Repositioning satellite soil moisture for agricultural drought monitoring: Misconceptions, bottlenecks, and future directions

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Soil moisture is a key variable linking terrestrial water, energy, and carbon cycles. Satellite microwave remote sensing offers an effective means to monitor surface soil moisture (SSM) across large regions, with passive radiometry and active scatterometer providing all-weather, cloud-penetrating observations. Long-term SSM products such as SMAP, SMOS, AMSR2, ASCAT, and Fengyun-3 WindRAD have supported a wide range of applications, including water balance assessment, flood detection, and drought monitoring. Among these, agricultural drought monitoring is especially crucial for safeguarding crop production, food security, and ecological resilience. This commentary revisits the principles of SSM-based drought assessment, clarifies several overlooked misconceptions, identifies methodological bottlenecks, and outlines next-generation research directions to advance satellite-based agricultural drought monitoring.

CONCEPTS, CONSTRAINTS, AND DEVELOPMENT OF SSM-BASED AGRICULTURAL DROUGHT INDICES

General concepts and constraints

Drought is commonly classified into three types: meteorological drought, hydrological drought, and agricultural drought. Agricultural drought, which is our focus herein, arises when soil moisture declines to levels insufficient for plant water uptake, inducing plant water stress and subsequent reductions in crop yield. Thus, SSM serves as the core variable for diagnosing agricultural drought in satellite-based frameworks.

Historically, drought monitoring relied mainly on precipitation- and temperature-based indices, constrained by the lack of large-scale soil moisture observations. Approaches[1] such as the Crop Moisture Index (CMI), Comprehensive Crop-Specific Drought Index (CSDI), Evapotranspiration Deficit Index (ETDI), and Surface Water Supply Index (SWSI) were developed as extensions of the Palmer Drought Severity Index (PDSI) and Standardized Precipitation Index (SPI), substituting precipitation (P) deficits with anomalies in evapotranspiration (ET) or surface water balance (P minus ET).[2] While informative for atmospheric drought, such indices inherit two constraints:

(i) they assume agricultural drought is solely a downstream effect of meteorological drought, and

(ii) they rely on modeled hydrometeorological variables that cannot represent human interventions such as irrigation or land management.

The emergence of satellite microwave observations revolutionized agricultural drought assessment by enabling direct, consistent, and spatially comprehensive monitoring of soil moisture anomalies. These SSM datasets provide objective evidence of drought conditions, offering a more accurate alternative to model-based or precipitation-derived indices (Figure 1A) and supporting improved agricultural drought monitoring when extended to root-zone moisture through modeling approaches.

BASIC FORMULATION OF SATELLITE-SSM BASED DROUGHT MONITORING INDEX

Recent microwave missions, particularly L-band radiometers (SMOS, SMAP), have substantially improved SSM accuracy and temporal consistency. Most SSM-based drought indices follow a normalized formulation anchored by two soil hydraulic limits: field capacity (SSM_{fc}) and wilting point (SSM_{wp}). A general "Agricultural Drought Index (ADI)" can be expressed as:

$$ADI = \frac{SSM - SSM_{fc}}{SSM_{fc} - SSM_{wp}} \tag{1}$$

The *ADI* reflects the degree of soil moisture deficit by quantifying the relative position of the actual soil moisture within the range defined by the soil's key hydraulic parameters. A positive *ADI* value indicates that soil moisture exceeds the field capacity, implying surplus water availability for vegetation growth or potential surface waterlogging. As *ADI* decreases from 0 toward -1, the soil gradually transitions from a no-stress condition to increasingly severe plant water stress, signifying a progressive intensification of drought severity.

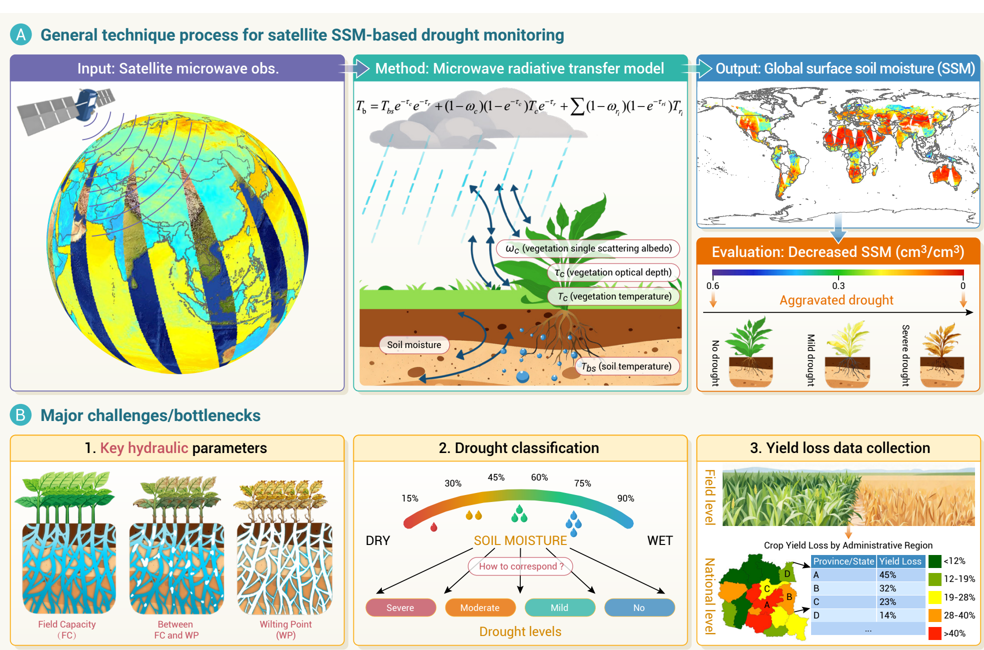

Figure 1. Conceptual framework and key limitations of satellite SSM–based agricultural drought monitoring (A) General technique process for satellite SSM-based drought monitoring (using passive microwave techniques). (B) Major challenges and bottlenecks of currently recognized satellite-based drought monitoring methodologies.

METHODOLOGICAL BOTTLENECKS IN CURRENT SATELLITE-SSM DROUGHT MONITORING

Despite recent advances, several bottlenecks remain for the currently prevailing ADI-type drought monitoring approaches based on satellite-derived SSM (Figure 1B).

(1) Bottleneck 1—Scale mismatch in the key hydraulic parameters. Field capacity (SSM_{fc}) and wilting point (SSM_{wp}) are defined from laboratory-measured soil water retention curves at the point scale, whereas satellite SSM represents kilometer-scale (10^1–10^2 km) averages. This intrinsic scale mismatch, together with strong sub-pixel heterogeneity in soil texture and moisture states, constitutes

the physical root cause of uncertainty when applying the hydraulic parameters derived from widely used pedotransfer functions (PTFs)[3] to satellite observations. Because PTFs inherit laboratory-scale assumptions, their error structures are inconsistent with those of satellite SSM retrievals (e.g., ~0.04 cm^3/cm^3 in RMSE for SMAP), which can readily lead to *ADI* values violating physical constraints (< −1 or > 0) over coarse footprints. This scale-induced inconsistency remains a fundamental but under-recognized limitation in current SSM-based drought indices.

(2) **Bottleneck 2—Crop-agnostic drought severity thresholds.** A robust drought monitoring framework should not only define the mathematical formulation of the ADI but also establish a reliable criterion linking ADI values to specific drought severity categories (e.g., *mild*, *moderate*, *severe*, or *extreme drought*). The classification criteria currently in widespread use are largely derived from the Food and Agriculture Organization (FAO)'s *Guidelines for Computing Crop Water Requirements*.[4] However, the FAO-recommended thresholds are based on the mean water stress levels averaged across multiple crop types, rather than being crop-specific. In practice, each pixel observed by satellite sensors may correspond to a distinct and homogeneous crop type with its own water stress tolerance and physiological response. Consequently, applying such generalized, multi-crop average thresholds to classify drought severity can lead to misrepresentation of actual drought conditions at the pixel scale.

(3) Bottleneck 3—Limited and coarse validation through crop yield data. Assessing the accuracy of agricultural drought monitoring remains a major challenge. Comparisons with meteorological or hydrological indices are common but insufficient, as these reflect distinct physical processes. Crop yield loss provides the most direct validation metric, yet yield data are often available only annually and are costly to collect over large areas. Effective validation thus requires spatially extensive, high-quality yield datasets that align with the temporal and spatial resolutions of SSM retrievals, along with ancillary information on crop phenology and management. Furthermore, crop yield variability is affected not only by drought but also by other biophysical and socio-economic factors such as pest outbreaks, fertilization, and technological advancement. These confounding influences complicate the isolation of drought effects, underscoring the need for multi-source datasets and integrated evaluation frameworks that couple satellite, field, and model-based evidence.

DIRECTIONS FOR NEXT-GENERATION SATELLITE-BASED AGRICULTURAL DROUGHT MONITORING

Future research should focus on improving satellite-based monitoring of agricultural drought from the following perspectives:

(1) **Direction 1—Long-term multi-mission SSM fusion and hydraulic parameter refinement**. Refining key soil hydraulic parameters requires more temporally consistent and spatially detailed soil moisture records. Although PTF-based estimates are uncertain, field capacity and wilting point can be statistically approximated from long-term SSM time series—using, for example, the 95th and 5th percentiles of ranked SSM observations. The reliability of this approach depends on both the temporal span and consistency of SSM data. Therefore, integrating multi-mission observations (e.g., SSM/I since 1987, AMSR-E since 2002, SMOS since 2009, and SMAP since 2015) is crucial for constructing a harmonized, long-term global dataset. The ESA Climate Change Initiative (CCI) SSM product exemplifies this integration. However, further improvements in inter-sensor calibration are required. In particular, calibration should move beyond purely statistical harmonization of SSM retrievals and instead emphasize physically consistent rescaling within microwave radiative or scattering transfer models, including frequency-dependent adjustment of observation inputs and associated model parameters, to ensure retrievals correspond to a consistent effective penetration depth. Since soil hydraulic behavior varies across scales, future work should also emphasize spatial downscaling of long-term SSM records through fusion with high-resolution optical or radar data sensitive to surface moisture gradients.

(2) **Direction 2—Integrating remote sensing with process-based crop growth models.** Ambiguities in classifying drought severity can be mitigated by coupling satellite SSM with crop growth simulation models. These models elucidate how varying soil water deficits translate into crop yield losses, enabling more objective, crop-specific drought thresholds. Evaluating model sensitivity at resolutions comparable to satellite SSM observations will enhance the physical consistency between remotely sensed indicators and agricultural impacts. Incorporating high-resolution crop-type maps as a foundational data layer is equally essential, as drought effects and water stress responses differ markedly among crop species.

(3) **Direction 3—Toward scalable validation through combined use of crop yield data and remote-sensing proxies.** Crop yield records provide the most direct benchmark for evaluating satellite-based drought monitoring, yet they remain sparse and difficult to obtain at large scales due to data privacy, commercial constraints, and reporting inconsistencies. While establishing an open, community-driven global crop yield database, analogous to the International Soil Moisture Network (ISMN) for in situ soil moisture,[5] would substantially advance validation efforts, more immediately applicable alternatives are also needed. High-resolution remote sensing-based yield proxies, such as solar-induced chlorophyll fluorescence (SIF) or seasonally integrated vegetation indices (e.g., NDVI, EVI), offer scalable and cost-effective indicators of drought-induced productivity loss. Integrating these proxies with limited available yield statistics can provide a practical pathway for large-scale, multi-temporal validation of satellite-based agricultural drought indices.

SUMMARY AND OUTLOOKS

Satellite-derived SSM has become a foundation for agricultural drought monitoring, offering direct, global observations of surface hydrological dynamics. Yet misconceptions about soil hydraulic parameters, crop-agnostic drought thresholds, and the lack of large-scale yield data hamper current approaches. Future progress hinges on multi-mission SSM integration, crop-aware and physically based drought indices, and community-driven yield data sharing. Together, these developments can reshape agricultural drought monitoring into a more accurate, scalable, and operationally meaningful system.

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AUTHOR CONTRIBUTIONS

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

DECLARATION OF INTERESTS

The authors declare no competing interests.