

REMOTE SENSING FOR SUSTAINABLE IRRIGATION MANAGEMENT: CURRENT APPROACHES AND FUTURE PERSPECTIVES

TÉLÉDÉTECTION POUR UNE GESTION DURABLE DE L'IRRIGATION : APPROCHES ACTUELLES ET PERSPECTIVES D'AVENIR

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ABSTRACT

Given the increasing pressure on water resources and uncertainty related to future climatic developments, there is much debate regarding improving water use efficiency in agriculture. Such debate hinges on comprehensive information on both the qualitative and quantitative state of water resources as well as their current use in irrigated agriculture. However, obtaining that information can often be challenging, especially since networks for measuring hydrological data and for tracking irrigation water use are often sparse. This is where remote sensing can offer valuable supplementary insights to inform irrigation management.

Remote sensing approaches have evolved considerably over the past decades, with a great diversity of satellite data becoming available, offering ever-higher degrees of temporal and spatial resolution. From classifying irrigated crops, to assessing the availability and use of irrigation water resources, remote sensing can deliver actionable insights for both researchers and stakeholders. In addition, new satellite missions, multi-sensor data fusion, and integrations with machine learning and artificial intelligence can help refine irrigation water management. Increasingly, remote sensing data is also being integrated into operational tools designed for stakeholders and managers.

This contribution offers an overview of how remote sensing contributes to irrigation water management, including the imagery and tools that are available. We further highlight general limitations of remote sensing in irrigation water management - from restricted temporal and spatial resolutions, over questions of implementation, to a lack of co-creation that often poses a barrier to the adoption of operational tools - as well as offering perspectives to overcome them. To arrive at this synthesis, we have pooled the opinions and insights of researchers and experts from international organisations involved in irrigation water management, such as the World Bank and the UN's Food and Agriculture Organisation (FAO), in a series of three online workshops.

Keywords: Remote sensing; irrigation water management; machine learning and artificial intelligence; temporal and spatial resolutions; online workshops.

RESUME

Au vu de la pression accrue sur les ressources en eau et des incertitudes liées aux évolutions climatiques futures, l'amélioration de l'efficacité de l'utilisation de l'eau en agriculture fait l'objet de nombreux débats. Un tel débat repose sur des informations complètes à la fois sur l'état qualitatif et quantitatif des ressources en eau ainsi que sur leur utilisation actuelle dans l'agriculture irriguée.

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Cependant, peut souvent, il est difficile de recueillir ces informations, d'autant plus que les réseaux de calcul des données hydrologiques et de suivi de l'utilisation de l'eau d'irrigation sont souvent rares. C'est là que la télédétection peut offrir des informations supplémentaires précieuses pour orienter la gestion de l'irrigation.

Les approches de la télédétection ont considérablement évolué au cours des dernières décennies, grâce à la disponibilité d'une grande diversité des données satellitaires, offrant des degrés toujours plus élevés de résolution temporelle et spatiale. Depuis la classification des cultures irriguées à l'évaluation de la disponibilité et de l'utilisation des ressources en eau d'irrigation, la télédétection peut fournir des informations exploitables pour les chercheurs et les parties prenantes. En outre, les nouvelles missions satellitaires, la fusion de données provenant des capteurs multiples et l'intégration de l'apprentissage automatique et de l'intelligence artificielle peuvent aider à affiner la gestion de l'eau d'irrigation. De plus en plus, les données de télédétection sont également intégrées dans des outils opérationnels conçus pour les parties prenantes et les gestionnaires.

Cette contribution offre un aperçu de la façon dont la télédétection contribue à la gestion de l'eau d'irrigation, y compris les images et les outils disponibles. Nous soulignons en outre les limites générales de la télédétection en ce qui concerne la gestion de l'eau d'irrigation – allant des résolutions temporelles et spatiales restreintes relatives aux questions de mise en œuvre, à un manque de co-création qui constitue souvent un obstacle à l'adoption d'outils opérationnels — tout en proposant des perspectives pour les surmonter. Pour parvenir à cette synthèse, nous avons rassemblé les opinions et les perspectives des chercheurs et des experts provenant des organisations internationales impliquées dans la gestion de l'eau d'irrigation, telles que la Banque mondiale et l'Organisation des Nations Unies pour l'alimentation et l'agriculture (FAO), dans le cadre d'une série de trois ateliers en ligne.

Mots-clés: Télédétection; Gestion de l'eau d'irrigation; Apprentissage automatique et intelligence artificielle; Résolutions temporelles et spatiales; Ateliers en ligne.

INTRODUCTION

Worldwide, irrigated agriculture accounts for 40% of food production on a mere 20% of agricultural land (FAO 2011)⁶. It is also heavily impacted by climate change, with shifts in temperature and precipitation patterns driving changes in land use, in water demand and in the availability of freshwater resources for irrigation. As such, it is critical to understand both the present situation of irrigated agriculture as well as the hydrological, agricultural, and meteorological processes providing its framework. Especially since rainfed and irrigated systems are codependent, resource assessment should be performed on a systematic level for the watershed as a whole. However, this understanding is often limited by a lack of available data on aspects such as the type of crops grown, the amount and state of freshwater resources. This lack of data is particularly pronounced in areas of the world where site-specific measurements and reporting networks are not well-developed and frequently underfunded, or in contexts where data availability is limited due to secrecy or paywalls. Here, remote sensing (RS)⁷ can provide valuable insights to help address these challenges, from the assessment of the state of resources to the allocation of their use, bridging the gap in time and space between randomly available point source data on consumption to a full territory.

Over the past decades, the usefulness of RS in addressing these needs has increased significantly since high-resolution, high-frequency satellite data have become widely – and, most of the time, freely and more easily – available. For instance, since state of the art syntheses for remote sensing in water resources management were first published in the late 1990s and early 2000s (e.g. Bastiaanssen 1998),

⁶ While the exactness of these figures has been criticised recently (cf. Puy et al. 2025), they are retained as useful estimates and guideposts in UN and FAO publications and are currently being updated.

⁷ For the purposes of this paper, the term "RS" is taken to mean earth observation (EO) via satellites, rather than RS via sensors borne by in-situ instruments, drones, or planes. While the latter can provide valuable insights, they are more costly, and their data are usually not widely accessible.

the European Space Agency's (ESA) launched its Copernicus program, especially the Sentinel constellation. This constellation provides both optical and synthetic aperture radar (SAR) imagery at up to 10-m resolution every 6 days or less, making it possible to observe crop evolutions at a farm plot level, independent – in the case of SAR – of weather conditions. Similarly, images from NASA's Landsat satellites became freely available in 2008, though their 30m spatial resolution and 16-day temporal resolution limit their capacity to provide operational information for irrigated agriculture, especially at plot scale. These are merely two out of a large variety of satellite missions currently in orbit or soon to be launched, which can provide valuable data for irrigated agriculture. Others, for instance, provide additional thermal infrared (TIR) or altimetry data. Increasingly, these data are being integrated into ready-to-use webmapping tools. In addition, recent trends have been towards leveraging cloud computing, artificial intelligence and machine learning, and multi-sensor data fusion. Overall, it can be observed that over the past decades, the application of RS in irrigation has moved from research and analysis purposes to operational services – from mapping existing challenges to supporting solutions.

The purpose of this contribution is to provide an overview of the current use of RS in irrigated agriculture, the data available, barriers to implementation and how to overcome them, as well as potential future developments. To this end, three online workshops were conducted in spring 2026 to pool the insights and experience of experts involved in the use of RS in irrigated agriculture at multiple levels, from researchers, over engineers and managers of irrigation schemes, to coordinators of international programmes by organisations such as the World Bank and the UN's Food and Agriculture Organisation (FAO). The outcomes are presented below, outlining the current areas of application for RS in irrigated agriculture, highlighting recent advances and their usefulness, and discussing remaining challenges. Finally, this contribution also offers an outlook and recommendations for future directions to pursue.

DEPLOYING RS IN IRRIGATED AGRICULTURE: GENERAL AREAS OF APPLICATION

Irrigation occurs at the crossroads of three different domains – water, land, and agriculture (cf. Fig. 1). Data from RS missions can be used to provide information on all three. In terms of characterising freshwater, RS can be used to gain insights into the dynamics of rivers, lakes, reservoirs, drains and wetlands – their current extent and water levels, their long-term trends, quality parameters, and relation to processes such as groundwater recharge. In the domain of land, RS is capable of identifying different types of land use and land cover (LULC) classes. In the domain of agriculture, it can help identify different crops, phenology, and practices.

At the intersections of these domains, RS can be used to determine parameters relevant for irrigated agriculture, such as cropping patterns and potential yields, soil moisture, water logging, and salinisation or actual evapotranspiration (ETa) and water stress. As such, it can be useful to a multiplicity of stakeholders⁸, from decision-makers determining the management of water resources in an entire river basin, over the heads of regional irrigation systems, to individual farmers trying to reach decisions on how to most efficiently manage irrigation across their blocks and plots. The availability of historical remote sensing datasets is also a major advantage, as it enables retrospective assessments of irrigated agriculture over the past decade with good spatial and temporal resolutions, including changes in crop patterns, irrigation extent, crop water use, and vegetation conditions over time. Furthermore, the capacity to analyze past seasonal management under different agro-climatic circumstances can help to better forecast future solutions, especially taking into account the poorly known impacts of climate change.

How exactly remote sensing can be deployed in irrigated agriculture depends on the broad families of stakes that need to be addressed, on the interests of the people who are going to use the data produced, and on the scales at which analyses are conducted (cf. Fig 2). While it is hard to find RS data with a lot of added value for small farmers – at the daily, plot-level scale required – RS can provide valuable

⁸ The term "stakeholder" is used despite its potential colonialist connotations (Reed et al. 2024) as it is still the more current terminology, especially in operational contexts.

insights for data-backed decisions at the scales of irrigated perimeters and larger farming systems, for both managers and planners operating on seasonal or multi-annual levels.

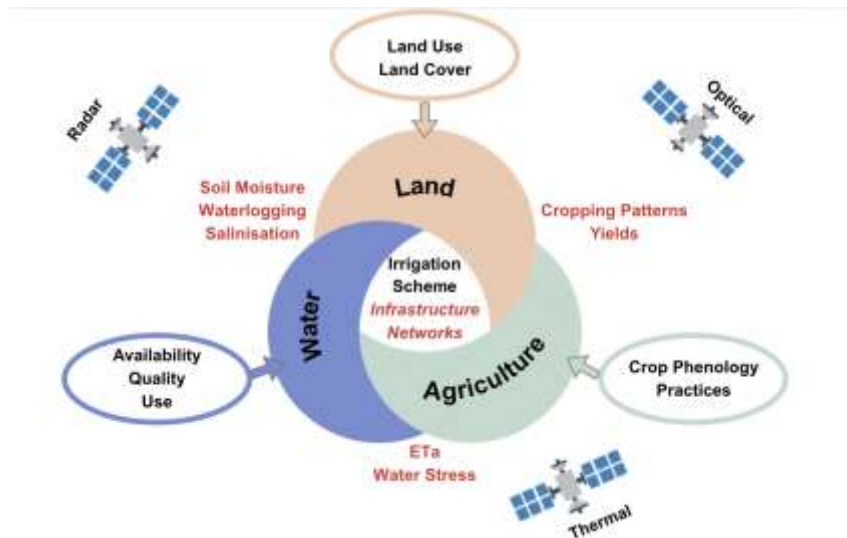


Figure 1: Overview of RS at the intersection of water, land, and agriculture.

For instance, from the perspective of irrigated scheme managers, expectations of the information RS can provide are mainly structured around three axes. The first concerns the dynamic mapping of irrigated and non-irrigated areas, which is essential for water resource management, agronomic decision-making, and addressing economic and environmental challenges. The second axis focuses on crop mapping and monitoring at the plot level, enabling yield estimation, improved water withdrawal management, input optimization, and monitoring of agricultural practices. The third need concerns the estimation of water use at the plot level through actual evapotranspiration, a key indicator for optimizing irrigation, managing crop water stress, and detecting potential anomalies in irrigation systems.

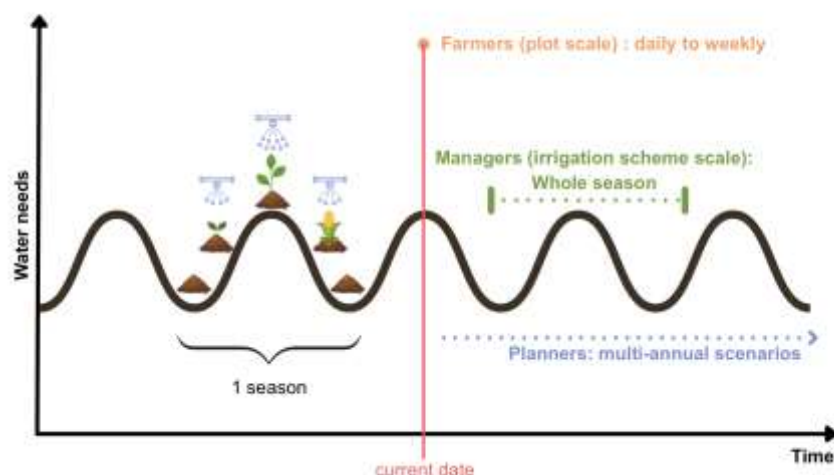


Figure 2: Spatial and temporal scales at which different stakeholders leverage RS for irrigation water management.

In general, RS provides useful quantitative measurements for assessing water stocks and fluxes, as well as a valuable tool for spatial pattern analysis, trend detection, and system-level diagnostics. This is particularly relevant for water governance and accounting concerns. Furthermore, qualitative indicators

are sometimes just as useful as quantitative ones – radar-based soil moisture tracking, for instance, has limited robustness but can be used to detect irrigation.

In terms of assessing water stocks and fluxes, numerous existing approaches harness RS to both identify reservoirs and other sources of irrigation water, and for water accounting. Both optical and SAR imagery is used to assess their surface extent while RS altimetry measurements can help analyse variations in the water levels of sufficiently large water bodies (cf. Orieschnig et al. 2022, Pekel et al. 2016, Zhan et al. 2026). Similarly, numerous studies use RS to provide insights into the type of irrigation deployed as well as the extent of irrigation schemes, the quantities of water used, and their distribution (e.g. Jalilvand et al. 2026, Peña-Arancibia et al. 2025). On a basin-wide scale, RS can also be used to better understand dynamics that will have significant effects on the future availability of irrigation water resources. For instance, it has been widely used to track the evolution of snow cover and glaciers, which gives critical insights to management agencies at the watershed level regarding the evolution of water resources during low-flow periods (e.g. Gascoin et al. 2019). Another major application area is the analysis of soil moisture via satellite products, which allows for both an understanding of how much water is currently available through soil storage in an agricultural system and, as this quantity evolves, how irrigation needs and applications change over time (cf. for instance Faridani et al. 2025, Huang et al. 2025).

Crucially in terms of fluxes, RS allows for an estimation of actual evapotranspiration (ETa). Optimal ETa retrieval from RS data can be obtained by combining simple water budget models, TIR-derived ETa information in the absence of clouds, and radar-derived information on irrigation occurrence or phenology (Crow et al. 2025). Systematic reviews have found that different models perform best in different situations and geographical contexts and that no single model consistently outperforms the others. It is also important to consider the uncertainties and varying accuracies associated with each model (cf. Tran et al. 2023). Yet RS products and methods are rarely accompanied by an estimate of their respective uncertainty. Nevertheless, remotely-sensed ETa estimates can still provide valuable bases for decision-making and further modelling approaches (cf. Fisher et al. 2026, Fisher et al. 2017). The latter, especially water balance models, also benefit from other remotely sensed parameters mentioned above as indirect inputs, such as precipitation estimates, snow cover, soil moisture, and LULC. Current trends are to use data-driven and ensemble models as well as increasingly hybrid approaches (combining AI and physical models) to compensate for the lack of a sound robust mechanistic framework. Combined surface energy balance models map ETa at the plot level and radar imagery maps soil moisture evolution and can inform irrigation timing.

On the side of harnessing RS for a better understanding of spatial patterns and trends, existing approaches use it to perform land use and land cover analyses, as well as to assess vegetation status, including crop type mapping, monitoring of the phenological cycle, and pinpointing water stress (cf. e.g. Jamshidi et al. 2021, Veloso et al. 2016). Recently, promising studies have leveraged multi-temporal methods and foundation models (cf. Ji et al 2018, Yin et al. 2025, Zhong et al. 2019). Beyond that, RS is invaluable when it comes to assessing irrigation performance⁹, equity and reliability, as well as to monitoring changes and anomalies (such as the expansion or contraction of irrigated areas as well as unintended or unauthorized irrigation, e.g. Fuentes et al. 2024). Furthermore, it sees applications in irrigated agriculture in both forecasting and early warning (e.g. drought and yield proxies), compliance and governance (e.g. abstraction control, water accounting), and infrastructure mapping or condition assessment (e.g. Zhao et al. 2025).

RECENT ADVANCES IN RS FOR IRRIGATED AGRICULTURE

Considerable advances over the past years have significantly enhanced the usefulness of remote sensing for irrigated agriculture.

⁹ See Bastiaanssen and Bos (1999) for an early review and Elshaikh, Jiao and Yang (2018) for a more recent summary.

As outlined above, both the general availability of NASA's Landsat archives and the ESA's Sentinel imagery have considerably facilitated the application of RS in irrigated agriculture. Beyond that, however, several recent and upcoming satellite missions provide promising data. Among recently-launched missions, the Surface Water and Ocean Topography (SWOT) by NASA and the Centre National des Études Spatiales (CNES, the French space agency), in partnership with the UK Space Agency and the Canadian Space Agency stands out, which has been providing altimetry data for water bodies since 2022 (Fu et al. 2024). Similarly, NISAR, launched in July 2025 by NASA and the Indian Space Research Organisation (ISRO), will soon be providing data on crops and soil moisture throughout the vegetation cycle at a 10-m resolution and 12-day revisit times thanks to its dual SAR sensors (Chowdhury 2024). Among upcoming missions, the ESA's Fluorescence Explorer (FLEX) will yield information about global plant health following its launch in September 2026 (Moreno 2022), while the TRISHNA mission (Gamet et al. 2023) will provide daily ETa and surface water stress estimates at less than 100m resolution. Furthermore, an increasing number of nano-satellites operated by private entities provide information to bridge the gap left by public ones, though pricing remains prohibitive for many users.

Another notable advance is the development of multi-sensor data fusion, which now makes it possible to combine information from optical, radar, and thermal satellites, thereby improving the robustness of analyses. So far, many people have tended to work on a single mission and to use it as a ubiquitous solution no matter its suitability for the analysis in questions. One of the major advantages of the ESA's Copernicus programme has been to foster multi-mission thinking, with numerous studies now combining Sentinel-1 and -2 images for applications such as LULC and surface water extent tracking (e.g. Bioresita et al. 2019, Orieschnig et al. 2022). Recent approaches further include data fusion with Sentinel-3 through machine learning to enhance ETa estimates (e.g. Guzinski et al. 2019).

In addition, deep learning approaches make it possible to better exploit the complexity of satellite signals while reducing dependence on large, perfectly labelled datasets. At the same time, cloud computing has become the new standard for many data-intensive RS applications in irrigated agriculture, with platforms such as Google Earth Engine (Gorelick et al. 2017) helping users streamline their computational efforts and accelerate and operationalise RS analyses.

Finally, there is also increasing hybridization between physical models and artificial intelligence, particularly for evapotranspiration estimation, with gains in performance and computational speeds (e.g. Fong et al. 2025, Hadadi, Moazenzadeh and Mohammadi 2022).

Despite its many upsides and recent positive developments, however, several limitations and challenges remain with respect to the use of RS in irrigated agriculture, as well as practical barriers to adoption.

LIMITATIONS, CHALLENGES, AND BARRIERS

One of the principal challenges of RS for the use in irrigated agriculture are the intrinsic limitations of different types of satellite data. Fundamentally, their spatial and temporal resolution are key factors to consider. For instance, even the moderately high temporal resolutions of Sentinel satellites may not be able to provide data at the frequency needed by individual farmers making decisions about the irrigation of their plots on a day-by-day basis (cf. Fig. 2). Similarly, optical data – which remain the most widely-used type of imagery – have serious restrictions in their use due to cloud cover. These limitations result in operational constraints, related to the need to produce fast, robust, and easily interpretable information, that can be neatly slotted into the workflows of decision-makers at appropriate times.

Complicating the situation is that agricultural systems are frequently complex and that results are contextually dependent, with approaches often having limited transferability. Methodologies and tools vary according to the objectives of the analyses to be carried out, the spatial configuration of the target area (climate zone, frequency of cloud cover, size of the farming systems etc.), the evolution of phenomena over time, the availability of ground-truth samples, among others. All these factors determine the choice of satellite, sensors, spatial and temporal resolutions, the constitution of ground-truth samples, as well as the pre-processing, processing, and post-processing required to obtain an

operational product for farmers and/or managers. Limitations arise mainly for very small, fragmented, or mixed plots, or for decisions requiring sub-plot heterogeneity, the development of drip or underground irrigation, which is not easily observable through RS, as well as practical barriers in the field. Regarding the latter, farmers often do not have the requisite skills to perform RS analyses, relying on free information or commercial services during their decision-making process instead. That process, though, is influenced by the type of irrigation system and resource access that they have – a farmer pumping from a borehole is largely autonomous, while others may be dependent on rotational access to shared water resources.

Another well-known limitation is the lack of ground reference data necessary to increase the accuracy of the RS analysis: on-site crop identification (and more generally a lack of information on poorly studied crop types), irrigation methods, water source, soil characteristics and contradictory yields estimations. While machine-learning and AI methods can reduce dependence on extensive field data (e.g. through transfer learning, weak supervision, or data fusion), they do not eliminate the need for independent validation, and may propagate biases if exogenous data errors are poorly understood. Integration of on-site sensors able to relay information on flows, precipitation and soil moisture can also provide near real-time data to be used as ground reference but their deployment needs a high investment cost that users can afford with difficulty and their maintenance poses further challenges.

Finally, one of the principal challenges and barriers to adoption is a lack of co-creation and knowledge transfer. While this is by no means a challenge unique to the application of RS in agriculture – it also applies to many digital decision-support systems, modelling tools, and innovation pathways – this structural innovation-governance problem is still important to mention in this context. Frequently, RS-based tools and solutions are being developed without explicitly taking into account the needs of stakeholders, or planning for the development of necessary training sessions, recorded tutorials, or informational materials (guidebooks, infographics etc.) to facilitate adoption. Even when such materials do exist, they are often written in a way that presupposes a level of RS knowledge exceeding that of the target audience, or they are not available in the language of the end users. A prime hurdle is also the lack of transparency with regard to accuracies and uncertainties, with the providers of RS-based datasets and tools using flags rather than overall accuracies, which can be difficult to understand and gauge for non-expert end users. To them differently-coloured pixels in an online map often do not provide actionable insights that are afforded by more easily applicable metrics. More generally speaking, the largest hurdle when it comes to knowledge transfers of RS-related products in irrigated agriculture is the lack of co-creation (cf. Castelli et al. 2025) in their development. In the vast majority of cases, tools, datasets, and even satellite missions are designed by a team of experts with scientific questions, political pressure, and economic framework conditions upmost on their minds. The on-the-ground needs, interests, and priorities of end-users are estimated at best, not taken into account at worst. It is rare that these actors are given a seat at the table during the conceptualisation or development phase. Instead, they are presented with a finished irrigation management tool or RS dataset and with an often-overwhelming amount of information about it. How it relates to their everyday needs or established irrigation practices is up to them to figure out. As a result, there is a considerable gap between the availability of information and tools leveraging RS for irrigation water management, and those farmers and irrigation scheme operators who integrate them into their daily activities.

OUTLOOK AND RECOMMENDATIONS

Overall, the salient points that emerged from the discussion above is the necessity of involving end-users in the co-creation of tools and even satellite missions, with their needs and data priorities considered from the start. Similarly, it is critical to keep them engaged throughout the process through participatory approaches as well as stake propagation. Collaboration with institutions such as local agricultural universities and local advisories can be a valuable stepping stone in bridging the gap with end users. To efficiently transform information into action, it is necessary to rely on a process of knowledge co-creation, rather than transfer, beginning in the earliest phases of the making of new tools, products, and missions.

On a similar note, it is especially important to promote awareness of the limitations and varying accuracies of RS applications in irrigated agriculture. This is particularly critical as various agencies are currently promoting the use of RS to assess the performance of irrigation operators and to evaluate the quality of their service. Others already use RS in water accounting and plan to expand its application. In this context of the institutionalization of data-driven decision making, the question of accuracy will be central when legal and financial decisions will be taken to evaluate the performance or the consumption of users. To end-users, RS solutions can easily appear as panaceas, especially when those end-users do not have the necessary training in the use of RS data and cannot contextualise the methods and approaches used.

Most critically, it is necessary to frame RS as an integrative component of data-oriented approaches in irrigated agriculture, rather than a universal solution. For instance, satellite data do not replace the necessary flow measurements within an irrigation system from the headworks to the plot: they are complementary and allow to show where water meters are missing. RS-based information must be integrated as a source to digital twins of hydraulic infrastructures completing metered data to enhance the operations of the system and lead to more efficient water management in a constructive loop. RS data can be a valuable puzzle piece in approaches integrating AI, ML, in-situ data, or the Internet of Things (IoT). Its principal value lies in making visible what was invisible before: estimates of the quantitative use of water resources in agriculture in space and time.

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