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REVIEW

Satellite Hydrology: A New Era in Monitoring Groundwater, Wetlands, and Drought Dynamics

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ABSTRACT

Satellite hydrology has reached a new era where a variety of earth observing systems, in conjunction with the development of data integrations, can provide a consistent monitoring of groundwater change, wetland dynamics, and drought evolution in regions where observations on the ground remain sparse or patchy. This synthesis review highlights the physical observables that are most useful to terrestrial hydrology: variable time-dependent gravity, passive and active microwave signals, optical reflectance, thermal infrared measurements, and altimetry, and this has been translated into hydrologic states and water fluxes: terrestrial water storage, ground water storage anomalies, inundation extent and hydroperiod, evapotranspiration, and multi-timescale drought indicators. We call attention to the role of satellite gravimetry in the transformation of basin-scale groundwater evaluation, synthetic aperture radar (SAR), and optical time series in transforming wetland science, however, to the characterization of hydroperiod and connectivity. In the case of drought, we recommend the use of both fast-responsive (soil moisture, evapotranspiration, thermal stress, and vegetation condition) in conjunction with slowly integrating storage anomalies to detect onset, intensification, and recovery, as well as rely on to diagnose the spread of deficits through the hydrologic system. In all these themes, we recognize the central action of enabling approaches that include multi-sensor fusion, data assimilation, and hybrid machine learning schemes in reducing ambiguity, scale gaps, and producing products of decision interest, and also highlighting ongoing issues in the quantification of uncertainty, consistency across long periods of time, and the separation of climate influence on human management of

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water. Research and operational priorities come as our final deduction to develop satellite hydrology to more trustworthy, explanation-seeking, and operationalizing monitoring designs of water security and ecosystem resilience.

Keywords: Satellite Hydrology; Groundwater Storage; Wetlands; Drought Monitoring; Data Assimilation

1. Introduction

Satellite hydrology has come of age from promising frontier research to a useful monitoring capability that's transforming our view of and knowledge of the terrestrial water cycle. Over the decades, hydrologists have been relying on an ad hoc and patchwork of in situ measurements, i.e., wells, stream gauges, weather stations, and field surveys, to tell the dynamics of groundwater, wetlands, and drought [1,2]. Immense long-term data has been generated by these networks; however, at a high cost, and tends to be patchy and biased geographically to richer areas and more reachable terrain. Many of the most important hydrologic processes (groundwater depletion under intensively cultivated plains, seasonal wetland expansion on remote floodplains, or the gradual-onset evolution of drought in large hydrologic basins) take place beyond the reach of field observations. At the same time, increases in the rate of climate variability, population growth, and growing demands for more intensive water management have put a greater need for consistent, transparent, and scalable information on water availability and hydrologic extremes. Satellite hydrology serves to overcome this need by providing repeatable measurements across national boundaries, political jurisdictions, and logistical constraints, which offer a new foundation for scientific discovery as well as water decisions [2,3].

What will make the present moment unique is not only the existence of satellites, but that the satellite observation system is now robust enough in diversity, and the computational ecosystem around this is mature enough, that we can support integrated hydrologic monitoring instead of single-remote-sensing-products. Modern satellite missions and constellations offer complementary views of the landscape: gravity sensing shows basin-scale changes in total water storage; microwave instruments constrain surface soil moisture and inundation signals; synthetic aperture radar (SAR) and optical imagery show surface water extent and wetland dynamics at finer and finer scales; altimetry measures water surface elevations in rivers, lakes, reservoirs, and some wetlands; and thermal infrared observations inform evapotranspiration and land surface energy balance. Individually, these observations do not have direct measures of "groundwater," "wetlands," or "drought." They measure relevant physical quantities (mass change, electromagnetic backscatter, brightness temperature, reflectance, surface elevation, and temperature) that are related to hydrologic states and fluxes using models, algorithms for retrieval, and through physical inference. The new era in satellite hydrology can be characterized by the ability to integrate these diverse observables into a coherent interpretation of water storage, movement, and stress, and increase the reliability and relevance of information derived from satellites [4].

Such integration is of particular value since the groundwater, wetlands, and drought have a shared point of invisibility and consequence to society. The largest available storage of freshwater in the world is groundwater, which cannot be observed directly in most cases. Point-based measurements of water levels are made at monitoring networks of wells, which are unevenly spread and may not be accessible to scientific or transboundary evaluation. In most areas, fundamental data on the rates of aquifer depletion, seasonal variations in storage, or recovery after wet years are still unclear. The satellites have changed this terrain by facilitating the storage-change observations at basin levels, which provide an independent constraint on groundwater dynamics where groundwater well data is scarce or concealed. Although this capability does not substitute local well networks, particularly in cases where the management would need to make field-level decisions, it offers a uniform view of the big picture, which can identify previously unknown hotspots of depletion, provide broad-scale indicators of recovery, and allow comparative evaluation between regions with differing climates and management regimes [5–7].

Conversely, wetlands are very visible in theory yet hard to observe in practice due to their dynamism, heterogeneity, and being frequently obstructed by vegetation, clouds, or seasonal flood patterns. They are highly dependent on their hydrologic behavior, not only in terms of extent, but also in terms of hydroperiod (when, how long, and how often to inundate), their connection to rivers and floodplains, and their relationship to groundwater. The functions of ecosystems governed by these dynamics are important well beyond the wetland borders, such as biodiversity support, flood management, sediment and nutrient processing, and greenhouse gas fluxes[8]. Conventional wetland lists are often static and fail to capture seasonal and interannual change, whereas field surveys have difficulties capturing remote and large floodplains. This has allowed the systematic mapping of wetland inundation and seasonal change because of the increasing availability of SAR and multi-spectral imagery and, more recently, of hydroperiod metrics that relate the dynamics of wetlands to ecological processes. Nevertheless, wetlands continue to be one of the most difficult to remotely sense due to the possibility of cover-up by vegetation, the use of different classification schemes in studies, and a lack of ground reference data. Moving away, then, from products of wetland areas to hydrologic characterization of wetland regimes that can be compared across regions and have conservation as well as water management value, is one central opportunity of satellite hydrology[9].

A third perspective on the importance of satellite hydrology is that drought is not a singular event, but rather a series of shortages spreading throughout the hydrologic system over time. The initial effects of a meteorological drought are precipitation deficit, although effects are felt when the soil moisture level becomes low (agricultural drought), streamflow and reservoir storage decline (hydrological drought), and groundwater storage becomes low with significant lag and lengthy recovery periods (groundwater drought). Because drought occurs over months to years, and it highly interacts with heat, vegetation, and human water consumption, it is notoriously hard to follow with the assistance of a single indicator[10]. The exceptional benefit that satellites provide lies in the fact that the various aspects of the drought cascade can be sampled: microwave soil moisture can be used to detect early signs of agricultural stress; thermal and optical data can be used to detect vegetation and evapotranspiration irregularities; surface water and altimetry can be used to monitor the lakes and reservoirs; and storage anomalies detected by gravity can be used to provide a larger perspective on cumulative deficits in terrestrial water storage. These observations, in principle, can reinforce previously warned-about droughts, more regular regional comparisons, and better diagnosis of more severe and recovery droughts. Practically, they require the combination of indicators of time scales and the cautious separation of differences between climate deficits and responses to management measures: higher pumping, release of reservoirs, or aggrandizement of irrigation[11].

One of the underlying common themes that connects groundwater, wetlands, and drought is that satellite observations often rarely provide the solution per se, but rather give constraints to be interpreted into a hydrologic system. In the case of groundwater, satellite gravity can measure variations in total water storage, whereas to isolate the groundwater variable, the changes in soil moisture, surface water, snow, and vegetation water usually need to be modeled, and data assimilated using land surface modeling[2,12,13]. In the case of wetlands, the SAR can identify wetlands flooded under vegetation, but converting the changes in backscatter to hydroperiod measures is important to classify the landscape and consider sensor geometry, vegetation dynamics, and mixed pixels. In the case of drought, anomalies of the vegetation indices or land surface temperature can represent stress, yet stress can be the result of heat, land cover change, pest outbreaks, or management choices and not solely moisture shortages. The major scientific problem in all three areas, thus, is inference: the construction of physically realistic and uncertainty-sensitive pathways between satellite measurements and hydrologic variables and fluxes, and their effects.

The growth of data assimilation, multi-sensor fusion, and machine learning has become a key empowering technology behind this jump in inference. To propagate uncertainty, data assimilation aims to combine satellite measurements with a hydrologic/on-model-based approach to create everything that meets physically consistent estimates of the state, including soil moisture and terrestrial water storage in a time-incremental manner. Multi-sensor fusion is a combination of complementary satellite signals to surmount one of the weaknesses of the objects individually—e.g., SAR to refine wetlands boundaries and optical imagery to add spectral dispersion or soil moisture and rainfall restrictions to yield better store partitioning on the basis of gravity metrics. Applied wisely influenced machine learning can be of use in downscaling, filling in gaps, and pattern recognition, particularly when physical models are restricted by uncertain parameters or sparse forcing data. Concurrently, these approaches may also create new risks: overfitting, spurious links, lack of transferability between regions, and latent biases that make operation adoption hard. The so-called new era in satellite hydrology is not a statement that the data are flawless, but rather the methodological toolbox lets the community get more hydrologically significant information, provided that the issue of uncertainty, scale, and interpretability are put into first-order considerations[14–17].

The most significant impediments between practical application and scientific ability are still uncertainty and scale mismatch. Satellite gravity offers an unprecedented picture of storage change on the basin scale, but the spatial resolution of the method is constrained by local understanding and introduces other problems, including signal leakage and filtering requirements[18]. The products of wetland and surface waters obtained using SAR or optical sensors can be extremely detailed, although the accuracy of classification can depend on the vegetation type, seasonal conditions, and viewing geometry, and the outcomes can also be sensitive to thresholds and training data. Drought indicators tend to confound numerous drivers, and should be viewed in local land–atmosphere and management backgrounds. Validation is not trivial either: well data (proprietary) are needed in groundwater monitoring; the field reference data in wetlands are sparse and expensive; drought effects are social-ecological and not easily measured regularly. A quality satellite hydrology model will thus require superior algorithms but clear uncertainty measurements, repeatability processing pipelines, as well as benchmarking practices so the user can track where and when products are worthy of the investment[19–21].

The review summarizes the satellite hydrology developments through the prism of three closely related fields of application, including groundwater monitoring, wetland dynamics, and drought evolution. We do not simply list handles to missions separately, but the ways that various types of satellite observables may be used to learn about the hydrologic states and processes, what has enabled this integration to be done, and what still restricts understanding. We begin by outlining the essence of satellite observables of the core satellite and the hydrologic variables to which they are informative, and the reasons why a multi-sensor synergy is needed to bridge the gap between storage and extent-flux nexus[2,12,13]. Our next focus is the methods of groundwater monitoring, the focus being the terrestrial water storage partitioning, the difference between the anomalies in storage and the groundwater levels, and the influence of human water-use on the formation of observed trends. We discuss the next wetland monitoring, paying attention to mapping inundation, deriving hydroperiod and connectivity measures, and relating hydrologic dynamics to ecosystem functioning. Next, we discuss the nature and dynamics of drought, with the focus on the multi-timescale-based monitoring, the event description, and the difficulty of separating between the climate and management-related observed deficits. Lastly, we touch upon cross-cutting facilitating approaches: data assimilation, machine learning, and uncertainty quantification, and suggest priorities on how to transform satellite hydrology once it is demonstrated in research to viable operational systems[12,22]. We summarize this review's conceptual framing linking satellite observables to hydrologic variables and applications in **Figure 1**.

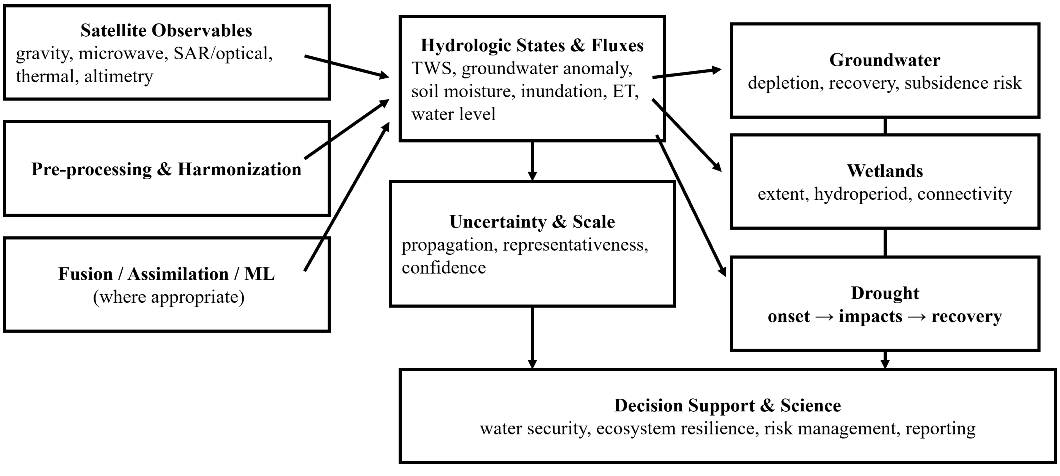

Figure 1. Conceptual framework of satellite hydrology for hidden, dynamic, and extreme water states.

However, by presenting satellite hydrology as a unified inferential investigation, as opposed to a set of products, this review hopes to explicate what satellites can already accomplish with reliable outcomes, where they are constrained, and in which areas the research directions are most prone to bring transformative benefits. Its general message is that it is not the external appearance of penetrating deep into the sky that is essential about satellite hydrology, but its inherent capability to view with complements to determine how water is stored, recycled, and drained across the landscapes, seasons, and stresses of society[2].

Unlike many previous satellite hydrology reviews that focus primarily on individual sensors, missions, or specific hydrologic variables, this review adopts an integrated inference perspective. We synthesize how diverse satellite observables, including gravimetry, microwave sensing, optical imagery, thermal observations, and altimetry, can be combined to infer hydrologic states and processes across groundwater systems, wetlands, and drought dynamics. By framing satellite hydrology through a storage–extent–flux conceptual model and emphasizing multi-sensor fusion, data assimilation, and uncertainty-aware interpretation, this review highlights emerging pathways that transform satellite observations into operational hydrologic intelligence. This integrative perspective aims to bridge disciplinary boundaries between hydrology, remote sensing, and water resource management.

2. Methodology: Literature Search and Selection Criteria

This review follows a structured literature survey to synthesize recent developments in satellite hydrology related to groundwater monitoring, wetland dynamics, and drought assessment. Scientific articles were collected from major academic databases, including Web of Science, Scopus, and Google Scholar. The search focused on publications between 2000 and 2024, reflecting the rapid expansion of satellite-based hydrologic observations during the era of modern Earth observation missions.

The primary search keywords included combinations of: satellite hydrology, terrestrial water storage, Gravity Recovery and Climate Experiment (GRACE) groundwater monitoring, wetland remote sensing, SAR inundation mapping, satellite drought monitoring, soil moisture remote sensing, and evapotranspiration from satellites. Additional references were identified through citation tracking of key review articles and highly cited research papers.

Studies were selected based on three criteria:

(1) Relevance to satellite-based observation of hydrologic processes,
(2) Methodological contribution or synthesis relevant to groundwater, wetlands, or drought monitoring, and
(3) Publication in peer-reviewed journals or authoritative reports.

The review prioritizes studies that demonstrate multi-sensor integration, data assimilation approaches, and satellite-derived hydrologic indicators, as these represent the most significant advances in satellite hydrology. Selected literature was then grouped into thematic categories corresponding to the three major applications examined in this review.

3. Satellite Observables and Hydrologic Variables

Satellite hydrology has been constructed on the process of translating remotely sensed physical signals into a hydrological meaning. Unlike the measurements, which can be made directly on the ground, which can sample water levels in a well or the discharge in a channel, satellite measurements record the change in the gravity field, electromagnetic emission and scattering, surface elevation, and surface temperature. These observables pertain to water storage, water extent, and water fluxes with physics-based retrieval algorithms, statistical inference, and hydrologic modeling[23]. This means that it is not simply a matter of getting satellite data, but rather of establishing plausible routes between observable variables of interest and whether the routes hold at the spatial and temporal scales at which it is operating, and what the uncertainty it brings with it at each step. This has been complicated in the context of groundwater monitoring, wetland mapping, and drought characterization by the fact that several water stores and processes can be driving the same signal, and also by the fact that human water management can alter hydrologic states in ways that mimic climate-driven variability. In this section, the key sensorics features of the satellites are employed in terrestrial hydrology, and their manner of translation to hydrologic variables is explained, and why it seems that robust monitoring depends on multi-sensor combinations, not any single mission or even product[24,25].

3.1. Core Satellite Observables Relevant to Terrestrial Hydrology

Gravity measurements with time vary give a unique basis to satellite hydrology since they are sensitive to mass variation, as opposed to surface optical characteristics or local dielectric effects. On land, the most significant time-varying mass signal is water, so that satellite gravimetry gives a direct constraint on variations in water storage on land, in the form of the cumulative volume of change in the vertical column. It is specifically this form of integration that renders gravimetry useful in the diagnosis of long-term groundwater conditions of the places where water can be successfully used in the diagnosis of the maintenance of water multi-season drought reservoirs, but it is also one of its main disadvantages, in the form that the signal is naturally spatially smoothed and is the cumulative of many water stores, skin moisture, surface water and in the given context, biomass water. Due to this, it means that aquifer-large-scale basin-scale assessment using gravimetry is potent but inadequate to answer component attribution or to answer local management inquiries that utilize factor variation at aquifer-scales[3,12,26].

Passive microwave radiometry is a measurement of the natural microwave emission of the land surface, often in the form of brightness temperature. The physical connection with hydrology is because microwave emission highly relies on the dielectric characteristics of a substance, and liquid water generates a unique dielectric response compared to dry ground. Therefore, passive microwave measurements can limit surface soil moisture and, in certain settings, wider surface wetness and inundation patterns. Passive microwave is not as affected by clouds as optical methods and can be depended on to sample on a day-night cycle. The same benefits, however, have costs, such as a rather coarse spatial resolution and some dependence on vegetation and surface roughness, and radio-frequency interference. The sensitivity is very superficial, as well, which implies that passive microwave retrievals are most directly related to near-surface soil moisture and not to the deeper root-zone moisture that controls most agricultural effects[27,28].

Active microwave sensors, especially synthetic aperture radar, bend the emitted pulses upon the earth's surface, and detect the backscatter emitted. Backscatter is dependent on the geometry and roughness of the surface, the dielectric properties of soil and water, and the structure and water content of vegetation. This multiple-factor sensitivity provides SAR with particular value in wetlands and floodplains, where open water tends to allow low backscatter to specular reflection, and there can be abundant scattering as stems bend on the water surface, leading to such a phenomenon as the so-called double-bounces. The SAR time series are thus able to trace the dynamics of inundation at a very fine spatial resolution and without much interference with the clouds. Simultaneously, SAR retrievals are not direct since the backscatter may vary based on incidence angle, roughness on water caused by winds, the phenology of vegetation and soil roughness. Such sensitivities imply that wetland and inundation products are frequently critical in terms of raw calibration, multi-temporal processing, and, more likely to be merged with optical data to cut down on ambiguity[29,30].

Measurements of optical reflectance in the visible, near-infrared, and shortwave infrared bands are still at the center of mapping surface water and vegetation dynamics. Water is normally lowly reflective in the near-infrared and the shortwave infrared, which allows the observation of open water bodies and saturated soils by spectral indices and classification techniques. Optical data are also the basis of vegetation greenness and phenology, which helps to obtain indirect data on water stress and ecosystem response. It is well researched that the constraints of optical sensing are hydrologically significant: the presence of clouds and aerosols, as well as low sunlight, can place systematic missed observations, especially in moist tropics and storm seasons, when hydro-optic extremes are most often observed. The long temporal records and the rather intuitive spectral interpretation of optical data make them essential to historical analysis and to creating consistent records of surface water and wetland change, particularly in association with radar data in cloudy conditions[31,32].

Thermal infrared measurements give the temperature of the land surface, and they are a diagnostic of the surface energy balance and a good indicator of evaporative cooling. With a reduced water supply, evapotranspiration is more likely to be reduced, moisture causes the temperature to increase on the surface of the land, and this leads to a physically understandable relationship between the informational signs of heat and the stress caused by drought. More direct estimation of evapotranspiration is also possible by combining thermal data with radiation, meteorological inputs, and surface properties obtained using optical imagery when surface energy balance modeling is used. Nevertheless, atmospheric conditions, surface emissivity, canopy structure, and heat advection also affect thermal measurements, and cloud contamination also affects thermal sensing as optical sensing. It implies that it would be better to think of thermal signals in the context of a greater multi-variable measurement and not on a case-by-case drought indicator[33].

Ground data altimetry, based on radar or laser measurements, gives estimates of the surface elevation along ground tracks of a satellite. In inland waters, temporal variation of the water level in lakes, reservoirs, and wide enough rivers can be measured by altimetry, and in some instances will also give constraints on water surfaces in floodplains and wetland complexes. Water level changes can be converted to changes in volumetric storage, thus giving a significant connection between water whereabouts and water stored. The performance of altimetry is affected by the width of the waterbody, topographic features around the waterbody, vegetation, and retracking quality of the waveforms, and it often cannot be properly processed and validated. Although facing these difficulties, altimetry has played an important role in linking hydrologic storage processes with surface water management and enhancing the separation of terrestrial water storage cues in the study of groundwater[34,35].

3.2. Translating Observables into Hydrologic Variables

The most relevant hydrologic variables to groundwater, wetlands, and drought may be considered to fall into three interconnected categories, namely, water storage states, surface water and inundation states, and water limitation and impact reflection through fluxes and diagnostics. All the categories are limited by the various satellite observables, and each has its own source of uncertainty and non-uniqueness[12,22,36]. The key strengths and limitations, the most common families of satellites observable, and the hydrologic variables of these variables are summarized in **Table 1**.

Table 1. Satellite observables, derived hydrologic variables, and typical uses in this review.

Satellite Observable Family	What Is Measured (Observable)	Primary Derived Hydrologic Variables	Most Relevant to	Typical Strengths	Common Limitations/Failure Modes
Time-variable gravity	Mass redistribution (gravity anomalies)	Terrestrial Water Storage (TWS) anomalies; inferred groundwater storage anomalies (via decomposition)	Groundwater trends; cumulative drought deficits	Integrates total storage change; independent of political boundaries	Coarse spatial resolution; component separation required; leakage/filtering artifacts
Passive microwave	Brightness temperature (emission linked to dielectric properties)	Surface soil moisture; surface wetness/coarse inundation signals	Drought onset; land–atmosphere coupling	All-weather, day/night sampling; rapid response to drying	Coarse footprint; vegetation/roughness effects; shallow sensing depth
SAR (active microwave)	Backscatter/coherence (structure + dielectric response)	Inundation extent; flooded vegetation; change detection; wetland dynamics	Wetlands; floods; connectivity	Cloud-insensitive; high spatial detail; detects flooding under some vegetation	Speckle/geometry effects; incidence-angle dependence; vegetation phenology confounding
Optical (VIS–NIR–SWIR)	Surface reflectance	Open water extent; moisture proxies; vegetation condition/phenology	Wetlands; surface water; drought impacts	Strong spectral separability; long archives; intuitive interpretation	Cloud/shadow gaps; water–shadow confusion; limited under dense canopy
Thermal infrared	Land surface temperature (LST)	Evapotranspiration (ET) (via energy balance); thermal stress; drought diagnostics	Drought intensity; water limitation	Direct link to evaporative cooling and stress	Cloud sensitivity; heat advection and land cover confounding
Altimetry (radar/laser)	Water surface elevation along tracks	Lake/reservoir/river levels; surface water storage (with area)	Hydrological drought; surface water management	Adds "vertical" constraint; supports volume estimation with extent	Limited to narrow/vegetated waters; requires careful corrections/retracking

The reason why water storage states are fundamental is that they indicate imbalances in inputs and outputs over time, and many tend to incorporate information over time. Satellite gravimetry has direct limits upon irregularities of the terrestrial water storage, or total change of groundwater, land moisture, surface water, ice and snow, and in certain applications, vegetation water. Terrestrial water storage anomalies are of particular informational use, especially in recognizing long-term deficits in multi-season droughts as well as in identifying long-term groundwater depletion caused by pumping. However, the very integrative aspect of the signal implies that the isolating of groundwater is usually associated with the need to remove other admixtures approximated by land surface models, reanalysis, snow products, and surface waters observations [37]. The resulting anomaly in groundwater storage is not an actual observation, but an inference, and its validity is determined by the quality of the element estimates and by the similarity and consistency of the spatial and temporal scales used by the datasets. Another important storage state is the soil moisture, which is restricted to a significant degree mostly by passive microwave, although it is usually improved upon by way of assimilation into land surface models to achieve deeper root-zone approximations. These deeper estimates are essential to the analysis of agricultural drought since crops are responsive to moisture availability throughout the root zone and not to surface conditions only [38].

Surface water and the inundation conditions of the landscape record the area and the time of water presence on the surface. Optical imagery offers the capability to map out open water and saturated surfaces with spectral separation, and SAR can offer strong mapping in cloud cover and can map out flooded vegetation that is not visible with the optical method. Based on these observations, the wetland extent can be mapped, although it is the hydroperiod, which is the timing, duration, frequency, and seasonal amplitude of inundation that is more hydrologically significant. Hydroperiod indicators are based on the time series analysis of inundation values and play the key role in the association of the wetland dynamics with the ecosystem functionality, suitability of the habitat, and biogeochemical cycle. Connectivity can also be inferred by monitoring spatiotemporal patterns of inundation and recession, especially where high-frequency observations of SAR are observed. Connectivity refers to how wetlands, floodplains, and channels exchange water over time. The accuracy of these variables is based on the ability to handle mixed pixels, vegetation masking, transferability of classification, and the existence of confounding seasonal signals that are not related to inundation [39].

Fluxes and diagnostic variables are the links between satellite measurements and the drought propagating and wetland-groundwater interaction regulating processes. Most climates dominate terrestrial water flux by evapotranspiration, and the relation is an important intermediary of drought effects. TOVE Tower: GIS/consistently available satellite-derived estimates are typically generated through the thermal infrared-based constraints within energy balance models, commonly with optical-derived vegetation and surface property data with meteorological driving forces [40]. Although ET estimates may not be precise, the anomalies can be very informative in diagnosing the limitation of moisture and the reaction of the plants. Diagnostic information based on optical reflectance of vegetation, and where present, other information, e.g., fluorescence, can be used to detect stress and changes in phenology, although these diagnostic methods must be interpreted with caution as vegetation reacts to a multiplicity of stressors and management actions. Satellite-based drought indices correspond to standardized anomalies, which are usually useful in making comparisons across space and time, but different indices are focused on various drought pathways. The anomalies in the soil moisture may be used to warn against the agricultural stress, the ET deviations may be sensitive to both water scarcity and heat impact, and terrestrial water storage deviations may be used to indicate hydrological deficits, but may be slow to detect local effects. That is why the concept of drought expressed in terms of satellites proves to be most effective when explicit integration of indicators at timescales is involved, as opposed to using one metric [41–44].

3.3. Scale Dependence, Non-Uniqueness, and Uncertainty Propagation

A central difficulty in satellite hydrology is that the mapping from observable to hydrologic variable is rarely one-to-one. Many observables are influenced by both hydrologic and non-hydrologic factors, and multiple hydrologic processes can produce similar signals. For example, a decrease in vegetation greenness might reflect soil moisture deficit, but it might also reflect harvest cycles, land cover change, nutrient limitation, pests, or wildfire. Elevated land surface temperature can indicate reduced evaporative cooling due to drought, but it can also be driven by heat advection, changes in albedo, or urbanization. SAR backscatter changes can reflect inundation, but they can also be produced by changes in vegetation structure or soil roughness. Even gravimetry, though physically tied to mass change, integrates multiple water stores and can be influenced by processing choices such as filtering and corrections, producing uncertainty in spatial attribution. These ambiguities are not peripheral; they determine whether satellite-based results can be interpreted confidently and whether they can be applied in decision contexts[45].

Scale dependence further complicates inference. Passive microwave soil moisture retrievals often represent footprints that are much larger than the fields where agricultural decisions are made. Gravimetry is typically interpreted at basin to sub-continental scales, whereas groundwater management is often implemented at aquifer to district scales with strong heterogeneity in pumping, recharge, and geology. Wetland mapping may achieve high spatial resolution with SAR or optical sensors, yet classification accuracy can vary locally with vegetation type and water depth, and temporal sampling may miss rapid flood pulses or short hydroperiod events. These scale mismatches mean that a key task in satellite hydrology is not merely to generate products, but to communicate what scales of interpretation are defensible and to develop methodologies that bridge scales through downscaling, data assimilation, and uncertainty-aware fusion[46,47].

Uncertainty arises throughout the processing chain, from instrument calibration and geolocation to retrieval assumptions and model structure. In practice, the most consequential uncertainties often arise when observables are converted into hydrologic variables through ancillary data and modeling. Partitioning terrestrial water storage into groundwater and other components requires accurate representation of soil moisture and snow, which can be biased due to forcing errors, parameter uncertainty, and incomplete process representation. Wetland classification depends on training data and thresholds that may not generalize. ET estimation depends on meteorological inputs and assumptions about canopy and aerodynamic resistance. Because these uncertainties can compound, there is increasing emphasis in the satellite hydrology literature on providing uncertainty estimates, conducting sensitivity analyses, and benchmarking products against independent observations where feasible. Transparent uncertainty characterization is not only a scientific best practice; it is essential for the operational uptake of satellite hydrology in water management and drought response[48,49].

3.4. Multi-Sensor Integration and the Storage–Extent–Flux Perspective

Multi-sensor integration has become the strategy of choice of modern satellite hydrology due to the inability of any single satellite that can be viewed to give a complete and ambiguous picture of the hydrologic reality. A storage-extent-flux conceptualization of integration can be applied as a reflection of the hydrologic balance. The main limitation of storage is due to gravimetry, and in the case of surface waters, due to the use of altimetry in combination with extent to determine the volume change. SAR and optical map inundation and open water give extent constraints because these data sources have spatial and temporal details that cannot be eliminated by the storage products. The constraints of fluxes are based on the estimation of evapotranspiration and on the products of satellite-derived precipitation, which inform on the processes of drought formation and recovery and of the sustenance of wetlands and groundwater systems[50].

In groundwater research, gravimetry offers a combined storage anomaly, which, in combination with soil moisture estimates and surface water limitations, can isolate the groundwater component with more credibility than any individual data. It is important to note specifically that surface-enriching surface water extents and altimetry in basins where they vary seasonally; otherwise, properties of reservoir operations or floodplain storage can otherwise be made to cause obfuscations in the inferred groundwater changes. SAR has been used in wetland research to map inundation at cloud-insensitive scales with optical data to offer spectral discrimination and vegetation data; combinations of the two can reduce cases of misclassification and provide more accurate estimations of the hydroperiod. When used, altimetry provides a vertical component that provides a means of partitioning out differences in the level of the water and differences in the change of extent of the area. In the case of drought monitoring, a combination of fast-responding variables like soil moisture and ET with slow-integrating storage anomalies of the gravimetry can be a more comprehensive characterization of the onset, intensification, and recovery phases. Another way this integration enhances the attainment of attribution is by identifying whether vegetation stress is linked to groundwater depletion, whether agricultural drought extends into hydrological drought, and whether the groundwater reservoir mitigates or exacerbates surface losses[51].

Combined, these points can lead to an understanding that satellite hydrology can be seen as an inference system, but not as a category of product. The value of satellites is best discovered through combinations of observables in physically consistent manners, by addressing the limits to scale and non-uniqueness, and by quantitatively expressing ambiguity and sharing such ambiguity. Below, these observables and derived variables are discussed in relation to the monitoring of groundwater, wetlands, and drought, as well as the development of new techniques to broaden the applicability and validity of satellite-based hydrologic data[52,53].

4. Groundwater Monitoring from Space

Groundwater is the most commonly used and most common freshwater source, and at the same time, it is the least observed part of the water cycle on the land. The processes which regulate storage change, in most aquifers, pumping, recharge, drainage to streams and wetlands, and managed aquifer recharge, take place below the surface and are moderated by irregular geology and man-made infrastructure. The conventional monitoring thus relies on wells and local geologic interpretation, which may be sparse and discontinuous, or even inaccessible in much of the area. The satellite hydrology has transformed this observational terrain by offering autonomous, spatially all-inclusive restrictions to the groundwater-related change, especially by observations, which combine basin to regional water storage. It is the primary scientific challenge to relate those satellite constraints to terrestrial water variables of significance to hydrologic knowledge and control, to abide by the limits set by the available spatial resolution, non-uniqueness, and uncertainty[54–56].

4.1. What Satellites Can and Cannot “Observe” about Groundwater

Groundwater satellite does not directly measure groundwater head, hydraulic conductivity, and pumping through satellites. The observations they can best make are those of the scale effect of groundwater. The strictest satellite constraint is on variations in mass, which on land are predominated by variations in the water storage that are incorporated by the entire vertical column. This is what has led to the introduction of satellite gravimetry for groundwater measurements: it is possible to identify long-term declines of terrestrial water storage that cannot be easily accounted for without a significant contribution of groundwater, particularly in highly pumped basins. The complementary satellite observations restrict variables interacting with groundwater, such as surface soil moisture and evapotranspiration, extent and level of surface water, and land deformation in compaction. Practically, space-based groundwater monitoring is an inference problem whereby numerous satellite signals, coupled with models and other ancillary data, are employed to isolate groundwater storage change and the rest of the hydrologic system and interpret that change in terms of drivers and consequences[57–60].

4.2. Terrestrial Water Storage as the Gateway to Groundwater Storage Change

The easiest route for the satellites to the groundwater is through terrestrial water storage anomalies. In theory, the storage of water on land can be demonstrated as the total of groundwater storage, soil water, surface water (rivers, lakes, reservoirs, floodplains), snow and ice, and minor items like canopy water. Satellite gravimetry puts limits on these total changes, but groundwater is not the only one. Groundwater storage change is thus normally determined as a residual by the difference between the total and non-groundwater storage changes. This breakdown has become a normal structure of regional groundwater evaluations since it capitalizes on the exceptional power of gravimetry-vertical combination, in addition to the fact that attribution needs supplementary data[61,62].

The residual method is sensitive and powerful. Inaccuracies or modeled soil moisture, snow water equivalent, or surface water storage can be directly transferred to modeled groundwater anomalies. It is not a constant sensitivity to climate. In snow-dominated basins, the seasonal signal may be overshadowed by uncertainties in both snow and glacier mass and groundwater feedback processes. Storage variability of surface water can be so high in monsoon climates with large floodplains and reservoirs that it may cause a person to misinterpret groundwater trends through the neglect of such a variable. In response, state-of-the-art groundwater inference is now beginning to use the residual as a coupled estimation problem where various components are jointly constrained with estimated uncertainty, preferably propagated using each input[57,63,64].

The conventional means of inference between gravity-inferred terrestrial water storage and groundwater storage anomalies, along with the key pathways of error and constraints, are summarized in **Figure 2**.

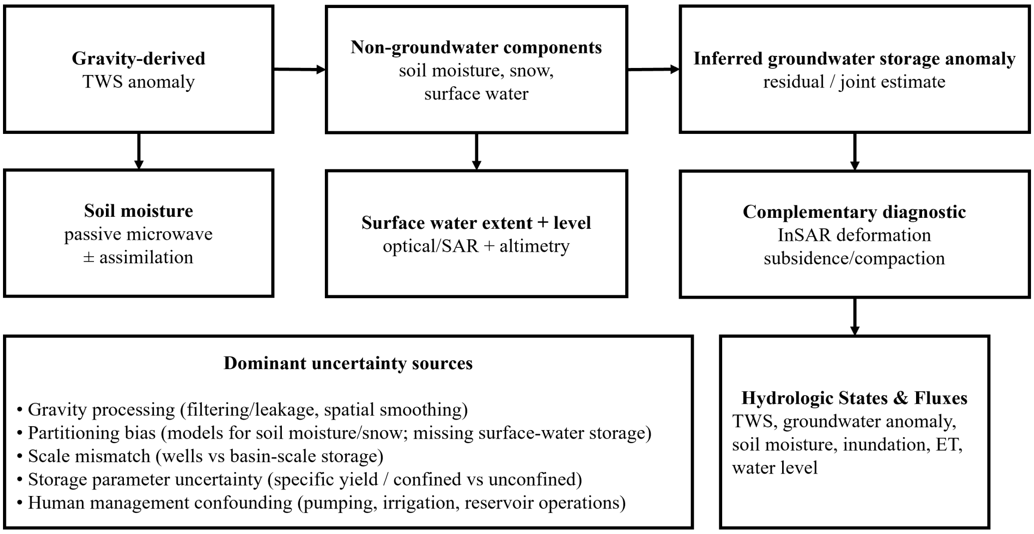

Figure 2. Groundwater-from-space workflow and error pathways.

4.3. Separating Climate-Driven Variability from Human Water Use

One of the characteristics of groundwater monitoring is that the storage of groundwater is both climatic and management-controlled, and usually in a manner that generates comparable storage information. Drought spells can lessen recharge and augment dependent usage upon pumping, having compounded falls that might be manifested as a unit-integrated indicator of depletion at space. Wet periods, on the other hand, may result in accelerated surface and soil moisture rates and slower groundwater reaction based on vadose-zone thickness, recharge routes, and pumping habits. The interpretation of the satellite-based groundwater anomalies, then, must be done with the concerns of time and mechanisms. Comparisons of terrestrial water storage change, precipitation change, evapotranspiration anomalous change, and surface water storage change can be used to diagnose the presence of observed deficits that are mainly supply-controlled, demand-controlled[65,66].

Non-stationarity is further increased by human water management. Irrigation has the potential to modify the evapotranspiration and surface temperature indicators, reservoir control can alter the apparent fraction between the surface and subsurface storage, and land use change can change the infiltration and runoff. Owing to this fact, attribution studies based on groundwater are increasingly incorporating autonomous indications of water use and administration as far as there are, including irrigation area, crop schedules, reservoir storage time arrangement, and documented pumping or allocation information. Although these constraints are not perfect, they can minimize the threat of attributing management-imposed signals to climate variability or vice versa[67].

4.4. From Storage Change to Groundwater Levels and Aquifer Condition

Whereas satellite gravimetry gives a constraint on abnormalities in groundwater storage on a large scale, groundwater management usually deals with water levels, drawdown, and thresholds in terms of wells, ecosystems, and land subsidence. Storage anomalies can only be translated into water-level change by means of hydrogeologic data, notably the specific yield, or storage coefficient, by which a change of stored volume can be correlated with a change of hydraulic head. This translation is conceptually simple in the unconfined aquifers, in which the variations in saturated thickness are the most dominant in storage changes, but are more complicated in the confined systems, where compressibility, retarded drainage, and elastic storage slow variations. The effective storage parameter in heterogeneous aquifers differs both spatially and occasionally with time as the water table passes through stratigraphic boundaries [62,68].

Consequently, storage-to-head conversion can best be justified by being seen as a scale-dependent approximation, as opposed to a scale-independent mapping. On regional scales, the comparison of satellite-derived storage variations to aggregated well observations can be made to provide an effective storage parameter and also to determine consistency. Satellite information may also be useful in management situations, even in cases where it is not directly converted into head, e.g., to detect sustained storage loss, to indicate the scale of drought-induced losses, or to assess the extent to which recovery in wet years is equal to the scale of previous depletion.

4.5. Complementary Satellite Constraints That Strengthen Groundwater Inference

Despite the fact that gravimetry is at the center of storage change, strong groundwater monitoring takes advantage of some other satellite measurements that balance other terms in the water balance and decrease uncertainty in the decomposition. Surface and root-zone soil moisture products: Surface and root-zone soil moisture products give information on the wetting and drying processes on a relatively short timescale to help de-trend near-surface variability against longer-term memory groundwater responses. Introduction of soil moisture to land surface models may lead to the enhancement of the model estimates of infiltration, partitioning of evapotranspiration, timing of recharge pulse phenomena, and thus, refining the non-groundwater parts, which are the subtraction of total storage [68].

The optical and radar images and altimetry are becoming increasingly valuable as surface water extent, and water levels are significant in basins where seasonal storage is dominated by reservoirs and floodplains. By including these constraints, the probability of attributing variability of surface water wrongly to groundwater in the residual calculation will be minimized, and the model will be able to better represent management effects, including the effect of a drought on the reservoir drawdown or the effect of a wet season on storage recovery [13].

A different signal that is highly relevant to groundwater in compressible aquifer systems is land deformation, in which interferometric synthetic aperture radar is used to measure deformation. Subsidence may convey groundwater extraction and contraction of the aquifer system, which may be linked with temporary impairment of storage in fine-grained sediments. Although deformation does not directly measure the change of groundwater storage, it is a good diagnostic of the effects of pumping and may be used to estimate regions where declining groundwater resources are associated with a disproportionate risk in the long term. Together with gravimetry and well information, observations of deformation may be used to supplement a more comprehensive evaluation of reversible storage change and irreversible structural effects [69].

4.6. Data Assimilation and Model–Data Integration for Groundwater Monitoring

Since satellite observations introduce a partial kind of constraint, it is commonly important to combine them with models to derive hydrologically consistent groundwater estimates. The data assimilation systems use data like the terrestrial water storage anomalies or soil moisture to modify land surface and hydrologic models in a manner that is sensitive to model dynamics and error statistics. Assimilation can lead to better estimations of recharge, imparting of the baseflow, and the development of storage, and it can offer continuous space and time dynamics where satellite data are patchy or rough [70].

Nevertheless, assimilation does not imply that things are right. Assimilation may give smooth and apparently physically consistent estimates which are systematically incorrect in the case of biased model structure, incorrect meteorological forcing, or incorrectly defined errors in observation. The difficulty that has been found on many occasions is that groundwater processes are often simplified or nonexistent in land surface models, particularly where the aquifer heterogeneity, pumping, and lateral groundwater flow are significant. This has encouraged more focus on coupled surface, subsurface modeling, hybrid assimilation approaches, which are more explicit in their treatment of the groundwater, and benchmarking exercises that compare assimilation products with independent well, streamflow measurements[71].

4.7. Validation Strategies and Benchmarking against Independent Observations

Validation is particularly challenging for groundwater because in situ data may be sparse, proprietary, or not representative of the spatial scales sensed by satellites. Wells measure head at points, while satellite gravimetry reflects integrated storage over large areas. Bridging this mismatch requires careful aggregation and comparison strategies, including spatial averaging of well anomalies, comparison within hydrogeologically coherent subregions, and explicit consideration of aquifer thickness and storage parameters.

Independent datasets can provide complementary validation pathways. Streamflow and baseflow indices can reflect groundwater contributions to rivers, offering indirect checks on inferred groundwater variability. Reservoir storage and surface water extent time series can be used to test whether the decomposition realistically represents surface storage terms. Land deformation time series can corroborate the presence of sustained pumping impacts in compressible systems. Where multiple independent constraints exist, consistency across them becomes a powerful form of validation, not because any single dataset is definitive, but because coherent interpretation across storage, flux, and impact indicators reduces the likelihood of spurious inference[58,72,73].

Benchmarking also benefits from event-based evaluation. Droughts, wet-year recharge events, and major management interventions provide natural experiments that test whether satellite-informed groundwater estimates respond with plausible timing and magnitude. For example, rapid surface wetting accompanied by delayed groundwater recovery is expected in many settings, whereas immediate and large inferred groundwater increases may suggest an over-attribution of surface signals to groundwater[74].

4.8. Limitations, Uncertainties, and the Conditions for Reliable Use

Monitoring of groundwater using space is limited in several basic ways. The most notable of them is spatial resolution: the history of storage effects created by gravity can be examined at best at basin to regional scales, and efforts to reveal small-aquifer dynamics may be overshadowed by leakage, filtering effects, or interface signals. Separating components adds further uncertainty since the groundwater is estimated indirectly and carries the mistakes of model-based calculations of the soil moisture, snow, and surface water. The interpretation can be confused by the human water management that modifies several components at the same time, e.g., when there is a boost in the evapotranspiration with irrigation, and a reduction in groundwater storage with pumping[75].

These restrictions do not deny the usefulness of satellite groundwater monitoring; they only establish its usage. The satellites are most effective in identifying macro trends, diagnosing the aggregate intensity of a multi-year deficit, relative changes between regions, and providing independent evidence in data-deficient basins. They are more ill-adapted towards solving local drawdown patterns, assigning changes to discrete well fields using no further data, or substituting regulatory monitoring networks. The important requirement of Science Citation Index (SCI)-standard synthesis, therefore, is that studies involving groundwater from space should not only report trends but also the uncertainty ranges and sensitivity to decomposition options and the spatial scales, in which the conclusions can be defendable[64,75–77]. **Table 2** synthesizes the targets of Mian groundwater, limitations of satellites, auxiliary demands, and predominant sources of uncertainties.

Table 2. Groundwater from space: Inference pathways, required ancillary data, and uncertainty sources.

Groundwater Quantity Targeted	Primary Satellite Constraint(s)	Main Inference Pathway	Key Ancillary Data Needed	Best-Fit Application Scale	Dominant Uncertainty Sources
Groundwater storage anomaly	Gravity-derived TWS anomalies	Decompose TWS into components; groundwater as residual	Soil moisture/snow from models; surface water storage (extent+level); basin masks	Large basins to regions	Model partitioning bias; surface water omission; filtering/leakage; scaling mismatch

Table 2. *Cont.*

Groundwater Quantity Targeted	Primary Satellite Constraint(s)	Main Inference Pathway	Key Ancillary Data Needed	Best-Fit Application Scale	Dominant Uncertainty Sources
Groundwater level change (approx.)	Gravity-derived groundwater storage anomaly	Convert storage to head change using storage parameters	Specific yield/storage coefficient; aquifer geometry; well data for calibration	Regional (not local)	Spatially variable storage parameters; confined/unconfined transitions; heterogeneity
Pumping/depletion hotspots (diagnostic)	TWS trends + surface indicators	Identify persistent negative trends + consistency checks	Land use/irrigation maps; precipitation/ET anomalies; management context	Regional screening	Attribution ambiguity (climate vs. pumping); reservoir operations; irrigation masking
Subsidence risk/compaction signal	InSAR deformation (often paired with groundwater context)	Relate deformation patterns to groundwater withdrawal and compaction	Geotechnical properties; well records; aquifer-system stratigraphy	Local to regional	Non-unique deformation causes; temporal decorrelation; depth attribution uncertainty
Recharge response and recovery	Soil moisture + ET + TWS (integrated)	Diagnose timing: surface wetting vs. storage recovery	Meteorological forcing; land surface/hydrologic models; streamflow/baseflow indices	Basin to regional	Recharge pathway uncertainty; forcing errors; lag interpretation; management changes

4.9. Toward Operational Groundwater Intelligence from Satellites

The future of the field is on the path of demonstration towards operationally relevant groundwater intelligence. This shift needs three improvements. The integration of multiple sensors should be the new norm. First, the explicit consideration of surface water storage and the constraint of soil moisture and evapotranspiration should be used to enhance partitioning and attribution. Second, quantification of uncertainty should cease to be a secondary factor in the system to primary product features, with transparent transfer of the observation and model constituents to inferred groundwater anomalies. Third, there is a necessity to have a greater connection between information on storage obtained with satellites and management variables like susceptibility to drought, subsidence probability, recovery potential, and success of interventions, e.g., the use of managed aquifer recharge[78–80].

Satellites have enabled the observation of change in groundwater on scales and in areas not previously observable, but the sense of such observability requires critical inference. In combination with terrestrial water storage limits and complementary satellite measurements, models, and independent validation, satellite hydrology represents a special, necessary, and rapidly growing view of the groundwater depletion, recovery, and drought resistance.

5. Wetlands: Extent, Hydroperiod, and Hydrologic Connectivity

Wetlands remain at the interface between the terrestrial and aquatic systems, and the defining feature, being periodically or persistently saturated and submerged, also makes them one of the most volatile and challenging landforms to observe regularly. Wetland water regimes fluctuate between hours and decades in reaction to rainfall, river stage, groundwater discharge, evapotranspiration demand, tidal variations, and human control. Their spatial structure is very heterogeneous, and mosaics of open water, emerging vegetation, floating plants, forested swamps, and saturated soils may occur in a short distance and seasonally. Traditional markets and field counts can record the existence and ecological status of wetlands in a specific region, yet it is tough to determine the period in time and time of onset of the inundation at the regional to worldwide scale, and especially the more distant floodplains, boreal peatlands, and tropical deltas. Wetland science and management have thus been dominated by the use of satellite hydrology to offer repeatable and spatially comprehensive data on inundation processes, allowing wetland extent mapping, characterizing the hydroperiod, and, more and more, assessing the hydrologic connectivity and functional response[81,82].

5.1. Conceptualizing Wetlands for Satellite Monitoring

One of the most common misunderstandings in the field of wetland remote sensing is the discrepancy between the ecological definitions and the attributes that can be observed with the help of satellites. Wetlands are normally categorized on the basis of vegetation, soil type, salinity, and geomorphic environment, whereas satellites are mainly sensitive to water, surface moisture, vegetation framework, and temporal variation[83]. Therefore, transferable descriptors in the case of hydrologic monitoring are those associated with the water regime. The extent of wetlands is best defined as that area, based on a selected inundation or saturation level at a particular moment, whereas the hare period presents seasonal and interannual statistics of water present, such as how often it occurs, how long it lasts, when it starts and finishes, and how much it expands and contracts. The concept of connectivity goes on to indicate how and when wetlands share their water with rivers, lakes, floodplains, or coastal waters, which highly determines the nutrient transportation, deposition of sediments, accessibility of habitats, and buffering of drought and floods[84,85].

Critically, not every wetland can equally be seen from space. Optical imagery can be easily used to map open-water marshes and shallow lakes during clear, cloudless days, but forested wetlands may conceal standing water under a canopy. Saturation of peatlands may occur in the absence of open water and generate low-level spectral signals that are sensitive to vegetation cover and topography. The tidal wetlands and deltas have high water-level oscillations, which may be aliased on a seasonal scale in case of sparse sampling. Such differences imply that monitoring of wetlands using satellites must clearly define the state of wetland under measurement, open water, inundation below plants, saturation at the surface, wetness in a combined wetness category, and must interpret the resulting products in that regard[86].

5.2. Satellite Observables and Retrieval Approaches for Wetland Extent

Optical reflectance data have continued to form the basis of mapping the boundaries of open water and wetlands since water possesses specific spectral characteristics, particularly low reflectance at near infrared and shortwave infrared wavelengths[87]. Optical methods can be used to outline water bodies and flooded areas using spectral indices or classified models on an example basis. On macro scales over extended archives, the optical imaging that is used will help with historical reconstruction to determine the change of wetland area as well as the identification of long-term trends of drainage, restoration, or climate-driven changes. Nevertheless, in cloud contamination, haze, sun glint, and seasonal limit of illuminations, and classifying dark surfaces like shadows, burnt surfaces, or some soils as water, unless quality control is strict, optical mapping is subject to such limitations. In forested swamps or overgrown marshes, optical data might also not be able to detect the water surface beneath the canopy at all, and thus cannot observe inundation in vegetated wetlands that contain a canopy[88,89].

Synthetic aperture radar has revolutionized wetland monitoring in the sense that it gives cloud-insensitive presence, and it is sensitive to the inundation processes that can be overlooked by optical sensors. SAR imagery regularly presents the dark water bodies as dark as a result of mirror reflections that are outside the sensor, and submerged vegetation as bright as a result of two-bounce scattering amid the vegetation components and the water-body surface[90]. The detection of inundation by SAR under both emergent and, under certain circumstances, woody vegetation, is possible with this physical behavior. The technique of multi-temporal SAR is particularly efficient, as such patterns of change are more likely to give a signal of flooding than one image, which is unrelated to the floods. However, retrievals of SAR are not necessarily easy. Rough or smooth winds may enhance the backscatter of open water, variation with incidence angle may cause a change in the distributions of backscatter, and changes in vegetation across seasons can resemble signals of inundation. Other issues that increase the difficulty of cross-site comparability include speckle noise, terrain effects, and different polarization modes. Consequently, the strongest SAR wetland products are often based on pre-processing, multi-date composing, and adding locally adaptive classification methods or trained machine learning[91].

Passive microwave observations complement that way in that they record large-scale wetness and inundation signals with high temporal content, with close all-weather capability.

They have a coarse spatial resolution that makes them uninformative over small wetlands, though acceptable in large floodplains and in peatland-heavy regions where the size of a regional inundation is coherently varying, or the surface wetness of the surface is coherently varying. Passive microwave is especially useful when the timing of seasons is to be characterized in areas where clouds are always present and where optical observations are inhibited, but the effects of vegetation and surface temperature on brightness temperature past hydrologic wetness must be considered[92].

Conventionally, wetland extent mapping is state-of-the-art by combining optical and SAR systems, capitalizing on the spectral separability of optical and all-weather inundation sensibility of SAR. Transport of information can be done by the use of rule-based compositions, stochastic amalgamation of water probability map, or a machine learning based model trained on multi-sensor information. Not only does it enhance spatial completeness, but it also increases seasonal and wetland-type robustness, especially when processes such as vegetation and land cover are explicitly modeled, which is the strongest advantage of fusion[29].

5.3. Hydroperiod: Moving from Snapshots to Water-Regime Metrics

The most significant hydrological development brought about by satellite time series can be seen in the fact that the measurement of the hydroperiod is now possible, instead of the use of fixed wetland mapping. Hydroperiod indicators describe the properties of wetlands as dynamic stores and connectors of water and tend to be generally more effective than maximum area in explaining ecological results. Hydroperiod is summarized using satellite-derived inundation or wetness time series. The frequencies of inundation (frequency of inundation events when a pixel is inundated), inundation duration (length of inundation events), timing of seasonal and recession, and interannual variability of the above frequencies provide a more comprehensive view of the variability in flood and wetness than statistics of individual typical floods and wetness. These measures are especially effective in floodplain systems where seasonal growth and shrinkage dictate the interchange of water, soil, and nutrients and in seasonal wetlands where hydroperiod dictates vegetative structure, breeding effectiveness and success of amphibians, and habitable locations[93].

To derive hydroperiod using satellites, sampling and observation gaps are to be taken into great consideration. The cloudy seasons might be missing in optical time series, creating a bias in the frequency and duration measures. SAR time series lessen this bias and can still be undersampled with respect to short-tailed events in case revisit intervals are many. This is particularly a problem with tidal wetlands, since the actual hydroperiod is a function of the tide stage, and observations obtained only at a specific time in the tidal cycle may be unrepresentative. These problems have stimulated methods which explicitly model observation probability, compose multi-sensor using multi-temporal density plots of time, and include ancillary hydrologic information, including river stage or tide models where possible. More and more products of hydroperiod describe not only the metric values, but also confidence measures, which indicate the density of observation and uncertainty in classification[13,94]. A concise comparison of satellite-derived wetland attributes, extent, hydroperiod, connectivity, and water level, and their typical use cases is provided in **Table 3**.

Table 3. Wetland monitoring products: Extent vs. hydroperiod vs. connectivity, and what each can support.

Wetland Attribute	What the Product Represents	Satellite Data Commonly Used	Typical Metric Examples	Best-Supported Applications	Key Caveats
Extent (snapshot)	Inundated/open-water area at an observation time	Optical and/or SAR	Water mask; inundation fraction	Mapping wetlands and flood extent; rapid event response	Strong dependence on clouds (optical); vegetation masking; threshold sensitivity
Hydroperiod	Statistical description of inundation timing/duration	SAR time series; optical time series; fused SAR+optical	Inundation frequency; duration; onset/recession dates; seasonal amplitude	Habitat and ecological integrity assessment; restoration evaluation	Requires adequate temporal sampling; observation gaps bias metrics
Flooded vegetation detection	Inundation beneath/emergent vegetation	SAR (polarization/seasonal change)	Flooded-vegetation class probability	Forested wetlands, marsh dynamics, floodplain processes	Backscatter confounded by phenology and incidence angle; calibration needed

Table 3. *Cont.*

Wetland Attribute	What the Product Represents	Satellite Data Commonly Used	Typical Metric Examples	Best-Supported Applications	Key Caveats
Connectivity (surface)	When/where wetlands connect to channels/floodplains	SAR/optical time series; altimetry where available	Connectivity duration; corridor persistence; threshold exceedance timing	Floodplain management; nutrient/sediment routing studies	Apparent connectivity ≠ functional exchange; topography and hydraulics matter
Water level (where feasible)	Vertical dynamics of wetland/lake surfaces	Altimetry + extent (often)	Stage time series; volume change (with area)	Storage accounting; drought impacts on lakes/reservoirs	Limited by narrow/vegetated water bodies; retracking/correction complexity

5.4. Hydrologic Connectivity and Exchange Processes

It is hard to find wetlands operating alone. Their capacities to reduce the impact of floods, regulate the quality of water, and sustain the ecosystem hinge greatly on their connections to the adjacent hydrodynamics. Floodplain wetlands both transfer water to rivers during overbank processes and, in most areas, experience seasonal changes of stage that regulate backwater inundation. The weakly-linked depressional wetlands can either be linked episodically by surface overflow or through shallow underlying ground routes. Coastal wetlands are connected to both the marine waters by the tides and storm surge, and the freshwater by the river discharge and the groundwater seepage. The ecological connection patterns are crucial to capture to study the drought resilience, nutrient movement, and the spreading flood waves[95].

The satellite observations present some sources of inferential connectivity. Spatiotemporal fire of flooding may also be recorded, that is, the flow of the flood along channel paths, and the retention of water at various landscape locations to identify hydraulically coupled corridors and isolated basins. Satellite data alone can further constrain directional gradients causing surface exchange when used in solving altimetry-derived water levels, which can then be employed going forward in estimating thresholds of connection occurrence and location. Passive microwave time series can supplement a high-resolution mapping in the case of a large floodplain, where they provide temporal context that can be used to sort out local classification noise versus coherent basin-scale inundation dynamics. However, space-to-space connectivity throws down a challenge as it relies on the topography at small scales, vegetation resistance, and channel morphology, and apparent surface connectivity does not necessarily mean actual functional exchange of water or solutes. Due to this, connectivity metrics tend to leverage the ability to combine satellite-based inundation dynamics with scaled model or network-based approaches to a graph with topographic pathways and thresholds coded in it[96,97].

5.5. Wetland–Groundwater Interactions and the Role of Evapotranspiration

One of the most important and most underestimated issues of wetland hydrology is the bidirectional interaction of wetlands and groundwater. Numerous wetlands continue to exist since they are replenished by the groundwater; some play the role of recharge areas during wet seasons, whereas others move between the two functions seasonally. With satellites only, it is hard to untangle these exchanges since the fluxes in the subsurface are not directly measured. Indirect constraints can, however, be offered by satellites. Continuous moisture in the case of meteorological drought, such as persistence, may indicate groundwater supply, especially where there are no surface water sources and high evapotranspiration[98]. On the other hand, the observation of fast-reducing wetlands in dry seasons can be indicative of dependency on surface run-offs, as well as rainfall. The estimates of evapotranspiration give further background since ET is a combination of the presence of water and vegetation demand. Sustained ET on wetlands in dry seasons may require evidence of access to stored water reserves, and reduced ET might reveal enduring salinity, temperature range, or disturbance stress on vegetation[99].

These patterns need careful interpretation as they may be dishearteningly confused by management and land cover change directly onto ET and vegetation. However, combined study of wetland extent, hydroperiod, ET anomalies, and where known, terrestrial water storage anomalies can aid in the diagnosis of how wetland persistence is controlled by the balance between surface and local precipitation and groundwater exchange and how they change with drought and restoration interventions[100].

5.6. Validation, Uncertainty, and Comparability across Regions

Wetland remote sensing products are complex to validate due to the heterogeneity of wetlands as well as due to the lack of coherent ground reference data. Plots that are not in the mixture of matching satellite pixels tend to be observed in field observations, so that they capture the depth of the water and the state of the vegetation. High-resolution airborne imagery may be useful as reference maps, but can only be provided temporarily, and unsynchronized with the satellite overpass. Further, the definition of the target state: a classification that is oriented towards an open water state can, at least, be inconsistent with the field judgments of soil saturation or shallow wetlands beneath vegetative canopy, not because the satellite product is erroneous, but by definition of a different wetness property. Reporting of SCI now therefore places more importance on the clarity of definition, validation, and a characterization of uncertainty to reflect mixed pixels and gaps between observations[101].

Another issue is comparability. The products of wetlands designed in one region will not be easily transferable to another since the scattering regime, vegetation type, and soil backgrounds vary. Transparent threshold approaches can be fragile in climates. Machine learning techniques can enhance performance with the need to have representative training data, and they have the possibility of learning region-specific artifacts. The comparability is best in the case when the products use land cover context, physically driven features, confidence score reporting, and protean wetland classes are used, such as forested wetlands, peatlands, and tidal systems[102].

5.7. Toward Operational Wetland Hydrology: Emerging Directions

The discipline is shifting away not only at mapping where wetlands are but also at monitoring how wetlands behave hydrologically, and this form of transition is directly associated with management and policy requirements. The metrics of hydroperiod can be used to determine the ecological integrity, restoration evaluation, and habitat planning. The indicators of connectivity could be used to assist with floodplain management and the planning of interventions that would recreate the natural pathways of exchange. Short-term flood monitoring with nearly real-time inundation data can be useful in flood response, whereas long-term records can measure trends related to climate change, drainage, and sea-level rise.

To realize the operation of wetland hydrology using satellites, further developments will be made in three areas. To start with, multi-sensor fusion needs to be made a norm, especially in cloudy areas and in wetlands with vegetation where single-sensor constraints are critical. Second, uncertainty reporting has to be enhanced, and the uncertainty density, ambiguity in classification, and seasonality bias should be explicitly modeled. Third, there should be stronger means of associating satellite-derived hydroperiod and connectivity variables with ecological and biogeochemical processes that are driving wetland conservation, such as carbon cycling, methane emissions, and biodiversity results. Wetlands, in this regard, provide an effective example of satellite hydrology overall: triumph lies not simply within the ability to sense the presence of water, but within the context of describing the complex of dynamics and exchanges that constitute hydrologic functioning[103,104].

6. Drought Dynamics and Satellite-Based Indicators

Drought is no longer a single variable process where shortages in atmospheric water availability, surpluses in atmospheric demand, reach into soils, vegetation, surface water, and groundwater with variable impacts, with different impacts happening in time and across sectors. Climate variability, land-atmospheric feedbacks, the landscape qualities, and, more than ever, the human-driven water management determine such propagation. Consequently, no individual satellite product can be described with great strength to reflect the drought. Rather, satellite hydrology can best assist with its combination of complementary indications, which make it possible to monitor various phases of drought development, including fast soil moisture variations and gradually accumulating shortages in the water storage on the land. Satellite value is notably high in areas lacking in situ networks, large or transboundary basin droughts, and where the stakeholders need timely information to be available across state borders. The contextual reform of the conceptualization of drought in satellite hydrology, the translation of satellite observables into drought signals at scales of time and space, and how collective frameworks enhance the provision of early warnings, the characterization of events, and the provision of attribution are reviewed[105–107].

6.1. Drought as a Cascading, Multi-Timescale Phenomenon

Hydrologically, drought is the word commonly referred to as a sequence that starts with meteorological abnormalities and ultimately includes more profound and long-term reservoir impacts. Meteorological drought is a condition of precipitation deficit and undesirable atmospheric environments, although its impact is manifested in the drying of soils and in reducing the amount of water available to plants. Agricultural drought is thus widely articulated as soil moisture and plant stress, which can escalate swiftly during hot seasons when the ability of water to devastate the ground is vast. Hydrological drought is an indicator of run-off, streamflow, reservoir storage, and lake level deficits, and in most cases, hydrological drought stays slow behind the meteorological abnormalities, due to reliance on the storage and route distributions of a catchment. Groundwater drought has the longest memory with a gradual buildup that continues even after the recovery of precipitation, owing to the slow recharge and pumping that occur in dry seasons[108].

Such a structure of timescale explains why it is the satellite hydrology that is sought after. The various types of satellite observables react to various components of the cascade, and by working together they can give a more comprehensive image than one indicator. Meanwhile, a cascade is not entirely natural. Drought spread may be mitigated or enhanced by irrigation, suppression or enhancement of drought propagation by reservoir operations, and pumping of groundwater (for example, displaying green vegetation in meteorological drought or causing meteorological drought to appear with almost normal rainfall). The satellite indicators need to be considered with regard to both management responses to factors and climate forcing to understand[109].

The result of the correlation analysis of the three drought indices (12-month Standardized Precipitation Evapotranspiration Index or SPEI-12, 12-month Standardized Ecological Drought Index or SEDI-12, and 12-month Standardized Soil Moisture Index or SSI-12) as depicted in **Figure 3** shows that there was a strong correlation between meteorological drought and ecohydrological drought (SPEI and SEDI, respectively), but yielded no results in the soil drought (SSI) with respect to ecohydrological drought in the region[110].

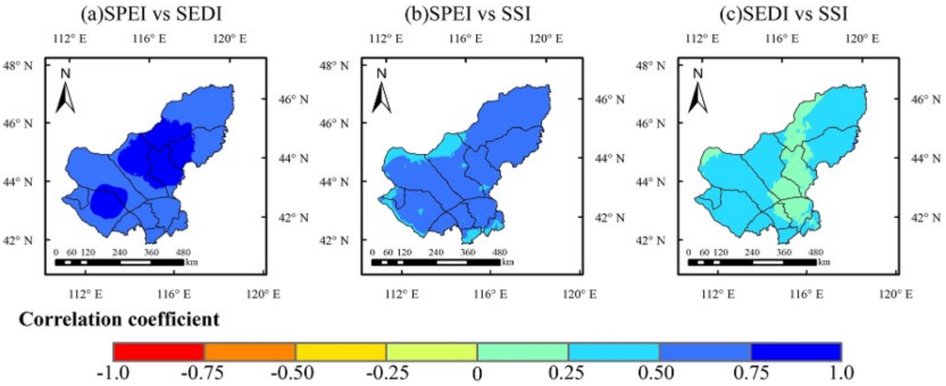

Figure 3. Multi-timescale drought cascade monitored by satellites. Correlation between annual (**a**) meteorological drought, (**b**) ecohydrological drought, and (**c**) soil drought (1990–2019).

6.2. Satellite Soil Moisture and the Onset of Agricultural Drought

Among the first hydrologic conditions to indicate a deficit of precipitation and high atmospheric demand is soil moisture, and soil moisture is directly mechanistically correlated with plant stress, extreme heat, and fire hazard. The best surface soil moisture satellite constraint is made by passive microwave measurements due to the high dielectric contrast of moist and dry soils. Although these retrievals can best be depended upon over low to moderate vegetation cover, they may be constrained by thick canopies, surface roughness, frozen soils, and radio-frequency interference. Irrespective of these shortcomings, the microwave measurements of soil moisture have been at the center of drought monitoring due to the ability to respond to the quick loss of near-surface water and give early warning prior to stress appearing in the vegetation indices.

The main problem is that the effect of drought is often based on the situation with moisture in the root zone, but not on the situation with moisture in the surface. Root-zone soil moisture estimation can be done by either linearizing the surface soil moisture measurements into land surface models or by optimal statistical methods that project surface anomalies downward through time. The model dependence is introduced by both methods, though each can enhance a great relevance in samples of agricultural drought, particularly when verified against in situ networks, and where uncertainty itself is presented as a function of the vegetation density and soil texture. Surface and root-zone moisture difference is also a factor in the recovery of droughts since the top layer can re-wet almost instantly after rain, with deeper groundwater being depleted, which results in untrue insights into recovery when observations are limited to the surface[111].

6.3. Evapotranspiration, Land Surface Temperature, and Plant Water Stress

Evapotranspiration connects the water supply to the demand in the atmosphere and is one of the main ways through which water scarcity can impact the ecosystem and agriculture. Estimation of ET on a satellite scale is typically based on thermal infrared measurements to put both constraints on the surface temperature and energy partitioning, typically in combination with both optical measurements of vegetation cover and surface properties and meteorological data. Under moisture-constrained conditions, lower evaporation cooling is likely to increase land surface temperature and inhibit ET, generating physically understandable drought signals. ET anomalies can thus give a clue on how severe the moisture limitation is, whether irrigation is effective, and how far the ecosystems sustain transpiration during the dry spells.

The ET and thermal signals should, however, be viewed with caution. Synoptic heat waves potentially cause high temperatures even in hydrated soils, and ET may be inhibited by non-water factors, such as pregnancy senescence, harvest, smoke, salinity stress, and disturbances such as pests or fire. During meteorological drought, in an irrigated landscape, ET can be elevated and hide the underlying water shortage and redistribute effects of drought to groundwater and surface water stores. All of these intricacies have resulted in growing interest in incorporating ET and land surface temperature proxies with soil moisture and soil storage limits and assessing ET-based drought diagnostics in a land cover and land management framework[112].

6.4. Vegetation Condition Metrics and Their Interpretation in Drought Monitoring

Time-series metrics and optical vegetation indices have been used to indirectly suggest the existence of drought effects since, in most systems, greenness of plants and canopy coverage are affected by the presence of water. Vegetation-based indicators can be very useful in defining agricultural drought in rainfed regimes, as well as in evaluating ecological drought effects, including low productivity or low phenology. They are also user-friendly and convenient to the stakeholders, and this has added to their operational use with most drought monitoring systems.

However, vegetation response cannot be directly measured as a measure of hydrologic drought, and it is also uncertain to interpret. Vegetation indices also combine various drivers such as radiation, temperature, nutrient status, management, and composition of species. Deep-rooted vegetation may keep the ecosystems green despite the lack of rainfall when the surface soils are dry, and irrigation may be the cause of greenness in croplands, as opposed to rainfall. The vegetation indices may also anticipate the onset of hydrologic deficit, especially when the plants utilize the stored soil moisture before detecting the visual stress. Due to these reasons, vegetation condition measures are most informative when they are considered impact measures instead of hydrologic condition measures like soil moisture and storage[113].

6.5. Surface Water Storage, Lake and Reservoir Dynamics, and Hydrological Drought

The most apparent forms of hydrological drought include decreased streamflow, decreased lakes and reduced reservoir levels. In addition to altimetry, which measures the water levels in appropriate water bodies, satellites help to monitor hydrological drought due to their capability to map surface water areas using optical and radar imagery. Extent and level information can be collected to make volumetric changes to storage that are directly pertinent to water supply and power management. The latter have found such use especially in areas where reservoir reporting is restricted or politicized and in measuring drought effects on large lakes and floodplains[108].

However, the management has a strong effect on the surface water indices. Releases at reservoirs, diversion activities, and flood-control regulations have the potential of modifying water levels in a manner that is unresponsive to meteorological conditions. It is, thus, necessary to separate managed drawdown and climate-driven deficit in attribution and in understanding surface water peculiarities in terms of drought. A combination of surface water observations and precipitation, ET, and anomalies in the storage of the terrestrial water can be used to diagnose whether the surface water decreases are due to deficits at the basin-wide scale or to operational choices.

6.6. Terrestrial Water Storage and Groundwater Drought: Cumulative Deficits and Recovery Lag

Satellite gravimetry-derived terrestrial water storage anomalies have offered a distinctive view of drought since they combine changes in surface water, soil moisture, snow, and groundwater. This finds TWS especially useful in a characterization of cumulative drought severity, defining deficits over multiple years, and characterization of recovery curves. TWS often goes on to decrease with the onset of meteorological drought due to higher pumping rates of groundwater; slower recovery of precipitation due to groundwater being depleted or because it is slower to recover than the deeper storage; and because depleted groundwater and soils refill before deep storage. TWS has both advantages and disadvantages in terms of integration, which is also a privilege for drought surveillance. It is an advantage since it records the entire system response, and it may give a visible picture of groundwater hidden drought, which is not easily seen in vegetation indices or minute measurements of soil moisture. This is a weakness since it is spatially coarse, and assigning deficits to specific components cannot be achieved without the decomposition of the models and other additional data[114]. To study drought, comparative and diagnostic applications of TWS are then most often the strongest: are the storage shortages deep and persistent, has it not yet fully recovered after wet periods, and are recurring droughts becoming cumulative, depleting the storage?

6.7. Integrated Drought Frameworks and Composite Indicators

Since drought processes and satellite sensitivities are varied, the concept of integrated frameworks has gained a lot of prominence. These frameworks are integrated to provide indicators that react to various timescales in an attempt to account for onset, intensification, peak severity, and recovery. A typical reasoning goes to associate the individual early-warning indicators (surface and root-zone soil moisture) with individual process and impact indicators (ET anomalies and vegetation condition) and system-level storage indicators (surface water volume and terrestrial water storage). This may be undertaken by making use of multi-variable dashboards and probabilistic drought likelihood mapping, or composite indices giving weights in regards to the relevance of the sector[115].

There are important methodological issues brought up by the architecture of composite drought indicators. Value judgments in embedding weightings of effects of particular impact that are considered more important can be embedded within a weighting scheme and can behave differently in different ecosystems and management regimes. The use of standard forms that define the anomalies using local climatology is capable of enhancing comparability, but can obscure non-stationarity due to climate change or land use. The synthesis of SCI-standard droughts is becoming more focused on transparent building of indicators, responsiveness to index alternatives, and an analysis in relation to independent impact data, e.g., crop yield anomalies, wildfire, streamflow deficiencies, or water supply constraints. **Table 4** provides a summary of drought indicators based on stage of drought, response time, confounders, and useful interpretation comments on indicators of drought, which are required to support indicator selection and interpretation[116,117].

Table 4. Satellite-informed drought indicators across the drought cascade and decision relevance.

Drought Stage/Type	Primary Satellite-Informed Indicators	Typical Response Time	What It's Best for	Common Confounders	Practical Interpretation Note
Meteorological context	Satellite precipitation products; atmospheric reanalyses (often paired)	Days–weeks	Forcing context; event framing	Orographic bias; gauge-sparse calibration	Use as context, not impact by itself
Agricultural drought (early)	Surface and root-zone soil moisture anomalies	Days–weeks	Early warning; crop stress risk	Dense vegetation; frozen soils; shallow depth	Root-zone estimates often model/data assimilation (DA) dependent
Agricultural/ecological stress	ET anomalies; LST anomalies; vegetation condition metrics	Weeks–months	Intensity and impact mapping; irrigation signal detection	Heatwaves; harvest/phenology; salinity, pests	Interpret with land cover/management context
Hydrological drought	Surface water extent; lake/reservoir levels and storage change	Weeks–months	Water supply and hydropower implications	Reservoir operations; diversions	Pair with management info where possible
Groundwater drought/cumulative deficit	TWS anomalies; inferred groundwater storage anomalies	Months–years	Multi-year severity; recovery lag	Component separation error; pumping responses	Best at basin to regional scales
Recovery assessment	Joint view of soil moisture + ET + surface water + TWS	Weeks–years	Detect incomplete recovery; compounding drought	Baseline shifts; management changes	Recovery is multi-component and often asynchronous

6.8. Attribution, Compounding Extremes, and the Role of Human Management

Attribution Research on the central in chief in the least drought is to what extent beyond climate forcing, internal variability, land-atmosphere interactions, and human water management cause observed drought severity and effects. Satellite hydrology also has a role to play in attribution through offering spatially explicit measurements of several drought pathways. An example is when a basin experiences modest falls in precipitation, but major terrestrial water storage reduction and steady vegetation greenness indicate that surface effects are being compensated by irrigation, groundwater pumping, but a subsurface depletion is increasing rapidly. Alternatively, vigorous ET retardation and vegetation stress with a rather low storage deficit could be a sign of rapid agricultural drought caused by heat and atmospheric demand.

Attribution is made even more difficult in the case of compounding extremes. Wildfire and land cover change can change hydrologic partitioning and surface energy balance, and heatwaves can exacerbate the effects of drought by increasing the demand for evaporation and decreasing the efficiency of plants in using water. Satellites are well-suited to record these dynamics of compounds since they record hydrologic states and surface responses of the land. The interpretation of the compound events, however, needs a keen distinction of cause and effect, especially because both vegetation and thermal signals can be in response to drought, as well as cause feedback on the development of drought via a response to moisture and temperature of the boundary layer[118,119].

6.9. From Monitoring to Decision Support: Operational Considerations

Satellite drought information should be timely, interpretable, and bear uncertainty characterization, commensurable to the risk-taking of the understanding user, before it can be useful in decision-making. Real-time availability and resiliency to clouds and missing data are needed for early warning, which reinforces the support of microwave-based soil moisture monitoring/radar-based surface water monitoring, as often augmented by model-based gap filling. To interpret it, the indicators must be tied to the influence on the sector, and the confounding variables must be taken into account (irrigation and management). This is necessary due to the nature of uncertainty characterization since false alarms may destroy trust, and the response to drought can be very costly both economically and socially[120].

Satellite hydrology has indicated the usage of single indicators as the basis of drought monitoring by multiplying the variables and using a multi-variable and multi-timescale perspective on drought dynamics. The observations of soil moisture by revealing the first onset, the thermal and ET, surface water observations, and variables such as hydrological droughts in both regulated bog systems and unregulated systems, and water storage anomalies in surface-terrestrial diagnose the cumulative shortages and lag between recovery. Solar-supported drought measurements that combine the two harmonious vistas into a physically informed structure and explicitly consider the issue of uncertainty and attribution in a situation where humans are operating within the water management system are, therefore, the most dependable satellite-based drought observations[121].

7. Enabling Methods, Integration, and Remaining Challenges

It is not only new sensors that lead to the practical effect of satellite hydrology, but a consequence of new methodologies that enable heterogeneous observations to be interoperable, physically interpretable, and operational. Each of groundwater, wetlands, and drought demands inference across scales, confounding signal separation, and making decisions or understanding processes using satellite observables. These needs have raised a collection of enabling techniques, such as data assimilation, multi-sensor fusion, machine learning, and uncertainty quantification, to be optional additions to core elements of contemporary satellite hydrology. Meanwhile, the same persistent challenges that plague the field, such as scale mismatch, retrieval bias, non-stationary variability under climate and land use change, a limited ground truth, and the inability to disentangle climate-induced variability and human management side effects, continue to pose significant challenges. This part summarizes the methodological principles underlying the new era and discusses the obstacles that ought to be tackled to transform satellite hydrology into robust, comparable, and decision-relevant[12,122].

7.1. Pre-Processing, Harmonization, and the Foundations of Interoperability

To integrate satellite data into the hydrologic analysis, they should be compared in all sensors, time, and space before they can be introduced. This is usually a step that goes unrecognized, though it is many times the prevailing factor of downstream reliability. Radiometric calibration, geometric correction, and quality screening are the first steps of harmonization to make sure that time series reflect actual environmental change and not sensor effects. This is atmospheric correction and cloud and shadow masking in the case of optical products; radiometric calibration, terrain correction, speckle reduction plan in the case of SAR imaging; atmospheric effects and emissivity in the case of thermal data; waveform retracking and geophysical correction in the case of altimetry. Even with community products not being raw observations, but instead retrieved with them, the inconsistency may arise due to differences in projection, spatial resolution, temporal compositing, and masking rules that are mistaken to be hydrologic signals[123,124].

It is also necessary in hydrologic integration that there needs to be alignment on the time scales since groundwater, wetlands, and drought react on different time scales, and satellite revisit intervals across missions are disparate. Interpretations can vary depending on decisions regarding temporal aggregation, particularly in measures of hydroperiod and brief inundation scales or detection of dry periods where the similarity between relative weekly and monthly resolution is exhaustive. Additional tradeoffs are brought by the spatial harmonization. The resampling of high-resolution inundation maps down to the coarse storage products may degrade important information, whereas down-sampling of coarse ones may provide a false impression of accuracy. These problems encourage workflows that keep native resolution where feasible, spread bureaucracy by aggregation, and expose the constraints of scale as well as express them not implicitly[125].

7.2. Data Assimilation: Imposing Physical Consistency and Filling Gaps

Assimilation of data has emerged as a focal means of resolving satellite findings to hydrologic states which are both time consistent and physically coherent. Simply, the principle of assimilation is using a dynamic model typically a land surface model or hydrologic model that is the combination of dynamic model and observations and in effect updating the states of the models including model and observation errors, but in a statistically sound manner. Assimilation of satellite soil moisture can be useful in drought monitoring, especially to estimate root-zone moisture and partitions of evapotranspiration and can be used to improve the skill of early warning. Assimilation of terrestrial water storage anomalies can be used in groundwater related applications, where it is necessary to test the evolution of basin-scale storage, and soil moisture assimilation can affect the timing and amount of recharge. In wetland and floodplain dynamics, in combination with coupled hydraulic–hydrologic systems assimilation is being increasingly employed to limit the extent of inundation and, where present, levels of the water[126].

The assimilation performance, however, is made on assumptions that can hardly be met in reality. Errors of observation are not often autonomous in either space or time, and retrieval bias may generate systematic misfits that assimilation may falsely attribute to errors in the state. Large model structural errors may occur, especially in areas where groundwater processes, irrigation, dam operations, and lateral flows are simplified or omitted. Devoid of grounded prejudice correction and inaccuracies characterization, assimilation may generate results that appear smooth and coarse but carry systematic mistakes. This has led to a change where bias is more explicitly treated, where ensembles are used to model uncertainty, and more realistic coupled models are created, which include the processes of groundwater and management. Particularly with regard to synthesis on the SCI-standard criterion, the point that the assimilation process is not a black box can be made, but it is a framework, and the credibility of the error models and the physical representation cannot be divorced[127].

7.3. Multi-Sensor Fusion: Reducing Ambiguity through Complementary Constraints

The resultant multi-sensor fusion has come to represent the operational philosophy of satellite hydrology, as it is the only way to approach the non-uniqueness of single observables. The fusion can be at a number of levels. On the most basic level, this is the composition of water maps of optical and SAR data to minimize the gaps created by clouds and enhance the maps of wetland extent. On a higher level, it integrates both the gravimetric storage limitations and the surface water area with altimetry-based levels to provide a more inspired representation of surface water storage, besides isolating groundwater anomalies more authoritatively. Fusion in drought evaluation. Fusion combines rapid indicators of soil moisture and evapotranspiration with the slow indicators of storage anomalies themselves so as to measure the droughts on both changes over time.

Fusion hydrologic value is greatest where it is informed by the understanding of the processes, as opposed to being purely statistical in combination. An example of such is that storage area elevation relationships make it physically important to integrate surface water level and surface water extent, and land surface energy and water balance make it physically worthwhile to integrate soil moisture and ET. Probabilistic representations are increasingly being deployed in fusion frameworks, which (unlike their inflexible predictive character) generate likelihood maps or ensembles, expressing not only the most reasonable hydrologic state, but their uncertainty to the associated extent. This is necessary especially in wetlands, where the degree of classification is sensitive to the type of vegetation and the density at which the individual knows the system, and in drought, when indicators can separate due to disparities in the response rates of components of the system[128].

7.4. Machine Learning and Hybrid Modeling: Opportunity and Risk

Machine learning has grown fast in satellite hydrology due to its ability to harness high-dimensional information in multi-sensor datasets to learn nonlinear relationships, as well as provide practical functions, such as downscaling, gap-filling, and classification. Machine Learning (ML)-based models can be used to outperform threshold-based systems in wetland mapping as they can learn context-dependent differences between water, vegetation and moist soil. Within drought monitoring, ML can combine indicators to give probabilistic estimates of drought likelihood, and can even enhance forecasts of drought effects, e.g., abnormal crop yields or danger of fires when provided with research of historical predictions. ML may help to break down groundwater terrestrial water storage by training relationships involving climate, land cover, surface water and storage change, or training models that are computationally infeasible.

Although these advantages are there, ML presents risks which have particularly significant implications in hydrology. Models are capable of learning spurious relationships that fail to extrapolate during periods of climate extremities or changing land covers. This is because performance can plummet in areas unlike the training data, but it is also typical due to the heterogeneity of the world and nonhomogeneous ground truth coverage. Black-box models can be limited in their physical interpretability, which can make them difficult to trust and accept in the management context. These issues have promoted growing attention to hybrid methods, including inserting physical constraints into ML, like mass balance consistency, non-negativity of storage modification, or energy balance organization to estimate ET. Physics-informed and physics-guided ML seek to ensure the freedom of data-driven methods with the guardrails necessary to achieve reliable extrapolation, yet, is still a developing research field and needs to be carefully benchmarked[129].

7.5. Uncertainty Quantification and Benchmarking: From Optional to Essential

The uncertainty level is not some side point as far as satellite hydrology is concerned; rather, it is the hallmark of any form of inference. Any residuals that are obtained as groundwater anomalies will take on the uncertainties of all the subtracted components. Measurements of the wetland hydroperiod rely on the level of observation and classification. The indicators of drought depend on the normative climatology to be standardized, and confounding agents like irrigation and heatwaves. In order to responsibly use satellite information, uncertainty should be measured, reported, and, wherever feasible, verified.

The present practice is very broad. Some of these give pixel-level uncertainty information using retrieval theory, whereas others give global error information that is not necessarily local performance. The ensemble approach is being employed to express uncertainty among many model structures, parameter sets, and forcing datasets. ML-based mapping can use cross-validation and out-of-sample testing, but both can be misleading when it comes to estimating performance in the real world because spatial autocorrelation is not addressed adequately, or in cases where training and test are not actually independent. The advantage of having many independent reference datasets in hydrologic benchmarking is not the definitiveness of any particular reference, but rather that when the constraints are independent and any consensus increases. As an example, the severity of drought based on an anomaly in the soil moisture and ET can be assessed in relation to stream flow shortage, reservoir inventory, and documented effects; groundwater drainage based on gravimetry may be checked for underground well tendencies and subsidence. Not only is SCI-standard synthesis becoming more demanding, but studies represent their uncertainty pathway, rather than the final estimate[130].

7.6. Scale Mismatch and Representativeness: The Persistent Barrier

The major problem when using satellites to respond to groundwater, wetlands, and drought is perhaps a scale mismatch. Basin scales are necessary in gravimetry, whereas sub-basin scales are a frequently necessary level of management decision-making. Relative to field-level agriculture, soil moisture products may be coarse; relative to wetland maps, they can be fine relative to the hydrologic models available to assimilate or make projections. Representativeness is still a problem even in the existence of high-resolution products, since a satellite pixel in many cases is made up of a mixture of land cover and hydrologic conditions. These amount to additional doubt by using point-based observations that are aggregated to hemisphere footprints of the satellite, and insensitive comparisons may result in biased or erroneous findings on either of the two.

The solution to the problem of scale mismatch involves methodological and communication solutions. Downscaling and disaggregation may be value-added methods whenever based on physical relationships and verified on a strong basis, but can not be regarded as producing new information out of thin air. Scale bridging Scale bridging can be done by constraining the model states against observations using assimilation, the reliability of which determines how credible it remains. In every part of the communication, it is important that there is a statement in the satellite products and analyses that there is a defensible level of inference, and they must not imply any local accuracy of any signal when the underlying signal is regional. This is especially when dealing with groundwater, where coarse storage aberration may occasionally be mistaken as a direct result of local drawdown trends[14,131].

7.7. Non-Stationarity, Bias, and the Challenge of Long-Term Consistency

Trends and extremes are examined with satellite hydrology because it is becoming increasingly used in order to evaluate magnitude and changes over a decade; however, evaluations over extended periods are hard to sustain. Artificial time series shifts due to sensor variations, drift in the orbit, changes in the algorithm, and cross-mission variations are possible. In the meantime, the climate system is evolving, land cover and land management are changing, i.e., statistical relations obtained on the historically available data might be invalid in the future. This non-stationarity is particularly on the phenomena of drought, where the extravagant climate on which the anomalies have been calculated is changing in turn, in wetland processes, where restoration, drainage, and sea-level rise are modifying hydrologic regimes. The non-stationarity of groundwater systems is also determined by a pattern of pumping and recharge paths, which varies depending on policy, economics, and infrastructure.

Long-term consistency also means that climate data records should be carefully constructed, the version of algorithms documented, and it must be possible to use them to accept changing baselines. Trend analyses have the advantage of sensitivity tests to the processing options, explicit identification of breakpoints that can indicate the change of algorithms or sensors. In the case of ML-based products, non-stationarity is an incentive to the use of methods that focus on physical constraints and do not just consider performance under average conditions[132].

7.8. Human Water Management: The Hardest "Unobserved Variable"

The fact that much of the strongest signal in the interpretation of satellite hydrology is due to the human management is perhaps the most severe problem when it comes to interpreting the signal, but the management variables themselves are observable at best, and are not well quantified at worst. Irrigation alters soil moisture and ET and may obscure the effects of drought, as well as increasing groundwater depletion. The process of reservoir operations changes the storage of surface water without the influence of meteorological forcing. Urbanization and drainage convert the runoff and infiltration routes. Such interventions are capable of causing satellite visible alterations which appear to be climate signals without the presence of a management context.

The development of this challenge is moving on in various directions. Remote sensing can map the extent of irrigated area, the pattern of crops, and the size of a reservoir, providing indirect restrictions on the behavior of management. Other studies include reported use of water, allocation data, or policy interventions when they are available, but some of them rely on inverse methods to infer the intensity of pumping or irrigation based on inconsistencies between the observed and modeled water balance elements. Eventually, to address the management process comprehensively involves the combination of satellite hydrology and socio-hydrologic data streams and decision algorithms, and some form of transparency of aspects of management that are being represented, and those that are being ignored[132].

7.9. Toward Operational, Decision-Relevant Satellite Hydrology

It is more than just better algorithms that develop into operational systems; it needs to be reliable, interpretable, and user-centered. This requires monitoring of droughts operationally to have near real-time delivery, being unable to be fooled by a lack of data and indicators that match decision thresholds. Wetland operational monitoring needs to be operationalized as well as to have regular measures of hydroperiod and confidence measures, which are usable under regulations and conservation use. Operational ground-water intelligence demands strong partitioning of the water storage on the earth, clear uncertainty reporting, and prudent framing so as not to be misunderstood at lesser scales than the capability of the observer.

In each of the three spheres, a current practice is to view satellite hydrology products as multi-, evidence-based, probabilistic, but not deterministic. Players hugging together satellite observations and models along with ground information, with a representation of uncertainty explicitly in mind, stand a greater chance of helping in believable decisions than any individual good. The above-named remaining problems are thus not just technical in nature; they spell out the scientific and institutional effort to achieve the new age of satellite hydrology to provide sustainable value in groundwater, wetlands, and the dynamics of drought monitoring[133].

8. Conclusions

Satellite hydrology is redefining what could be seen regarding the terrestrial water cycle by rendering major aspects of water storage as well as surface processes visible, comparable, and even more trackable over time. In the case of groundwater, satellite measurements have been used to carry out regional evaluations of storage change previously unmeasurable in data-deficient or politically fragmented environments, which provide an autonomous check on long-term depletion, drought-related drawdown, and recovery rate. In wetlands, radar and optical time series technology has seen the shift in focus away from the stable inventory towards dynamic description of inundation cycles, hydroperiod, and, more and more, hydrologic connectivity, a measure that is more indicative and responsive of wetland function and vulnerability. In the case of drought, the capability to observe numerous aspects of the drought cascade, such as soil moisture, evapotranspiration, thermal stress, water surface extent and levels, and anomaly in terrestrial water storage, has provided the basis of integrated, multi-scale monitoring systems that have the potential to support earlier warning and more coherent diagnosis of severity and recovery compared to those of individual indicators.

Simultaneously, the key point of the given review is that satellite hydrology is not a direct measurement system, but an inference system. The satellites represent observables, rather than hydrologic truths, and sound interpretation requires explicit action on scale, non-uniqueness, and uncertainty. The anomalies of gravity-based storage should be partitioned in a careful way to be able to come up with the inference of groundwater, with the dynamics of surface water and snow as first-order terms when feasible. The wetland inundation maps should be interpreted regarding what can be observed- open water, flooded vegetation, or wetness on the surface, and the measurement of the hydroperiod needs to consider gaps in the observation and also the confidence of the classification. Drought indicators should not be seen as an alternative to measures and should thoughtfully be considered as a part of a cascade and be analyzed in the context of the sectoral differences that they are expected to signal. In all fields, humanity is becoming the largest confounder, and increasingly, the most potent driver of human water management, necessitating various satellite products, with irrigation, reservoir operations, pumping, and land use change information.

The engines of the new era that are reviewed here, which include multi-sensor fusion, data assimilation, machine learning, and uncertainty quantification, are the responsibility of the field as well. The increase of physical consistency and gap filling can be created through fusion and assimilation, and sometimes increases the biases unless the error structures and model drawbacks are addressed explicitly. Machine learning can enhance mapping and downscaling, which will have to be limited and evaluated during benchmarking to prevent spurious relationships and low transferability in a changing climate and land use. The characterization of uncertainty is not possible anymore as an option; it is required to have credible trend-detection, attribution of events, and decision support. Applications that best perform, such as the treatment of satellite-derived products as probabilistic evidence, cross-stratified with independent observations, and interpreted as having a hydrologic and management context, are therefore considered to be the most influential.

In the future, the following priorities appear in terms of research and practice. The former is standard, physically directed assimilation of storage extent flux data, and explicit evolution of uncertainties of every part. The latter is enhanced climate and management signal separation with a more realistic representation of irrigation, pumping, and reservoir operations, aided by remote sensing evaluation of human water utilization and through socio-hydrologic information integration. The third is more emphasis on functional metrics, groundwater resilience, recovery potential, wetland hydroperiod and connectivity regimes, and drought indicators in relation to impacts as opposed to one variable mapping. Lastly, converting research to operations will demand uniform, readable processing pipelines, uniform meaning between regions and products of communication that are commensurate with the scale, and these underlying observations.

Overall, satellite hydrology has given a potent avenue to observe groundwater transformation, wetlands interaction, plus drought progression, especially at the regional and global levels where conventional monitoring is still incomplete. The following developmental step will be not only measured based on new missions and improved resolution, but also the capacity of the community to incorporate the observation into consistent hydrologic stories, measure the uncertainty openly, relate satellite data to answerable water security, ecosystem lawfulness, and drought hazard interrogatives.

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Conflicts of Interest

The author declares no conflict of interest.

References

[1] Penatti, N.C., Almeida, T.I.R.d., Ferreira, L.G., et al., 2015. Satellite-Based Hydrological Dynamics of the World's Largest Continuous Wetland. Remote Sensing of Environment. 170, 1–13. DOI: https://doi.org/10.1016/j.rse.2015.08.031

[2] Ndehedehe, C., 2022. Satellite Remote Sensing of Terrestrial Hydrology. Springer: Cham, Switzerland. DOI: https://doi.org/10.1007/978-3-030-99577-5

[3] Levizzani, V., Cattani, E., 2019. Satellite Remote Sensing of Precipitation and the Terrestrial Water Cycle in a Changing Climate. Remote Sensing. 11(19), 2301. DOI: https://doi.org/10.3390/rs11192301

[4] Cukier, D., Kon, F., 2018. A Maturity Model for Software Startup Ecosystems. Journal of Innovation and Entrepreneurship. 7(1), 14. DOI: https://doi.org/10.1186/s13731-018-0091-6

[5] Ehrensperger, R., Sauerwein, C., Breu, R., 2023. A Maturity Model for Digital Business Ecosystems from an IT Perspective. Journal of Universal Computer Science. 29(1), 34–72. DOI: https://doi.org/10.3897/jucs.79494

[6] Popereshnyak, S., Grinenko, S., Grinenko, O., et al., 2019. Methods for Assessing the Maturity Levels of Software Ecosystems. In Proceedings of the 2019 International Workshop on Cyber Hygiene (CybHyg 2019), Kyiv, Ukraine, 30 November 2019; pp. 251–261.

[7] Thomson, L., Kamalaldin, A., Sjödin, D., et al., 2022. A Maturity Framework for Autonomous Solutions in Manufacturing Firms: The Interplay of Technology, Ecosystem, and Business Model. International Entrepreneurship and Management Journal. 18(1), 125–152. DOI: https://doi.org/10.1007/s11365-020-00717-3

[8] Craft, C., 2022. Creating and Restoring Wetlands: From Theory to Practice. Elsevier: Amsterdam, The Netherlands. DOI: https://doi.org/10.1016/B978-0-12-823981-0.00002-2

[9] Yuan, S., Liang, X., Lin, T., et al., 2025. A Comprehensive Review of Remote Sensing in Wetland Classification and Mapping. arXiv preprint. arXiv:2504.10842. DOI: https://doi.org/10.48550/arXiv.2504.10842

[10] Hopkinson, C., Fuoco, B., Grant, T., et al., 2020. Wetland Hydroperiod Change along the Upper Columbia River Floodplain, Canada, 1984 to 2019. Remote Sensing. 12(24), 4084. DOI: https://doi.org/10.3390/rs12244084

[11] Nhamo, L., Magidi, J., Dickens, C., 2017. Determining Wetland Spatial Extent and Seasonal Variations of the Inundated Area Using Multispectral Remote Sensing. Water SA. 43(4), 543–552. DOI: https://doi.org/10.4314/wsa.v43i4.02

[12] McCabe, M.F., Rodell, M., Alsdorf, D.E., et al., 2017. The Future of Earth Observation in Hydrology. Hydrology and Earth System Sciences. 21(7), 3879–3914. DOI: https://doi.org/10.5194/hess-21-3879-2017

[13] Papa, F., Frappart, F., 2021. Surface Water Storage in Rivers and Wetlands Derived from Satellite Observations: A Review of Current Advances and Future Opportunities for Hydrological Sciences. Remote Sensing. 13(20), 4162. DOI: https://doi.org/10.3390/rs13204162

[14] Sheffield, J., Wood, E.F., Pan, M., et al., 2018. Satellite Remote Sensing for Water Resources Management: Potential for Supporting Sustainable Development in Data-Poor Regions. Water Resources Research. 54(12), 9724–9758. DOI: https://doi.org/10.1029/2017WR022437

[15] Brisco, B., 2015. Mapping and Monitoring Surface

Water and Wetlands with Synthetic Aperture Radar. In: Tiner, R.W., Lang, M.W., Klemas, V. (Eds.). Remote Sensing of Wetlands: Applications and Advances. CRC Press: Boca Raton, FL, USA. pp. 119–136.

[16] Sahour, H., Kemink, K.M., O'Connell, J., 2021. Integrating SAR and Optical Remote Sensing for Conservation-Targeted Wetlands Mapping. Remote Sensing. 14(1), 159. DOI: https://doi.org/10.3390/rs14010159

[17] Amani, M., 2018. Combination of Optical and SAR Remote Sensing Data for Wetland Mapping and Monitoring [Master's Thesis]. Memorial University of Newfoundland: St. John's, NL, Canada.

[18] Cumming, G.S., Cumming, D.H., Redman, C.L., 2006. Scale Mismatches in Social-Ecological Systems: Causes, Consequences, and Solutions. Ecology and Society. 11(1), 14. DOI: https://doi.org/10.5751/ES-01569-110114

[19] Merchant, M., 2025. Enhanced Characterization of Wet Arctic Ecosystems Using Earth Observation Satellite Data and Machine Learning [PhD Thesis]. University of Guelph: Guelph, ON, Canada.

[20] Pelosi, C., Goulard, M., Balent, G., 2010. The Spatial Scale Mismatch between Ecological Processes and Agricultural Management: Do Difficulties Come from Underlying Theoretical Frameworks? Agriculture, Ecosystems & Environment. 139(4), 455–462. DOI: https://doi.org/10.1016/j.agee.2010.09.004

[21] Ascough, J., Maier, H., Ravalico, J., et al., 2008. Future Research Challenges for Incorporation of Uncertainty in Environmental and Ecological Decision-Making. Ecological Modelling. 219(3–4), 383–399. DOI: https://doi.org/10.1016/j.ecolmodel.2008.07.015

[22] Jiang, D., Wang, K., 2019. The Role of Satellite-Based Remote Sensing in Improving Simulated Streamflow: A Review. Water. 11(8), 1615. DOI: https://doi.org/10.3390/w11081615

[23] Turnbull, L., Wainwright, J., Brazier, R.E., 2008. A Conceptual Framework for Understanding Semi-Arid Land Degradation: Ecohydrological Interactions across Multiple Space and Time Scales. Ecohydrology. 1(1), 23–34. DOI: https://doi.org/10.1002/eco.4

[24] Yan, D., Wang, Y., Qin, D., et al., 2025. Hydrological Geography: Theoretical Framework, Research Progress, and Future Development Directions. Geographical Research Bulletin. 4, 186–224. DOI: https://doi.org/10.50908/grb.4.0_186

[25] Trenberth, K.E., 1999. Conceptual Framework for Changes of Extremes of the Hydrological Cycle with Climate Change. Climatic Change. 42(1), 327–339. DOI: https://doi.org/10.1023/A:1005488920935

[26] Bogena, H., White, T., Bour, O., et al., 2018. Toward Better Understanding of Terrestrial Processes through Long-Term Hydrological Observatories. Vadose Zone Journal. 17(1), 1–10. DOI: https://doi.org/10.2136/vzj2018.10.0194

[27] Duan, S.-B., Han, X.-J., Huang, C., et al., 2020. Land Surface Temperature Retrieval from Passive Microwave Satellite Observations: State-of-the-Art and Future Directions. Remote Sensing. 12(16), 2573. DOI: https://doi.org/10.3390/rs12162573

[28] Njoku, E.G., 2023. Surface Temperature Estimation over Land Using Satellite Microwave Radiometry. In: Choudhury, B.J., Kerr, Y.H., Njoku, E.G., et al. (Eds.). Passive Microwave Remote Sensing of Land–Atmosphere Interactions. CRC Press: London, UK. pp. 509–530.

[29] Meng, L., Yan, C., Lv, S., et al., 2024. Synthetic Aperture Radar for Geosciences. Reviews of Geophysics. 62(3), e2023RG000821. DOI: https://doi.org/10.1029/2023RG000821

[30] Lu, J., Wang, W., Wang, X., et al., 2023. Active Array Antennas for High Resolution Microwave Imaging Radar. Springer: Singapore. DOI: https://doi.org/10.1007/978-981-99-1475-3

[31] Zhou, Y., Dong, J., Xiao, X., et al., 2017. Open Surface Water Mapping Algorithms: A Comparison of Water-Related Spectral Indices and Sensors. Water. 9(4), 256. DOI: https://doi.org/10.3390/w9040256

[32] Thompson, D.R., Guanter, L., Berk, A., et al., 2019. Retrieval of Atmospheric Parameters and Surface Reflectance from Visible and Shortwave Infrared Imaging Spectroscopy Data. Surveys in Geophysics. 40(3), 333–360. DOI: https://doi.org/10.1007/s10712-018-9488-9

[33] Kalma, J.D., McVicar, T.R., McCabe, M.F., 2008. Estimating Land Surface Evaporation: A Review of Methods Using Remotely Sensed Surface Temperature Data. Surveys in Geophysics. 29(4), 421–469. DOI: https://doi.org/10.1007/s10712-008-9037-z

[34] Sun, G., Ranson, K., Kharuk, V., et al., 2003. Validation of Surface Height from Shuttle Radar Topography Mission Using Shuttle Laser Altimeter. Remote Sensing of Environment. 88(4), 401–411. DOI: https://doi.org/10.1016/j.rse.2003.09.001

[35] Brenner, A.C., DiMarzio, J.P., Zwally, H.J., 2007. Precision and Accuracy of Satellite Radar and Laser Altimeter Data over the Continental Ice Sheets. IEEE Transactions on Geoscience and Remote Sensing. 45(2), 321–331. DOI: https://doi.org/10.1109/TGRS.2006.887172

[36] Hunt, R.J., Walker, J.F., Krabbenhoft, D.P., 1999. Characterizing Hydrology and the Importance of Ground-Water Discharge in Natural and Constructed Wetlands. Wetlands. 19(2), 458–472. DOI: https://doi.org/10.1007/BF03161777

[37] Milly, P.C.D., 1994. Climate, Soil Water Storage, and the Average Annual Water Balance. Water Resources Research. 30(7), 2143–2156. DOI: https:

//doi.org/10.1029/94WR00586

[38] Hipel, K.W., Ben-Haim, Y., 2002. Decision Making in an Uncertain World: Information-Gap Modeling in Water Resources Management. IEEE Transactions on Systems, Man, and Cybernetics Part C. 29(4), 506–517. DOI: https://doi.org/10.1109/5326.798765

[39] Trigg, M.A., Michaelides, K., Neal, J.C., et al., 2013. Surface Water Connectivity Dynamics of a Large Scale Extreme Flood. Journal of Hydrology. 505, 138–149. DOI: https://doi.org/10.1016/j.jhydrol.2013.09.035

[40] Chen, J., Li, Y., Shu, L., et al., 2023. The Influence of the 2022 Extreme Drought on Groundwater Hydrodynamics in the Floodplain Wetland of Poyang Lake Using a Modeling Assessment. Journal of Hydrology. 626, 130194. DOI: https://doi.org/10.1016/j.jhydrol.2023.130194

[41] Safeeq, M., Fares, A., 2016. Groundwater and Surface Water Interactions in Relation to Natural and Anthropogenic Environmental Changes. In: Fares, A. (Ed.). Emerging Issues in Groundwater Resources. Springer: Cham, Switzerland. pp. 289–326. DOI: https://doi.org/10.1007/978-3-319-32008-3_11

[42] Baker, A.A., Treble, P.C., Andersen, M.S., et al., 2015. Caves: Observatories of Australia's Diffuse Groundwater Recharge History. National Centre for Groundwater Research and Training: Bedford Park, Australia.

[43] Liu, Y., 2019. Impacts of Climate Variation and Change on Hydrologic and Vegetation Dynamics [PhD Thesis]. Duke University: Durham, NC, USA.

[44] Lin, N., Jiang, R., Liu, Q., et al., 2022. Quantifying the Spatiotemporal Variation of Evapotranspiration of Different Land Cover Types and the Contribution of Its Associated Factors in the Xiliao River Plain. Remote Sensing. 14(2), 252. DOI: https://doi.org/10.3390/rs14020252

[45] Bourdin, D.R., Fleming, S.W., Stull, R.B., 2012. Streamflow Modelling: A Primer on Applications, Approaches and Challenges. Atmosphere-Ocean. 50(4), 507–536. DOI: https://doi.org/10.1080/07055900.2012.734276

[46] Band, L.E., 1999. Spatial Hydrography and Landforms. In: Longley, P.A., Goodchild, M.F., Maguire, D.J., et al. (Eds.). Geographical Information Systems. John Wiley & Sons: New York, NY, USA. pp. 527–542.

[47] Muste, M., Lee, K., Kim, D., et al., 2020. Revisiting Hysteresis of Flow Variables in Monitoring Unsteady Streamflows. Journal of Hydraulic Research. 58(6), 867–887. DOI: https://doi.org/10.1080/00221686.2020.1786742

[48] Gahegan, M., Ehlers, M., 2000. A Framework for the Modelling of Uncertainty between Remote Sensing and Geographic Information Systems. ISPRS Journal of Photogrammetry and Remote Sensing. 55(3), 176–188. DOI: https://doi.org/10.1016/S0924-2716(00)00018-6

[49] von Clarmann, T., Degenstein, D.A., Livesey, N.J., et al., 2020. Overview: Estimating and Reporting Uncertainties in Remotely Sensed Atmospheric Composition and Temperature. Atmospheric Measurement Techniques. 13(8), 4393–4436. DOI: https://doi.org/10.5194/amt-13-4393-2020

[50] Milani, L., 2012. Multi-Sensor Satellite Precipitation Estimate for Hydrogeological Hazard Mitigation [PhD Thesis]. Università degli Studi di Ferrara: Ferrara, Italy.

[51] Faridani Bardaskan, F., 2023. Novel Satellite-Based Methodologies for Multi-Sensor and Multi-Scale Environmental Monitoring to Preserve Natural Capital [PhD Thesis]. University of Basilicata Matera: Matera, Italy.

[52] Khan, S.I., Chang, N.-B., Hong, Y., et al., 2024. Remote Sensing Technologies for Multi-Scale Hydrological Studies: Advances and Perspectives. In: Thenkabail, P.S. (Ed.). Remote Sensing Handbook, Volume V. CRC Press: Boca Raton, FL, USA. pp. 37–64. DOI: https://doi.org/10.1201/9781003541400-4

[53] Woods, D., 2023. Integrated Hydrologic Validation of Satellite Precipitation over the United States [PhD Thesis]. The University of Oklahoma: Norman, OK, USA.

[54] Zektser, I., Loaiciga, H.A., 1993. Groundwater Fluxes in the Global Hydrologic Cycle: Past, Present and Future. Journal of Hydrology. 144(1–4), 405–427. DOI: https://doi.org/10.1016/0022-1694(93)90182-9

[55] Kuang, X., Liu, J., Scanlon, B.R., et al., 2024. The Changing Nature of Groundwater in the Global Water Cycle. Science. 383(6686), eadf0630. DOI: https://doi.org/10.1126/science.adf0630

[56] Mishra, N., Khare, D., Gupta, K.K., et al., 2014. Impact of Land Use Change on Groundwater: A Review. Advances in Water Resource and Protection. 2(2), 28–41.

[57] Becker, M.W., 2006. Potential for Satellite Remote Sensing of Ground Water. Groundwater. 44(2), 306–318. DOI: https://doi.org/10.1111/j.1745-6584.2005.00123.x

[58] Adams, K.H., Reager, J.T., Rosen, P., et al., 2022. Remote Sensing of Groundwater: Current Capabilities and Future Directions. Water Resources Research. 58(10), e2022WR032219. DOI: https://doi.org/10.1029/2022WR032219

[59] Bobba, A., Bukata, R., Jerome, J., 1992. Digitally Processed Satellite Data as a Tool in Detecting Potential Groundwater Flow Systems. Journal of Hydrology. 131(1–4), 25–62. DOI: https://doi.org/10.1016/0022-1694(92)90212-E

[60] Eamus, D., Zolfaghar, S., Villalobos-Vega, R., et al., 2015. Groundwater-Dependent Ecosystems: Re-

cent Insights from Satellite and Field-Based Studies. Hydrology and Earth System Sciences. 19(10), 4229–4256. DOI: https://doi.org/10.5194/hess-19-4229-2015

[61] Humphrey, V., Rodell, M., Eicker, A., 2023. Using Satellite-Based Terrestrial Water Storage Data: A Review. Surveys in Geophysics. 44(5), 1489–1517. DOI: https://doi.org/10.1007/s10712-022-09754-9

[62] Feng, W., Shum, C.K., Zhong, M., et al., 2018. Groundwater Storage Changes in China from Satellite Gravity: An Overview. Remote Sensing. 10(5), 674. DOI: https://doi.org/10.3390/rs10050674

[63] MacDougall, M.D.J., 2019. Impact of Long- and Short-Term Geodynamic Processes on Hydrocarbon Reservoirs in the Grand Banks [Master's Thesis]. Queen's University: Kingston, ON, Canada.

[64] Ndehedehe, C., 2023. Satellite Hydrology Programmes: Capabilities and Benefits. In Hydro-Climatic Extremes in the Anthropocene. Springer: Cham, Switzerland. pp. 81–133. DOI: https://doi.org/10.1007/978-3-031-37727-3_4

[65] Tolomio, M., Borin, M., 2018. Water Table Management to Save Water and Reduce Nutrient Losses from Agricultural Fields: 6 Years of Experience in North-Eastern Italy. Agricultural Water Management. 201, 1–10. DOI: https://doi.org/10.1016/j.agwat.2018.01.009

[66] Vlotman, W., Jansen, H., 2003. Controlled Drainage for Integrated Water Management. In Proceedings of the 9th International Drainage Workshop of ICID, Utrecht, The Netherlands, 10–13 September 2003.

[67] Liu, S., Huang, S., Xie, Y., et al., 2019. Assessing the Non-Stationarity of Low Flows and Their Scale-Dependent Relationships with Climate and Human Forcing. Science of the Total Environment. 687, 244–256. DOI: https://doi.org/10.1016/j.scitotenv.2019.06.025

[68] Liu, P., Din, A.H.M., Hamden, M.H., 2023. A Review of Satellite-Based Monitoring of Groundwater Storage Changes and Depletion Consequences. IOP Conference Series: Earth and Environmental Science. 1274, 012004. DOI: https://doi.org/10.1088/1755-1315/1274/1/012004

[69] Gao, H., 2015. Satellite Remote Sensing of Large Lakes and Reservoirs: From Elevation and Area to Storage. Wiley Interdisciplinary Reviews: Water. 2(2), 147–157. DOI: https://doi.org/10.1002/wat2.1065

[70] Döll, P., Schmied, H.M., Schuh, C., et al., 2014. Global-Scale Assessment of Groundwater Depletion and Related Groundwater Abstractions: Combining Hydrological Modeling with Information from Well Observations and GRACE Satellites. Water Resources Research. 50(7), 5698–5720. DOI: https://doi.org/10.1002/2014WR015595

[71] Condon, L.E., Kollet, S., Bierkens, M.F.P., et al., 2021. Global Groundwater Modeling and Monitoring: Opportunities and Challenges. Water Resources Research. 57(12), e2020WR029500. DOI: https://doi.org/10.1029/2020WR029500

[72] Gebremedhin, M.A., 2024. Integrating In-Situ Data with Satellite-Derived Products to Assess Surface-Groundwater Interactions and Sustainability of Groundwater Resources in Semi-Arid Environment. DATA Archiving and Networked Services (DANS): The Hague, The Netherlands.

[73] Fankhauser, K., Macharia, D., Coyle, J., et al., 2022. Estimating Groundwater Use and Demand in Arid Kenya through Assimilation of Satellite Data and In-Situ Sensors with Machine Learning toward Drought Early Action. Science of the Total Environment. 831, 154453. DOI: https://doi.org/10.1016/j.scitotenv.2022.154453

[74] Raju, D., 2025. Groundwater Depletion and Sustainability in Merced County, California: Analyzing Current Trends Scenarios Using GIS Tools [Master's Thesis]. The University of Arizona: Tucson, AZ, USA.

[75] Masood, A., Tariq, M.A.U.R., Hashmi, M.Z.U.R., et al., 2022. An Overview of Groundwater Monitoring through Point-to Satellite-Based Techniques. Water. 14(4), 565. DOI: https://doi.org/10.3390/w14040565

[76] Riaz, A., Nijhuis, S., Bobbink, I., 2025. The Role of Spatial Planning in Landscape-Based Groundwater Recharge: A Systematic Literature Review. Water. 17(6), 862. DOI: https://doi.org/10.3390/w17060862

[77] Ndehedehe, C., 2022. Groundwater from Space. In Satellite Remote Sensing of Terrestrial Hydrology. Springer: Cham, Switzerland. pp. 211–230. DOI: https://doi.org/10.1007/978-3-030-99577-5_9

[78] Shaikh, M., Birajdar, F., 2024. Artificial Intelligence in Groundwater Management: Innovations, Challenges, and Future Prospects. International Journal of Science and Research Archive. 11(1), 502–512. DOI: https://doi.org/10.30574/ijsra.2024.11.1.0105

[79] Davis, G.B., Rayner, J.L., Donn, M.J., 2023. Advancing "Autonomous" Sensing and Prediction of the Subsurface Environment: A Review and Exploration of the Challenges for Soil and Groundwater Contamination. Environmental Science and Pollution Research. 30(8), 19520–19535. DOI: https://doi.org/10.1007/s11356-022-25125-8

[80] Pourmorad, S., Kabolizade, M., Dimuccio, L.A., 2024. Artificial Intelligence Advancements for Accurate Groundwater Level Modelling: An Updated Synthesis and Review. Applied Sciences. 14(16), 7358. DOI: https://doi.org/10.3390/app14167358

[81] Sharma, L.K., Naik, R., 2024. Wetland Ecosystems. In Conservation of Saline Wetland Ecosystems: An Initiative towards UN Decade of Ecological Restoration. Springer: Singapore. pp. 3–32. DOI: https://doi.org/10.1007/978-981-97-5069-6_1

[82] Tiner, R.W., 2016. Wetland Indicators: A Guide to Wetland Formation, Identification, Delineation, Classification, and Mapping. CRC Press: Boca Raton, FL, USA.

[83] Hu, S., Niu, Z., Chen, Y., 2017. Global Wetland Datasets: A Review. Wetlands. 37(5), 807–817. DOI: https://doi.org/10.1007/s13157-017-0927-z

[84] Ozesmi, S.L., Bauer, M.E., 2002. Satellite Remote Sensing of Wetlands. Wetlands Ecology and Management. 10(5), 381–402. DOI: https://doi.org/10.1023/A:1020908432489

[85] Guo, M., Li, J., Sheng, C., et al., 2017. A Review of Wetland Remote Sensing. Sensors. 17(4), 777. DOI: https://doi.org/10.3390/s17040777

[86] Niu, Z., Gong, P., Cheng, X., et al., 2009. Geographical Characteristics of China's Wetlands Derived from Remotely Sensed Data. Science in China Series D: Earth Sciences. 52(6), 723–738. DOI: https://doi.org/10.1007/s11430-009-0075-2

[87] Adam, E., Mutanga, O., Rugege, D., 2010. Multispectral and Hyperspectral Remote Sensing for Identification and Mapping of Wetland Vegetation: A Review. Wetlands Ecology and Management. 18(3), 281–296. DOI: https://doi.org/10.1007/s11273-009-9169-z

[88] Rundquist, D.C., Narumalani, S., Narayanan, R.M., 2001. A Review of Wetlands Remote Sensing and Defining New Considerations. Remote Sensing Reviews. 20(3), 207–226. DOI: https://doi.org/10.1080/02757250109532435

[89] Klemas, V., 2013. Remote Sensing of Emergent and Submerged Wetlands: An Overview. International Journal of Remote Sensing. 34(18), 6286–6320. DOI: https://doi.org/10.1080/01431161.2013.800656

[90] Guo, Z., Wu, L., Huang, Y., et al., 2022. Water-Body Segmentation for SAR Images: Past, Current, and Future. Remote Sensing. 14(7), 1752. DOI: https://doi.org/10.3390/rs14071752

[91] Nath, R.K., Deb, S., 2010. Water-Body Area Extraction from High Resolution Satellite Images—An Introduction, Review, and Comparison. International Journal of Image Processing. 3(6), 353–372.

[92] Rouzegari, N., Bolboli Zadeh, M., Jimenez Arellano, C., et al., 2025. Passive Microwave Imagers, Their Applications, and Benefits: A Review. Remote Sensing. 17(9), 1654. DOI: https://doi.org/10.3390/rs17091654

[93] Rodríguez-Rodríguez, M., Halmos, L., Jiménez-Bonilla, A., et al., 2025. Assessing the Impact of Groundwater Extraction and Climate Change on a Protected Playa-Lake System in the Southern Iberian Peninsula: La Ratosa Natural Reserve. Geographies. 5(2), 21. DOI: https://doi.org/10.3390/geographies5020021

[94] Kissel, A.M., Halabisky, M., Scherer, R.D., et al., 2020. Expanding Wetland Hydroperiod Data via Satellite Imagery for Ecological Applications. Frontiers in Ecology and the Environment. 18(8), 432–438. DOI: https://doi.org/10.1002/fee.2233

[95] Michielotto, A., 2025. Management Strategies for Coastal Ecosystems in the Face of Climate Change and Increasing Human Pressure [PhD Thesis]. University of Padua: Padua, Italy.

[96] Alves, B., Angnuureng, D.B., Morand, P., et al., 2020. A Review on Coastal Erosion and Flooding Risks and Best Management Practices in West Africa: What Has Been Done and Should Be Done. Journal of Coastal Conservation. 24(3), 38. DOI: https://doi.org/10.1007/s11852-020-00755-7

[97] Sáez-Ardura, F., Parra-Salazar, M., Vallejos-Romero, A., et al., 2025. Exploring the Socio-Environmental Regulation of Water—A Systematic Review of Sustainable Watershed Management. Sustainability. 17(4), 1588. DOI: https://doi.org/10.3390/su17041588

[98] Rafiei, V., Nejadhashemi, A., Mushtaq, S., et al., 2022. Groundwater-Surface Water Interactions at Wetland Interface: Advancement in Catchment System Modeling. Environmental Modelling & Software. 152, 105407. DOI: https://doi.org/10.1016/j.envsoft.2022.105407

[99] Volik, O., Petrone, R., Price, J., 2023. Wetlands as Integral Parts of Surface Water–Groundwater Interactions in the Athabasca Oil Sands Area: Review and Synthesis. Environmental Reviews. 32(2), 145–172. DOI: https://doi.org/10.1139/er-2023-0064

[100] Xin, P., Wilson, A., Shen, C., et al., 2022. Surface Water and Groundwater Interactions in Salt Marshes and Their Impact on Plant Ecology and Coastal Biogeochemistry. Reviews of Geophysics. 60(1), e2021RG000740. DOI: https://doi.org/10.1029/2021RG000740

[101] Dronova, I., 2015. Object-Based Image Analysis in Wetland Research: A Review. Remote Sensing. 7(5), 6380–6413. DOI: https://doi.org/10.3390/rs70506380

[102] Mahdavi, S., Salehi, B., Granger, J., et al., 2018. Remote Sensing for Wetland Classification: A Comprehensive Review. GIScience & Remote Sensing. 55(5), 623–658. DOI: https://doi.org/10.1080/15481603.2017.1419602

[103] Moomaw, W.R., Chmura, G.L., Davies, G.T., et al., 2018. Wetlands in a Changing Climate: Science, Policy and Management. Wetlands. 38(2), 183–205. DOI: https://doi.org/10.1007/s13157-018-1023-8

[104] Gallant, A.L., 2015. The Challenges of Remote Monitoring of Wetlands. Remote Sensing. 7(8), 10938–10950. DOI: https://doi.org/10.3390/rs70810938

[105] Panu, U., Sharma, T., 2002. Challenges in Drought Research: Some Perspectives and Future Directions. Hy-

drological Sciences Journal. 47(S1), S19–S30. DOI: https://doi.org/10.1080/02626660209493019

[106] Shiau, J.-T., 2023. Causality-Based Drought Propagation Analyses among Meteorological Drought, Hydrologic Drought, and Water Shortage. Science of the Total Environment. 888, 164216. DOI: https://doi.org/10.1016/j.scitotenv.2023.164216

[107] AghaKouchak, A., Mirchi, A., Madani, K., et al., 2021. Anthropogenic Drought: Definition, Challenges, and Opportunities. Reviews of Geophysics. 59(2), e2019RG000683. DOI: https://doi.org/10.1029/2019RG000683

[108] Van Loon, A.F., 2015. Hydrological Drought Explained. Wiley Interdisciplinary Reviews: Water. 2(4), 359–392. DOI: https://doi.org/10.1002/wat2.1085

[109] Wu, J., Liu, Z., Yao, H., et al., 2018. Impacts of Reservoir Operations on Multi-Scale Correlations between Hydrological Drought and Meteorological Drought. Journal of Hydrology. 563, 726–736. DOI: https://doi.org/10.1016/j.jhydrol.2018.06.053

[110] Ma, J., Gao, J., 2023. Cascading Effects of Drought in Xilin Gol Temperate Grassland, China. Scientific Reports. 13(1), 10926. DOI: https://doi.org/10.1038/s41598-023-38002-2

[111] Seneviratne, S.I., Corti, T., Davin, E.L., et al., 2010. Investigating Soil Moisture–Climate Interactions in a Changing Climate: A Review. Earth-Science Reviews. 99(3–4), 125–161. DOI: https://doi.org/10.1016/j.earscirev.2010.02.004

[112] Wanniarachchi, S., Sarukkalige, R., 2022. A Review on Evapotranspiration Estimation in Agricultural Water Management: Past, Present, and Future. Hydrology. 9(7), 123. DOI: https://doi.org/10.3390/hydrology9070123

[113] Gouveia, C., Trigo, R., Beguería, S., et al., 2017. Drought Impacts on Vegetation Activity in the Mediterranean Region: An Assessment Using Remote Sensing Data and Multi-Scale Drought Indicators. Global and Planetary Change. 151, 15–27. DOI: https://doi.org/10.1016/j.gloplacha.2016.06.011

[114] Yao, C., Shum, C., Luo, Z., et al., 2022. An Optimized Hydrological Drought Index Integrating GNSS Displacement and Satellite Gravimetry Data. Journal of Hydrology. 614, 128647. DOI: https://doi.org/10.1016/j.jhydrol.2022.128647

[115] AghaKouchak, A., Farahmand, A., Melton, F.S., et al., 2015. Remote Sensing of Drought: Progress, Challenges and Opportunities. Reviews of Geophysics. 53(2), 452–480. DOI: https://doi.org/10.1002/2014RG000456

[116] Nie, W., Kumar, S.V., Arsenault, K.R., et al., 2021. Towards Effective Drought Monitoring in the Middle East and North Africa (MENA) Region: Implications from Assimilating Leaf Area Index and Soil Moisture into the Noah-MP Land Surface Model for Morocco. Hydrology and Earth System Sciences Discussions. 26(9), 1–36. DOI: https://doi.org/10.5194/hess-2021-263

[117] Zaitchik, B.F., Tuholske, C., 2021. Earth Observations of Extreme Heat Events: Leveraging Current Capabilities to Enhance Heat Research and Action. Environmental Research Letters. 16(11), 111002. DOI: https://doi.org/10.1088/1748-9326/ac30c0

[118] Roundy, J.K., Wood, E.F., 2015. The Attribution of Land–Atmosphere Interactions on the Seasonal Predictability of Drought. Journal of Hydrometeorology. 16(2), 793–810. DOI: https://doi.org/10.1175/JHM-D-14-0121.1

[119] Zhang, L., Yu, X., Zhou, T., et al., 2023. Understanding and Attribution of Extreme Heat and Drought Events in 2022: Current Situation and Future Challenges. Advances in Atmospheric Sciences. 40(11), 1941–1951. DOI: https://doi.org/10.1007/s00376-023-3171-x

[120] Yu, R., Chen, S., Xie, Y., et al., 2025. Foundation Models for Environmental Science: A Survey of Emerging Frontiers. arXiv preprint. arXiv:2504.04280. DOI: https://doi.org/10.48550/arXiv.2504.04280

[121] Schwartz, C.C., 2024. Further Developing Drought Early Warning Information Systems Using Mixed-Methods and Multiple Streams of Data [PhD Thesis]. The University of Nebraska–Lincoln: Lincoln, NE, USA.

[122] Tauro, F., Selker, J., van de Giesen, N., et al., 2018. Measurements and Observations in the XXI Century (MOXXI): Innovation and Multi-Disciplinarity to Sense the Hydrological Cycle. Hydrological Sciences Journal. 63(2), 169–196. DOI: https://doi.org/10.1080/02626667.2017.1420191

[123] Schultz, G.A., 1988. Remote Sensing in Hydrology. Journal of Hydrology. 100(1–3), 239–265. DOI: https://doi.org/10.1016/0022-1694(88)90187-4

[124] Xu, X., Li, J., Tolson, B.A., 2014. Progress in Integrating Remote Sensing Data and Hydrologic Modeling. Progress in Physical Geography. 38(4), 464–498. DOI: https://doi.org/10.1177/0309133314536583

[125] Schumann, G., Bates, P.D., Horritt, M.S., et al., 2009. Progress in Integration of Remote Sensing-Derived Flood Extent and Stage Data and Hydraulic Models. Reviews of Geophysics. 47(4). DOI: https://doi.org/10.1029/2008RG000274

[126] Liu, Y., Weerts, A.H., Clark, M., et al., 2012. Advancing Data Assimilation in Operational Hydrologic Forecasting: Progresses, Challenges, and Emerging Opportunities. Hydrology and Earth System Sciences. 16(10), 3863–3887. DOI: https://doi.org/10.5194/hess-16-3863-2012

[127] Moradkhani, H., 2008. Hydrologic Remote Sensing and Land Surface Data Assimilation. Sensors. 8(5), 2986–3004. DOI: https://doi.org/10.3390/s8052986

[128] Meehan, T.G., 2022. Advancements in Measuring and Modeling the Mechanical and Hydrological Properties of Snow and Firn: Multi-Sensor Analysis, Integration, and Algorithm Development [PhD Thesis]. Boise State University: Boise, ID, USA.

[129] Hasan, F., Medley, P., Drake, J., et al., 2024. Advancing Hydrology through Machine Learning: Insights, Challenges, and Future Directions Using the CAMELS, Caravan, GRDC, CHIRPS, PERSIANN, NLDAS, GLDAS, and GRACE Datasets. Water. 16(13), 1904. DOI: https://doi.org/10.3390/w16131904

[130] McMillan, H.K., Westerberg, I.K., Krueger, T., 2018. Hydrological Data Uncertainty and Its Implications. Wiley Interdisciplinary Reviews: Water. 5(6), e1319. DOI: https://doi.org/10.1002/wat2.1319

[131] Lopez, T., Al Bitar, A., Biancamaria, S., et al., 2020. On the Use of Satellite Remote Sensing to Detect Floods and Droughts at Large Scales. Surveys in Geophysics. 41(6), 1461–1487. DOI: https://doi.org/10.1007/s10712-020-09618-0

[132] Kallache, M., Rust, H., Kropp, J., 2005. Trend Assessment: Applications for Hydrology and Climate Research. Nonlinear Processes in Geophysics. 12(2), 201–210. DOI: https://doi.org/10.5194/npg-12-201-2005

[133] Edwards, W.K., Bellotti, V., Dey, A.K., et al., 2003. The Challenges of User-Centered Design and Evaluation for Infrastructure. In Proceedings of the SIGCHI Conference on Human Factors in Computing Systems (CHI 2003), Ft. Lauderdale, FL, USA, 5–10 April 2003; pp. 297–304. DOI: https://doi.org/10.1145/642611.642664