beyond the capability of the currently available L-band microwave SM sensors such as SMAP and SMOS. Such differential effects of environmental conditions and sensor limitations on satellite retrievals have contributed to the discordance in the remote-sensing measurements of SM and ET in space and time. Recent advancements in hyper-resolution process-based and/or artificial intelligence-based models have thus filled in the gap by providing continental scale space-time continuous SM and ET estimates. The fusion of multi-satellite, multi-scale observations has also offered promising results in providing SM and ET data sets with high temporal and spatial resolutions. Using machine learning in conjunction with available in situ SM networks to downscale satellite-derived data sets has also demonstrated encouraging results in achieving high-resolution SM products.

While we provide an exhaustive list of state-of-the-science applications of SM and ET for multidisciplinary applications, we also recognize the critical limitations of the current technology and provide a vision for future technological and methodological developments to support some of the most pressing issues of hydrology and associated fields. We emphasize that despite progress, current and future work should focus on developing high-resolution (less than 100 m), sub-daily SM and ET products, which may then enable the evaluation of hydrological processes occurring at finer scales, generally not captured in current data sets. Developments in designing Synthetic Aperture Radar based P-band sensors have shown promising results in expanding the scope of remote-sensor-based SM measurements to the rootzone profile. While most decision support systems have traditionally relied on platform-specific applications, a cascading application of multiplatform, multi-satellite synchronization can revolutionize data acquisition and application by combining platforms such as CubeSats with larger thermal, microwave, or hyperspectral space-borne sensors. Watershed developments in cloud computing technology have the potential to play a larger role in societal applications of high-resolution SM and ET data sets for decision support and community development. Open-source data sharing has significant potential to enhance the scope of hydrologic science development and its application transcended borders. Such developments can revolutionize the societal application of hydrological science by supporting unprecedented applications such as field-scale crop yield management and drought impact assessment, landslide and wildfire monitoring, insurance payouts to farmers and producers, land tractability for farm management and national security, and precision agriculture, among others. The availability of such data sets will be a great equalizer in the data-poor regions of the world, especially the global south, and be a catalyst for socio-economic development.

Data Availability Statement

No soil moisture or evapotranspiration data sets were used in this study. The review of the various data products was based on the information described in the original papers/technical notes, which were listed as references in Tables 1 and 2.

References

- Abdollahipour, A., Ahmadi, H., & Aminnejad, B. (2022). A review of downscaling methods of satellite-based precipitation estimates. *Earth Science Informatics*, 15(1), 1–20. <https://doi.org/10.1007/s12145-021-00669-4>
- Abi, A. Z., & Melesse, A. M. (2017). Evaluation of watershed scale changes in groundwater and soil moisture storage with the application of GRACE satellite imagery data. *Catena*, 153, 50–60. <https://doi.org/10.1016/j.catena.2017.01.036>
- Aboelsoud, H. M., Habib, A., Engel, B., Hashem, A. A., Abou El-Hassan, W., Govind, A., et al. (2023). The combined impact of shallow groundwater and soil salinity on evapotranspiration using remote sensing in an agricultural alluvial setting. *Journal of Hydrology: Regional Studies*, 47, 101372. <https://doi.org/10.1016/j.ejrh.2023.101372>
- Abowarda, A. S., Bai, L., Zhang, C., Long, D., Li, X., Huang, Q., & Sun, Z. (2021). Generating surface soil moisture at 30 m spatial resolution using both data fusion and machine learning toward better water resources management at the field scale. *Remote Sensing of Environment*, 255, 112301. <https://doi.org/10.1016/j.rse.2021.112301>
- Ahlmer, A.-K., Cavalli, M., Hansson, K., Koutsouris, A. J., Crema, S., & Kalantari, Z. (2018). Soil moisture remote-sensing applications for identification of flood-prone areas along transport infrastructure. *Environmental Earth Sciences*, 77(14), 533. <https://doi.org/10.1007/s12665-018-7704-z>
- Ajjur, S. B., & Al-Ghamdi, S. G. (2021). Evapotranspiration and water availability response to climate change in the Middle East and North Africa. *Climatic Change*, 166(3–4), 28. <https://doi.org/10.1007/s10584-021-03122-z>
- Akbar, R., Prager, S., Silva, A. R., Moghaddam, M., & Entekhabi, D. (2021). Wireless sensor network informed UAV path planning for soil moisture mapping. *IEEE Transactions on Geoscience and Remote Sensing*, 60, 1–13. <https://doi.org/10.1109/tgrs.2021.3088658>
- Alessi, M. J., Herrera, D. A., Evans, C. P., DeGaetano, A. T., & Ault, T. R. (2022). Soil moisture conditions determine land-atmosphere coupling and drought risk in the Northeastern United States. *Journal of Geophysical Research: Atmospheres*, 127(6), 1–14. <https://doi.org/10.1029/2021jd034740>
- Allen, R. G., Tasumi, M., & Trezza, R. (2007). Satellite-based energy balance for mapping evapotranspiration with internalized calibration (METRIC)—Model. *Journal of Irrigation and Drainage Engineering*, 133(4), 380–394. [https://doi.org/10.1061/\(asce\)0733-9437\(2007\)133:4\(380\)](https://doi.org/10.1061/(asce)0733-9437(2007)133:4(380))

those of the authors and should not be interpreted as representing the official policies, either expressed or implied, of the ARO, NSF, NOAA or the U.S. Government. The U.S. Government authorizes and distributes reprints for Government purposes notwithstanding any copyright notation herein. K.A. Endsley was supported in part by NASA's Early Career Investigator Program (Grant 80NSSC24K1051). M. Jampani was supported by the CGIAR Initiative on Asian Mega-Deltas (AMD) and the CGIAR Trust Fund contributors (<https://www.cgiar.org/funders>). Y. Fang, L. Li, and M. Shi were supported by the Earth and Biological Sciences Directorate (EBSD)'s Laboratory Directed Research and Development (LDRD) Program at Pacific Northwest National Laboratory (PNNL). PNNL is a multi-program national laboratory operated for the U.S. Department of Energy (DOE) by Battelle Memorial Institute under Contract No. DE-AC05-76RL01830. The authors would like to thank Professor Ole Wendroth (University of Kentucky) and an anonymous reviewer for the constructive comments on the original version of the manuscript.

- Amici, S., Spiller, D., Ansalone, L., & Miller, L. (2022). Wildfires temperature estimation by complementary use of hyperspectral PRISMA and thermal (ECOSTRESS & L8). *Journal of Geophysical Research: Biogeosciences*, 127(12), e2022JG007055. <https://doi.org/10.1029/2022JG007055>
- Anderson, M., Gao, F., Knipper, K., Hain, C., Dulaney, W., Baldocchi, D., et al. (2018). Field-scale assessment of land and water use change over the California Delta using remote sensing. *Remote Sensing*, 10(6), 889. <https://doi.org/10.3390/rs10060889>
- Anderson, M. C., Hain, C., Wardlow, B., Pimstein, A., Mecikalski, J., & Kustas, W. (2012). A thermal-based evaporative stress index for monitoring surface moisture depletion. In *Remote sensing of drought: Innovative monitoring approaches* (pp. 145–167).
- Anderson, M. C., Norman, J. M., Mecikalski, J. R., Otkin, J. A., & Kustas, W. P. (2007). A climatological study of evapotranspiration and moisture stress across the continental United States based on thermal remote sensing: 1. Model formulation. *Journal of Geophysical Research*, 112(D10). <https://doi.org/10.1029/2006jd007506>
- Anderson, M. C., Yang, Y., Xue, J., Knipper, K. R., Yang, Y., Gao, F., et al. (2021). Interoperability of ECOSTRESS and Landsat for mapping evapotranspiration time series at sub-field scales. *Remote Sensing of Environment*, 252, 112189. <https://doi.org/10.1016/j.rse.2020.112189>
- Anderson, M. C., Zolin, C. A., Sentelhas, P. C., Hain, C. R., Semmens, K., Yilmaz, M. T., et al. (2016). The evaporative stress index as an indicator of agricultural drought in Brazil: An assessment based on crop yield impacts. *Remote Sensing of Environment*, 174, 82–99. <https://doi.org/10.1016/j.rse.2015.11.034>
- Andreadis, K. M., Meason, D. F., Höck, B., Lad, P., & Das, N. (2022). Evaluation of multiscale SMAP soil moisture products in forested environments. *IEEE Geoscience and Remote Sensing Letters*, 19, 1–5. <https://doi.org/10.1109/lgrs.2022.3184177>
- Andreasen, M., Jensen, K. H., Desilets, D., Franz, T. E., Zreda, M., Bogen, H. R., & Looms, M. C. (2017). Status and perspectives on the cosmic-ray neutron method for soil moisture estimation and other environmental science applications. *Vadose Zone Journal*, 16(8), 1–11. <https://doi.org/10.2136/vzj2017.04.0086>
- Aragon, B., Cawse-Nicholson, K., Hulley, G., Houborg, R., & Fisher, J. B. (2023). K-sharp: A segmented regression approach for image sharpening and normalization. *Science of Remote Sensing*, 8, 100095. <https://doi.org/10.1016/j.srs.2023.100095>
- Aragon, B., Houborg, R., Tu, K., Fisher, J. B., & McCabe, M. (2018). CubeSats enable high spatiotemporal retrievals of crop-water use for precision agriculture. *Remote Sensing*, 10(12), 1–23. <https://doi.org/10.3390/rs10121867>
- Aragon, B., Ziliani, M. G., Houborg, R., Franz, T. E., & McCabe, M. F. (2021). CubeSats deliver new insights into agricultural water use at daily and 3 m resolutions. *Scientific Reports*, 11(1), 12131. <https://doi.org/10.1038/s41598-021-91646-w>
- Armanios, D. E., & Fisher, J. B. (2014). Measuring water availability with limited ground data: Assessing the feasibility of an entirely remote-sensing-based hydrologic budget of the Rufiji Basin, Tanzania, using TRMM, GRACE, MODIS, SRB, and AIRS. *Hydrological Processes*, 28(3), 853–867. <https://doi.org/10.1002/hyp.9611>
- Asner, G. P., Jones, M. O., Martin, R. E., Knapp, D. E., & Hughes, R. F. (2008). Remote sensing of native and invasive species in Hawaiian forests. *Remote Sensing of Environment*, 112(5), 1912–1926. <https://doi.org/10.1016/j.rse.2007.02.043>
- Asner, G. P., Knapp, D. E., Kennedy-Bowdoin, T., Jones, M. O., Martin, R. E., Boardman, J., & Hughes, R. F. (2008). Invasive species detection in Hawaiian rainforests using airborne imaging spectroscopy and LiDAR. *Remote Sensing of Environment*, 112(5), 1942–1955. <https://doi.org/10.1016/j.rse.2007.11.016>
- Azimi, S., Dariane, A. B., Modanesi, S., Bauer-Marschallinger, B., Bindlish, R., Wagner, W., & Massari, C. (2020). Assimilation of Sentinel 1 and SMAP-based satellite soil moisture retrievals into SWAT hydrological model: The impact of satellite revisit time and product spatial resolution on flood simulations in small basins. *Journal of Hydrology*, 581, 124367. <https://doi.org/10.1016/j.jhydrol.2019.124367>
- Babaeian, E., Sadeghi, M., Jones, S. B., Montzka, C., Vereecken, H., & Tuller, M. (2019). Ground, proximal, and satellite remote sensing of soil moisture. *Reviews of Geophysics*, 57(2), 530–616. <https://doi.org/10.1029/2018rg000618>
- Babaeian, E., & Tuller, M. (2023). Proximal sensing of evapotranspiration. In M. J. Goss & M. Oliver (Eds.), *Encyclopedia of soils in the environment* (2nd ed., pp. 610–617). Academic Press.
- Badgley, G., Fisher, J. B., Jiménez, C., Tu, K. P., & Vinukollu, R. (2015). On uncertainty in global terrestrial evapotranspiration estimates from choice of input forcing datasets. *Journal of Hydrometeorology*, 16(4), 1449–1455. <https://doi.org/10.1175/jhm-d-14-0040.1>
- Baldocchi, D. D., Keeney, N., Rey-Sanchez, C., & Fisher, J. B. (2022). Atmospheric humidity deficits tell us how soil moisture deficits down-regulate ecosystem evaporation. *Advances in Water Resources*, 159, 104100. <https://doi.org/10.1016/j.advwatres.2021.104100>
- Bastiaanssen, W. G., Menenti, M., Feddes, R. A., & Holtslag, A. A. M. (1998). A remote sensing surface energy balance algorithm for land (SEBAL). 1. Formulation. *Journal of Hydrology*, 212, 198–212. [https://doi.org/10.1016/s0022-1694\(98\)00253-4](https://doi.org/10.1016/s0022-1694(98)00253-4)
- Bauer-Marschallinger, B., Freeman, V., Cao, S., Paulik, C., Schaufeler, S., Stachl, T., et al. (2018). Toward global soil moisture monitoring with Sentinel-1: Harnessing assets and overcoming obstacles. *IEEE Transactions on Geoscience and Remote Sensing*, 57(1), 520–539. <https://doi.org/10.1109/tgrs.2018.2858004>
- Bauer-Marschallinger, B., Paulik, C., Hochstöger, S., Mistelbauer, T., Modanesi, S., Ciabatta, L., et al. (2018b). Soil moisture from fusion of scatterometer and SAR: Closing the scale gap with temporal filtering. *Remote Sensing*, 10(7), 1030. <https://doi.org/10.3390/rs10071030>
- Benami, E., Jin, Z., Carter, M. R., Ghosh, A., Hijmans, R. J., Hobbs, A., et al. (2021). Uniting remote sensing, crop modelling and economics for agricultural risk management. *Nature Reviews Earth & Environment*, 2(2), 140–159. <https://doi.org/10.1038/s43017-020-00122-y>
- Berger, K., Machwitz, M., Kycko, M., Kefauver, S. C., Van Wittenbergh, S., Gerhards, M., et al. (2022). Multi-sensor spectral synergies for crop stress detection and monitoring in the optical domain: A review. *Remote Sensing of Environment*, 280, 113198. <https://doi.org/10.1016/j.rse.2022.113198>
- Boelman, N. T., Asner, G. P., Hart, P. J., & Martin, R. E. (2007). Multi-trophic invasion resistance in Hawaii: Bioacoustics, field surveys, and airborne remote sensing. *Ecological Applications*, 17(8), 2137–2144. <https://doi.org/10.1890/07-0004.1>
- Bogen, H. R., Huisman, J. A., Oberdörster, C., & Vereecken, H. (2007). Evaluation of a low-cost soil water content sensor for wireless network applications. *Journal of Hydrology*, 344(1–2), 32–42. <https://doi.org/10.1016/j.jhydrol.2007.06.032>
- Briciu-Burghina, C., Zhou, J., Ali, M. I., & Regan, F. (2022). Demonstrating the potential of a low-cost soil moisture sensor network. *Sensors*, 22(3), 987. <https://doi.org/10.3390/s22030987>
- Brocca, L., Barbeta, S., Camici, S., Ciabatta, L., Dari, J., Filippucci, P., et al. (2024). A digital twin of the terrestrial water cycle: A glimpse into the future through high-resolution Earth observations. *Frontiers in Science*, 1, 1190191. <https://doi.org/10.3389/fsci.2023.1190191>
- Brombacher, J., de Oliveira Silva, I. R., Degen, J., & Pelgrum, H. (2022). A novel evapotranspiration based irrigation quantification method using the hydrological similar pixels algorithm. *Agricultural Water Management*, 267, 107602. <https://doi.org/10.1016/j.agwat.2022.107602>
- Brust, C., Kimball, J. S., Maneta, M. P., Jencso, K., He, M., & Reichle, R. H. (2021). Using SMAP Level-4 soil moisture to constrain MOD16 evapotranspiration over the contiguous USA. *Remote Sensing of Environment*, 255, 112277. <https://doi.org/10.1016/j.rse.2020.112277>
- Budyko, M. I. (1956). *Тепловой баланс земной поверхности* (*Heat Balance of the Earth's Surface*) (p. 255). Gidrometeoizdat, Leningrad.
- Budyko, M. I. (1974). *Climate and life* (p. 508). Academic Press.

- Buitink, J., Swank, A. M., van der Ploeg, M., Smith, N. E., Benninga, H. J. F., van der Bolt, F., et al. (2020). Anatomy of the 2018 agricultural drought in The Netherlands using in situ soil moisture and satellite vegetation indices. *Hydrology and Earth System Sciences*, 24(12), 6021–6031. <https://doi.org/10.5194/hess-24-6021-2020>
- Burt, C. M., Mutziger, A. J., Allen, R. G., & Howell, T. A. (2005). Evaporation research: Review and interpretation. *Journal of Irrigation and Drainage Engineering*, 131(1), 37–58. [https://doi.org/10.1061/\(asce\)0733-9437\(2005\)131:1\(37\)](https://doi.org/10.1061/(asce)0733-9437(2005)131:1(37))
- Butcher, K., Wick, A. F., DeSutter, T., Chatterjee, A., & Harmon, J. (2016). Soil salinity: A threat to global food security. *Agronomy Journal*, 108(6), 2189–2200. <https://doi.org/10.2134/agonj2016.06.0368>
- Cai, S., Song, X., Hu, R., Leng, P., Li, X., Guo, D., et al. (2021). Spatiotemporal characteristics of agricultural droughts based on soil moisture data in Inner Mongolia from 1981 to 2019. *Journal of Hydrology*, 603, 127104. <https://doi.org/10.1016/j.jhydrol.2021.127104>
- Calvin, K., Wise, M., Kyle, P., Clarke, L., & Edmonds, J. (2017). A hindcast experiment using the GCAM 3.0 agriculture and land-use module. *Climate Change Economics*, 8(1), 1750005. <https://doi.org/10.1142/s2010007817500051>
- Cammalleri, C., Anderson, M. C., Gao, F., Hain, C. R., & Kustas, W. P. (2014). Mapping daily evapotranspiration at field scales over rainfed and irrigated agricultural areas using remote sensing data fusion. *Agricultural and Forest Meteorology*, 186, 1–11. <https://doi.org/10.1016/j.agrformet.2013.11.001>
- Cao, Q., Yu, D., Georgescu, M., & Wu, J. (2016). Impacts of urbanization on summer climate in China: An assessment with coupled land-atmospheric modeling. *Journal of Geophysical Research: Atmospheres*, 121(18), 10–505. <https://doi.org/10.1002/2016jd025210>
- Carranza, C., Nolet, C., Pezij, M., & van der Ploeg, M. (2021). Root zone soil moisture estimation with Random Forest. *Journal of Hydrology*, 593, 125840. <https://doi.org/10.1016/j.jhydrol.2020.125840>
- Cawse-Nicholson, K., Anderson, M., Yang, Y., Yang, Y., Hook, S., Fisher, J. B., et al. (2021). Evaluation of a CONUS-wide ECOSTRESS DisALEXI evapotranspiration product. *Ieee Journal of Selected Topics in Applied Earth Observations and Remote Sensing*, 14, 10117–10133. <https://doi.org/10.1109/jstars.2021.3111867>
- Cawse-Nicholson, K., Townsend, P. A., Schimel, D., Assiri, A. M., Blake, P. L., Buongiorno, M. F., et al. (2021). NASA's surface biology and geology designated observable: A perspective on surface imaging algorithms. *Remote Sensing of Environment*, 257(112349), 1–25. <https://doi.org/10.1016/j.rse.2021.112349>
- Chan, S., Bindlish, R., O'Neill, P., Jackson, T., Njoku, E., Dunbar, S., et al. (2018). Development and assessment of the SMAP enhanced passive soil moisture product. *Remote Sensing of Environment*, 204, 931–941. <https://doi.org/10.1016/j.rse.2017.08.025>
- Chaney, N. W., Metcalfe, P., & Wood, E. F. (2016). HydroBlocks: A field-scale resolving land surface model for application over continental extents. *Hydrological Processes*, 30(20), 3543–3559. <https://doi.org/10.1002/hyp.10891>
- Chen, F., Crow, W. T., & Ryu, D. (2014). Dual forcing and state correction via soil moisture assimilation for improved rainfall–runoff modeling. *Journal of Hydrometeorology*, 15(5), 1832–1848. <https://doi.org/10.1175/jhm-d-14-0002.1>
- Chen, H., Huang, J. J., Dash, S. S., Lan, Z., Gao, J., McBean, E., & Singh, V. P. (2022). Development of a three-source remote sensing model for estimation of urban evapotranspiration. *Advances in Water Resources*, 161, 104126. <https://doi.org/10.1016/j.advwatres.2022.104126>
- Chen, J. M., & Liu, J. (2020). Evolution of evapotranspiration models using thermal and shortwave remote sensing data. *Remote Sensing of Environment*, 237, 111594. <https://doi.org/10.1016/j.rse.2019.111594>
- Chen, Q., Fan, J., Yin, Y., & Han, B. (2020). Aerosol impacts on mesoscale convective systems forming under different vertical wind shear conditions. *Journal of Geophysical Research: Atmospheres*, 125(3), e2018JD030027. <https://doi.org/10.1029/2018jd030027>
- Chew, C. C., & Small, E. E. (2018). Soil moisture sensing using spaceborne GNSS reflections: Comparison of CYGNSS reflectivity to SMAP soil moisture. *Geophysical Research Letters*, 45(9), 4049–4057. <https://doi.org/10.1029/2018gl077905>
- Choularton, R. J., & Krishnamurthy, P. K. (2019). How accurate is food security early warning? Evaluation of FEWS NET accuracy in Ethiopia. *Food Security*, 11(2), 333–344. <https://doi.org/10.1007/s12571-019-00909-y>
- Christian, J. I., Basara, J. B., Hunt, E. D., Otkin, J. A., & Xiao, X. (2020). Flash drought development and cascading impacts associated with the 2010 Russian Heatwave. *Environmental Research Letters*, 15(9), 094078. <https://doi.org/10.1088/1748-9326/ab9faf>
- Christian, J. I., Basara, J. B., Otkin, J. A., Hunt, E. D., Wakefield, R. A., Flanagan, P. X., & Xiao, X. (2019). A methodology for flash drought identification: Application of flash drought frequency across the United States. *Journal of Hydrometeorology*, 20(5), 833–846. <https://doi.org/10.1175/jhm-d-18-0198.1>
- Clarizia, M. P., Pierdicca, N., Costantini, F., & Floury, N. (2019). Analysis of CYGNSS data for soil moisture retrieval. *Ieee Journal of Selected Topics in Applied Earth Observations and Remote Sensing*, 12(7), 2227–2235. <https://doi.org/10.1109/jstars.2019.2895510>
- Colliander, A., Cosh, M. H., Kelly, V. R., Kraatz, S., Bourgeau-Chavez, L., Siqueira, P., et al. (2020). SMAP detects soil moisture under temperate forest canopies. *Geophysical Research Letters*, 47(19), e2020GL089697. <https://doi.org/10.1029/2020gl089697>
- Colliander, A., Fisher, J. B., Halverson, G., Merlin, O., Misra, S., Bindlish, R., et al. (2017). Spatial downscaling of SMAP soil moisture using MODIS land surface temperature and NDVI during SMAPVEX15. *IEEE Geoscience and Remote Sensing Letters*, 14(11), 2107–2111. <https://doi.org/10.1109/lgrs.2017.2753203>
- Cong, Z., Shen, Q., Zhou, L., Sun, T., & Liu, J. (2017). Evapotranspiration estimation considering anthropogenic heat based on remote sensing in urban area. *Science China Earth Sciences*, 60(4), 659–671. <https://doi.org/10.1007/s11430-016-0216-3>
- Cook, B. I., Mankin, J. S., Marvel, K., Williams, A. P., Smerdon, J. E., & Anchukaitis, K. J. (2020). Twenty-first century drought projections in the CMIP6 forcing scenarios. *Earth's Future*, 8(6), e2019EF001461. <https://doi.org/10.1029/2019ef001461>
- Cooley, S. S., Fisher, J. B., & Goldsmith, G. R. (2022). Convergence in water use efficiency within plant functional types across contrasting climates. *Nature Plants*, 8(4), 341–345. <https://doi.org/10.1038/s41477-022-01131-z>
- Cornelis, W. M., Gabriels, D., & Hartmann, R. (2004). A parameterization for the threshold shear velocity to initiate deflation of dry and wet sediment. *Geomorphology*, 9, 43–51.
- Cosh, M. H., Caldwell, T. G., Baker, C. B., Bolten, J. D., Edwards, N., Goble, P., et al. (2021). Developing a strategy for the national coordinated soil moisture monitoring network. *Vadose Zone Journal*, 20(4), e20139. <https://doi.org/10.1002/vzj2.20139>
- Covey, K. R., & Megonigal, J. P. (2019). Methane production and emissions in trees and forests. *New Phytologist*, 222(1), 35–51. <https://doi.org/10.1111/nph.15624>
- Crosby, T. W., & Wang, Y. (2021). Effects of irrigation management on chipping potato (*Solanum tuberosum* L.) Production in the Upper Midwest of the US. *Agronomy*, 11(4), 768. <https://doi.org/10.3390/agronomy11040768>
- Crow, W. T., Berg, A. A., Cosh, M. H., Loew, A., Mohanty, B. P., Panciera, R., et al. (2012). Upscaling sparse ground-based soil moisture observations for the validation of coarse-resolution satellite soil moisture products. *Reviews of Geophysics*, 50(2). <https://doi.org/10.1029/2011rg000372>
- Dabrowska-Zielinska, K., Musial, J., Malinska, A., Budzynska, M., Gurdak, R., Kiryla, W., et al. (2018). Soil moisture in the Biebrza Wetlands retrieved from Sentinel-1 imagery. *Remote Sensing*, 10(12), 1979. <https://doi.org/10.3390/rs10121979>

- Dai, Y., Shangguan, W., Wei, N., Xin, Q., Yuan, H., Zhang, S., et al. (2019). A review of the global soil property maps for Earth system models. *Soils*, 5(2), 137–158. <https://doi.org/10.5194/soil-5-137-2019>
- Dari, J., Brocca, L., Modanesi, S., Massari, C., Tarpanelli, A., Barbetta, S., et al. (2023). Regional data sets of high-resolution (1 and 6 km) irrigation estimates from space. *Earth System Science Data*, 15(4), 1555–1575. <https://doi.org/10.5194/essd-15-1555-2023>
- Das, N. N., Entekhabi, D., Dunbar, R. S., Chaubell, M. J., Colliander, A., Yueh, S., et al. (2019). The SMAP and Copernicus Sentinel 1A/B microwave active-passive high resolution surface soil moisture product. *Remote Sensing of Environment*, 233, 111380. <https://doi.org/10.1016/j.rse.2019.111380>
- De Cáceres, M., Mencuccini, M., Martin-StPaul, N., Limousin, J. M., Coll, L., Poyatos, R., et al. (2021). Unravelling the effect of species mixing on water use and drought stress in Mediterranean forests: A modelling approach. *Agricultural and Forest Meteorology*, 296, 108233. <https://doi.org/10.1016/j.agrformet.2020.108233>
- Dembélé, M., Ceperley, N., Zwart, S. J., Salvatore, E., Mariethoz, G., & Schaeffli, B. (2020). Potential of satellite and reanalysis evaporation datasets for hydrological modelling under various model calibration strategies. *Advances in Water Resources*, 143, 103667. <https://doi.org/10.1016/j.advwatres.2020.103667>
- Desai, A. R., Khan, A. M., Zheng, T., Paleri, S., Butterworth, B., Lee, T. R., et al. (2021). Multi-sensor approach for high space and time resolution land surface temperature. *Earth and Space Science*, 8(10), e2021EA001842. <https://doi.org/10.1029/2021ea001842>
- Dong, J., Akbar, R., Short Gianotti, D. J., Feldman, A. F., Crow, W. T., & Entekhabi, D. (2022). Can surface soil moisture information identify evapotranspiration regime transitions? *Geophysical Research Letters*, 49(7), e2021GL097697. <https://doi.org/10.1029/2021gl097697>
- Dong, J., & Crow, W. T. (2018). Use of satellite soil moisture to diagnose climate model representations of European soil moisture-air temperature coupling strength. *Geophysical Research Letters*, 45(23), 12884–12891. <https://doi.org/10.1029/2018gl080547>
- Dorigo, W., Wagner, W., Albergel, C., Albrecht, F., Balsamo, G., Brocca, L., et al. (2017). ESA CCI Soil Moisture for improved Earth system understanding: State-of-the art and future directions. *Remote Sensing of Environment*, 203, 185–215. <https://doi.org/10.1016/j.rse.2017.07.001>
- Du, J., Kimball, J. S., Bindlish, R., Walker, J. P., & Watts, J. D. (2022). Local scale (3-m) soil moisture mapping using SMAP and Planet SuperDove. *Remote Sensing*, 14(15), 3812. <https://doi.org/10.3390/rs14153812>
- Du, J., Kimball, J. S., Jencso, K., Hoyleman, Z., Brust, C., Ketchum, D., et al. (2024). Machine-learning based multi-layer soil moisture forecasts—An application case study of the Montana 2017 flash drought. *Water Resources Research*, 60(10), e2023WR036973. <https://doi.org/10.1029/2023wr036973>
- Du, J., Kimball, J. S., Sheffield, J., Pan, M., Fisher, C. K., Beck, H. E., & Wood, E. F. (2021). Satellite flood inundation assessment and forecast using SMAP and landsat. *Ieee Journal of Selected Topics in Applied Earth Observations and Remote Sensing*, 14, 6707–6715. <https://doi.org/10.1109/jstars.2021.3092340>
- Du, R., Chen, J., Zhang, Z., Chen, Y., He, Y., & Yin, H. (2022). Simultaneous estimation of surface soil moisture and salinity during irrigation with the moisture-salinity-dependent spectral response model. *Agricultural Water Management*, 265, 107538. <https://doi.org/10.1016/j.agwat.2022.107538>
- Eeswaran, R., Nejadhashemi, A. P., Alves, F. C., & Saravi, B. (2021). Evaluating the applicability of soil moisture-based metrics for gauging the resiliency of rainfed agricultural systems in the midwestern United States. *Soil and Tillage Research*, 205, 104818. <https://doi.org/10.1016/j.still.2020.104818>
- El Masri, B., Rahman, A. F., & Dragoni, D. (2019). Evaluating a new algorithm for satellite-based evapotranspiration for North American ecosystems: Model development and validation. *Agricultural and Forest Meteorology*, 268, 234–248. <https://doi.org/10.1016/j.agrformet.2019.01.025>
- Endsley, K. A., & Zhao, M. (2023). *MODIS MOD16 global terrestrial evapotranspiration (ET) algorithm (v0.1.0)*. Zenodo. <https://doi.org/10.5281/zenodo.8408564>
- Enoki, T., & Drake, D. R. (2017). Alteration of soil properties by the invasive tree *Psidium cattleianum* along a precipitation gradient on O'ahu Island, Hawai'i. *Plant Ecology*, 218(8), 947–955. <https://doi.org/10.1007/s11258-017-0742-x>
- Entekhabi, D., Njoku, E. G., O'Neill, P. E., Kellogg, K. H., Crow, W. T., Edelstein, W. N., et al. (2010). The soil moisture active passive (SMAP) mission. *Proceedings of the IEEE*, 98(5), 704–716. <https://doi.org/10.1109/jproc.2010.2043918>
- Falalakis, G., & Gemitzi, A. (2020). A simple method for water balance estimation based on the empirical method and remotely sensed evapotranspiration estimates. *Journal of Hydroinformatics*, 22(2), 440–451. <https://doi.org/10.2166/hydro.2020.182>
- Famiglietti, C. A., Fisher, J. B., Halverson, G., & Borbas, E. E. (2018). Global validation of MODIS near-surface air and dew point temperatures. *Geophysical Research Letters*, 45(15), 7772–7780. <https://doi.org/10.1029/2018gl077813>
- Fang, B., Lakshmi, V., Cosh, M., Liu, P. W., Bindlish, R., & Jackson, T. J. (2022). A global 1-km downscaled SMAP soil moisture product based on thermal inertia theory. *Vadose Zone Journal*, 21(2), e20182. <https://doi.org/10.1002/vzj2.20182>
- Farahani, H. J., Howell, T. A., Shuttleworth, W. J., & Bausch, W. C. (2007). Evapotranspiration: Progress in measurement and modeling in agriculture. *Transactions of the American Society of Agricultural and Biological Engineers*, 50(5), 1627–1638. <https://doi.org/10.13031/2013.23965>
- Farahmand, A., Stavros, E. N., Reager, J. T., Behrangi, A., Randerson, J. T., & Quayle, B. (2020). Satellite hydrology observations as operational indicators of forecasted fire danger across the contiguous United States. *Natural Hazards and Earth System Sciences*, 20(4), 1097–1106. <https://doi.org/10.5194/nhess-20-1097-2020>
- Farrell, M. M., Fisher, J. B., Jiao, W., Key, K. B., & Barnes, M. L. (2022). Thermal remote sensing for plant ecology from leaf to globe. *Journal of Ecology*, 110(9), 1996–2014. <https://doi.org/10.1111/1365-2745.13957>
- Faridatul, M. I., Wu, B., Zhu, X., & Wang, S. (2020). Improving remote sensing based evapotranspiration modelling in a heterogeneous urban environment. *Journal of Hydrology*, 581, 124405. <https://doi.org/10.1016/j.jhydrol.2019.124405>
- Feldman, A. F., Koster, R. D., Cawse-Nicholson, K., Crow, W. T., Holmes, T. R. H., & Poulter, B. (2024). Soil moisture profiles of ecosystem water use revealed with ECOSTRESS. *Geophysical Research Letters*, 51(8). <https://doi.org/10.1029/2024gl108326>
- Feldman, A. F., Short Gianotti, D. J., Dong, J., Akbar, R., Crow, W. T., McColl, K. A., et al. (2023). Remotely sensed soil moisture can capture dynamics relevant to plant water uptake. *Water Resources Research*, 59(2), e2022WR033814. <https://doi.org/10.1029/2022wr033814>
- Feldman, A. F., Short Gianotti, D. J., Trigo, I. F., Salvucci, G. D., & Entekhabi, D. (2019). Satellite-based assessment of land surface energy partitioning—soil moisture relationships and effects of confounding variables. *Water Resources Research*, 55(12), 10657–10677. <https://doi.org/10.1029/2019wr025874>
- Felton, A. J., Fisher, J. B., Hufkens, K., Purdy, A. J., Spawn-Lee, S. A., Duloisy, L. F., & Goldsmith, G. R. (2025). Global estimates of the storage and transit time of water through vegetation. *Nature Water*, 3, 1–11. <https://doi.org/10.1038/s44221-024-00365-9>
- Feng, S., Huang, X., Zhao, S., Qin, Z., Fan, J., & Zhao, S. (2022). Evaluation of several satellite-based soil moisture products in the continental US. *Sensors*, 22(24), 9977. <https://doi.org/10.3390/s22249977>

- Fereidoon, M., Koch, M., & Brocca, L. (2019). Predicting rainfall and runoff through satellite soil moisture data and SWAT modelling for a poorly gauged basin in Iran. *Water*, 11(3), 594. <https://doi.org/10.3390/w11030594>
- Fisher, J. B. (2022). Hydrosat: Towards daily, field-scale, global evapotranspiration from space. In *AGU Fall Meeting Abstracts* (Vol. 2022, p. H45D-07).
- Fisher, J. B., Baldocchi, D. D., Misson, L., Dawson, T. E., & Goldstein, A. H. (2007). What the towers don't see at night: Nocturnal sap flow in trees and shrubs at two AmeriFlux sites in California. *Tree Physiology*, 27(4), 597–610. <https://doi.org/10.1093/treephys/27.4.597>
- Fisher, J. B., DeBiase, T. A., Qi, Y., Xu, M., & Goldstein, A. H. (2005). Evapotranspiration models compared on a Sierra Nevada forest ecosystem. *Environmental Modelling & Software*, 20(6), 783–796. <https://doi.org/10.1016/j.envsoft.2004.04.009>
- Fisher, J. B., Halverson, G., Valdez, J., Nelson, M., Davidoff, S., Cooley, S., et al. (2023). Water management for the State of New Mexico. In *NASA Water Resources Applications Team Meeting*.
- Fisher, J. B., Lee, B., Purdy, A. J., Halverson, G. H., Dohlen, M. B., Cawse-Nicholson, K., et al. (2020). ECOSTRESS: NASA's next generation mission to measure evapotranspiration from the International Space Station. *Water Resources Research*, 56(4), 1–20. <https://doi.org/10.1029/2019wr026058>
- Fisher, J. B., Malhi, Y., Bonal, D., Da Rocha, H. R., De Araujo, A. C., Gamo, M., et al. (2009). The land–atmosphere water flux in the tropics. *Global Change Biology*, 15(11), 2694–2714. <https://doi.org/10.1111/j.1365-2486.2008.01813.x>
- Fisher, J. B., Melton, F., Middleton, E., Hain, C., Anderson, M., Allen, R., et al. (2017). The future of evapotranspiration: Global requirements for ecosystem functioning, carbon and climate feedbacks, agricultural management, and water resources. *Water Resources Research*, 53(4), 2618–2626. <https://doi.org/10.1002/2016wr020175>
- Fisher, J. B., Tu, K. P., & Baldocchi, D. D. (2008). Global estimates of the land–atmosphere water flux based on monthly AVHRR and ISLSCP-II data, validated at 16 FLUXNET sites. *Remote Sensing of Environment*, 112(3), 901–919. <https://doi.org/10.1016/j.rse.2007.06.025>
- Fisher, J. B., Whittaker, R. J., & Malhi, Y. (2011). ET come home: Potential evapotranspiration in geographical ecology. *Global Ecology and Biogeography*, 20(1), 1–18. <https://doi.org/10.1111/j.1466-8238.2010.00578.x>
- Ford, T. W., Harris, E., & Quiring, S. M. (2014). Estimating root zone soil moisture using near-surface observations from SMOS. *Hydrology and Earth System Sciences*, 18(1), 139–154. <https://doi.org/10.5194/hess-18-139-2014>
- Franzleubbers, A., Steiner, J., Karlen, D., Griffin, T., Singer, J., & Tanaka, D. (2011). Rainfed farming systems in the USA. In P. Tow, I. Cooper, I. Partridge, & C. Birch (Eds.), *Rainfed farming systems* (pp. 511–560). Springer.
- French, A. N., Hunsaker, D. J., Bounoua, L., Karnieli, A., Luckett, W. E., & Strand, R. (2018). Remote sensing of evapotranspiration over the Central Arizona irrigation and Drainage District, USA. *Agronomy*, 8(12), 278. <https://doi.org/10.3390/agronomy8120278>
- Funk, R., Reuter, H. I., Hoffmann, C., Engel, W., & Ötli, D. (2008). Effect of moisture on fine dust emission from tillage operations on agricultural soils. *Earth Surface Processes and Landforms: The Journal of the British Geomorphological Research Group*, 33(12), 1851–1863. <https://doi.org/10.1002/esp.1737>
- Gao, F., Masek, J., Schwaller, M., & Hall, F. (2006). On the blending of the Landsat and MODIS surface reflectance: Predicting daily Landsat surface reflectance. *IEEE Transactions on Geoscience and Remote Sensing*, 44(8), 2207–2218. <https://doi.org/10.1109/tgrs.2006.872081>
- García-Santos, V., Sánchez, J. M., & Cuxart, J. (2022). Evapotranspiration acquired with remote sensing thermal-based algorithms: A state-of-the-art review. *Remote Sensing*, 14(14), 3440. <https://doi.org/10.3390/rs14143440>
- Gauci, V., Pangala, S. R., Shenkin, A., Barba, J., Bastviken, D., Figueiredo, V., et al. (2024). Global atmospheric methane uptake by upland tree woody surfaces. *Nature*, 631(8022), 796–800. <https://doi.org/10.1038/s41586-024-07592-w>
- Ge, X., Wang, J., Ding, J., Cao, X., Zhang, Z., Liu, J., & Li, X. (2019). Combining UAV-based hyperspectral imagery and machine learning algorithms for soil moisture content monitoring. *PeerJ*, 7, e6926. <https://doi.org/10.7717/peerj.6926>
- Ginoux, P., Chin, M., Tegen, I., Prospero, J. M., Holben, B., Dubovik, O., & Lin, S. J. (2001). Sources and distributions of dust aerosols simulated with the GOCART model. *Journal of Geophysical Research*, 106(D17), 20255–20273. <https://doi.org/10.1029/2000jd000053>
- Ginoux, P., Prospero, J. M., Gill, T. E., Hsu, N. C., & Zhao, M. (2012). Global-scale attribution of anthropogenic and natural dust sources and their emission rates based on MODIS Deep Blue aerosol products. *Reviews of Geophysics*, 50(3). <https://doi.org/10.1029/2012rg000388>
- Grimmond, C. S. B., & Oke, T. R. (1986). Urban water balance: 2. Results from a suburb of Vancouver, British Columbia. *Water Resources Research*, 22(10), 1404–1412. <https://doi.org/10.1029/wr022i10p01404>
- Gruber, A., De Lannoy, G., Albergel, C., Al-Yaari, A., Brocca, L., Calvet, J. C., et al. (2020). Validation practices for satellite soil moisture retrievals: What are (the) errors? *Remote Sensing of Environment*, 244, 111806. <https://doi.org/10.1016/j.rse.2020.111806>
- Gruber, A., Su, C. H., Crow, W. T., Zwieback, S., Dorigo, W. A., & Wagner, W. (2016). Estimating error cross-correlations in soil moisture data sets using extended collocation analysis. *Journal of Geophysical Research: Atmospheres*, 121(3), 1208–1219. <https://doi.org/10.1002/2015jd024027>
- Guerrero-Salazar, P. L. A., & Yevjevich, V. M. (1975). *Analysis of drought characteristics by the theory of runs* (Vol. 80). Colorado State University.
- Guilod, B., Orlowsky, B., Miralles, D., Teuling, A. J., & Seneviratne, S. I. (2015). Reconciling spatial and temporal soil moisture effects on afternoon rainfall. *Nature Communications*, 6(1), 6443. <https://doi.org/10.1038/ncomms7443>
- Han, Q., Zeng, Y., Zhang, L., Wang, C., Prikaziuk, E., Niu, Z., & Su, B. (2023). Global long term daily 1 km surface soil moisture dataset with physics informed machine learning. *Scientific Data*, 10(1), 101. <https://doi.org/10.1038/s41597-023-02011-7>
- Hassani, A., Azapagic, A., & Shokri, N. (2021). Global predictions of primary soil salinization under changing climate in the 21st century. *Nature Communications*, 12(1), 6663. <https://doi.org/10.1038/s41467-021-26907-3>
- Heidbüchel, I., Güntner, A., & Blume, T. (2016). Use of cosmic-ray neutron sensors for soil moisture monitoring in forests. *Hydrology and Earth System Sciences*, 20(3), 1269–1288. <https://doi.org/10.5194/hess-20-1269-2016>
- Hirschi, M., Mueller, B., Dorigo, W., & Seneviratne, S. I. (2014). Using remotely sensed soil moisture for land-atmosphere coupling diagnostics: The role of surface vs. root-zone soil moisture variability. *Remote Sensing of Environment*, 154, 246–252. <https://doi.org/10.1016/j.rse.2014.08.030>
- Hirschi, M., Seneviratne, S. I., Alexandrov, V., Boberg, F., Boroneant, C., Christensen, O. B., et al. (2011). Observational evidence for soil-moisture impact on hot extremes in southeastern Europe. *Nature Geoscience*, 4(1), 17–21. <https://doi.org/10.1038/ngeo1032>
- Hobbins, M., Jansma, T., Sarmiento, D. P., McNally, A., Magadzire, T., Jayanthi, H., et al. (2023). A global long-term daily reanalysis of reference evapotranspiration for drought and food-security monitoring. *Scientific Data*, 10(1), 746. <https://doi.org/10.1038/s41597-023-02648-4>
- Hobeichi, S., Abramowitz, G., & Evans, J. (2020). Conserving land–atmosphere synthesis suite (CLASS). *Journal of Climate*, 33(5), 1821–1844. <https://doi.org/10.1175/jcli-d-19-0036.1>
- Hobeichi, S., Abramowitz, G., & Evans, J. P. (2021). Robust historical evapotranspiration trends across climate regimes. *Hydrology and Earth System Sciences*, 25(7), 3855–3874. <https://doi.org/10.5194/hess-25-3855-2021>

- Hong, S. H., Hendrickx, J. M., & Borchers, B. (2011). Down-scaling of SEBAL derived evapotranspiration maps from MODIS (250 m) to Landsat (30 m) scales. *International Journal of Remote Sensing*, 32(21), 6457–6477. <https://doi.org/10.1080/01431161.2010.512929>
- Hornbuckle, B., Walker, V., Eichinger, B., Wallace, V., & Yildirim, E. (2017). Soil surface roughness observed during SMAPVEX16-IA and its potential consequences for SMOS and SMAP. In *2017 IEEE International Geoscience and Remote Sensing Symposium (IGARSS)* (pp. 2027–2030). IEEE.
- Houtz, D., Horvath, L., & Schwank, M. (2023). Vehicle mounted L-band radiometer for remote sensing of turfgrass soil moisture. In *IGARSS 2023-2023 IEEE International Geoscience and Remote Sensing Symposium* (pp. 4824–4827).
- Huang, J., Desai, A. R., Zhu, J., Hartemink, A. E., Stoy, P. C., Loheide, S. P., et al. (2020). Retrieving heterogeneous surface soil moisture at 100 m across the globe via fusion of remote sensing and land surface parameters. *Frontiers in Water*, 2, 578367. <https://doi.org/10.3389/frwa.2020.578367>
- Huang, J., Hartemink, A. E., Arriaga, F., & Chaney, N. W. (2019). Unraveling location-specific and time-dependent interactions between soil water content and environmental factors in cropped sandy soils using Sentinel-1 and moisture probes. *Journal of Hydrology*, 575, 780–793. <https://doi.org/10.1016/j.jhydrol.2019.05.075>
- Huang, J., Wang, T., Wang, W., Li, Z., & Yan, H. (2014). Climate effects of dust aerosols over East Asian arid and semiarid regions. *Journal of Geophysical Research: Atmospheres*, 119(19), 11–398. <https://doi.org/10.1002/2014jd021796>
- Huang, S., Zhang, X., Chen, N., Ma, H., Fu, P., Dong, J., et al. (2022). A novel fusion method for generating surface soil moisture data with high accuracy, high spatial resolution, and high spatio-temporal continuity. *Water Resources Research*, 58(5), e2021WR030827. <https://doi.org/10.1029/2021wr030827>
- Ines, A. V. M., Das, N. N., Hansen, J. W., & Njoku, E. G. (2013). Assimilation of remotely sensed soil moisture and vegetation with a crop simulation model for maize yield prediction. *Remote Sensing of Environment*, 138, 149–164. <https://doi.org/10.1016/j.rse.2013.07.018>
- Ishizuka, M., Mikami, M., Leys, J., Yamada, Y., Heidenreich, S., Shao, Y., & McTainsh, G. H. (2008). Effects of soil moisture and dried raindrop crust on saltation and dust emission. *Journal of Geophysical Research*, 113(D24). <https://doi.org/10.1029/2008jd009955>
- Jackson, T. J. (1993). III. Measuring surface soil moisture using passive microwave remote sensing. *Hydrological Processes*, 7(2), 139–152. <https://doi.org/10.1002/hyp.3360070205>
- Jacobs, C., Elbers, J., Broilma, R., Hartogensis, O., Moors, E., Márquez, M. T. R. C., & van Hove, B. (2015). Assessment of evaporative water loss from Dutch cities. *Building and Environment*, 83, 27–38. <https://doi.org/10.1016/j.buildenv.2014.07.005>
- Jamroen, C., Komkum, P., Fongkerd, C., & Krongpha, W. (2020). An intelligent irrigation scheduling system using low-cost wireless sensor network toward sustainable and precision agriculture. *IEEE Access*, 8, 172756–172769. <https://doi.org/10.1109/access.2020.3025590>
- Jarchow, C. J., Du, J., Kimball, J. S., Kuhlman, A., & Steckley, D. (2024). Multi-source machine learning and spaceborne remote sensing data accurately predict three-dimensional soil moisture in an in-service uranium disposal cell. *Journal of Environmental Management*, 369, 122254. <https://doi.org/10.1016/j.jenvman.2024.122254>
- Jeffrey, L. C., Moras, C. A., Tait, D. R., Johnston, S. G., Call, M., Sipso, J. Z., et al. (2023). Large methane emissions from tree stems complicate the wetland methane budget. *Journal of Geophysical Research: Biogeosciences*, 128(12), e2023JG007679. <https://doi.org/10.1029/2023jg007679>
- Jencso, K., Parker, B., Rath, M., Syner, M., Fuchs, B., Johnson, S., et al. (2019). Lessons learned from the 2017 drought across. In *NOAA National Integrated Drought Information System*.
- Jiang, L., Shi, C., Sun, S., & Liang, X. (2020). Fusion of in-situ soil moisture and land surface model estimates using localized ensemble optimum interpolation over China. *Journal of Meteorological Research*, 34(6), 1335–1346. <https://doi.org/10.1007/s13351-020-0033-7>
- Jiang, Y., & Weng, Q. (2017). Estimation of hourly and daily evapotranspiration and soil moisture using downscaled LST over various urban surfaces. *GIScience and Remote Sensing*, 54(1), 95–117. <https://doi.org/10.1080/15481603.2016.1258971>
- Jiménez, C., Martens, B., Miralles, D. M., Fisher, J. B., Beck, H. E., & Fernández-Prieto, D. (2018). Exploring the merging of the global land evaporation WACMO-ET products based on local tower measurements. *Hydrology and Earth System Sciences*, 22(8), 4513–4533. <https://doi.org/10.5194/hess-22-4513-2018>
- Jiménez, C., Prigent, C., Mueller, B., Seneviratne, S. I., McCabe, M. F., Wood, E. F., et al. (2011). Global intercomparison of 12 land surface heat flux estimates. *Journal of Geophysical Research*, 116(D2), D02102. <https://doi.org/10.1029/2010jd014545>
- Jin, C., Luo, X., Xiao, X., Dong, J., Li, X., Yang, J., & Zhao, D. (2019). The 2012 flash drought threatened US Midwest agroecosystems. *Chinese Geographical Science*, 29(5), 768–783. <https://doi.org/10.1007/s11769-019-1066-7>
- Joshi, R. C., Jensen, A., Pascolini-Campbell, M., & Fisher, J. B. (2024). Coupling between evapotranspiration, water use efficiency, and evaporative stress index strengthens after wildfires in New Mexico, USA. *International Journal of Applied Earth Observation and Geo-information*, 135, 104238. <https://doi.org/10.1016/j.jag.2024.104238>
- Jung, M., Koirala, S., Weber, U., Ichii, K., Gans, F., Camps-Valls, G., et al. (2019). The FLUXCOM ensemble of global land-atmosphere energy fluxes. *Scientific Data*, 6(1), 74. <https://doi.org/10.1038/s41597-019-0076-8>
- Kagawa, A., Sack, L., Duarte, K. E., & James, S. (2009). Hawaiian native forest conserves water relative to timber plantation: Species and stand traits influence water use. *Ecological Applications*, 19(6), 1429–1443. <https://doi.org/10.1890/08-1704.1>
- Kannenbergh, S. A., Barnes, M. L., Bowling, D. R., Driscoll, A. W., Guo, J. S., & Anderegg, W. R. (2023). Quantifying the drivers of ecosystem fluxes and water potential across the soil-plant-atmosphere continuum in an arid woodland. *Agricultural and Forest Meteorology*, 329, 109269. <https://doi.org/10.1016/j.agrformet.2022.109269>
- Karthikeyan, L., Pan, M., Wanders, N., Kumar, D. N., & Wood, E. F. (2017). Four decades of microwave satellite soil moisture observations: Part 1. A review of retrieval algorithms. *Advances in Water Resources*, 109, 106–120. <https://doi.org/10.1016/j.advwatres.2017.09.006>
- Ke, Y., Im, J., Park, S., & Gong, H. (2016). Downscaling of MODIS one kilometer evapotranspiration using Landsat-8 data and machine learning approaches. *Remote Sensing*, 8(3), 215. <https://doi.org/10.3390/rs8030215>
- Ke, Y., Im, J., Park, S., & Gong, H. (2017). Spatiotemporal downscaling approaches for monitoring 8-day 30 m actual evapotranspiration. *ISPRS Journal of Photogrammetry and Remote Sensing*, 126, 79–93. <https://doi.org/10.1016/j.isprsjprs.2017.02.006>
- Kemp, P. R., Reynolds, J. F., Pachepsky, Y., & Chen, J.-L. (1997). A comparative modeling study of soil water dynamics in a desert ecosystem. *Water Resources Research*, 33(1), 73–90. <https://doi.org/10.1029/96wr03015>
- Kerr, Y. H., Waldteufel, P., Richaume, P., Wigneron, J. P., Ferrazzoli, P., Mahmoodi, A., et al. (2012). The SMOS soil moisture retrieval algorithm. *IEEE Transactions on Geoscience and Remote Sensing*, 50(5), 1384–1403. <https://doi.org/10.1109/tgrs.2012.2184548>
- Kim, H., & Lakshmi, V. (2018). Use of cyclone global navigation satellite system (CYGNSS) observations for estimation of soil moisture. *Geophysical Research Letters*, 45(16), 8272–8282. <https://doi.org/10.1029/2018gl078923>
- Kim, H., Zohaib, M., Cho, E., Kerr, Y. H., & Choi, M. (2017). Development and assessment of the sand dust prediction model by utilizing microwave-based satellite soil moisture and reanalysis datasets in East Asian desert areas. *Advances in Meteorology*, 2017, 1–13. <https://doi.org/10.1155/2017/1917372>

- Kim, S., Kumar, M., & Kam, J. (2023). Rain-fed to irrigation-fed transition of agriculture exacerbates meteorological drought in cropped regions but moderates elsewhere. *Environmental Research Letters*, 18(7), 074024. <https://doi.org/10.1088/1748-9326/acdfbf>
- Kim, Y., Park, H., Kimball, J. S., Colliander, A., & McCabe, M. F. (2023). Global estimates of daily evapotranspiration using SMAP surface and root-zone soil moisture. *Remote Sensing of Environment*, 298, 113803. <https://doi.org/10.1016/j.rse.2023.113803>
- Knott, C., Lee, C., Salmeron, M., & Wendroth, O. (2022). Irrigation principles and tools. In *A comprehensive guide to corn management in Kentucky*. University of Kentucky, Martin Gatton College of Agriculture, Food, and Environment, ID 139.
- Kok, J. F., Storelvmo, T., Karydis, V. A., Adebisi, A. A., Mahowald, N. M., Evan, A. T., et al. (2023). Mineral dust aerosol impacts on global climate and climate change. *Nature Reviews Earth & Environment*, 4(2), 71–86. <https://doi.org/10.1038/s43017-022-00379-5>
- Kolassa, J., Reichle, R. H., Liu, Q., Alemohammad, S. H., Gentile, P., Aida, K., et al. (2018). Estimating surface soil moisture from SMAP observations using a Neural Network technique. *Remote Sensing of Environment*, 204, 43–59. <https://doi.org/10.1016/j.rse.2017.10.045>
- Kool, D., Agam, N., Lazarovitch, N., Heitman, J. L., Sauer, T. J., & Ben-Gal, A. (2014). A review of approaches for evapotranspiration partitioning. *Agricultural and Forest Meteorology*, 184, 56–70. <https://doi.org/10.1016/j.agrformet.2013.09.003>
- Koster, R. D., Crow, W. T., Reichle, R. H., & Mahanama, S. P. (2018). Estimating basin-scale water budgets with SMAP soil moisture data. *Water Resources Research*, 54(7), 4228–4244. <https://doi.org/10.1029/2018wr022669>
- Koster, R. D., Feldman, A. F., Holmes, T. R. H., Anderson, M. C., Crow, W. T., & Hain, C. (2024). Estimating hydrological regimes from observational soil moisture, evapotranspiration, and air temperature data. *Journal of Hydrometeorology*, 25(3), 495–513. <https://doi.org/10.1175/jhm-d-23-0140.1>
- Koster, R. D., Guo, Z., Yang, R., Dirmeyer, P. A., Mitchell, K., & Puma, M. J. (2009). On the nature of soil moisture in land surface models. *Journal of Climate*, 22(16), 4322–4335. <https://doi.org/10.1175/2009jcli2832.1>
- Krishnamurthy R. P. K., Fisher, J. B., Choularton, R. J., & Kareiva, P. M. (2022). Anticipating drought-related food security changes. *Nature Sustainability*, 5(11), 956–964. <https://doi.org/10.1038/s41893-022-00962-0>
- Krishnamurthy R. P. K., Fisher, J. B., Schimel, D. S., & Kareiva, P. M. (2020). Applying tipping point theory to remote sensing science to improve early warning drought signals for food security. *Earth's Future*, 8(3), e2019EF001456. <https://doi.org/10.1029/2019ef001456>
- Krueger, E. S., Levi, M. R., Achieng, K. O., Bolten, J. D., Carlson, J. D., Coops, N. C., et al. (2022). Using soil moisture information to better understand and predict wildfire danger: A review of recent developments and outstanding questions. *International Journal of Wildland Fire*, 32(2), 111–132. <https://doi.org/10.1071/wf22056>
- Krueger, E. S., Ochsner, T. E., Carlson, J. D., Engle, D. M., Twidwell, D., & Fuhlendorf, S. D. (2016). Concurrent and antecedent soil moisture relate positively or negatively to probability of large wildfires depending on season. *International Journal of Wildland Fire*, 25(6), 657–668. <https://doi.org/10.1071/wf15104>
- Krueger, E. S., Ochsner, T. E., Engle, D. M., Carlson, J. D., Twidwell, D., & Fuhlendorf, S. D. (2015). Soil moisture affects growing-season wildfire size in the southern Great Plains. *Soil Science Society of America Journal*, 79(6), 1567–1576. <https://doi.org/10.2136/sssaj2015.01.0041>
- Lakshmi, V., & Fang, B. (2023). *SMAP-derived 1-km downscaled surface soil moisture product, version 1*. NASA National Snow and Ice Data Center Distributed Active Archive Center. <https://doi.org/10.5067/U8QZ2AXE5V7B>
- Lawston, P. M., Santanello Jr, J. A., & Kumar, S. V. (2017). Irrigation signals detected from SMAP soil moisture retrievals. *Geophysical Research Letters*, 44(23), 11–860. <https://doi.org/10.1002/2017gl075733>
- Lee, J. E., Oliveira, R. S., Dawson, T. E., & Fung, I. (2005). Root functioning modifies seasonal climate. *Proceedings of the National Academy of Sciences of the United States of America*, 102(49), 17576–17581. <https://doi.org/10.1073/pnas.0508785102>
- Lei, F., Crow, W. T., Holmes, T. R. H., Hain, C., & Anderson, M. C. (2018). Global investigation of soil moisture and latent heat flux coupling strength. *Water Resources Research*, 54(10), 8196–8215. <https://doi.org/10.1029/2018wr023469>
- Lesk, C., Anderson, W., Rigden, A., Coast, O., Jägermeyr, J., McDermid, S., et al. (2022). Compound heat and moisture extreme impacts on global crop yields under climate change. *Nature Reviews Earth & Environment*, 3(12), 872–889. <https://doi.org/10.1038/s43017-022-00368-8>
- Li, L., Bisht, G., Hao, D., & Leung, L. R. (2024). Global 1 km land surface parameters for kilometer-scale Earth system modeling. *Earth System Science Data*, 16(4), 2007–2032. <https://doi.org/10.5194/essd-16-2007-2024>
- Li, L., Yang, Z. L., Matheny, A. M., Zheng, H., Swenson, S. C., Lawrence, D. M., et al. (2021). Representation of plant hydraulics in the Noah-MP land surface model: Model development and multiscale evaluation. *Journal of Advances in Modeling Earth Systems*, 13(4), e2020MS002214. <https://doi.org/10.1029/2020ms002214>
- Li, Z. L., Leng, P., Zhou, C., Chen, K. S., Zhou, F. C., & Shang, G. F. (2021). Soil moisture retrieval from remote sensing measurements: Current knowledge and directions for the future. *Earth-Science Reviews*, 218, 103673. <https://doi.org/10.1016/j.earscirev.2021.103673>
- Littell, J. S., Peterson, D. L., Riley, K. L., Liu, Y., & Luce, C. H. (2016). A review of the relationships between drought and forest fire in the United States. *Global Change Biology*, 22(7), 2353–2369. <https://doi.org/10.1111/gcb.13275>
- Liu, L., Ciais, P., Wu, M., Padrón, R. S., Friedlingstein, P., Schwaab, J., et al. (2023). Increasingly negative tropical water–interannual CO₂ growth rate coupling. *Nature*, 618(7966), 755–760. <https://doi.org/10.1038/s41586-023-06056-x>
- Liu, L., Gudmundsson, L., Hauser, M., Qin, D., Li, S., & Seneviratne, S. I. (2020). Soil moisture dominates dryness stress on ecosystem production globally. *Nature Communications*, 11(1), 4892. <https://doi.org/10.1038/s41467-020-18631-1>
- Liu, P. W., Bindlish, R., Fang, B., Lakshmi, V., O'Neill, P. E., Yang, Z., et al. (2021). Assessing disaggregated SMAP soil moisture products in the United States. *Ieee Journal of Selected Topics in Applied Earth Observations and Remote Sensing*, 14, 2577–2592. <https://doi.org/10.1109/jstars.2021.3056001>
- Liu, Y., Wang, W., & Liu, Y. (2018). ESA CCI soil moisture assimilation in SWAT for improved hydrological simulation in Upper Huai River Basin. *Advances in Meteorology*, 2018(1), 7301314. <https://doi.org/10.1155/2018/7301314>
- Liu, Y., Zhu, Y., Ren, L., Otkin, J., Hunt, E. D., Yang, X., et al. (2020). Two different methods for flash drought identification: Comparison of their strengths and limitations. *Journal of Hydrometeorology*, 21(4), 691–704. <https://doi.org/10.1175/jhm-d-19-0088.1>
- Lloyd-Hughes, B. (2012). A spatio-temporal structure-based approach to drought characterisation. *International Journal of Climatology*, 32(3), 406–418. <https://doi.org/10.1002/joc.2280>
- Loew, A., Peng, J., & Borsche, M. (2016). High-resolution land surface fluxes from satellite and reanalysis data (HOLAPS v1. 0): Evaluation and uncertainty assessment. *Geoscientific Model Development*, 9(7), 2499–2532. <https://doi.org/10.5194/gmd-9-2499-2016>
- Long, D., Bai, L., Yan, L., Zhang, C., Yang, W., Lei, H., et al. (2019). Generation of spatially complete and daily continuous surface soil moisture of high spatial resolution. *Remote Sensing of Environment*, 233, 111364. <https://doi.org/10.1016/j.rse.2019.111364>
- Loomis, J., Koontz, S., Miller, H., & Richardson, L. (2015). Valuing geospatial information: Using the contingent valuation method to estimate the economic benefits of Landsat satellite imagery. *Photogrammetric Engineering & Remote Sensing*, 81(8), 647–656. <https://doi.org/10.14358/pers.81.8.647>

- López López, P., Sutanudjaja, E. H., Schellekens, J., Sterk, G., & Bierkens, M. F. (2017). Calibration of a large-scale hydrological model using satellite-based soil moisture and evapotranspiration products. *Hydrology and Earth System Sciences*, 21(6), 3125–3144. <https://doi.org/10.5194/hess-21-3125-2017>
- Magotra, B., Prakash, V., Saharia, M., Getirana, A., Kumar, S., Pradhan, R., et al. (2024). Towards an Indian land data assimilation system (ILDAS): A coupled hydrologic-hydraulic system for water balance assessments. *Journal of Hydrology*, 629, 130604. <https://doi.org/10.1016/j.jhydrol.2023.130604>
- Mahour, M., Tolpekin, V., Stein, A., & Sharifi, A. (2017). A comparison of two downscaling procedures to increase the spatial resolution of mapping actual evapotranspiration. *ISPRS Journal of Photogrammetry and Remote Sensing*, 126, 56–67. <https://doi.org/10.1016/j.isprsjprs.2017.02.004>
- Manfreda, S., Brocca, L., Moramarco, T., Melone, F., & Sheffield, J. (2014). A physically based approach for the estimation of root-zone soil moisture from surface measurements. *Hydrology and Earth System Sciences*, 18(3), 1199–1212. <https://doi.org/10.5194/hess-18-1199-2014>
- Mao, J., Fu, W., Shi, X., Ricciuto, D. M., Fisher, J. B., Dickinson, R. E., et al. (2015). Disentangling climatic and anthropogenic controls on global terrestrial evapotranspiration trends. *Environmental Research Letters*, 10(9), 094008. <https://doi.org/10.1088/1748-9326/10/9/094008>
- Mao, Q., Peng, J., & Wang, Y. (2021). Resolution enhancement of remotely sensed land surface temperature: Current status and perspectives. *Remote Sensing*, 13(7), 1306. <https://doi.org/10.3390/rs13071306>
- Martens, B., Miralles, D. G., Lievens, H., Van Der Schalie, R., De Jeu, R. A. M., Fernández-Prieto, D., et al. (2017). GLEAM v3: Satellite-based land evaporation and root-zone soil moisture. *Geoscientific Model Development*, 10(5), 1903–1925. <https://doi.org/10.5194/gmd-10-1903-2017>
- Marticorena, B., Chatenet, B., Rajot, J. L., Traoré, S., Coulibaly, M., Diallo, A., & Kaly, H. (2017). Temporal variability of mineral dust concentrations over West Africa: Analyses of a pluriannual monitoring from the AMMA Sahelian Dust Transect. *Atmospheric Chemistry and Physics*, 17(14), 8847–8867.
- Massari, C., Brocca, L., Moramarco, T., Tramblay, Y., & Lescot, J. F. D. (2014). Potential of soil moisture observations in flood modelling: Estimating initial conditions and correcting rainfall. *Advances in Water Resources*, 74, 44–53. <https://doi.org/10.1016/j.advwatres.2014.08.004>
- Mbabazi, D., Sehgal, V., & Mohanty, B. (2024). Global terrestrial water–energy coupling across scales. *Ecohydrology*, e2743(2). <https://doi.org/10.1002/eco.2743>
- McCabe, M., Miralles, D., Jimenez, C., Ershadi, A., Fisher, J. B., Mu, Z., et al. (2013). Global-scale estimation of land surface heat fluxes from space: Product assessment and intercomparison. In G. P. Petropoulos (Ed.), *Remote sensing of energy fluxes and soil moisture content* (p. 538). CRC Press, Taylor & Francis Group.
- McGlinchy, J., Soenen, S., Fisher, J. B., Devicigil, D., Kleynhans, T., Zhang, Y., et al. (2023). Synthetic daily 20-meter surface temperature measurements from space: Hydrosat daily surface temperature (HDST). In *IGARSS 2023-2023 IEEE International Geoscience and Remote Sensing Symposium* (pp. 7459–7462).
- Megonigal, J. P., Brewer, P. E., & Knee, K. L. (2020). Radon as a natural tracer of gas transport through trees. *New Phytologist*, 225(4), 1470–1475. <https://doi.org/10.1111/nph.16292>
- Melo, D. C. D., Anache, J. A. A., Borges, V. P., Miralles, D. G., Martens, B., Fisher, J. B., et al. (2021). Are remote sensing evapotranspiration models reliable across South American ecoregions? *Water Resources Research*, 57(11), e2020WR028752. <https://doi.org/10.1029/2020wr028752>
- Melton, F., Huntington, J., Grimm, R., Herring, J., Hall, M., Rollison, D., et al. (2022). OpenET: Filling the biggest data gap in water management for the Western United States. *Journal of the American Water Resources Association*, 58(6), 971–994. <https://doi.org/10.1111/1752-1688.12956>
- Merlin, O., Escorihuela, M. J., Mayoral, M. A., Hagolle, O., Al Bitar, A., & Kerr, Y. (2013). Self-calibrated evaporation-based disaggregation of SMOS soil moisture: An evaluation study at 3 km and 100 m resolution in Catalunya, Spain. *Remote Sensing of Environment*, 130, 25–38. <https://doi.org/10.1016/j.rse.2012.11.008>
- Michel, D., Jimenez, C., Miralles, D. G., Jung, M., Hirschi, M., Ershadi, A., et al. (2016). The WACMOS-ET project—Part 1: Tower-scale evaluation of four remote sensing-based evapotranspiration algorithms. *Hydrology and Earth System Sciences*, 20(2), 803–822. <https://doi.org/10.5194/hess-20-803-2016>
- Miller, D. L., Alonzo, M., Roberts, D. A., Tague, C. L., & McFadden, J. P. (2020). Drought response of urban trees and turfgrass using airborne imaging spectroscopy. *Remote Sensing of Environment*, 240, 111646. <https://doi.org/10.1016/j.rse.2020.111646>
- Miralles, D. G., Brutsaert, W., Dolman, A. J., & Gash, J. H. (2020). On the use of the term “Evapotranspiration”. *Water Resources Research*, 56(11), e2020WR028055. <https://doi.org/10.1029/2020wr028055>
- Miralles, D. G., De Jeu, R. A. M., Gash, J. H., Holmes, T. R. H., & Dolman, A. J. (2011). Magnitude and variability of land evaporation and its components at the global scale. *Hydrology and Earth System Sciences*, 15(3), 967–981. <https://doi.org/10.5194/hess-15-967-2011>
- Miralles, D. G., Gentile, P., Seneviratne, S. I., & Teuling, A. J. (2019). Land–atmospheric feedbacks during droughts and heatwaves: State of the science and current challenges. *Annals of the New York Academy of Sciences*, 1436(1), 19–35. <https://doi.org/10.1111/nyas.13912>
- Miralles, D. G., Jimenez, C., Jung, M., Michel, D., Ershadi, A., McCabe, M. F., et al. (2016). The WACMOS-ET project—Part 2: Evaluation of global terrestrial evaporation data sets. *Hydrology and Earth System Sciences*, 20(2), 823–842. <https://doi.org/10.5194/hess-20-823-2016>
- Mishra, D., Sehgal, V., & Mohanty, B. P. (2023). Thermodynamic bounds of terrestrial water-energy coupling and resiliency in global ecosystems. *Authoria Preprints*.
- Mladenova, I. E., Bolten, J. D., Crow, W. T., Anderson, M. C., Hain, C. R., Johnson, D. M., & Mueller, R. (2017). Intercomparison of soil moisture, evaporative stress, and vegetation indices for estimating corn and soybean yields over the US. *Ieee Journal of Selected Topics in Applied Earth Observations and Remote Sensing*, 10(4), 1328–1343. <https://doi.org/10.1109/jstars.2016.2639338>
- Mo, K. C., & Lettenmaier, D. P. (2015). Heat wave flash droughts in decline. *Geophysical Research Letters*, 42(8), 2823–2829. <https://doi.org/10.1002/2015gl064018>
- Mo, K. C., & Lettenmaier, D. P. (2016). Precipitation deficit flash droughts over the United States. *Journal of Hydrometeorology*, 17(4), 1169–1184. <https://doi.org/10.1175/jhm-d-15-0158.1>
- Modanesi, S., Massari, C., Camici, S., Brocca, L., & Amarnath, G. (2020). Do satellite surface soil moisture observations better retain information about crop-yield variability in drought conditions? *Water Resources Research*, 56(2), e2019WR025855. <https://doi.org/10.1029/2019wr025855>
- Molero, B., Leroux, D. J., Richaume, P., Kerr, Y. H., Merlin, O., Cosh, M. H., & Bindlish, R. (2018). Multi-timescale analysis of the spatial representativeness of in situ soil moisture data within satellite footprints. *Journal of Geophysical Research: Atmospheres*, 123(1), 3–21. <https://doi.org/10.1002/2017jd027478>
- Mondal, P., Walter, M., Miller, J., Epanchin-Niell, R., Gedan, K., Yawatkari, V., et al. (2023). The spread and cost of saltwater intrusion in the US Mid-Atlantic. *Nature Sustainability*, 6(11), 1352–1362. <https://doi.org/10.1038/s41893-023-01186-6>

- Moreira, A. A., Ruhoff, A. L., Roberti, D. R., de Arruda Souza, V., da Rocha, H. R., & de Paiva, R. C. D. (2019). Assessment of terrestrial water balance using remote sensing data in South America. *Journal of Hydrology*, 575, 131–147. <https://doi.org/10.1016/j.jhydrol.2019.05.021>
- Mu, Q., Zhao, M., & Running, S. W. (2011). Improvements to a MODIS global terrestrial evapotranspiration algorithm. *Remote Sensing of Environment*, 115(8), 1781–1800. <https://doi.org/10.1016/j.rse.2011.02.019>
- Mueller, B., Seneviratne, S. I., Jiménez, C., Corti, T., Hirschi, M., Balsamo, G., et al. (2011). Evaluation of global observations-based evapotranspiration datasets and IPCC AR4 simulations. *Geophysical Research Letters*, 38(6), L06402. <https://doi.org/10.1029/2010gl046230>
- Myeni, L., Moeletsi, M. E., & Clulow, A. D. (2019). Present status of soil moisture estimation over the African continent. *Journal of Hydrology: Regional Studies*, 21, 14–24. <https://doi.org/10.1016/j.ejrh.2018.11.004>
- NASA. (2018). Landsat science. Landsat 9 project on track, U.S. General Accounting Office Assesses. Retrieved from <https://landsat.gsfc.nasa.gov/article/landsat-9-project-on-track-u-s-general-accounting-office-assesses/>
- Ndehedehe, C. E., Okwuashi, O., Ferreira, V. G., & Agutu, N. O. (2018). Exploring evapotranspiration dynamics over sub-Saharan Africa (2000–2014). *Environmental Monitoring and Assessment*, 190(7), 1–19. <https://doi.org/10.1007/s10661-018-6780-6>
- Nelson, J. A., Carvalhais, N., Cuntz, M., Delpierre, N., Knauer, J., Ogée, J., et al. (2018). Coupling water and carbon fluxes to constrain estimates of transpiration: The TEA algorithm. *Journal of Geophysical Research: Biogeosciences*, 123(12), 3617–3632. <https://doi.org/10.1029/2018jg004727>
- Nguyen, H., Wheeler, M. C., Otkin, J. A., Cowan, T., Frost, A., & Stone, R. (2019). Using the evaporative stress index to monitor flash drought in Australia. *Environmental Research Letters*, 14(6), 064016. <https://doi.org/10.1088/1748-9326/ab2103>
- Nicholson, S. E., Tucker, C. J., & Ba, M. B. (1998). Desertification, drought, and surface vegetation: An example from the West African Sahel. *Bulletin of the American Meteorological Society*, 79(5), 815–830. [https://doi.org/10.1175/1520-0477\(1998\)079<0815:ddasva>2.0.co;2](https://doi.org/10.1175/1520-0477(1998)079<0815:ddasva>2.0.co;2)
- Ning, J., Yao, Y., Tang, Q., Li, Y., Fisher, J. B., Zhang, X., et al. (2023). Soil moisture at 30 m from multiple satellite datasets fused by random forest. *Journal of Hydrology*, 625, 130010. <https://doi.org/10.1016/j.jhydrol.2023.130010>
- Niu, G. Y., Yang, Z. L., Mitchell, K. E., Chen, F., Ek, M. B., Barlage, M., et al. (2011). The community Noah land surface model with multi-parameterization options (Noah-MP): 1. Model description and evaluation with local-scale measurements. *Journal of Geophysical Research*, 116(D12), D12109. <https://doi.org/10.1029/2010jd015139>
- Njoku, E. G., & Entekhabi, D. (1996). Passive microwave remote sensing of soil moisture. *Journal of Hydrology*, 184(1–2), 101–129. [https://doi.org/10.1016/0022-1694\(95\)02970-2](https://doi.org/10.1016/0022-1694(95)02970-2)
- Njoku, E. G., & Li, L. (1999). Retrieval of land surface parameters using passive microwave measurements at 6–18 GHz. *IEEE Transactions on Geoscience and Remote Sensing*, 37(1), 79–93. <https://doi.org/10.1109/36.739125>
- Nouri, H., Beecham, S., Hassanli, A. M., & Kazemi, F. (2013). Water requirements of urban landscape plants: A comparison of three factor-based approaches. *Ecological Engineering*, 57, 276–284. <https://doi.org/10.1016/j.ecoleng.2013.04.025>
- Ochsner, T. E., Cosh, M. H., Cuenca, R. H., Dorigo, W. A., Draper, C. S., Hagimoto, Y., et al. (2013). State of the art in large-scale soil moisture monitoring. *Soil Science Society of America Journal*, 77(6), 1888–1919. <https://doi.org/10.2136/sssaj2013.03.0093>
- Ochsner, T. E., Linde, E., Haffner, M., & Dong, J. (2019). Mesoscale soil moisture patterns revealed using a sparse in situ network and regression kriging. *Water Resources Research*, 55(6), 4785–4800. <https://doi.org/10.1029/2018wr024535>
- O'Neill, P. E., Chan, S., Njoku, E. G., Jackson, T., Bindlish, R., & Chaubell, J. (2018). *SMAP L3 radiometer global daily 36 km EASE-grid soil moisture, Version 5* (pp. 1–82). National Snow and Ice Data Center.
- Orth, R., & Seneviratne, S. I. (2014). Using soil moisture forecasts for sub-seasonal summer temperature predictions in Europe. *Climate Dynamics*, 43(12), 3403–3418. <https://doi.org/10.1007/s00382-014-2112-x>
- O, S., Hou, X., & Orth, R. (2020). Observational evidence of wildfire-promoting soil moisture anomalies. *Scientific Reports*, 10(1), 1–8. <https://doi.org/10.1038/s41598-020-67530-4>
- O, S., & Park, S. K. (2023). Flash drought drives rapid vegetation stress in arid regions in Europe. *Environmental Research Letters*, 18(1), 014028. <https://doi.org/10.1088/1748-9326/acae3a>
- Osman, M., Zaitchik, B. F., Badr, H. S., Otkin, J., Zhong, Y., Lorenz, D., et al. (2022). Diagnostic classification of flash drought events reveals distinct classes of forcings and impacts. *Journal of Hydrometeorology*, 23(2), 275–289. <https://doi.org/10.1175/jhm-d-21-0134.1>
- Otkin, J. A., Anderson, M. C., Hain, C., & Svoboda, M. (2014). Examining the relationship between drought development and rapid changes in the evaporative stress index. *Journal of Hydrometeorology*, 15(3), 938–956. <https://doi.org/10.1175/jhm-d-13-0110.1>
- Otkin, J. A., Lewis, W. E., Lenzen, A. J., McNoldy, B. D., & Majumdar, S. J. (2017). Assessing the accuracy of the cloud and water vapor fields in the hurricane WRF (HWRF) model using satellite infrared brightness temperatures. *Monthly Weather Review*, 145(5), 2027–2046. <https://doi.org/10.1175/mwr-d-16-0354.1>
- Otkin, J. A., Svoboda, M., Hunt, E. D., Ford, T. W., Anderson, M. C., Hain, C., & Basara, J. B. (2018). Flash droughts: A review and assessment of the challenges imposed by rapid-onset droughts in the United States. *Bulletin of the American Meteorological Society*, 99(5), 911–919. <https://doi.org/10.1175/bams-d-17-0149.1>
- Pan, S., Pan, N., Tian, H., Friedlingstein, P., Sitch, S., Shi, H., et al. (2020). Evaluation of global terrestrial evapotranspiration using state-of-the-art approaches in remote sensing, machine learning and land surface modeling. *Hydrology and Earth System Sciences*, 24(3), 1485–1509. <https://doi.org/10.5194/hess-24-1485-2020>
- Pangala, S. R., Enrich-Prast, A., Basso, L. S., Peixoto, R. B., Bastviken, D., Hornibrook, E. R., et al. (2017). Large emissions from floodplain trees close the Amazon methane budget. *Nature*, 552(7684), 230–234. <https://doi.org/10.1038/nature24639>
- Pangala, S. R., Gowing, D. J., Hornibrook, E. R., & Gauci, V. (2014). Controls on methane emissions from *Alnus glutinosa* saplings. *New Phytologist*, 201(3), 887–896. <https://doi.org/10.1111/nph.12561>
- Pangala, S. R., Hornibrook, E. R., Gowing, D. J., & Gauci, V. (2015). The contribution of trees to ecosystem methane emissions in a temperate forested wetland. *Global Change Biology*, 21(7), 2642–2654. <https://doi.org/10.1111/gcb.12891>
- Parajuli, P. B., Risal, A., Ouyang, Y., & Thompson, A. (2022). Comparison of SWAT and MODIS evapotranspiration data for multiple time-scales. *Hydrology*, 9(6), 103. <https://doi.org/10.3390/hydrology9060103>
- Parker, T., Gallant, A., Hobbins, M., & Hoffmann, D. (2021). Flash drought in Australia and its relationship to evaporative demand. *Environmental Research Letters*, 16(6), 064033. <https://doi.org/10.1088/1748-9326/abfe2c>
- Pascolini-Campbell, M., Fisher, J. B., & Reager, J. T. (2021). GRACE-FO and ECOSTRESS synergies constrain fine-scale impacts on the water balance. *Geophysical Research Letters*, 48(15), e2021GL093984. <https://doi.org/10.1029/2021gl093984>
- Pascolini-Campbell, M., Lee, C., Stavros, N., & Fisher, J. B. (2022). ECOSTRESS reveals pre-fire vegetation controls on burn severity for Southern California wildfires of 2020. *Global Ecology and Biogeography*, 31(10), 1976–1989. <https://doi.org/10.1111/geb.13526>
- Pascolini-Campbell, M. A., Reager, J. T., & Fisher, J. B. (2020). GRACE-based mass conservation as a validation target for basin-scale evapotranspiration in the contiguous United States. *Water Resources Research*, 56(2), e2019WR026594. <https://doi.org/10.1029/2019wr026594>

- Pejchar, L., Lepczyk, C. A., Fantle-Lepczyk, J. E., Hess, S. C., Johnson, M. T., Leopold, C. R., et al. (2020). Hawaii as a microcosm: Advancing the science and practice of managing introduced and invasive species. *BioScience*, 70(2), 184–193. <https://doi.org/10.1093/biosci/biz154>
- Pelgrum, H., Miltenburg, I., Cheema, M., Klaasse, A., & Bastiaanssen, W. (2010). ETLook a novel continental evapotranspiration algorithm. In *Remote Sensing and Hydrology Symposium, Jackson Hole, Wyoming, USA* (Vol. 1085, p. 1087).
- Pendergrass, A. G., Meehl, G. A., Pulwarty, R., Hobbins, M., Hoell, A., AghaKouchak, A., et al. (2020). Flash droughts present a new challenge for subseasonal-to-seasonal prediction. *Nature Climate Change*, 10(3), 191–199. <https://doi.org/10.1038/s41558-020-0709-0>
- Peng, J., Albergel, C., Balenzano, A., Brocca, L., Cartus, O., Cosh, M. H., et al. (2021). A roadmap for high-resolution satellite soil moisture applications—confronting product characteristics with user requirements. *Remote Sensing of Environment*, 252, 112162. <https://doi.org/10.1016/j.rse.2020.112162>
- Peng, J., Loew, A., Merlin, O., & Verhoest, N. E. (2017). A review of spatial downscaling of satellite remotely sensed soil moisture. *Reviews of Geophysics*, 55(2), 341–366. <https://doi.org/10.1002/2016rg000543>
- Peng, Y., Yang, Z., Zhang, Z., & Huang, J. (2024). A Machine learning-based high-resolution soil moisture mapping and spatial-temporal analysis: The mlhrsm package. *Agronomy*, 14(3), 421. <https://doi.org/10.3390/agronomy14030421>
- Perkins, K. S., Nimmo, J. R., Medeiros, A. C., Szutu, D. J., & von Allmen, E. (2014). Assessing effects of native forest restoration on soil moisture dynamics and potential aquifer recharge, Auwahi, Maui. *Ecology*, 95(5), 1437–1451. <https://doi.org/10.1002/eco.1469>
- Petropoulos, G. P., Ireland, G., & Barrett, B. (2015). Surface soil moisture retrievals from remote sensing: Current status, products & future trends. *Physics and Chemistry of the Earth, Parts A/B/C*, 83–84, 36–56.
- Petropoulos, G. P., Srivastava, P. K., Piles, M., & Pearson, S. (2018). Earth observation-based operational estimation of soil moisture and evapotranspiration for agricultural crops in support of sustainable water management. *Sustainability*, 10(1), 181. <https://doi.org/10.3390/su10010181>
- Piepmeyer, J. R., Johnson, J. T., Mohammed, P. N., Bradley, D., Ruf, C., Aksoy, M., et al. (2013). Radio-frequency interference mitigation for the soil moisture active passive microwave radiometer. *IEEE Transactions on Geoscience and Remote Sensing*, 52(1), 761–775. <https://doi.org/10.1109/tgrs.2013.2281266>
- Pierre, C., Bergametti, G., Marticorena, B., Mougin, E., Bouet, C., & Schmechtig, C. (2012). Impact of vegetation and soil moisture seasonal dynamics on dust emissions over the Sahel. *Journal of Geophysical Research*, 117(D6). <https://doi.org/10.1029/2011jd016950>
- Pitz, S. L., Megonigal, J. P., Chang, C. H., & Szlavecz, K. (2018). Methane fluxes from tree stems and soils along a habitat gradient. *Biogeochemistry*, 137(3), 307–320. <https://doi.org/10.1007/s10533-017-0400-3>
- Planet. (2023). Planet soil water content: Technical specification. Version 1.0.0, May, 2023. Retrieved from https://assets.planet.com/docs/Planet_soil_water_content_product_specification.pdf
- Polhamus, A., Fisher, J. B., & Tu, K. P. (2013). What controls the error structure in evapotranspiration models? *Agricultural and Forest Meteorology*, 169, 12–24. <https://doi.org/10.1016/j.agrformet.2012.10.002>
- Poulos, H. M., Barton, A. M., Koch, G. W., Kolb, T. E., & Thode, A. E. (2021). Wildfire severity and vegetation recovery drive post-fire evapotranspiration in a southwestern pine-oak forest, Arizona, USA. *Remote Sensing in Ecology and Conservation*, 7(4), 579–591. <https://doi.org/10.1002/rse2.210>
- Povak, N. A., Hessburg, P. F., Giardina, C. P., Reynolds, K. M., Heider, C., Salminen, E., et al. (2017). A watershed decision support tool for managing invasive species on Hawai'i Island, USA. *Forest Ecology and Management*, 400, 300–320. <https://doi.org/10.1016/j.foreco.2017.05.046>
- Proctor, J., Rigden, A., Chan, D., & Huybers, P. (2022). More accurate specification of water supply shows its importance for global crop production. *Nature Food*, 3(9), 753–763. <https://doi.org/10.1038/s43016-022-00592-x>
- Prospero, J. M., Ginoux, P., Torres, O., Nicholson, S. E., & Gill, T. E. (2002). Environmental characterization of global sources of atmospheric soil dust identified with the Nimbus 7 Total Ozone Mapping Spectrometer (TOMS) absorbing aerosol product. *Reviews of Geophysics*, 40(1), 2–12. <https://doi.org/10.1029/2000rg000095>
- Purdy, A. J., Fisher, J. B., Goulden, M. L., Colliander, A., Halverson, G., Tu, K., & Famiglietti, J. S. (2018). SMAP soil moisture improves global evapotranspiration. *Remote Sensing of Environment*, 219, 1–14. <https://doi.org/10.1016/j.rse.2018.09.023>
- Purdy, A. J., Fisher, J. B., Goulden, M. L., & Famiglietti, J. S. (2016). Ground heat flux: An analytical review of 6 models evaluated at 88 sites and globally. *Journal of Geophysical Research: Biogeosciences*, 121(12), 3045–3059. <https://doi.org/10.1002/2016jg003591>
- Purdy, A. J., Kawata, J., Fisher, J. B., Reynolds, M., Om, G., Ali, Z., et al. (2019). Designing drought indicators. *Bulletin of the American Meteorological Society*, 100(11), 2327–2341. <https://doi.org/10.1175/bams-d-18-01461>
- Qin, L., Yan, C., Yu, L., Chai, M., Wang, B., Hayat, M., et al. (2022). High-resolution spatio-temporal characteristics of urban evapotranspiration measured by unmanned aerial vehicle and infrared remote sensing. *Building and Environment*, 222, 109389. <https://doi.org/10.1016/j.buildenv.2022.109389>
- Rana, G., & Katerji, N. (2000). Measurement and estimation of actual evapotranspiration in the field under Mediterranean climate: A review. *European Journal of Agronomy*, 13(2–3), 125–153. [https://doi.org/10.1016/S1161-0301\(00\)00070-8](https://doi.org/10.1016/S1161-0301(00)00070-8)
- Rao, K., Anderegg, W. R., Sala, A., Martínez-Vilalta, J., & Konings, A. G. (2019). Satellite-based vegetation optical depth as an indicator of drought-driven tree mortality. *Remote Sensing of Environment*, 227, 125–136. <https://doi.org/10.1016/j.rse.2019.03.026>
- Reichle, R. H., De Lannoy, G. J. M., Liu, Q., Ardizzone, J. V., Colliander, A., Conaty, A., et al. (2017). Assessment of the SMAP Level-4 surface and root-zone soil moisture product using in situ measurements. *Journal of Hydrometeorology*, 18(10), 2621–2645. <https://doi.org/10.1175/jhm-d-17-0063.1>
- Ren, D., Wei, B., Xu, X., Engel, B., Li, G., Huang, Q., et al. (2019). Analyzing spatiotemporal characteristics of soil salinity in arid irrigated agroecosystems using integrated approaches. *Geoderma*, 356, 113935. <https://doi.org/10.1016/j.geoderma.2019.113935>
- Reynolds, J. F., Kemp, P., & Tenhunen, J. D. (2000). Effects of long-term rainfall variability in evapotranspiration and soil water distribution in the Chihuahuan Desert: A modeling analysis. *Plant Ecology*, 150(1–2), 145–159. <https://doi.org/10.1023/a:1026530522612>
- Rigden, A. J., Mueller, N. D., Holbrook, N. M., Pillai, N., & Huybers, P. (2020). Combined influence of soil moisture and atmospheric evaporative demand is important for accurately predicting US maize yields. *Nature Food*, 1(2), 127–133. <https://doi.org/10.1038/s43016-020-0028-7>
- Robinson, D. A., Campbell, C. S., Hopmans, J. W., Hornbuckle, B. K., Jones, S. B., Knight, R., et al. (2008). Soil moisture measurement for ecological and hydrological watershed-scale observatories: A review. *Vadose Zone Journal*, 7(1), 358–389. <https://doi.org/10.2136/vzj2007.0143>
- Rocha, A. D., Vulova, S., Meier, F., Förster, M., & Kleinschmit, B. (2022). Mapping evapotranspirative and radiative cooling services in an urban environment. *Sustainable Cities and Society*, 85, 104051. <https://doi.org/10.1016/j.scs.2022.104051>
- Ruess, P. J., Konar, M., Wanders, N., & Bierkens, M. (2023). Irrigation by crop in the continental United States from 2008 to 2020. *Water Resources Research*, 59(2), e2022WR032804. <https://doi.org/10.1029/2022wr032804>

- Ryu, Y., Baldocchi, D. D., Kobayashi, H., Van Ingen, C., Li, J., Black, T. A., et al. (2011). Integration of MODIS land and atmosphere products with a coupled-process model to estimate gross primary productivity and evapotranspiration from 1 km to global scales. *Global Biogeochemical Cycles*, 25(4). <https://doi.org/10.1029/2011gb004053>
- Saadi, S., Pattey, E., Jégo, G., & Champagne, C. (2022). Prediction of rainfed corn evapotranspiration and soil moisture using the STICS crop model in eastern Canada. *Field Crops Research*, 287, 108664. <https://doi.org/10.1016/j.fcr.2022.108664>
- Sadeghi, M., Babaeian, E., Tuller, M., & Jones, S. B. (2017). The optical trapezoid model: A novel approach to remote sensing of soil moisture applied to Sentinel-2 and Landsat-8 observations. *Remote Sensing of Environment*, 198, 52–68. <https://doi.org/10.1016/j.rse.2017.05.041>
- Sadeghi, M., Ebtehaj, A., Crow, W. T., Gao, L., Purdy, A. J., Fisher, J. B., et al. (2020). Global estimates of land surface water fluxes from SMOS and SMAP satellite soil moisture data. *Journal of Hydrometeorology*, 21(2), 241–253. <https://doi.org/10.1175/jhm-d-19-0150.1>
- Sapfluxnet. (2024). SAPFLUXNET: A global database of sap flow measurements. Retrieved from https://sapfluxnet.creaf.cat/#sfn_features
- Sax, D. F., & Gaines, S. D. (2008). Species invasions and extinction: The future of native biodiversity on islands. *Proceedings of the National Academy of Sciences of the United States of America*, 105(1), 11490–11497. <https://doi.org/10.1073/pnas.0802290105>
- Sazib, N., Bolten, J. D., & Mladenova, I. E. (2021). Leveraging NASA soil moisture active passive for assessing fire susceptibility and potential impacts over Australia and California. *Ieee Journal of Selected Topics in Applied Earth Observations and Remote Sensing*, 15, 779–787. <https://doi.org/10.1109/jstars.2021.3136756>
- Scanlon, T. M., & Kustas, W. P. (2010). Partitioning carbon dioxide and water vapor fluxes using correlation analysis. *Agricultural and Forest Meteorology*, 150(1), 89–99. <https://doi.org/10.1016/j.agrformet.2009.09.005>
- Scanlon, T. M., & Kustas, W. P. (2012). Partitioning evapotranspiration using an eddy covariance-based technique: Improved assessment of soil moisture and land-atmosphere exchange dynamics. *Vadose Zone Journal*, 11(3), vzj20120025. <https://doi.org/10.2136/vzj2012.0025>
- Scanza, R. A., Mahowald, N., Ghan, S., Zender, C. S., Kok, J. F., Liu, X., et al. (2015). Modeling dust as component minerals in the community atmosphere model: Development of framework and impact on radiative forcing. *Atmospheric Chemistry and Physics*, 15(1), 537–561. <https://doi.org/10.5194/acp-15-537-2015>
- Schmugge, T. J., Kustas, W. P., Ritchie, J. C., Jackson, T. J., & Rango, A. (2002). Remote sensing in hydrology. *Advances in Water Resources*, 25(8–12), 1367–1385.
- Schwaab, J., Meier, R., Mussetti, G., Seneviratne, S., Bürgi, C., & Davin, E. L. (2021). The role of urban trees in reducing land surface temperatures in European cities. *Nature Communications*, 12(1), 6763. <https://doi.org/10.1038/s41467-021-26768-w>
- Schwalm, C. R., Anderegg, W. R. L., Michalak, A. M., Fisher, J. B., Biondi, F., Koch, G., et al. (2017). Global patterns of drought recovery. *Nature*, 548(7666), 202–205. <https://doi.org/10.1038/nature23021>
- Sehgal, V., Gaur, N., & Mohanty, B. P. (2021a). Global surface soil moisture drydown patterns. *Water Resources Research*, 57(1), e2020WR027588. <https://doi.org/10.1029/2020wr027588>
- Sehgal, V., Gaur, N., & Mohanty, B. P. (2021b). Global flash drought monitoring using surface soil moisture. *Water Resources Research*, 57(9), 1–25. <https://doi.org/10.1029/2021wr029901>
- Sehgal, V., & Mohanty, B. P. (2024). Preferential hydrologic states and tipping characteristics of global surface soil moisture. *Water Resources Research*, 60(4), e2023WR034858. <https://doi.org/10.1029/2023wr034858>
- Sehgal, V., Mohanty, B. P., & Reichle, R. H. (2024). Rootzone soil moisture dynamics using terrestrial water-energy coupling. *Geophysical Research Letters*, 51(19), e2024GL110342. <https://doi.org/10.1029/2024gl110342>
- Sehgal, V., & Sridhar, V. (2019). Watershed-scale retrospective drought analysis and seasonal forecasting using multi-layer, high-resolution simulated soil moisture for Southeastern US. *Weather and Climate Extremes*, 23, 100191. <https://doi.org/10.1016/j.wace.2018.100191>
- Senanayake, I. P., Pathira Arachchilage, K. R., Yeo, I. Y., Khaki, M., Han, S. C., & Dahlhaus, P. G. (2024). Spatial downscaling of satellite-based soil moisture products using machine learning techniques: A review. *Remote Sensing*, 16(12), 2067. <https://doi.org/10.3390/rs16122067>
- Seneviratne, S. I., Lehner, I., Gurtz, J., Teuling, A. J., Lang, H., Moser, U., et al. (2010). Investigating soil moisture-climate interactions in a changing climate: A review. *Earth-Science Reviews*, 99(3–4), 125–161. <https://doi.org/10.1016/j.earscirev.2010.02.004>
- Seneviratne, S. I., Lehner, I., Gurtz, J., Teuling, A. J., Lang, H., Moser, U., et al. (2012). Swiss prealpine Rietholz bach research catchment and lysimeter: 32 year time series and 2003 drought event. *Water Resources Research*, 48(6). <https://doi.org/10.1029/2011wr011749>
- Shang, K., Yao, Y., Liang, S., Zhang, Y., Fisher, J. B., Chen, J., et al. (2021). DNN-MET: A deep neural networks method to integrate satellite-derived evapotranspiration products, eddy covariance observations and ancillary information. *Agricultural and Forest Meteorology*, 308–309(108582), 1–20. <https://doi.org/10.1016/j.agrformet.2021.108582>
- Sheffield, J., Andreadis, K. M., Wood, E. F., & Lettenmaier, D. P. (2009). Global and continental drought in the second half of the twentieth century: Severity-area-duration analysis and temporal variability of large-scale events. *Journal of Climate*, 22(8), 1962–1981. <https://doi.org/10.1175/2008jcli2722.1>
- Shi, M., Li, L., Lin, X., Fang, Y., & Hou, Z. (2024). An ML-based terrestrial data fusion and augmentation framework to enable advanced understanding of the terrestrial carbon and water interactions (No. PNNL-36677). Pacific Northwest National Laboratory (PNNL).
- Shi, M., Worden, J. R., Bailey, A., Noone, D., Risi, C., Fu, R., et al. (2022). Amazonian terrestrial water balance inferred from satellite-observed water vapor isotopes. *Nature Communications*, 13(1), 2686. <https://doi.org/10.1038/s41467-022-30317-4>
- Shuttleworth, W. J., & Wallace, J. S. (1985). Evaporation from sparse crops-an energy combination theory. *Quarterly Journal of the Royal Meteorological Society*, 111(469), 839–855. <https://doi.org/10.1256/smsqj.46909>
- Shuttleworth, W. J., & Wallace, J. S. (2009). Calculating the water requirements of irrigated crops in Australia using the Matt-Shuttleworth approach. *Transactions of the American Society of Agricultural and Biological Engineers*, 52(6), 1895–1906. <https://doi.org/10.13031/2013.29217>
- Silvertown, J., Araya, Y., & Gowing, D. (2015). Hydrological niches in terrestrial plant communities: A review. *Journal of Ecology*, 103(1), 93–108. <https://doi.org/10.1111/1365-2745.12332>
- Singh, G., & Das, N. N. (2022). A data-driven approach using the remotely sensed soil moisture product to identify water-demand in agricultural regions. *Science of the Total Environment*, 837, 155893. <https://doi.org/10.1016/j.scitotenv.2022.155893>
- Soleimani Sardoo, F., Mesbahzadeh, T., Salajeghe, A., Zehtabian, G., Ranjbar, A., Miglietta, M. M., & Krakauer, N. (2022). Antecedent soil moisture conditions influenced vertical dust flux: A case study in Iran using WRF-Chem model. *Land*, 11(6), 819. <https://doi.org/10.3390/land11060819>
- Song, P., Zhang, Y., Guo, J., Shi, J., Zhao, T., & Tong, B. (2022). A 1 km daily surface soil moisture dataset of enhanced coverage under all-weather conditions over China in 2003–2019. *Earth System Science Data*, 14(6), 2613–2637. <https://doi.org/10.5194/essd-14-2613-2022>
- Srivastava, P. K. (2017). Satellite soil moisture: Review of theory and applications in water resources. *Water Resources Management*, 31(10), 3161–3176. <https://doi.org/10.1007/s11269-017-1722-6>

- Stoy, P., El-Madany, T., Fisher, J. B., Gentine, P., Gerken, T., Good, S., et al. (2019). Reviews and syntheses: Turning the challenges of partitioning ecosystem evaporation and transpiration into opportunities. *Biogeosciences*, 16(19), 3747–3775. <https://doi.org/10.5194/bg-16-3747-2019>
- Su, Z. (2002). The Surface Energy Balance System (SEBS) for estimation of turbulent heat fluxes. *Hydrology and Earth System Sciences*, 6(1), 85–100. <https://doi.org/10.5194/hess-6-85-2002>
- Taghvaeian, S., Andales, A. A., Allen, L. N., Kisekka, I., O'Shaughnessy, S. A., Porter, D. O., et al. (2020). Irrigation scheduling for agriculture in the United States: The progress made and the path forward. *Transactions of the American Society of Agricultural and Biological Engineers*, 63(5), 1603–1618. <https://doi.org/10.13031/trans.14110>
- Taghvaeian, S., Neale, C. M. U., Osterberg, J. C., Sritharan, S. I., & Watts, D. R. (2018). Remote sensing and GIS techniques for assessing irrigation performance: Case study in Southern California. *Journal of Irrigation and Drainage Engineering*, 144(6), 05018002. [https://doi.org/10.1061/\(asce\)ir.1943-4774.0001306](https://doi.org/10.1061/(asce)ir.1943-4774.0001306)
- Takahashi, K., Sakabe, A., Azuma, W. A., Itoh, M., Imai, T., Matsumura, Y., et al. (2022). Insights into the mechanism of diurnal variations in methane emission from the stem surfaces of *Alnus japonica*. *New Phytologist*, 235(5), 1757–1766. <https://doi.org/10.1111/nph.18283>
- Talat, N. (2020). Alleviation of soil salinization and the management of saline soils, climate change, and soil interactions. In *Climate change and soil interactions* (pp. 305–329). Elsevier.
- Talib, A., Desai, A. R., Huang, J., Thom, J., Panuska, J. C., & Stoy, P. (2024). Improving parameterization of a regional irrigation scheduling program for evapotranspiration estimation with eddy covariance measurements.
- Talsma, C. J., Good, S. P., Jimenez, C., Martens, B., Fisher, J. B., Miralles, D. G., et al. (2018). Partitioning of evapotranspiration in remote sensing-based models. *Agricultural and Forest Meteorology*, 260, 131–143. <https://doi.org/10.1016/j.agrformet.2018.05.010>
- Talsma, C. J., Good, S. P., Miralles, D. G., Fisher, J. B., Martens, B., Jimenez, C., & Purdy, A. J. (2018). Sensitivity of evapotranspiration components in remote sensing-based models. *Remote Sensing*, 10(10), 1601. <https://doi.org/10.3390/rs10101601>
- Tang, X., Li, H., Desai, A. R., Nagy, Z., Luo, J., Kolb, T. E., et al. (2014). How is water-use efficiency of terrestrial ecosystems distributed and changing on Earth? *Scientific Reports*, 4(1), 7483. <https://doi.org/10.1038/srep07483>
- Tangdamrongsub, N., Han, S. C., Yeo, I. Y., Dong, J., Steele-Dunne, S. C., Willgoose, G., & Walker, J. P. (2020). Multivariate data assimilation of GRACE, SMOS, SMAP measurements for improved regional soil moisture and groundwater storage estimates. *Advances in Water Resources*, 135, 103477. <https://doi.org/10.1016/j.advwatres.2019.103477>
- Tanny, J. (2013). Microclimate and evapotranspiration of crops covered by agricultural screens: A review. *Biosystems Engineering*, 114(1), 26–43. <https://doi.org/10.1016/j.biosystemseng.2012.10.008>
- Taylor, C. M., De Jeu, R. A. M., Guichard, F., Harris, P. P., & Dorigo, W. A. (2012). Afternoon rain more likely over drier soils. *Nature*, 489(7416), 423–426. <https://doi.org/10.1038/nature11377>
- Thaxton, J. M., Cordell, S., Cabin, R. J., & Sandquist, D. R. (2012). Non-native grass removal and shade increase soil moisture and seedling performance during Hawaiian dry forest restoration. *Restoration Ecology*, 20(4), 475–482. <https://doi.org/10.1111/j.1526-100x.2011.00793.x>
- Tian, S., Tregoning, P., Renzullo, L. J., Van Dijk, A. I., Walker, J. P., Pauwels, V. R., & Allgeyer, S. (2017). Improved water balance component estimates through joint assimilation of GRACE water storage and SMOS soil moisture retrievals. *Water Resources Research*, 53(3), 1820–1840. <https://doi.org/10.1002/2016wr019641>
- Touma, D., Ashfaq, M., Nayak, M. A., Kao, S.-C. C., & Diffenbaugh, N. S. (2015). A multi-model and multi-index evaluation of drought characteristics in the 21st century. *Journal of Hydrology*, 526, 196–207. <https://doi.org/10.1016/j.jhydrol.2014.12.011>
- Tripathy, K. P., Mukherjee, S., Mishra, A. K., Mann, M. E., & Williams, A. P. (2023). Climate change will accelerate the high-end risk of compound drought and heatwave events. *Proceedings of the National Academy of Sciences of the United States of America*, 120(28), e2219825120. <https://doi.org/10.1073/pnas.2219825120>
- Tuller, M., Babaeian, E., & Jones, S. B. (2023). Proximal sensing of soil moisture. In M. J. Goss & M. Oliver (Eds.), *Encyclopedia of soils in the environment* (2nd ed., pp. 591–599). Academic Press.
- Uddin, K., Matin, M. A., & Meyer, F. J. (2019). Operational flood mapping using multi-temporal Sentinel-1 SAR images: A case study from Bangladesh. *Remote Sensing*, 11(13), 1581. <https://doi.org/10.3390/rs11131581>
- Ulaby, F. T., Long, D. G., Blackwell, W. J., Elachi, C., Fung, A. K., Ruf, C., et al. (2014). *Microwave radar and radiometric remote sensing* (Vol. 4). University of Michigan Press.
- Vergopolan, N., Chaney, N. W., Beck, H. E., Pan, M., Sheffield, J., Chan, S., & Wood, E. F. (2020). Combining hyper-resolution land surface modeling with SMAP brightness temperatures to obtain 30-m soil moisture estimates. *Remote Sensing of Environment*, 242, 111740. <https://doi.org/10.1016/j.rse.2020.111740>
- Vergopolan, N., Chaney, N. W., Pan, M., Sheffield, J., Beck, H. E., Ferguson, C. R., et al. (2021). SMAP-HydroBlocks, a 30-m satellite-based soil moisture dataset for the conterminous US. *Scientific Data*, 8(1), 264. <https://doi.org/10.1038/s41597-021-01050-2>
- Volk, J. M., Huntington, J., Melton, F. S., Allen, R., Anderson, M. C., Fisher, J. B., et al. (2024). Assessing the accuracy of OpenET satellite-based evapotranspiration data to support water resource and land management applications. *Nature Water*, 1–13.
- Volk, J. M., Huntington, J., Melton, F. S., Allen, R., Anderson, M. C., Fisher, J. B., et al. (2023). Development of a benchmark Eddy flux evapotranspiration dataset for evaluation of satellite-driven evapotranspiration models over the CONUS. *Agricultural and Forest Meteorology*, 331(109307), 1–17. <https://doi.org/10.1016/j.agrformet.2023.109307>
- Vulova, S., Rocha, A. D., Meier, F., Nouri, H., Schulz, C., Soulsby, C., et al. (2023). City-wide, high-resolution mapping of evapotranspiration to guide climate-resilient planning. *Remote Sensing of Environment*, 287, 113487. <https://doi.org/10.1016/j.rse.2023.113487>
- Wan, H., McLaughlin, D., Shao, Y., van Eerden, B., Ranganathan, S., & Deng, X. (2021). Remotely-sensed evapotranspiration for informed urban forest management. *Landscape and Urban Planning*, 210, 104069. <https://doi.org/10.1016/j.landurbplan.2021.104069>
- Wanders, N., Karssenbergh, D., De Roo, A., De Jong, S. M., & Bierkens, M. F. P. (2014). The suitability of remotely sensed soil moisture for improving operational flood forecasting. *Hydrology and Earth System Sciences*, 18(6), 2343–2357. <https://doi.org/10.5194/hess-18-2343-2014>
- Wang, C., Fu, B., Zhang, L., & Xu, Z. (2019). Soil moisture–plant interactions: An ecohydrological review. *Journal of Soils and Sediments*, 19, 1–9. <https://doi.org/10.1007/s11368-018-2167-0>
- Wang, L., Caylor, K. K., Villegas, J. C., Barron-Gafford, G. A., Breshears, D. D., & Huxman, T. E. (2010). Partitioning evapotranspiration across gradients of woody plant cover: Assessment of a stable isotope technique. *Geophysical Research Letters*, 37(9). <https://doi.org/10.1029/2010gl043228>
- Wang, M., Wyatt, B. M., & Ochsner, T. E. (2023). Accurate statistical seasonal streamflow forecasts developed by incorporating remote sensing soil moisture and terrestrial water storage anomaly information. *Journal of Hydrology*, 626, 130154. <https://doi.org/10.1016/j.jhydrol.2023.130154>
- Wang, Y., Gao, M., Chen, H., Fu, X., Wang, L., & Wang, R. (2023). Soil moisture and salinity dynamics of drip irrigation in saline-alkali soil of Yellow River basin. *Frontiers in Environmental Science*, 11, 345. <https://doi.org/10.3389/fenvs.2023.1130455>

- Wang, Y., Li, R., Liang, M., Ma, J., Yang, Y., & Zheng, H. (2023). Impact of crop types and irrigation on soil moisture downscaling in water-stressed cropland regions. *Environmental Impact Assessment Review*, 100, 107073. <https://doi.org/10.1016/j.eiar.2023.107073>
- Wang, Y., Mao, J., Brelsford, C. M., Ricciuto, D. M., Yuan, F., Shi, X., et al. (2024). Thermal, water, and land cover factors led to contrasting urban and rural vegetation resilience to extreme hot months. *PNAS Nexus*, 3(4), pgae147. <https://doi.org/10.1093/pnasnexus/pgae147>
- Ward, H. C., Kotthaus, S., Järvi, L., & Grimmond, C. S. B. (2016). Surface urban energy and water balance scheme (SUEWS): Development and evaluation at two UK sites. *Urban Climate*, 18, 1–32. <https://doi.org/10.1016/j.uclim.2016.05.001>
- Weerasinghe, I., Bastiaanssen, W., Mul, M., Jia, L., & van Griensven, A. (2020). Can we trust remote sensing evapotranspiration products over Africa? *Hydrology and Earth System Sciences*, 24(3), 1565–1586. <https://doi.org/10.5194/hess-24-1565-2020>
- Wen, J., Fisher, J. B., Parazoo, N. C., Hu, L., Litvak, M. E., & Sun, Y. (2022). Resolve the clear-sky continuous diurnal cycle of high-resolution ECOSTRESS evapotranspiration and land surface temperature. *Water Resources Research*, 58(9), e2022WR032227. <https://doi.org/10.1029/2022wr032227>
- Wen, W., Timmermans, J., Chen, Q., & van Bodegom, P. M. (2020). A review of remote sensing challenges for food security with respect to salinity and drought threats. *Remote Sensing*, 13(1), 6. <https://doi.org/10.3390/rs13010006>
- Wernicke, L. J., Chew, C. C., & Small, E. E. (2024). SMAP/CYGNSS EASE-Grid Soil Moisture. (NSIDC-0797, Version 1) [Dataset]. Boulder, Colorado USA. NASA National Snow and Ice Data Center Distributed Active Archive Center. [describe subset used if applicable]. <https://doi.org/10.5067/8OODMTVR6RT9>
- Westerband, A. C., Bialic-Murphy, L., Weisenberger, L. A., & Barton, K. E. (2020). Intraspecific variation in seedling drought tolerance and associated traits in a critically endangered, endemic Hawaiian shrub. *Plant Ecology & Diversity*, 13(2), 159–174. <https://doi.org/10.1080/17550874.2020.1730459>
- Wilder, B. A., & Kinoshita, A. M. (2022). Incorporating ECOSTRESS evapotranspiration in a paired catchment water balance analysis after the 2018 Holy Fire in California. *Catena*, 215, 106300. <https://doi.org/10.1016/j.catena.2022.106300>
- Williams, D., Cable, W., Hultine, K., Hoedjes, J., Yepez, E., Simonneau, V., et al. (2004). Evapotranspiration components determined by stable isotope, sap flow and eddy covariance techniques. *Agricultural and Forest Meteorology*, 125(3–4), 241–258. <https://doi.org/10.1016/j.agrformet.2004.04.008>
- Wu, J., Feng, Y., Liang, L., He, X., & Zeng, Z. (2022). Assessing evapotranspiration observed from ECOSTRESS using flux measurements in agroecosystems. *Agricultural Water Management*, 269, 107706. <https://doi.org/10.1016/j.agwat.2022.107706>
- Wyatt, B. M., Ochsner, T. E., Krueger, E. S., & Jones, E. T. (2020). In-situ soil moisture data improve seasonal streamflow forecast accuracy in rainfall-dominated watersheds. *Journal of Hydrology*, 590, 125404. <https://doi.org/10.1016/j.jhydrol.2020.125404>
- Xie, J., Qi, T., Hu, W., Huang, H., Chen, B., & Zhang, J. (2022). Retrieval of live fuel moisture content based on multi-source remote sensing data and ensemble deep learning model. *Remote Sensing*, 14(17), 4378. <https://doi.org/10.3390/rs14174378>
- Xie, Z., Yao, Y., Zhang, X., Liang, S., Fisher, J. B., Chen, J., et al. (2022). The global LAnd surface satellite (GLASS) evapotranspiration product version 5.0: Algorithm development and preliminary validation. *Journal of Hydrology*, 610, 127990. <https://doi.org/10.1016/j.jhydrol.2022.127990>
- Xu, J., Yao, Y., Liang, S., Fisher, J. B., Jia, K., Zhang, X., et al. (2019). Merging the MODIS and Landsat terrestrial latent heat flux products using the multiresolution tree method. *IEEE Transactions on Geoscience and Remote Sensing*, 57(5), 2811–2823. <https://doi.org/10.1109/tgrs.2018.2877807>
- Xu, L., Zhou, H., Du, L., Yao, H., & Wang, H. (2015). Precipitation trends and variability from 1950 to 2000 in arid lands of Central Asia. *Journal of Arid Land*, 7(4), 514–526. <https://doi.org/10.1007/s40333-015-0045-9>
- Yao, Y., Liang, S., Li, X., Chen, J., Liu, S., Jia, K., et al. (2017). Improving global terrestrial evapotranspiration estimation using support vector machine by merging three process-based algorithms. *Agricultural and Forest Meteorology*, 242, 55–74. <https://doi.org/10.1016/j.agrformet.2017.04.011>
- Yao, Y., Liang, S., Li, X., Hong, Y., Fisher, J. B., Zhang, N., et al. (2014). Bayesian multimodel estimation of global terrestrial latent heat flux from eddy covariance, meteorological, and satellite observations. *Journal of Geophysical Research: Atmospheres*, 119(8), 4521–4545. <https://doi.org/10.1002/2013jd020864>
- Yao, Y., Zhang, Y., Liu, Q., Liu, S., Jia, K., Zhang, X., et al. (2019). Evaluation of a satellite-derived model parameterized by three soil moisture constraints to estimate terrestrial latent heat flux in the Heihe River basin of Northwest China. *Science of the Total Environment*, 695, 133787. <https://doi.org/10.1016/j.scitotenv.2019.133787>
- Ye, N., Walker, J. P., Gao, Y., PopStefanija, I., & Hills, J. (2024). Comparison between thermal-optical and L-band passive microwave soil moisture remote sensing at farm scales: Towards UAV-based near-surface soil moisture mapping. *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing*, 17, 633–642. <https://doi.org/10.1109/jstars.2023.3329015>
- Yepez, E. A., Huxman, T. E., Ignace, D. D., English, N. B., Weltzin, J. F., Castellanos, A. E., & Williams, D. G. (2005). Dynamics of transpiration and evaporation following a moisture pulse in semiarid grassland: A chamber-based isotope method for partitioning flux components. *Agricultural and Forest Meteorology*, 132(3–4), 359–376. <https://doi.org/10.1016/j.agrformet.2005.09.006>
- Yu, Y., Mao, J., Thornton, P. E., Notaro, M., Wulfschleger, S. D., Shi, X., et al. (2020). Quantifying the drivers and predictability of seasonal changes in African fire. *Nature Communications*, 11(1), 2893. <https://doi.org/10.1038/s41467-020-16692-w>
- Yu, Y., Mao, J., Wulfschleger, S. D., Chen, A., Shi, X., Wang, Y., et al. (2022). Machine learning-based observation-constrained projections reveal elevated global socioeconomic risks from wildfire. *Nature Communications*, 13(1), 1250. <https://doi.org/10.1038/s41467-022-28853-0>
- Yu, Z., Chen, J., Chen, J., Zhan, W., Wang, C., Ma, W., et al. (2024). Enhanced observations from an optimized soil-canopy-photosynthesis and energy flux model revealed evapotranspiration-shading cooling dynamics of urban vegetation during extreme heat. *Remote Sensing of Environment*, 305, 114098. <https://doi.org/10.1016/j.rse.2024.114098>
- Yuan, Q., Xu, H., Li, T., Shen, H., & Zhang, L. (2020). Estimating surface soil moisture from satellite observations using a generalized regression neural network trained on sparse ground-based measurements in the continental US. *Journal of Hydrology*, 580, 124351. <https://doi.org/10.1016/j.jhydrol.2019.124351>
- Yuan, X., Wang, L., Wu, P., Ji, P., Sheffield, J., & Zhang, M. (2019). Anthropogenic shift towards higher risk of flash drought over China. *Nature Communications*, 10(1), 1–8. <https://doi.org/10.1038/s41467-019-12692-7>
- Yuan, X., Wang, Y., Ji, P., Wu, P., Sheffield, J., & Otkin, J. A. (2023). A global transition to flash droughts under climate change. *Science*, 380(6641), 187–191. <https://doi.org/10.1126/science.abn6301>
- Zacharakis, I., & Tsihrintzis, V. A. (2023). Integrated wildfire danger models and factors: A review. *Science of the Total Environment*, 899, 165704. <https://doi.org/10.1016/j.scitotenv.2023.165704>
- Zeppelino, V. L. R., Battisti, D. S., & Baker, M. B. (2019). The origin of soil moisture evaporation “regimes”. *Journal of Climate*, 32(20), 6939–6960. <https://doi.org/10.1175/jcli-d-19-0209.1>

- Zhan, X., Fang, L., Yin, J., Schull, M., Liu, J., Hain, C., et al. (2021). Remote sensing of evapotranspiration for global drought monitoring. In H. Wu, D. P. Lettenmaier, Q. Tang, & P. J. Ward (Eds.), *Global drought and flood*. <https://doi.org/10.1002/9781119427339.ch2>
- Zhang, K., Kimball, J. S., & Running, S. W. (2016). A review of remote sensing based actual evapotranspiration estimation. *Wiley Interdisciplinary Reviews: Water*, 3(6), 834–853. <https://doi.org/10.1002/wat2.1168>
- Zhang, L., Marshall, M., Nelson, A., & Vrieling, A. (2021). A global assessment of PT-JPL soil evaporation in agroecosystems with optical, thermal, and microwave satellite data. *Agricultural and Forest Meteorology*, 306, 108455. <https://doi.org/10.1016/j.agrformet.2021.108455>
- Zhang, Q., Yuan, Q., Jin, T., Song, M., & Sun, F. (2022). SGD-SM 2.0: An improved seamless global daily soil moisture long-term dataset from 2002 to 2022. *Earth System Science Data Discussions*, 2022(10), 1–22. <https://doi.org/10.5194/essd-14-4473-2022>
- Zhang, Y., Kong, D., Gan, R., Chiew, F. H., McVicar, T. R., Zhang, Q., & Yang, Y. (2019). Coupled estimation of 500 m and 8-day resolution global evapotranspiration and gross primary production in 2002–2017. *Remote Sensing of Environment*, 222, 165–182. <https://doi.org/10.1016/j.rse.2018.12.031>
- Zhang, Y., Liang, S., Ma, H., He, T., Wang, Q., Li, B., et al. (2023). Generation of global 1-km daily soil moisture product from 2000 to 2020 using ensemble learning. *Earth System Science Data Discussions*, 2023(5), 1–37. <https://doi.org/10.5194/essd-15-2055-2023>
- Zhao, H., Di, L., Sun, Z., Hao, P., Yu, E., Zhang, C., & Lin, L. (2021). Impacts of soil moisture on crop health: A remote sensing perspective. In *2021 9th International Conference on Agro-Geoinformatics* (pp. 1–4). Agro-Geoinformatics.
- Zhao, M., Liu, Y., & Konings, A. G. (2022). Evapotranspiration frequently increases during droughts. *Nature Climate Change*, 12(11), 1024–1030. <https://doi.org/10.1038/s41558-022-01505-3>
- Zhao, W. L., Gentile, P., Reichstein, M., Zhang, Y., Zhou, S., Wen, Y., et al. (2019). Physics-constrained machine learning of evapotranspiration. *Geophysical Research Letters*, 46(24), 14496–14507. <https://doi.org/10.1029/2019gl085291>
- Zheng, C., Jia, L., & Zhao, T. (2023). A 21-year dataset (2000–2020) of gap-free global daily surface soil moisture at 1-km grid resolution. *Scientific Data*, 10(1), 139. <https://doi.org/10.1038/s41597-023-01991-w>
- Zheng, D., Wang, X., Van Der Velde, R., Ferrazzoli, P., Wen, J., Wang, Z., et al. (2018). Impact of surface roughness, vegetation opacity and soil permittivity on L-band microwave emission and soil moisture retrieval in the third pole environment. *Remote Sensing of Environment*, 209, 633–647. <https://doi.org/10.1016/j.rse.2018.03.011>
- Zhou, S., Yu, B., Zhang, Y., Huang, Y., & Wang, G. (2016). Partitioning evapotranspiration based on the concept of underlying water use efficiency. *Water Resources Research*, 52(2), 1160–1175. <https://doi.org/10.1002/2015wr017766>
- Zhu, Y., Murugesan, S. B., Masara, I. K., Myint, S. W., & Fisher, J. B. (2024). Examining wildfire dynamics using ECOSTRESS data with machine learning approaches: The case of South-Eastern Australia's black summer. *Remote Sensing in Ecology and Conservation*. in press. <https://doi.org/10.1002/rse2.422>
- Zipper, S. C., & Loheide, S. P., II. (2014). Using evapotranspiration to assess drought sensitivity on a subfield scale with HRMET, a high resolution surface energy balance model. *Agricultural and Forest Meteorology*, 197, 91–102. <https://doi.org/10.1016/j.agrformet.2014.06.009>

Erratum

The originally published version of this article contained an error in one affiliation. The affiliations for coauthor Joshua B. Fisher are as follows: Schmid College of Science and Technology, Chapman University, Orange, CA, USA, and Hydrosat USA, Washington, DC, USA. This may be considered the authoritative version of record.