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Remote Sensing Hydrology Revisited: Advances, Persistent Challenges, and a Science-Driven Agenda for the Next Decade

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Abstract In the WRR 50th Anniversary Special Collection, Lettenmaier et al. (2015, https://doi.org/10.1002/2015WR017616) provided a timely account of how satellite remote sensing evolved from a niche capability in hydrology into a mainstream driver of hydrologic discovery, as the community shifted from imagery toward validated Earth Observation (EO) products and open-access data systems. In this Commentary for the WRR 60th Anniversary Special Collection, we revisit and extend that synthesis and argue that the next step is not just more EO data, but a more accountable remote sensing hydrology. The challenge is to integrate remote sensing more directly into hydrologic science questions in ways that ground networks alone cannot provide consistently across scales. We center this Commentary on a core question: How can EO be used, credibly and consistently, to quantify where water is stored, how it moves, and how the hydrologic cycle is changing, in ways that improve hydrologic understanding and decision value beyond what ground networks alone can provide? We summarize key advances since 2015 that sharpen water-cycle observability, expand analysis-ready data systems and computation, and accelerate hybrid inference, while highlighting persistent challenges that continue to limit credible hydrologic inference near thresholds and extremes. We conclude with a science-driven agenda focused on closing observability gaps, improving record coherence, advancing uncertainty-aware inference, strengthening end-to-end traceability from measurements to societal impacts, and sustaining climate-quality EO records for hydrologic science in a changing climate, while recognizing that these advances will depend on continuity of observing capability and credible follow-on mission strategies.

Plain Language Summary Satellites now observe many parts of the water cycle, including precipitation, soil moisture, evapotranspiration, surface water, and total water storage. A 2015 *Water Resources Research* 50th Anniversary Special Collection paper by Lettenmaier et al. described how these observations became widely used in hydrology. This Commentary updates that story by centering on a North Star question: How can Earth observations be used, credibly and consistently, to determine where water is stored, how it moves, and how these patterns are changing, in ways that improve decisions beyond what ground measurements alone can provide? We highlight what has improved most since 2015, including new observing capabilities, better access to analysis-ready data, and stronger inference methods, while also identifying persistent challenges that still limit reliability for hydrologic extremes and water management. We further conclude that progress in the next decade will depend not only on better science and integration, but also on sustaining climate-quality data records and continuity of follow-on EO missions. Together, these science questions and research priorities define a path toward more reliable and societally useful remote sensing hydrology.

Key Points:

- Remote sensing observations increasingly constrain estimates of water storage, movement, and change beyond what in situ networks alone can
- Observability and inference have advanced hydrology, but snow, extremes, scale mismatch, and record coherence remain major challenges
- A science-driven agenda emphasizes uncertainty traceability from sensor to decision, Earth Observation record continuity, and mission sustainability

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1. Why Revisit Lettenmaier et al. (2015) for the WRR 60th Anniversary?

The WRR 60th Anniversary Special Collection invited Commentaries that update influential articles with new perspective and insight. Lettenmaier et al. (2015) serves as a natural anchor, having documented the fundamental transition in hydrology from occasional, application-driven use of remote sensing imagery to routine reliance on curated Earth Observation (EO) products. This transition has accelerated over the last decade, with EO-enabled information now playing a critical role in addressing hydrologic science and application of floods, droughts, and

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managed-water decisions. Lettenmaier et al. (2015) highlighted two enduring insights. First, early remote-sensing contributions relevant to hydrology often appeared outside the field due to barriers such as immature algorithms, limited data access, and the specialized expertise needed to interpret measurements and retrieval assumptions. The advent of the Earth Observing System era, along with community validation, open data policies, and hydrology-focused assessment papers, has lowered these barriers and broadened credible hydrologic use. Second, key "unresolved problems" remain—such as snow water equivalent (SWE) estimation, partitioning total water-storage change into its component stores, estimating river discharge, and resolving surface water-groundwater dynamic connectivity—requiring both improved observing strategies and stronger inference frameworks to connect measurements to hydrologic states, fluxes, and impacts.

A decade later, EO has matured into a system-level capability supporting both hydrologic discovery and applications at broad scales. Hydrology research now increasingly focuses on integrated water cycle questions and coupled water-human dynamics, rather than isolated variables. In this context, Remote Sensing Hydrology (RSH) is best viewed through an integrative science question, with consistency and closure as a scientific benchmark (i.e., the ability to reconcile multi-sensor, multi-source observations of water storage, movement, and distribution to close water budgets across scales and time). Achieving this integration is essential for advancing water prediction, from flood and drought forecasting to water resources systems planning and management.

For the next decade, the central question is not whether remote sensing matters to hydrology, but how to structure EO-enabled hydrologic science so it can be rigorously evaluated and translated into practice to address the field's core questions. This motivates a science-driven revisit of Lettenmaier et al. (2015). Rather than viewing remote sensing data production as an endpoint, we examine how remote sensing transforms hydrology's ability to answer fundamental questions about water storage, movement, and change, and how those questions define a science-driven agenda for the next decade. This framing aligns with community-wide priorities that recognize remote sensing as essential information infrastructure for understanding Earth system dynamics and supporting societal needs.

2. From EO Data to Science: A Pathway to Hydrologic Intelligence

As emphasized by the landmark "Opportunities in the Hydrologic Sciences" report, foundational advances in physical hydrology are ultimately driven by new observations (NRC, 1991). Remote sensing has a long history in hydrology, with multiple syntheses documenting both progress and persistent challenges (Durand et al., 2021; Rodell & Reager, 2023; Sheffield et al., 2018). Here, remote sensing refers primarily to the science and technology of measuring Earth from a distance, whereas EO refers more broadly to all of the observational infrastructure that supports hydrologic science and applications. Although the phrase RSH is still used somewhat informally, discussions have increasingly shifted from inventories of products toward the hydrologic science they can enable. Accordingly, a science-first way to further clarify and explicitly frame the field of RSH is to start from the community's core questions and define what hydrology seeks from remote sensing. The *North Star science question* is: How can EO be used—consistently and credibly—to quantify where water is stored, how it moves, and why its distribution patterns are changing, in ways that improve hydrologic understanding and decisions, especially at regional-to-global scales beyond what ground networks alone can provide? Here, "consistently" refers to whether EO-enabled estimates and inferences remain coherent across sensors, scales, components, and time periods in integrated hydrologic analysis, whereas "credibly" refers to whether they are physically interpretable, uncertainty-aware, and fit for the hydrologic science questions.

Three interconnected questions are key to this goal:

1. *Water storage*: Where is water stored (snow, soil moisture, surface water, and total water storage (TWS)), how is it exchanged among stores, and how are storage anomalies evolving?
2. *Water movement*: Where, when, and how does water move across landscapes and through river networks, and what does that imply for discharge, connectivity, and hydrologic hazards?
3. *Water change*: How and why are the spatiotemporal patterns of storage and movement changing across space and time scales, and what do those changes imply for coupled climate–water–human systems?

Across these questions, the overarching scientific objective is hydrologic intelligence: translating remote sensing measurements—together with their uncertainty characterization—into constraints, state updates, attribution, forecasts, and decision-relevant information metrics. In this view, remote sensing contributes not only "more

observations," but also a pathway to testable, uncertainty-aware inference and intelligence to improve our understanding and prediction of water-cycle dynamics across scales.

3. Advances: From EO Data to Hydrologic Intelligence and Decision Services

Building on Lettenmaier et al. (2015), the most consequential changes extend beyond simply having more EO. Instead, there has been a practical shift toward greater hydrologic observability, stronger inference, and closer integration of EO into hydrologic intelligence and decision services.

3.1. Advance 1—Better Observing Capabilities and Continuity for Key Water-Cycle Variables

RSH has undergone a step change in hydrologic observability, driven by multi-sensor retrievals—including active and passive microwave, optical and thermal sensors, altimetry, gravimetry, and radar—and by major gains in record continuity. EO capabilities now increasingly provide constraints on estimates of precipitation, soil moisture, terrestrial water storage, and surface water across a far broader range of spatial and temporal scales than was possible a decade ago. Representative examples include precipitation products spanning the PERSIANN family, CMORPH, GSMaP, and NASA's TMPA/IMERG products (Huffman et al., 2020; Sadeghi et al., 2021; Zhu et al., 2026); terrestrial water-storage constraints from GRACE and GRACE Follow-On (Chandanpurkar et al., 2025; Rodell et al., 2018); and global soil-moisture constraints strengthened by Soil Moisture and Ocean Salinity and Soil Moisture Active Passive (SMAP; Das et al., 2018). The emerging Surface Water and Ocean Topography (SWOT) era has further transformed surface water observation by enabling global space-based constraints on river discharge for the first time, although important refinement and validation challenges remain (Andreadis et al., 2025; Cerbelaud et al., 2026). SWOT also supports observation of water-surface elevation variability and storage change in approximately 6 million lakes and reservoirs—orders of magnitude more than previous satellite systems could resolve (Ma et al., 2026; Wang et al., 2025). In parallel, although Landsat, MODIS and Synthetic Aperture Radar (SAR) have been available for decades, their hydrologic use was initially limited. It has now matured into a routine and powerful capability for mapping inundation, surface water extent, and land-surface change relevant to floods and hydrologic connectivity (Freeman et al., 2019), with the NASA-ISRO SAR (NISAR) era poised to extend these constraints further.

3.2. Advance 2—Analysis-Ready EO, Cloud-Scale Computation, and Improved Reproducibility

The practical barriers of downloading, preprocessing, and harmonizing EO data sets have diminished as open platforms and analysis-ready products matured, shifting effort from data wrangling to inference, benchmarking, and reproducible workflows. This matters because the science questions—storage, movement, and change—are inherently integrative and cannot be answered reliably with isolated products or one-off processing pipelines. Given the convergence of high-performance computing, multidecadal observations, and historical ground networks, integrative EO workflows are becoming more tractable. Examples include NASA's Earthdata/EOSDIS cloud transition toward shared archive and analysis services; NOAA's cloud-based open-data dissemination through Amazon Web Service; and European Space Agency's Copernicus Data Space Ecosystem, which couples open Sentinel access with APIs, JupyterLab, openEO, and browser-based analysis tools. Together, these systems illustrate how the practical bottleneck is shifting from data access toward benchmarking, fusion, and reproducible hydrologic inference. Building on the Earth Information System vision articulated in NASEM's 2018 decadal strategy (NASEM, 2018), it is now increasingly feasible to constrain water-budget closure at watershed scales and to combine multiple physical constraints to improve retrievals (Liao & Barros, 2025).

3.3. Advance 3—Expanded Inference Workflows Through Data Assimilation, Hybrid Learning-Enabled Modeling

Because EO rarely provides complete direct observation of all hydrologic states and fluxes, progress depends on inference engines that translate partial, uncertain observations into dynamically consistent estimates, forecasts, and attribution. Since 2015, these workflows have broadened through tighter integration of process-based modeling, data assimilation (DA), inversion, and machine learning-based approaches, alongside recent efforts on the development of Digital Twins (Barros, 2024). Machine learning has moved from niche experimentation toward enabling roles in data extraction, fusion, QA/QC, emulator development, and hybrid physics-informed inference that can complement DA and calibration (Guilloteau et al., 2025). Recent syntheses increasingly

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treat water-budget closure and cross-component consistency as explicit evaluation targets, not optional diagnostics. For example, Dorigo et al. (2021) show that at annual scales many surface and atmospheric water budgets can be closed to within ∼10% residual in many cases, supporting more integrated, multi-component estimation. Other examples include EO-informed state updating in hydrologic and land-surface models, probabilistic multisensor precipitation inference, and hybrid workflows that combine process constraints with machine learning to improve closure, attribution, and forecast consistency.

3.4. Advance 4—From EO to Decision Services: Operational Hazard and Water Management Systems

EO is no longer used primarily for retrospective studies; it increasingly powers near-real-time monitoring and decision support for floods, landslides, drought, and managed water systems. These services operationalize EO by combining satellite observations with hydrologic models/inference and impacts to produce actionable alerts and situational awareness under latency and reliability constraints. Illustrative examples include NASA Global Flood Monitoring System (Adler et al., 2022; Hong et al., 2007), European Flood Awareness System, JAXA's Today's Earth system (Ma et al., 2024), the PERSIANN-CCS-CDR (Sadeghi et al., 2021), NASA global landslide hazard situational awareness system (Hong et al., 2006; Kirschbaum & Stanley, 2018), and satellite-informed U.S. drought monitoring systems. The key point is the shift from EO data sets to integrated systems, where performance expectations, uncertainty communication, and decision relevance are primary requirements.

Since 2015, EOs have become a routine tool for integrated assessment of water-cycle processes and for hydrologic applications at regional-to-global scales. A major part of this broader progress has been a scale revolution in EO: spatial resolution has improved, revisit intervals have shortened, and multisensor integration has expanded the range of hydrologic processes that can be estimated from space. Current EO systems are also better able to resolve heterogeneity in water-cycle dynamics across a broader range of spatial and temporal scales. At the same time, these gains remain shaped by tradeoffs among footprint size, revisit frequency, spectral capability, and orbit design, leaving some rapidly evolving hydrologic processes, such as storm and flood dynamics, still difficult to observe continuously. Collectively, these advances have substantially improved our ability to observe and infer water storage and movement—especially in regions where in situ networks are sparse.

4. Persistent Challenges: From Observability Limits to Decision-Grade Hydrology

Despite great progress, an uncomfortable truth remains: we do not yet have a comprehensive global observing system capable of monitoring the water cycle at the spatial and temporal scales most relevant to society. Achieving water budget consistency (closure) often becomes even harder at these critical scales. Robust, decision-grade RSH is therefore still limited by four interlinked persistent challenges: Observation, Uncertainty, Inference, and Decision Value. These challenges are increasingly visible precisely because observing systems and computation have improved; they reveal where conclusions remain sensitive to missing or scale-mismatched observables, inconsistent records, uncertainty that is, not yet operationally usable, and weak traceability from measurements to decisions.

Challenge 1—Observation (missing terms and scale mismatch). The science questions that matter most in hydrology often require finer-scale, more fully coupled terrestrial–atmospheric observability than current EO systems can routinely provide. Several key observables remain inadequately constrained at scales relevant to management and decision-making. SWE in complex terrain is a canonical example: passive microwave retrievals can saturate at high SWE and, as for many other EO variables, struggle with spatial heterogeneity in regions of complex terrain, land cover, and surface substrates (Guilloteau et al., 2017)—precisely where water-supply predictability depends strongly on snow storage. More broadly, spatiotemporal scale mismatch and limited water phase discrimination continue to hinder closure-ready constraints across the full water cycle. For example, TWS observations from gravimetry provide powerful large-scale constraints, but their coarse effective resolution makes it difficult to attribute signals to sub-basin processes or to partition liquid and solid water storage (e.g., snow, ice, and permafrost) from groundwater, soil moisture, vegetation water content, and surface water without additional information. Temporally, SWOT observations are typically available only one to four times within a 21-day repeat cycle, while SAR observations, including those anticipated from NISAR, are intermittent and often missing the peak evolution of storm events. This observational sparsity limits the ability to track hazards such as floods continuously from atmospheric forcing into terrestrial response. In addition, EO-based hydrologic

research has focused primarily on terrestrial states and fluxes, while near-surface atmospheric water fluxes—such as lower-tropospheric moisture transport and cloud-water dynamics—remain comparatively underconstrained.

Challenge 2—Uncertainty (credibility for change and extremes). In this Commentary, "errors" refer to departures of EO estimates from reference values, whereas "uncertainty" refers more broadly to what is not known and how that lack of knowledge is characterized, structured, and communicated for downstream inference and decision use. Errors are often regime-dependent, exhibiting diel (day–night) and seasonal patterns that reflect underlying physical processes, and can be correlated in space and time. Uncertainty is not captured by a single value; instead, it has a complex structure shaped by sensor physics, retrieval assumptions, surface conditions, and sampling strategies. As a result, EO-related uncertainty is still inconsistently characterized and, crucially, not routinely packaged in forms that are useful for practitioners in uncertainty propagation workflows. This limitation is particularly critical for change detection and extremes: when the scientific focus is on trends, abrupt transitions (such as floods or flash droughts), regime shifts, thresholds, or tail risks, even small biases and correlations can dominate inferred signals (Sheffield et al., 2018). These issues often prevent robust water-budget closure, resulting in substantial residuals at basin scales. The challenge of record coherence further complicates matters: as products, sensors, and algorithms evolve, cross-sensor inconsistency, record inhomogeneity, and calibration drift can obscure the distinction between true environmental change and artifacts (Vargas et al., 2025). Recent advances, particularly those enabled by machine learning and large data sets, show promise for extracting information from multisensor observations and predicting associated uncertainties (Liao & Barros, 2025; Singh & Barros, 2026).

Challenge 3—Inference (turning partial observability into hydrologic intelligence). These uncertainty limitations do not stop at the product level and propagate directly into inference. As noted above, remote sensing rarely provides complete direct observation of all hydrologic states and fluxes. The scientific burden therefore shifts to inference—using process models, DA, inversion, and hybrid learning—to translate partial, uncertain observations into dynamically consistent estimates, attribution, and forecasts. However, inference remains limited by several factors: (a) incomplete observation operators and challenges in scale mismatch; (b) the difficulty of assimilating multi-sensor products with correlated errors; and (c) a lack of standardized, uncertainty-aware benchmarking that evaluates performance both in observations and in decision-impact regimes. Inference is particularly hindered when EO products are provided only as deterministic fields (even with simple error bounds), rather than as probabilistic outputs (e.g., full distributions or ensembles) that would better serve downstream users and advanced assimilation frameworks. When closure constraints are weak, the inference chain can amplify biases or yield mutually inconsistent states and fluxes.

Challenge 4—Decision value (from hydrologic skill to actionable outcomes). Even when RSH estimates improve, decision value is not guaranteed. While mean skill improves, conditional errors that govern tail behavior and threshold exceedances can remain poorly quantified or inconsistently propagated across the EO → inference → impact chain. Applications require outcome-based evaluation metrics, not just traditional hydrologic skill scores. The central question becomes: when does EO-enabled inference measurably improve decisions, and for whom? This gap is amplified near thresholds and extremes, where management decisions are most sensitive and where uncertainty propagation is most consequential. Furthermore, because the global water cycle is increasingly deviating from its natural state, traditional inference models often fail if they ignore human activities (Oki & Kanae, 2006). Being able to directly observe anthropogenic modifications—such as irrigation impacts, reservoir operations, and man-made transfers—using remote sensing is now a critical requirement for accurate RSH (Ishikawa et al., 2025). Finally, for operational hazards, end-to-end latency can determine whether EO adds practical value, especially for floods and short-fuse water management decisions.

Cross-cutting requirement—End-to-end traceability (accountability). Across all four challenges, the field still lacks widely adopted end-to-end traceability, namely the ability to track how a specific remote sensing measurement, with quantified uncertainty, changes inferred states and fluxes, alters forecasts, and ultimately affects decisions and socioeconomic outcomes. Traceability is what turns RSH from a collection of products and case studies into an accountable science that can be trusted for high-stakes applications. Table 1 summarizes unsolved problems organized by four interlinked persistent challenge domains that drive next-decade research priorities.

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Table 1
Illustrative Unresolved Problems in Remote Sensing Hydrology That Shape Next-Decade Research Priorities, Organized by Four Challenge Domains: Observation (O), Uncertainty (U), Inference (I), and Decision Value (D)

Domain	Unresolved problem	Why it blocks progress
O	Hydrologic state estimation in complex terrain and cold regimes at decision-relevant resolution and revisit frequency	Retrieval of major states (snow, precipitation, soil moisture, ET, etc.) remains weakly understood in complex and cold environments
O	Partitioning total water-storage change into groundwater, soil moisture, snow, and surface water components	Storage components are not uniquely constrained without multi-source fusion
O	Surface-water dynamics and connectivity, including inundation and floodplain exchange at management-relevant scales	Limited observability constrains flood intelligence and understanding of hydrologic connectivity
O	Soil moisture observability with uncertainty characterization suitable for extremes and water-budget analysis	Soil moisture heterogeneity often dominates uncertainty in extremes and water-budget diagnostics
O	Constraining unobserved missing terms at scale, including infiltration, recharge, and discharge pathways	Budget closure and attribution require terms that must be inferred credibly
U	Homogeneous multi-sensor records for trends and regime shifts	Inhomogeneity and drift can be mistaken for real hydroclimatic change
U	Structured remote sensing data error models usable in inference, including bias, correlation, scaling, and regime dependence	Fusion, DA, calibration, and machine-learning remain fragile without usable error structures
U	Propagating uncertainty into tail risk and threshold-based metrics	Decisions depend on conditional errors, not mean skill alone
U	Stability tests that separate sensor or algorithm inconsistency from real hydroclimatic change	Such tests are needed for credible change detection and attribution across eras
I	Multi-sensor DA and inversion that account for correlated errors	State updates can become internally inconsistent and double count information
I	Discharge and transport inference at scale with calibrated uncertainty	Ungauged regions require EO-constrained discharge estimates with credible uncertainty
I	Cross-component consistency among P, ET, Q, ΔS, etc. without artificial sources or sinks	Forced integration in inference can violate physical laws
I	Robust inference under nonstationarity in climate, land use, and hydrologic system change	Models calibrated to past regimes can fail as processes and constraints shift
D	Outcome-based evaluation metrics, including lead time, robustness, cost/loss, and equity	Higher hydrologic skill scores do not automatically translate into better decision values
D	Observing and attributing human modification, including pumping, irrigation, reservoir operations, and man-made interbasin transfers	Human-managed water systems dominate many basins; ignoring them breaks attribution and hydrologic relevance
D	End-to-end traceability from remote sensing measurement to prediction, decision, and impact	Without auditability, workflows cannot be trusted in high-stakes applications

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5. Science Questions and Research Priorities for the Next Decade

Progress over the next decade will be most effective if it is organized around science questions that are both hydrologically central and observability-aware, and if those questions are paired with research priorities that align with the four challenge domains (EO, uncertainty characterization, hydrologic inference, and decision value) within an end-to-end framework. Below we summarize core science questions that define what should be answered and related research priorities.

5.1. Science Questions (What We Need to Answer)

- *Water-budget consistency and closure across scales*: When, where, and at what scales can EO-constrained water budgets close (annual → monthly → event), and which variables dominate residuals during extremes? How can the closure be pushed to finer scales (subbasin) without being dominated by scale mismatch, correlated errors, and cross-dataset inconsistencies?
- *Storage partitioning*: How can we better partition and attribute changes in terrestrial water storage into its dynamic stores (surface water, snow, soil moisture, groundwater) and phase-partitioned solid/liquid components in ways that remain consistent with observed states and, more critically, fluxes?
- *Movement and transport*: How can EO (including SWOT-era river observations and SAR-based inundation extent) be combined with inference to quantify discharge, river network connectivity, and floodplain exchange with calibrated uncertainty?
- *Change detection and attribution*: How can we design multi-sensor records, benchmarks, and stability tests that support trend and regime-shift attribution despite evolving sensors and algorithms?
- *Missing and unobservable variables*: What observing strategies and model–data fusion methods can close the basin-scale SWE gap in mountains and cold regions, and how would closing it change water-supply predictability? Which "unobservable" terms (atmospheric moisture convergence, vapor transport, infiltration, some anthropogenic terms) must be inferred, and what observation-driven modeling is required to keep budgets and attribution honest?
- *Uncertainty accountability*: What uncertainty and error models are needed so EO products can be used consistently in retrievals, calibration, DA, and hybrid learning—including correlated and regime-dependent errors?
- *Human modification*: How are human modifications to the water cycle distributed in space and time, how do they propagate through hydrologic systems to reshape water availability, extreme-risk susceptibility, and nutrient cycling, and how reliably can EO detect these changes, particularly where in situ observations are sparse?
- *Decision value*: Under what forms and conditions does EO-enabled inference measurably improve hazard and water-management decisions, and what metrics best capture lead time, latency, reliability, robustness, cost/loss, and equity-relevant performance, beyond what ground networks alone can do?

5.2. Research Priorities (What Must Improve to Answer the Science Questions)

To make these questions tractable, advances are needed on five connected fronts:

- *EO observability and scale match*: Move from simply measuring more variables to delivering higher hydrologic information content at scales more consistent with hydrologic processes and decisions. Key needs include improved observability of SWE and storage partitioning, solid precipitation and extremes, finer-resolution constraints on terrestrial water storage from future time-variable gravity missions, and more frequent monitoring of surface-water dynamics and river hydraulics (Tsang et al., 2022). Progress will depend not only on expanding variable coverage, but also on improving scale harmony across atmospheric, terrestrial, and hydrologic observations so that EO can better support closure, attribution, and prediction.
- *EO record continuity and mission sustainability*: Beyond improving observability, the next decade must also protect continuity in hydrologic observing capability. Robust change detection, attribution, and long-term hydrologic benchmarking require sustained, climate-quality EO records with stable calibration, documented uncertainty, and explicit cross-mission consistency. This makes mission continuity and follow-on planning a scientific priority, not merely a programmatic one. Successful experimental hydrologic missions should not remain isolated demonstrations; where their value is established, inter-agency pathways are needed to transition them into sustained observing programs. More fundamentally, the community should move

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beyond opportunistic use of sensors designed primarily for other disciplines and articulate clearer requirements for hydrology-relevant missions, including whether planned footprint sizes, revisit intervals, and channel configurations are adequate for management- and process-relevant scales. Finally, uniform retrospective reprocessing of historical records whenever major algorithm changes are introduced should become standard community practice to preserve record coherence, interpretability, and long-term stability.

- *Uncertainty characterization (usable error structures)*: Make uncertainty and error structures interpretable across communities. Priorities include characterization of the error that enables tying sensor uncertainty to physics; transparent uncertainty reporting conventions and benchmarks; spatiotemporally correlated error models (including regime dependence) suitable for calibration, DA, and hybrid learning; and end-to-end uncertainty propagation from EO products into outcome-based risk metrics that allow "skill" to be interpreted in outcome terms rather than as generic error bars. Additionally, for some high-variance variables, the community should consider transitioning from purely deterministic EO fields toward probabilistic distributions or ensembles to better serve advanced assimilation frameworks. For example, a single deterministic precipitation field with a bulk uncertainty estimate may be adequate for visualization or simple retrospective analysis, but it is often insufficient for downstream DA or risk analysis, where users need to know whether uncertainty is concentrated in storm timing, location, intensity, or spatial structure. Accordingly, such a transition must include standardized schemes for extracting robust deterministic estimates from these probabilities to ensure that the data remains accessible and actionable for non-specialist end-users.
- *Hydrologic inference (models + DA + hybrid learning)*: Strengthen the inference engines that convert partial observability into hydrologic intelligence. Priorities include multi-sensor DA/inversion that accounts for correlated errors and scale mapping; hybrid inference that improves predictive skill while preserving conservation and interpretability; and explicit treatment of budget consistency (closure) as a benchmark—especially at seasonal-to-subseasonal and event scales relevant to extremes and impacts.
- *Decision and impacts (outcome-based assessment)*: Move from hydrologic metrics to decision value. Priorities include outcome-based assessment (lead time, robustness, cost/loss, equity), explicit representation of exposure and vulnerability when translating hazards into impacts, and the direct assimilation of satellite-observed human activities (withdrawals, irrigation, reservoir operations, transfers) so attribution and decision support remain credible in increasingly human-dominated basins. Different applications might well require customized metrics of utility.

These fronts are not independent: application needs define what must be observed and sustained through data-record continuity; uncertainty determines what can be trusted; inference converts partial observability into holistic estimates; and outcomes provide the standard for judging success. Across all fronts, a unifying methodological requirement is end-to-end traceability—the ability to track how remote sensing measurements (with stated uncertainty) influence inferred states and fluxes, forecasts, and ultimately decisions. End-to-end traceability transforms remote sensing-enabled hydrologic science from a collection of case studies into cumulative, decision-relevant knowledge.

6. Closing Perspective

Lettenmaier et al. (2015) captured the moment when EO products became sufficiently mature and accessible to reshape mainstream hydrologic research. A decade later, the opportunity at hand is to consolidate these advances into a clearer, science-driven practice: using EO—together with explicit uncertainty characterization—to quantify water storage, movement, and change, and to translate that knowledge into decision value for hazards, water management, and resilience. Progress in the next decade will depend less on simply expanding the number of available products and more on coordinated advances that (a) close key observability gaps, especially for snow, groundwater, and storage partitioning; (b) improve record coherence for robust change detection and attribution; and (c) strengthen uncertainty-aware hydrologic inference and end-to-end traceability from measurements to impacts.

If WRR's first 60 years documented how remote sensing entered hydrology, the next era can document how the community made RSH accountable, credible across scales, reliable for extremes, transparent about uncertainty, and explicit in its societal relevance. Remote sensing observations are no longer merely auxiliary data sets; they are becoming foundational information infrastructure for a changing planet. Yet this progress should not be taken for granted: without mission continuity, credible follow-on strategies, and sustained climate-quality records, some of today's observational advances may not endure into the next decade. A science-driven research roadmap,

grounded in the North Star science question and matched by sustained commitment to data record continuity and mission sustainability, can help ensure that RSH continues to advance in capability, continuity, credibility, and societal value.

Conflict of Interest

The authors declare no conflicts of interest relevant to this study.

Availability Statement

This Commentary does not present new observational, experimental, or model-generated data sets.

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Erratum

The originally published version of this article contained a typographical error. Coauthor Ana Barros's name has been corrected to Ana P. Barros. This may be considered the authoritative version of record.

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