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## Open-access remote sensing data for cooperation in transboundary water management

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### ABSTRACT

Open-access remote sensing products provide data for transboundary water management. This study presents a comprehensive overview of the applications, uncertainties and implications of these remote sensing data products in the context of transboundary water management. Focusing on different stages within the transboundary cooperation continuum, we delineate the potential role and application of remote sensing data at the various stages of this cooperation. Despite the uncertainties and capacity requirements for data acquisition, processing and interpretation, we argue that remote sensing broadens opportunities to monitor, assess, forecast, track or validate compliance in transboundary basins, thereby challenging traditional notions of water data exclusivity.

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Remote sensing; transboundary water management; water conflict; cooperative water management; water data sharing

## Introduction

Sustainable development in transboundary basins requires cooperation and operational arrangement on water management among riparian states (Bernauer & Böhmelt, 2020; McCracken & Meyer, 2018; Yalew et al., 2021). Such cooperation requires data and information exchange across political and/or administrative boundaries. A ‘regular exchange of data and information’ between riparian states was outlined as a duty in the 1997 United Nations’ ‘Convention on the Law of the Non-Navigational Uses of International Watercourses’ (United Nations, 1997). In practice, however, only 30–50% of transboundary agreements in different continents include a direct mechanism for information sharing (Gerlak et al., 2011). The need for regular data and information exchange is again emphasized in the United Nations’ Sustainability Development Goals (SDGs) on transboundary water management (United Nations, 2015). Many transboundary basins, however, still lack operational arrangements for water cooperation and data-sharing mechanisms. As the sole indicator of transboundary water cooperation in SDG 6.5.2 considers the ‘Proportion of transboundary basin area with an operational

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arrangement for water cooperation' (United Nations, 2015). However, only a small number of countries reported that all their transboundary basins are covered by cooperation and data exchange arrangements with respect to the SDG 6.5.2 indicator (UNECE, 2021).

There are many cases where there is disagreement over data and models used for transboundary water management, as well as on the water availability and/or use in a basin (Heggy et al., 2021). Such disagreements can negatively influence negotiations and delay agreements over the management of shared waters. Assessment studies on transboundary basins sometimes present biased overviews based on the data and perspective of only one or two of the riparian countries (Uereyen & Kuenzer, 2019). Lack of timely and accurate data or lack of willingness to share it among riparian states – a major challenge for operational as well as strategic planning in transboundary water management – leads to suspicion, conflict and confrontation (Carius et al., 2004; Mianabadi et al., 2020).

In recent decades, information from remote sensing data has served as a complementary source of data for water management, thanks to improvements in remote sensing data coverage, accuracy and resolution. Sensors onboard satellites can now provide time-series of spatially distributed data that can be used to derive key hydrological variables such as rainfall (Beck et al., 2017; Stisen & Sandholt, 2010), evapotranspiration (ET) (Irmak, 2012; Zhang et al., 2016), changes in the water levels of lakes and rivers (Frappart et al., 2006; Morris & Gill, 1994), extent of lakes and reservoirs (Cai et al., 2016; Duan & Bastiaanssen, 2013; Gao, 2015; Pekel et al., 2016), and groundwater storage anomalies (Castellazzi et al., 2018; Sun, 2013). Continuing advancements in remote sensing technology and data acquisition as well as data assimilation approaches can therefore improve efforts to assess natural resources for conservation and sustainable water management.

More importantly, many of the remote sensing data or products are open access. These open-access data or products present an opportunity for supporting transboundary water management. While remote sensing data can be used for water resources management in general, its application for water management in transboundary basins may play an important role in addressing unique challenges such as data-sharing problems and regulation/compliance monitoring issues between riparian states. Furthermore, remote sensing challenges the exclusivity of transboundary water data by government bodies. The availability of such open-access remote sensing data to individual, non-governmental organisations (NGOs) and/or researchers accelerates the 'democratization' of water data (Craglia & Shanley, 2015). Nevertheless, it is important to recognize that the journey towards a complete data democracy can be obstructed by challenges such as power and resource imbalances, particularly in transboundary settings.

In this study, we offer an updated summary of the utilization of open-access remote sensing products for transboundary water management. We specifically focus on water bodies that span multiple sovereign nations, a context where such data are vital due to the absence of a unified authority enforcing data sharing. Our emphasis is on 'basins' as defined by the 1997 UN Watercourse Convention, which includes both surface water flows and underlying groundwater resources. We delve into the application of remote sensing-derived data through a review of the latest literature, highlighting key examples

of remote sensing-derived estimates of basic water balance components such as precipitation (P), evapotranspiration (E) and changes in water storage ( $\Delta S/\Delta t$ ). The study evaluates the applicability, accuracy and uncertainty associated with these remote sensing-derived data products and discusses their implications in fostering cooperation in transboundary water management. The study targets water experts, diplomats and other stakeholders involved in transboundary water challenges, aiming to bridge the gap between the technical understanding of remote sensing and its practical policy applications.

## Data needs and the role of remote sensing

Data needs for transboundary water management are essentially the same as any other basin except that the data acquisition across borders is often challenging. Data required for water management in general relate to applications such as estimation of the basin water balance, water budget or water accounting for deciding on water entitlements, the monitoring and management of floods and droughts, the monitoring of water quality and water pollution in particular, groundwater assessment, agricultural water management including irrigation water use assessment, and monitoring of ecological conditions. Some of the most important variables needed for estimating the above include data on water availability, stream flow, water abstractions, use and consumption from groundwater and surface water, water quality and groundwater recharge (Sheffield et al., 2018). Such data are often required at different spatial and temporal resolutions in different contexts. Short latencies or long time-series of data are required for various applications, such as long-term planning and infrastructure design, disaster forecasting and response or real-time operational management. In transboundary contexts, hydrological variables related to a water-sharing agreement (e.g., inflow to a country or water level in a specific reservoir) may require dedicated monitoring. Furthermore, water resources are also strongly linked with the management of land and other resources (Leb, 2020), and thus additional data such as land-use and land cover change, vegetation health, biomass accumulation and land degradation, are important data requirements.

Remote sensing provides the opportunity to directly or indirectly derive the data and information required to meet data needs on these and related hydrological components, such as precipitation, ET, water storage (surface/ground) and water level. Sheffield et al. (2018) provide a comprehensive description of the data required for water resources management, including data derived from remote sensing, *in-situ* measurements and modelling, and their limitations. In this section, we focus our review on existing information based on remote sensing-derived data from some of these major hydrological components required for water resources assessment in transboundary basins, including associated uncertainties.

### Precipitation

Precipitation is one of the primary hydrological variables in the water cycle. Ground-based measurements of rainfall (rain gauges) are often sparsely located. Satellite remote sensing has been used to estimate precipitation on the global scale, covering diverse areas of the Earth's surface, including deserts, high mountains and oceans which are infeasible

to monitor using conventional rain gauges or meteorological radars (Sun et al., 2018; Tian & Peters-Lidard, 2010). A continuous and open-access availability of precipitation datasets is an important criterion for transboundary water management. Only a few satellite precipitation products meet these criteria. These include GPM (Global Precipitation Measurement Mission), CHIRPS (Climate Hazards Group InfraRed Precipitation with Station), PERSIANN (Precipitation Estimation from Remotely Sensed Information using Artificial Neural Networks), CMORPH (Climate Morphing technique), and MSWEP (Multi-Source Weighted-Ensemble Precipitation). Passive microwave sensors, such as those on board the TRMM and GPM satellites, measure the natural microwave emissions from the Earth's surface and atmosphere. The detected microwave radiation is directly related to the temperature and moisture levels in the atmosphere, which can be used to estimate precipitation (Lettenmaier et al., 2015). Remote sensing is a valuable source of precipitation data, not only because it enables data gathering in areas where stations are sparse and unevenly distributed, but also because the low level of collaboration in most transboundary waters makes the collection of precipitation data more difficult, restricting a comprehensive understanding of hydrological processes in shared basins. It is also important to note that most remote sensing precipitation products are based on assimilation of satellite data and gauge data (Sheffield et al., 2018). While remote sensing data provide extensive coverage, gauge data offer localized accuracy. This synergy aims to maximize the strengths of both data types. However, in regions where gauge data are scarce or unavailable, the calibration and validation of remote sensing precipitation estimates may be compromised, potentially leading to larger errors in precipitation estimates (Gleason et al., 2018).

### ***Evapotranspiration (ET)***

ET is another primary component of the water cycle with important implications in transboundary river basins, particularly in the context of agricultural water management, such as for irrigation. It is one of the most important hydrological components, functioning as a water depletion mechanism, and its key role in moisture flux (Kalma et al., 2008; Srivastava et al., 2013). ET is often estimated indirectly using potential ET and a variety of land surface parameters derived from climatological data (Liou & Kar, 2014). Remote sensing-derived ET products primarily make use of thermal infrared and optical remote sensing data, in addition to climatological data, to estimate parameters such as land surface temperature and vegetation indices, which are incorporated into models like the surface energy balance and the Penman–Monteith equation to estimate ET (Bastiaanssen et al., 1998; Pelgrum et al., 2010). Direct measurements of ET are mainly based on a variety of complex measurements such as lysimeters and/or eddy covariance techniques (Ghiat et al., 2021). In addition to the limited utility of such measurements at local, field or landscape levels, their accessibility is also constrained (Ashouri et al., 2016; Singh et al., 2021). Some of the continuous and open-access ET products include SSEBop (Operational Simplified Energy Balance), MODIS (Moderate Resolution Imaging Spectroradiometer) ET, and WaPOR (Water Productivity through Open access of Remotely sensed derived data). Remote sensing data can be used to estimate actual ET of river basins (Gonzalez-

Dugo et al., 2009; Vinukollu et al., 2011; Zhang et al., 2016). Accurate ET data are essential to understand the water balance of a basin, to monitor and forecast droughts, as well as to estimate agricultural water consumption so as to improve the efficiency of irrigation systems.

### ***Surface water and groundwater storage***

The use of remote sensing data for surface and reservoir water detection, delineation and/or monitoring changes is an established practice in the literature (Bhangale et al., 2020; Bijeesh & Narasimhamurthy, 2020; Huang et al., 2018). Remote sensing data can be used to derive information on surface water levels using radar altimetry (Frappart et al., 2006; Morris & Gill, 1994), when combined with other datasets, volumes (Cai et al., 2016; Gao, 2015), and reservoir impoundment or water releases from reservoirs (Deng et al., 2020; Muala et al., 2014). Changes in surface water extent are often determined using time series of optical satellite data at various resolutions depending on the scale of application. The Global Surface Water Explorer (Pekel et al., 2016) is an example of the more recent open-access global datasets on surface water dynamics. Techniques such as the Synthetic Aperture Radar (SAR) are used for applications such as to determine inundation extents for mapping floods under cloudy conditions (e.g., Tarpanelli et al., 2022) and/or to detect variations in water levels of lakes, rivers and reservoirs, allowing researchers to indirectly infer changes in water storage (Brisco, 2015). The GRACE satellite system estimates groundwater changes by tracking variations in the Earth's gravitational field, a technique that enables indirect measurement of total terrestrial water storage, including groundwater, by assessing changes in the gravitational pull between twin satellites (Rodell et al., 2004; Wahr et al., 2004). This provides data on total water storage variations including surface water, snowpack, soil and groundwater (Tapley et al., 2004). Overall, remote sensing data can be used to detect and monitor changes in surface water bodies, such as the volume and surface area of lakes, groundwater recharge and storage.

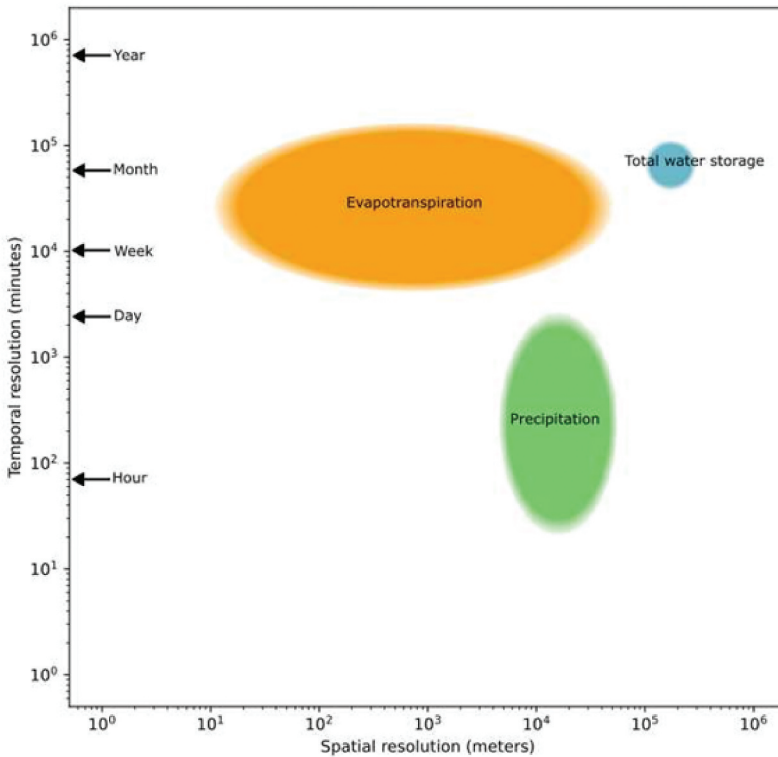
### ***Other remote sensing data***

In addition to the major hydrologic components often required for water budget assessment in river basins, remote sensing-derived data products are also applied for measuring other important components for basin water assessment, including snow cover, depth and/or snow water equivalent (Shi et al., 2016; Xu et al., 1993), soil moisture content (Mohanty et al., 2017), water level-derived streamflow (Michailovsky et al., 2012), and flood inundation extent and/or depth (Rosser et al., 2017). The application of remote sensing data for land-use/land-cover and soil characterization, important variables in most basin water assessment models, is a well-documented practice in the water resources literature (Brown et al., 2022; Gómez et al., 2016; Kussul et al., 2017; Pareeth et al., 2019). Other remote sensing applications include water pollution/water quality observation (Ritchie & Cooper, 2001; Wang & Yang, 2019), wetland assessment and monitoring (Munyati, 2000; Perennou et al., 2018), water productivity and/or water-use efficiency (Cai et al., 2013; Karimi et al., 2013), and biomass productivity (Qi et al., 2019).

## Uncertainties associated with remote sensing data

The availability of open-access and spatially and temporally continuous remote sensing data significantly aids in managing water resources, transboundary or otherwise. However, the quality of the varied remote sensing data products is subject to several factors. These include the spatial and temporal resolution of the data, the algorithms used in estimating variables, and the presence of ground-truth data that can be used for validation (Figure 1). In the context of transboundary basin agreements and practices, stakeholders have traditionally depended on conventionally collected hydrological data (Leb, 2020). This reliance often results in a certain level of resistance or scepticism towards adopting data from newer sources such as remote sensing. As such, it becomes imperative to offer accurate and thorough reporting on the uncertainties and error margins tied to remote sensing-derived data. Such information is particularly important when comparing the data's reliability with those sourced from conventional methods.

Remote sensing-based measurement and/or data can introduce several sources of errors during data acquisition, processing, analysis, conversion and presentation (McMillan et al., 2018; Tian & Peters-Lidard, 2010). Data processing errors in remote sensing occur during the initial stages of handling and refining raw data obtained from satellite sensors. These include radiometric errors (sensor inconsistencies, atmospheric effects or variations in surface reflection), geometric rectification errors (distortions in



**Figure 1.** Spatial and temporal resolution of remote sensing data products for major hydrologic components.

the spatial positioning of pixels in the image), and bias correction errors (systematic inaccuracies introduced by the sensor (Slater, 1985) or the processing chain (Povey & Grainger, 2015). Data analysis errors occur during the interpretation and evaluation of the processed data, which include classification errors, generalization errors, parametrization errors and data gaps (Mayr et al., 2019). For example, the data obtained from optical sensors are often contaminated by clouds (which can introduce radiometric errors) resulting in data gaps which for many applications are statistically filled (which can introduce data analysis errors; Siabi et al., 2022). These gap filling approaches can introduce uncertainties in the estimates depending on the geographical location and the ability of cloud-masking algorithms to accurately detect clouds (Foody, 2002). The undetected clouds and the cloud shadow after applying cloud masks are also a key source of uncertainties. Modelling based on remote sensing data can further introduce errors including on spatial and temporal representation and interpretation.

The remote sensing methods employed to estimate precipitation from spaceborne instruments are, for example, affected by both relative errors (difference between the remote sensing data estimate and ground observations) and uncertainties (range of values within which the estimated value lies with some level of confidence from the ground observation data; Massari & Maggioni, 2020). According to Massari and Maggioni (2020), the most common sources of uncertainty in remote sensing precipitation data are related to sampling uncertainty due to limited satellite overpasses, processing errors (parameter calibration, gap filling) and/or errors in the a priori databases. Such uncertainties are challenging to quantify, particularly over a large area in data-scarce regions, and remain largely unknown, limiting the usefulness of remote sensing precipitation data. Additionally, the inherent discrepancy between point-based gauge measurements and area-based (or pixel-based) remote sensing measurements presents another challenge. While gauge data provide precise measurements at specific locations, remote sensing data provide averaged measurements over a larger area (the pixel size). This fundamental difference can introduce additional uncertainties when comparing or combining these two types of data, and needs to be carefully considered in data analysis and interpretation. Some studies, however, report that satellite-derived products sometimes outperform gauge data during calibration of conceptual models (Awange et al., 2016; Stephens et al., 2022).

Uncertainties in ET products are mainly attributed to the discrepancies in the forcing datasets such as meteorological data, solar radiation, soil moisture stress and water storage changes (Ali et al., 2022). Furthermore, model structural limitations of the water and energy balances and vegetation processes can contribute to this (Jung et al., 2019). Although non-remote sensing-derived ET data generated with, for example, hydrological models are arguably equally uncertain and come with their own intrinsic flaws (Puy et al., 2022), it is still difficult to conduct a comprehensive and systematic evaluation of remote sensing-derived ET products due to limited ground data (Weerasinghe et al., 2020). The reported uncertainties of remote sensing ET data vary widely. For example, Velpuri et al. (2013) reported a mean uncertainty of up to 50% on point and 25% on basin scale ET, while Rodell et al. (2011) found that water budget-based estimates of monthly ET are often too large to be of use. Furthermore, Badgley et al. (2015) reported that choice of forcing data can produce up to 20% difference in global monthly mean ET, while Karimi and Bastiaanssen (2015) reported an overall 95%

accuracy on seasonal ET estimates from remote sensing-based models for a particular water accounting case.

With regard to water storage and groundwater data, uncertainties remain large. For example, while GRACE data are useful for tracking total water storage variations (Tapley et al., 2004), the coarse spatial and temporal resolutions – pixel sizes of roughly 300–400 km at approximately monthly scale – present a large uncertainty in total storage assessment (Long et al., 2014; Richey et al., 2015).

Overall, the level of accuracy of remote sensing data for water resources management depends on a variety of factors, including the specific data products being used and the methods employed to analyse and interpret the data. The main uncertainties generally depend on the spatial and temporal resolution of specific datasets, accuracy of the specific sensor, cloud cover and other atmospheric conditions, and data processing methods applied to the estimation or quantification of these datasets.

### **Opportunities and challenges of remote sensing data in transboundary cases**

As remote sensing data have become increasingly pivotal in transboundary water management over recent decades, it has begun to transform how data access is viewed. This non-exclusive open-access data encourage broad participation, allowing various stakeholders such as NGOs, academics and individuals to join in the process of data analysis and decision-making. As it does not allow a single riparian country to monopolize, it provides opportunities to foster an inclusive and cooperative attitude towards water management. The realization of this potential, however, hinges on adequate internet access, suitable infrastructure, and the ability to process and interpret this data, highlighting the need for capacity-building in this regard.

Besides the data required for water resources management in general, such as for water budget assessment ( $P$ ,  $ET$ ,  $\Delta S/\Delta t$ ) as described above, remote sensing data have the potential to support cooperation in transboundary basin management. As described by Sadoff and Grey (2002, 2005), the process of cooperation in transboundary river basin can be represented as a continuum framework, from unilateral action/dispute to coordination, collaboration and joint action/integration (Figure 2). In this ‘Continuum of Cooperation’, the initiation of cooperation, that is, the transition from unilateral action towards cooperation can involve information sharing and regional assessments of water resources. Then a transition from cooperation to collaboration can involve converging national agendas in adapting plans to mitigate regional costs or to capture regional gains as well as joint preparation and investment. Finally, a transition from joint collaboration to joint action can involve joint equity ownership of assets, institutions and/or project design and assessment.

In situations where cooperation is just starting, for example, remote sensing data and applications such as general precipitation assessment and ET mapping and monitoring (Figure 2, left side) are more relevant. For example, in the case of the Mekong basin, which is shared by six countries in Southeast Asia, cooperation has progressed to the stage of joint management through the establishment of the Mekong River Commission (MRC) to coordinate and manage the shared water resources (Hensengerth, 2009). In such cases, remote sensing data can be used to



changes in ecosystem health and biodiversity. As cooperation strengthens in transboundary basins, remote sensing data can play a crucial role in enforcing compliance with water agreements and conservation measures, providing open-access and spatially distributed data to support equitable resource management and conflict resolution.

It is important to note, however, that the stages or phases of cooperation outlined in [Figure 2](#) are not necessarily sequential and may not necessarily be achieved by all transboundary river basins. Furthermore, the level of cooperation among countries can vary depending on a variety of factors, including the level of conflict or political tensions between the countries, the level of trust between them, and the availability of resources for cooperation (Martin et al., 2011).

A wide range of remote sensing applications for transboundary water management exist in the literature ([Table 1](#)). Some of these applications involve, for example, the use of remote sensing data for monitoring compliance of transboundary agreements (Bretreger et al., 2021), water level of reservoirs and rivers (Biancamaria et al., 2011; Seyler et al., 2008), flood inundation modelling and forecasting (Amarnath et al., 2016; Dubey et al., 2021), and monitoring and assessment of transboundary aquifer storage changes (Fallatah et al., 2017; Voss et al., 2013). Further applications include monitoring of land cover change (Khoshnoodmotlagh et al., 2020; Schulte to Bühne et al., 2017).

Overall, remote sensing data can be a valuable source of information for transboundary water management, as it provides timely and cost-effective data over large areas on various hydrological, meteorological and land cover variables. Existing earth observation and remote sensing based geospatial decision support systems on transboundary basins, for example, SERVIR tools (SERVIR-Amazonia, 2023; SERVIR-Mekong, 2023), part of the SERVIR-Global initiative (Flores et al., 2018), provide valuable information for water resources management for riparian states beyond their political border, thereby presenting viable alternatives whenever on-ground observations are lacking or unavailable. The SERVIR-Mekong decision support tools, for example, enable the MRC and its member states monitor flood and drought for decision-making and planning processes in the

**Table 1.** Studies on remote sensing applications in transboundary basins (note that the colour shade the message conveyed in [Figure 2](#)).

Broad categories	Applications	References
Monitoring	Water level of reservoirs	Gao (2015); Muala et al. (2014); Seyler et al. (2008)
	Water level of rivers	Biancamaria et al. (2011); Hossain et al. (2013)
	Reservoir operation rules (construction/filling of dams), monitoring	Muala et al. (2014); Eldardiry and Hossain (2019); Kim et al. (2022); Das et al. (2022)
	Pollution/water quality	Ritchie and Cooper (2001); Wang and Yang (2019)
	Wetland/environmental/ecological flow	Munyati (2000); Perennou et al. (2018)
Assessment	Water use/consumption estimation/efficiency, e.g., irrigation	Bretreger et al. (2022); Akbari and Torabi Haghighi (2022)
	Water resources assessment/water accounting/water budget	Karimi et al. (2013); Kumar et al. (2022); Chen et al. (2021)
	Storage change of transboundary aquifers	Voss et al. (2013); Fallatah et al. (2017); Khaki and Awange (2019)
Forecasting	Water productivity, water use efficiency, net primary productivity	Karimi et al. (2013); Cai et al. (2013); Qi et al. (2019)
	Flood forecasting	Dubey et al. (2021); Biancamaria et al. (2011)
Compliance	Drought forecasting	Zhang et al. (2020); Das et al. (2022)
	Enforcement of transboundary water agreement/regulation	Merem and Twumasi (2008); Ragettli et al. (2017); Bretreger et al. (2021)

Mekong basin (Das et al., 2022). Remote sensing data can cover large areas at relatively high spatial resolutions; some satellite sensors can provide estimates of P and ET at resolutions as fine as 1 km or less, much finer than the resolution of most ground-based weather stations. Therefore, remote sensing data can provide spatially distributed information of areas where most of the water is generated and of those locations where most of the water is consumed. On the other hand, temporal resolution of P can be as high as 3 hourly and near real time, which provides opportunity in establishing flood and drought forecasting models at basin level. This information can be compared with existing plans and agreements on water allocation and use among countries and competing sectors.

Using remote sensing data in models and frameworks such as the WA+ (water accounting plus; Karimi et al., 2013), for example, one can further produce an assessment of water resources availability and use, as well as evaluate the impact of future development plans in transboundary basins. Furthermore, open-access remote sensing data supports transparency and allows for re-examinability of data and information compared with traditional measurements: in case of disagreements on assessment results, riparian states can reprocess the raw data retroactively and examine the results. The characteristics of remote sensing data are therefore instrumental for establishing a dialogue in transboundary water management. The evaluation of remote sensing data, the assessment of its accuracy and related uncertainty can therefore be joint processes to foster such a dialogue. Furthermore, while countries may occasionally contest the validity and accuracy of remote sensing data, its universally accessible nature fosters non-governmental cooperation in transboundary water management, even regardless of formal governmental consensus.

While generally cost-effectiveness, wide and repeatable coverage, and reasonably favourable accuracy make remote sensing data valuable sources of environmental data (Zhang et al., 2016), challenges related to consistency under diverse conditions, and limited availability of calibration and validation datasets remain important (Bhattarai & Wagle, 2021). Furthermore, the presence of open-access remote sensing data does not automatically mean that they will be used for transboundary water management. Cooperation in transboundary water management is also influenced by other considerations such as differences in legal frameworks, historical practices, technical abilities, and cultural backgrounds (Ibrahim, 2020; Timmerman & Langaas, 2005).

Besides the more measurable aspects of uncertainty related to remote sensing data which can be very large in some products and cases, however, there is also scepticism and perceived uncertainty associated with the utility of remote sensing data (Povey & Grainger, 2015). *In-situ* data, which, while also subject to errors and uncertainties, tend to be regarded as 'truth'. However, it is important to note that there is no agreed convention to systematically report uncertainty when reporting hydrological data even when using *in-situ* data. Furthermore, the level of error or uncertainty in remote sensing data is location and climatic zone specific (Awange et al., 2016; Zhang et al., 2016). The same data product may perform badly in some location but may give good validation results elsewhere. Perceptions, however, can pose further challenges towards the uptake of some remote sensing data in transboundary water management.

The impact of uncertainty of remote sensing products in transboundary basins depends on the position of riparian states in the cooperation process. Under low cooperation condition, for example, any error can be politicized or, even worse, remote

sensing data can be used to mislead the public opinion (e.g., the ‘water panic’ in Wheeler et al. (2020, p. 6) ‘people feel losses much more acutely than gains of comparable size’; and they ‘feel water losses more acutely than they do losses of almost any other commodity’). It is, therefore, important that transboundary water management practitioners understand which remote sensing products are most appropriate for their situation and also identify the most important remote sensing data uncertainties. Notwithstanding the many promising potentials outlined earlier, remote sensing data may not be sufficient on its own for transboundary water management, as it does not provide detailed information about the physical, chemical and biological characteristics of water resources. Furthermore, it also lacks information on various social and hydro-political drivers in a shared basin. Remote sensing data are, therefore, likely to remain a complementary product in the near future, not least due to inaccuracy (real and/or perceived), uncertainty, limited validation datasets, and difficulty to rely on remote sensing data with respect to cloud cover and other atmospheric interferences. Ongoing research on technologies such as the SAR (Brisco, 2015), which can ‘see through’ clouds, aims to detect variations in the water levels of lakes, rivers and reservoirs. This could indirectly improve the estimation of remote sensing-derived hydrological components such as changes in water storage.

The human capacity for remote sensing data gathering, processing, analysing and storing information on shared waters is another challenge and could be a key priority for riparian states to develop (a certain level of) confidence in remote sensing data itself. This could, in turn, help to facilitate dialogue and promote joint factfinding in situations where remote sensing data give rise to unexpected, surprising, differing or even conflicting interpretations. Since remote sensing is capable of providing information about water use across political borders, it may be, and has been, perceived as a potential security concern because it enables the observation of water use in neighbouring countries. Ironically, and perhaps surprisingly, this may also create a new motivation for riparian states to share conventional (ground-observed) data. In any case, riparian states should ideally have an interest in building and maintaining strong technical capacity and competence in collecting, validating, interpreting and critically assessing data derived from remote sensing to be able to interrogate and corroborate any application with an impact on their shared waters. Such interrogation and corroboration of remote sensing data, including the assessment of its accuracy and related uncertainty, can be joint processes. This collaboration could ideally foster further dialogue on transboundary water management. Strengthening and promoting inter-institute and/or inter-university cooperation on remote sensing applications in specific transboundary river basins could prepare the grounds for a more formal intergovernmental transboundary cooperation on a more robust application of remote sensing data for transboundary water management.

## Conclusions

The increasing availability of open-access, timely remote sensing data presents an opportunity for water resources management in general. Such data are particularly useful for addressing unique transboundary water assessment challenges such as data-sharing and monitoring of compliance to transboundary water allocation agreements. Remote

sensing data complements existing models and could encourage riparian states to share conventional data, knowing other states may use these datasets.

The primary challenges to remote sensing data use in transboundary water management involve uncertainty, data collection and processing capacity, and other considerations such as legal and political perspectives. Despite its great potential for transboundary water management, the role of remote sensing data will most likely remain limited to a complementary one due to these challenges.

Despite this, remote sensing data present a real opportunity for transboundary basin management, particularly in data-scarce regions. However, for such an opportunity to materialize, it presupposes a strong technical capability for validating, interpreting and critically assessing remote sensing data on shared waters. It is thus in the interest of riparian states to build strong technical capacity and competence in remote sensing to be able to apply, interrogate and corroborate any application with an implication on their shared waters.

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## References

- Akbari, M., & Torabi Haghighi, A. (2022). Satellite-based agricultural water consumption assessment in the ungauged and transboundary Helmand basin between Iran and Afghanistan. *Remote Sensing Letters*, 13(12), 1236–1248.
- Ali, S., Wang, Q., Liu, D., Fu, Q., Rahaman, M. M., Faiz, M. A., & Cheema, M. J. M. (2022). Estimation of spatio-temporal groundwater storage variations in the lower transboundary Indus basin using grace satellite. *Journal of Hydrology*, 605, 127315. <https://doi.org/10.1016/j.jhydrol.2021.127315>
- Amarnath, G., Alahacoon, N., Gismalla, Y., Mohammed, Y., Sharma, B. R., & Smakhtin, V. (2016). Increasing early warning lead time through improved transboundary flood forecasting in the gash river basin, Horn of Africa. In T. E. Adams & T. C. Pagano (Eds.), *Flood forecasting* (pp. 183–200). Academic Press.
- Ashouri, H., Nguyen, P., Thorstensen, A., Hsu, K.-L., Sorooshian, S., & Braithwaite, D. (2016). Assessing the efficacy of high-resolution satellite-based PERSIANN-CDR precipitation product in simulating streamflow. *Journal of Hydrometeorology*, 17(7), 2061–2076.
- Awange, J. L., Ferreira, V. G., Forootan, E., Andam-Akorful, S., Agutu, N. O., & He, X. (2016). Uncertainties in remotely sensed precipitation data over Africa. *International Journal of Climatology*, 36(1), 303–323.
- Badgley, G., Fisher, J. B., Jiménez, C., Tu, K. P., & Vinukollu, R. (2015). On uncertainty in global terrestrial evapotranspiration estimates from choice of input forcing datasets. *Journal of Hydrometeorology*, 16(4), 1449–1455. <https://doi.org/10.1175/JHM-D-14-0040.1>
- Bastiaanssen, W. G., Menenti, M., Feddes, R. A., & Holtslag, A. A. M. (1998). A remote sensing surface energy balance algorithm for land (SEBAL) 1. Formulation. *Journal of Hydrology*, 212, 198–212. [https://doi.org/10.1016/S0022-1694\(98\)00253-4](https://doi.org/10.1016/S0022-1694(98)00253-4)

- Beck, H. E., Vergopolan, N., Pan, M., Levizzani, V., Van Dijk, A. I., Weedon, G. P., Brocca, L., Pappenberger, F., Huffman, G. J., & Wood, E. F. (2017). Global-scale evaluation of 22 precipitation datasets using gauge observations and hydrological modeling. *Hydrology and Earth System Sciences*, 21(12), 6201–6217.
- Bernauer, T., & Böhmelt, T. (2020). International conflict and cooperation over freshwater resources. *Nature Sustainability*, 3(5), 350–356.
- Bhangale, U., More, S., Shaikh, T., Patil, S., & More, N. (2020). Analysis of surface water resources using Sentinel-2 imagery. *Procedia Computer Science*, 171, 2645–2654. <https://doi.org/10.1016/j.procs.2020.04.287>
- Bhattacharai, N., & Wagle, P. (2021). Recent advances in remote sensing of evapotranspiration. *Remote Sensing*, 13(21), 4260. <https://doi.org/10.3390/rs13214260>
- Biancamaria, S., Hossain, F., & Lettenmaier, D. P. (2011). Forecasting transboundary river water elevations from space. *Geophysical Research Letters*, 38(11). <https://doi.org/10.1029/2011GL047290>
- Bijeesh, T., & Narasimhamurthy, K. (2020). Surface water detection and delineation using remote sensing images: A review of methods and algorithms. *Sustainable Water Resources Management*, 6(4), 1–23.
- Bretreger, D., Yeo, I. Y., & Hancock, G. (2022). Quantifying irrigation water use with remote sensing: Soil water deficit modelling with uncertain soil parameters. *Agricultural Water Management*, 260, 107299. <https://doi.org/10.1016/j.agwat.2021.107299>
- Bretreger, D., Yeo, I. Y., Kuczera, G., & Hancock, G. (2021). Remote sensing's role in improving transboundary water regulation and compliance: The Murray-Darling basin, Australia. *Journal of Hydrology X*, 13, 100112. <https://doi.org/10.1016/j.hydroa.2021.100112>
- Brisco, B. (2015). Mapping and monitoring surface water and wetlands with synthetic aperture radar. In *Remote sensing of wetlands: Applications and advances* (pp. 119–136).
- Brown, C. F., Brumby, S. P., Guzder-Williams, B., Birch, T., Hyde, S. B., Mazzariello, J., Czerwinski, W., Pasquarella, V. J., Haertel, R., Ilyushchenko, S., Schwehr, K., Weisse, M., Stolle, F., Hanson, C., Guinan, O., Moore, R., & Tait, A. M. (2022). Dynamic world, Near real-time global 10 m land use land cover mapping. *Scientific Data*, 9(1), 251. <https://doi.org/10.1038/s41597-022-01307-4>
- Bruckmann, L., Delbart, N., Descroix, L., & Bodian, A. (2022). Recent hydrological evolutions of the Senegal River flood (West Africa). *Hydrological Sciences Journal*, 67(3), 385–400. <https://doi.org/10.1080/02626667.2021.1998511>
- Cai, X., Feng, L., Hou, X., & Chen, X. (2016). Remote sensing of the water storage dynamics of large lakes and reservoirs in the Yangtze river basin from 2000 to 2014. *Scientific Reports*, 6(1), 1–9. <https://doi.org/10.1038/srep36405>
- Cai, X., Molden, D., Mainuddin, M., Sharma, B., Ahmad, M.-U.-D., & Karimi, P. (2013). Producing more food with less water in a changing world: Assessment of water productivity in 10 major river basins. In M. Fisher & S. Cook (Eds.), *Water, food and poverty in river basins* (pp. 290–310). Routledge.
- Carius, A., Dabelko, G. D., & Wolf, A. T. (2004). Water, conflict, and cooperation. *Environmental Change and Security Project Report*, 10, 60–66.
- Castellazzi, P., Longuevergne, L., Martel, R., Rivera, A., Brouard, C., & Chaussard, E. (2018). Quantitative mapping of groundwater depletion at the water management scale using a combined Grace/InSAR approach. *Remote Sensing of Environment*, 205, 408–418. <https://doi.org/10.1016/j.rse.2017.11.025>
- Chen, T., Song, C., Ke, L., Wang, J., Liu, K., & Wu, Q. (2021). Estimating seasonal water budgets in global lakes by using multi-source remote sensing measurements. *Journal of Hydrology*, 593, 125781. <https://doi.org/10.1016/j.jhydrol.2020.125781>
- Craglia, M., & Shanley, L. (2015). Data democracy—increased supply of geospatial information and expanded participatory processes in the production of data. *International Journal of Digital Earth*, 8(9), 679–693. <https://doi.org/10.1080/17538947.2015.1008214>
- Das, P., Hossain, F., Khan, S., Biswas, N. K., Lee, H., Piman, T., Meechaiya, C., Ghimire, U., & Hosen, K. (2022). Reservoir assessment tool 2.0: Stakeholder driven improvements to satellite

- remote sensing-based reservoir monitoring. *Environmental Modelling and Software*, 157, 105533. <https://doi.org/10.1016/j.envsoft.2022.105533>
- Deng, X., song, C., Liu, K., Ke, L., Zhang, W., Ma, R., Zhu, J., & Wu, Q. (2020). Remote sensing estimation of catchment-scale reservoir water impoundment in the upper Yellow river and implications for river discharge alteration. *Journal of Hydrology*, 585, 124791. <https://doi.org/10.1016/j.jhydrol.2020.124791>
- Dinh, K. D., Anh, T. N., Nguyen, N. Y., Bui, D. D., & Srinivasan, R. (2020). Evaluation of grid-based rainfall products and water balances over the Mekong river basin. *Remote Sensing*, 12(11), 1858. <https://doi.org/10.3390/rs12111858>
- Duan, Z., & Bastiaanssen, W. (2013). Estimating water volume variations in lakes and reservoirs from four operational satellite altimetry databases and satellite imagery data. *Remote Sensing of Environment*, 134, 403–416. <https://doi.org/10.1016/j.rse.2013.03.010>
- Dubey, A. K., Kumar, P., Chembolu, V., Dutta, S., Singh, R. P., & Rajawat, A. S. (2021). Flood modeling of a large transboundary river using WRF-Hydro and microwave remote sensing. *Journal of Hydrology*, 598, 126391. <https://doi.org/10.1016/j.jhydrol.2021.126391>
- Eldardiry, H., & Hossain, F. (2019). Understanding reservoir operating rules in the transboundary Nile river basin using macroscale hydrologic modeling with satellite measurements. *Journal of Hydrometeorology*, 20(11), 2253–2269. <https://doi.org/10.1175/JHM-D-19-0058.1>
- Fallatah, O. A., Ahmed, M., Save, H., & Akanda, A. S. (2017). Quantifying temporal variations in water resources of a vulnerable middle eastern transboundary aquifer system. *Hydrological Processes*, 31(23), 4081–4091. <https://doi.org/10.1002/hyp.11285>
- Flores, A., Coulter, D. S., Limaye, A. S., & Irwin, D. (2018). SERVIR: Connecting Earth observation satellite data to local science applications. In K. Vadrevu, T. Ohara, & C. Justice (Eds.), *Land-atmospheric research applications in South and Southeast Asia* (pp. 31–44). [https://doi.org/10.1007/978-3-319-67474-2\\_2](https://doi.org/10.1007/978-3-319-67474-2_2)
- Foody, G. M. (2002). Status of land cover classification accuracy assessment. *Remote Sensing of Environment*, 80(1), 185–201. [https://doi.org/10.1016/S0034-4257\(01\)00295-4](https://doi.org/10.1016/S0034-4257(01)00295-4)
- Frappart, F., Calmant, S., Cauhopé, M., Seyler, F., & Cazenave, A. (2006). Preliminary results of ENVISAT RA-2-derived water levels validation over the Amazon basin. *Remote Sensing of Environment*, 100(2), 252–264. <https://doi.org/10.1016/j.rse.2005.10.027>
- 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. <https://doi.org/10.1002/wat2.1065>
- Gerlak, A. K., Lautze, J., & Giordano, M. (2011). Water resources data and information exchange in transboundary water treaties. *International Environmental Agreements: Politics Law and Economics*, 11(2), 179–199.
- Ghiat, I., Mackey, H. R., & Al-Ansari, T. (2021). A review of evapotranspiration measurement models, techniques and methods for open and closed agricultural field applications. *Water*, 13(18), 2523. <https://doi.org/10.3390/w13182523>
- Gleason, C. J., Wada, Y., & Wang, J. (2018). A hybrid of optical remote sensing and hydrological modeling improves water balance estimation. *Journal of Advances in Modeling Earth Systems*, 10(1), 2–17. <https://doi.org/10.1002/2017MS000986>
- Gómez, C., White, J. C., & Wulder, M. A. (2016). Optical remotely sensed time series data for land cover classification: A review. *ISPRS Journal of Photogrammetry and Remote Sensing*, 116, 55–72. <https://doi.org/10.1016/j.isprsjprs.2016.03.008>
- Gonzalez-Dugo, M., Neale, C., Mateos, L., Kustas, W., Prueger, J., Anderson, M., & Li, F. (2009). A comparison of operational remote sensing-based models for estimating crop evapotranspiration. *Agricultural and Forest Meteorology*, 149(11), 1843–1853. <https://doi.org/10.1016/j.agrformet.2009.06.012>
- Heggy, E., Sharkawy, Z., & Abotalib, A. Z. (2021). Egypt's water budget deficit and suggested mitigation policies for the Grand Ethiopian Renaissance Dam filling scenarios. *Environmental Research Letters*, 16(7), 74022. <https://doi.org/10.1088/1748-9326/ac0ac9>
- Hensengerth, O. (2009). Transboundary river cooperation and the regional public good: The case of the Mekong river. *Contemporary Southeast Asia*, 326–349.

- Hossain, F., Siddique-E-Akbor, A. H., Mazumder, L. C., ShahNewaz, S. M., Biancamaria, S., Lee, H., & Shum, C. K. (2013). Proof of concept of an altimeter-based river forecasting system for transboundary flow inside Bangladesh. *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing*, 7(2), 587–601. Retrieved January 30, 2023, from <https://servir.ciat.cgiar.org/service-areas/#water>
- Huang, C., Chen, Y., Zhang, S., & Wu, J. (2018). Detecting, extracting, and monitoring surface water from space using optical sensors: A review. *Reviews of Geophysics*, 56(2), 333–360. <https://doi.org/10.1029/2018RG000598>
- Ibrahim, I. A. (2020). Legal implications of the use of big data in the transboundary water context. *Water Resources Management*, 34(3), 1139–1153. <https://doi.org/10.1007/s11269-020-02491-x>
- Irmak, A. (2012). *Evapotranspiration: Remote sensing and modeling*. IntechOpen.
- Jung, H. C., Getirana, A., Arsenault, K. R., Holmes, T. R., & McNally, A. (2019). Uncertainties in evapotranspiration estimates over West Africa. *Remote Sensing*, 11(8), 892. <https://doi.org/10.3390/rs11080892>
- 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. <https://doi.org/10.1007/s10712-008-9037-z>
- Karimi, P., & Bastiaanssen, W. G. (2015). Spatial evapotranspiration, rainfall and land use data in water accounting—Part 1: Review of the accuracy of the remote sensing data. *Hydrology and Earth System Sciences*, 19(1), 507–532. <https://doi.org/10.5194/hess-19-507-2015>
- Karimi, P., Bastiaanssen, W. G., Molden, D., & Cheema, M. J. M. (2013). Basin-wide water accounting based on remote sensing data: An application for the Indus basin. *Hydrology and Earth System Sciences*, 17(7), 2473–2486. <https://doi.org/10.5194/hess-17-2473-2013>
- Khaki, M., & Awange, J. (2019). Improved remotely sensed satellite products for studying Lake Victoria's water storage changes. *Science of the Total Environment*, 652, 915–926. <https://doi.org/10.1016/j.scitotenv.2018.10.279>
- Khoshnoodmotlagh, S., Verrelst, J., Daneshi, A., Mirzaei, M., Azadi, H., Haghighi, M., Hatamimanesh, M., & Marofi, S. (2020). Transboundary basins need more attention: Anthropogenic impacts on land cover changes in Aras River basin, monitoring and prediction. *Remote Sensing*, 12(20), 3329. <https://doi.org/10.3390/rs12203329>
- Kim, J. G., Kang, B., & Kim, S. (2022). Flood inflow estimation in an ungauged simple serial cascade of reservoir system using Sentinel-2 multi-spectral imageries: A case study of Imjin River, South Korea. *Remote Sensing*, 14(15), 3699. <https://doi.org/10.3390/rs14153699>
- Kumar, N., Singh, S. K., Singh, P. K., Gautam, D. K., Patle, P., Pandey, H. K., & Chauhan, P. (2022). Water accounting of a trans-boundary river basin using satellite observations and WA+ framework. *Physics and Chemistry of the Earth, Parts A/B/C*, 129, 103343. <https://doi.org/10.1016/j.pce.2022.103343>
- Kussul, N., Lavreniuk, M., Skakun, S., & Shelestov, A. (2017). Deep learning classification of land cover and crop types using remote sensing data. *IEEE Geoscience and Remote Sensing Letters*, 14(5), 778–782. <https://doi.org/10.1109/LGRS.2017.2681128>
- Leb, C. (2020). Data innovations for transboundary freshwater resources management: Are obligation related to information sharing exchange still needed? *Brill Research Perspectives in International Law*, 4(4), 3–78. <https://doi.org/10.1163/23529369-12340016>
- Lettenmaier, D. P., Alsdorf, D., Dozier, J., Huffman, G. J., Pan, M., & Wood, E. F. (2015). Inroads of remote sensing into hydrologic science during the WRR era. *Water Resources Research*, 51(9), 7309–7342. <https://doi.org/10.1002/2015WR017616>
- Liou, Y.-A., & Kar, S. K. (2014). Evapotranspiration estimation with remote sensing and various surface energy balance algorithms—A review. *Energies*, 7(5), 2821–2849. <https://doi.org/10.3390/en7052821>
- Long, D., Longuevergne, L., & Scanlon, B. R. (2014). Uncertainty in evapotranspiration from land surface modeling, remote sensing, and GRACE satellites. *Water Resources Research*, 50(2), 1131–1151. <https://doi.org/10.1002/2013WR014581>
- Martin, A., Rutagarama, E., Cascao, A., Gray, M., & Chhotray, V. (2011). Understanding the co-existence of conflict and cooperation: Transboundary ecosystem management in the

- Virunga Massif. *Journal of Peace Research*, 48(5), 621–635. <https://doi.org/10.1177/0022343311412410>
- Massari, C., & Maggioni, V. (2020). Error and uncertainty characterization. In V. Levizzani, C. Kidd, D. B. Kirschbaum, C. D. Kummerow, K. Nakamura, & F. J. Turk (Eds.), *Satellite precipitation measurement: Volume 2* (pp. 515–532). Springer.
- Mayr, S., Kuenzer, C., Gessner, U., Klein, I., & Rutzinger, M. (2019). Validation of earth observation time-series: A review for large-area and temporally dense land surface products. *Remote Sensing*, 11(22), 2616. <https://doi.org/10.3390/rs11222616>
- McCracken, M., & Meyer, C. (2018). Monitoring of transboundary water cooperation: Review of sustainable development goal indicator 6.5. 2 methodology. *Journal of Hydrology*, 563, 1–12. <https://doi.org/10.1016/j.jhydrol.2018.05.013>
- McMillan, H. K., Westerberg, I. K., & Krueger, T. (2018). Hydrological data uncertainty and its implications. *Wiley Interdisciplinary Reviews: Water*, 5(6), e1319. <https://doi.org/10.1002/wat2.1319>
- Merem, E. C., & Twumasi, Y. A. (2008). Using spatial information technologies as monitoring devices in international watershed conservation along the Senegal river basin of West Africa. *International Journal of Environmental Research and Public Health*, 5(5), 464–476. <https://doi.org/10.3390/ijerph5050464>
- Mianabadi, A., Davary, K., Mianabadi, H., & Karimi, P. (2020). International environmental conflict management in transboundary river basins. *Water Resources Management*, 34(11), 3445–3464. <https://doi.org/10.1007/s11269-020-02576-7>
- Michailovsky, C. I., McEnnis, S., Berry, P., Smith, R., & Bauer-Gottwein, P. (2012). River monitoring from satellite radar altimetry in the Zambezi river basin. *Hydrology and Earth System Sciences*, 16(7), 2181–2192. <https://doi.org/10.5194/hess-16-2181-2012>
- Mohammed, I. N., Bolten, J. D., Srinivasan, R., & Lakshmi, V. (2018). Satellite observations and modeling to understand the lower Mekong river basin streamflow variability. *Journal of Hydrology*, 564, 559–573. <https://doi.org/10.1016/j.jhydrol.2018.07.030>
- Mohanty, B. P., Cosh, M. H., Lakshmi, V., & Montzka, C. (2017). Soil moisture remote sensing: State-of-the-science. *Vadose Zone Journal*, 16(1), 1–9. <https://doi.org/10.2136/vzj2016.10.0105>
- Morris, C. S., & Gill, S. K. (1994). Variation of great lakes water levels derived from Geosat altimetry. *Water Resources Research*, 30(4), 1009–1017. <https://doi.org/10.1029/94WR00064>
- Muala, E., Mohamed, Y. A., Duan, Z., & Van der Zaag, P. (2014). Estimation of reservoir discharges from lake Nasser and Roseires reservoir in the Nile basin using satellite altimetry and imagery data. *Remote Sensing*, 6(8), 7522–7545. <https://doi.org/10.3390/rs6087522>
- Munyati, C. (2000). Wetland change detection on the Kafue Flats, Zambia, by classification of a multitemporal remote sensing image dataset. *International Journal of Remote Sensing*, 21(9), 1787–1806. <https://doi.org/10.1080/014311600209742>
- Nguyen, Q. L. (1982). The development of the Senegal river basin: An example in international cooperation. *Natural Resources Forum*, 6, 307–319. <https://doi.org/10.1111/j.1477-8947.1982.tb00253.x>
- Pareeth, S., Karimi, P., Shafiei, M., & De Fraiture, C. (2019). Mapping agricultural landuse patterns from time series of Landsat 8 using random forest based hierarchical approach. *Remote Sensing*, 11(5), 601. <https://doi.org/10.3390/rs11050601>
- Pekel, J. F., Cottam, A., Gorelick, N., & Belward, A. S. (2016). High-resolution mapping of global surface water and its long-term changes. *Nature*, 540(7633), 418–422. <https://doi.org/10.1038/nature20584>
- Pelgrum, H., Miltenburg, I., Cheema, M., Klaasse, A., & Bastiaanssen, W. (2010). ETLook a novel continental evapotranspiration algorithm. In *Remote Sensing and Hydrology 2010* (Proceedings of a symposium held at Jackson Hole, Wyoming, USA, September 2010) (Vol. 1085, p. 1087). IAHS.
- Perennou, C., Guelmami, A., Paganini, M., Philipson, P., Poulin, B., Strauch, A., Tottrup, C., Truckenbrodt, J., & Geijzendorffer, I. R. (2018). Mapping Mediterranean wetlands with remote sensing: A good-looking map is not always a good map. In D. A. Bohan, A. J. Dumbrell, G.

- Woodward, & M. Jackson (Eds.), *Advances in ecological research* (Vol. 58, pp. 243–277). Academic Press.
- Povey, A. C., & Grainger, R. G. (2015). Known and unknown unknowns: Uncertainty estimation in satellite remote sensing. *Atmospheric Measurement Techniques*, 8(11), 4699–4718. <https://doi.org/10.5194/amt-8-4699-2015>
- Puy, A., Sheikholeslami, R., Gupta, H. V., Hall, J. W., Lankford, B., Piano, S. L., Meier, J., Pappenberger, F., Porporato, A., Vico, G., & Saltelli, A. (2022). The delusive accuracy of global irrigation water withdrawal estimates. *Nature Communications*, 13(1), 3183. <https://doi.org/10.1038/s41467-022-30731-8>
- Qi, J., Tao, S., Pueppke, S. G., Espolov, T. E., Beksultanov, M., Chen, X., & Cai, X. (2019). Changes in land use/land cover and net primary productivity in the transboundary Ili-Balkhash basin of central Asia, 1995–2015. *Environmental Research Communications*, 2(1), 11006. <https://doi.org/10.1088/2515-7620/ab5e1f>
- Ragetti, S., Siegfried, T., & Herberz, T. (2017). Remotely-sensed mapping of irrigation area in the Chu-Talas river basin in Central Asia and application to compliance monitoring of transboundary water sharing. In *American Geophysical Union, Fall Meeting 2017, Abstracts* (Vol. 2017, pp. PA23B–0372).
- Richey, A. S., Thomas, B. F., Lo, M.-H., Famiglietti, J. S., Swenson, S., & Rodell, M. (2015). Uncertainty in global groundwater storage estimates in a total groundwater stress framework. *Water Resources Research*, 51(7), 5198–5216. <https://doi.org/10.1002/2015WR017351>
- Ritchie, J. C., & Cooper, C. M. (2001). Remote sensing techniques for determining water quality: Applications to TMDLS. *USDA, Water Environment Federation*.
- Rodell, M., Famiglietti, J. S., Chen, J., Seneviratne, S. I., Viterbo, P., Holl, S., & Wilson, C. R. (2004). Basin scale estimates of evapotranspiration using grace and other observations. *Geophysical Research Letters*, 31(20). <https://doi.org/10.1029/2004GL020873>
- Rodell, M., McWilliams, E. B., Famiglietti, J. S., Beaudoin, H. K., & Nigro, J. (2011). Estimating evapotranspiration using an observation based terrestrial water budget. *Hydrological Processes*, 25(26), 4082–4092. <https://doi.org/10.1002/hyp.8369>
- Rosser, J. F., Leibovici, D., & Jackson, M. (2017). Rapid flood inundation mapping using social media, remote sensing and topographic data. *Natural Hazards*, 87(1), 103–120. <https://doi.org/10.1007/s11069-017-2755-0>
- Sadoff, C. W., & Grey, D. (2002). Beyond the river: The benefits of cooperation on international rivers. *Water Policy*, 4(5), 389–403. [https://doi.org/10.1016/S1366-7017\(02\)00035-1](https://doi.org/10.1016/S1366-7017(02)00035-1)
- Sadoff, C. W., & Grey, D. (2005). Cooperation on international rivers: A continuum for securing and sharing benefits. *Water International*, 30(4), 420–427. <https://doi.org/10.1080/02508060508691886>
- Schulte to Bühne, H., Wegmann, M., Durant, S. M., Ransom, C., de Ornellas, P., Grange, S., Beatty, B., & Pettorelli, N. (2017). Protection status and national socio-economic context shape land conversion in and around a key transboundary protected area complex in West Africa. *Remote Sensing in Ecology and Conservation*, 3(4). <https://doi.org/10.1002/rse2.47>
- SERVIR-Amazonia. (2023). Geospatial information for improved environmental decision-making in the Amazon. Retrieved January 30, 2023, from <https://www.nasa.gov/servir/servir-amazonia/>
- SERVIR-Mekong. (2023, January 30). *Reservoir assessment tool for Lower Mekong Basin*. <https://ratmekong-servir.adpc.net/map/>
- Seyler, F., Calmant, S., da Silva, J., Filizola, N., Roux, E., Cochonneau, G., Vauchel, P., & Bonnet, M. P. (2008). Monitoring water level in large trans-boundary ungauged basins with altimetry: the example of ENVISAT over the Amazon basin. In *Proceedings Volume 7150, Remote Sensing of Inland, Coastal, and Oceanic Waters; 715017*. SPIE. <https://doi.org/10.1117/12.813258>
- Sheffield, J., Wood, E. F., Pan, M., Beck, H., Coccia, G., Serrat-Capdevila, A., & Verbist, K. (2018). Satellite remote sensing for water resources management: Potential for supporting sustainable development in data-poor regions. *Water Resources Research*, 54(12), 9724–9758. <https://doi.org/10.1029/2017WR022437>

- Shi, J., Xiong, C., & Jiang, L. (2016). Review of snow water equivalent microwave remote sensing. *Science China Earth Sciences*, 59(4), 731–745. <https://doi.org/10.1007/s11430-015-5225-0>
- Shin, S., Pokhrel, Y., Yamazaki, D., Huang, X., Torbick, N., Qi, J., Pattanakiat, S., Ngo-Duc, T., & Nguyen, T. D. (2020). High resolution modeling of river-floodplain-reservoir inundation dynamics in the Mekong river basin. *Water Resources Research*, 56(5), e2019WR026449. <https://doi.org/10.1029/2019WR026449>
- Siabi, N., Sanaeinejad, S. H., & Ghahraman, B. (2022). Effective method for filling gaps in time series of environmental remote sensing data: An example on evapotranspiration and land surface temperature images. *Computers and Electronics in Agriculture*, 193, 106619. <https://doi.org/10.1016/j.compag.2021.106619>
- Singh, P., Srivastava, P. K., & Mall, R. (2021). Estimation of potential evapotranspiration using insat-3d satellite data over an agriculture area. In P. K. Srivastava, M. Gupta, G. Tsakiris, & N. W. Quinn (Eds.), *Agricultural water management, theories and practices* (pp. 143–155). Elsevier.
- Slater, P. N. (1985). Radiometric considerations in remote sensing. *Proceedings of the IEEE*, 73(6), 997–1011. <https://doi.org/10.1109/PROC.1985.13231>
- Srivastava, P. K., Han, D., Rico Ramirez, M. A., & Islam, T. (2013). Comparative assessment of evapotranspiration derived from NCEP and ECMWF global datasets through weather research and forecasting model. *Atmospheric Science Letters*, 14(2), 118–125. <https://doi.org/10.1002/asl2.427>
- Stephens, C., Pham, H., Marshall, L., & Johnson, F. (2022). Which rainfall errors can hydrologic models handle? implications for using satellite-derived products in sparsely gauged catchments. *Water Resources Research*, 58(8), e2020WR029331. <https://doi.org/10.1029/2020WR029331>
- Stisen, S., Jensen, K. H., Sandholt, I., & Grimes, D. I. (2008). A remote sensing driven distributed hydrological model of the Senegal river basin. *Journal of Hydrology*, 354(1–4), 131–148. <https://doi.org/10.1016/j.jhydrol.2008.03.006>
- Stisen, S., & Sandholt, I. (2010). Evaluation of remote-sensing-based rainfall products through predictive capability in hydrological runoff modelling. *Hydrological Processes*, 24(7), 879–891. <https://doi.org/10.1002/hyp.7529>
- Sun, A. Y. (2013). Predicting groundwater level changes using grace data. *Water Resources Research*, 49(9), 5900–5912. <https://doi.org/10.1002/wrcr.20421>
- Sun, Q., Miao, C., Duan, Q., Ashouri, H., Sorooshian, S., & Hsu, K.-L. (2018). A review of global precipitation data sets: Data sources, estimation, and intercomparisons. *Reviews of Geophysics*, 56(1), 79–107. <https://doi.org/10.1002/2017RG000574>
- Tapley, B. D., Bettadpur, S., Watkins, M., & Reigber, C. (2004). The gravity recovery and climate experiment: Mission overview and early results. *Geophysical Research Letters*, 31(9). <https://doi.org/10.1029/2004GL019920>
- Tarpanelli, A., Mondini, A. C., & Camici, S. (2022). Effectiveness of Sentinel-1 and Sentinel-2 for flood detection assessment in Europe. *Natural Hazards and Earth System Sciences*, 22(8), 2473–2489. <https://doi.org/10.5194/nhess-22-2473-2022>
- Tian, Y., & Peters-Lidard, C. D. (2010). A global map of uncertainties in satellite-based precipitation measurements. *Geophysical Research Letters*, 37(24). <https://doi.org/10.1029/2010GL046008>
- Timmerman, J. G., & Langaas, S. (2005). Water information: What is it good for? The use of information in transboundary water management. *Regional Environmental Change*, 5(4), 177–187. <https://doi.org/10.1007/s10113-004-0087-6>
- Tran-Thanh, D., Rinasti, A. N., Gunasekara, K., Chaksan, A., & Tsukiji, M. (2022). GIS and remote sensing-based approach for monitoring and assessment of plastic leakage and pollution reduction in the lower Mekong river basin. *Sustainability*, 14(13), 7879. <https://doi.org/10.3390/su14137879>
- Ureyen, S., & Kuenzer, C. (2019). A review of earth observation-based analyses for major river basins. *Remote Sensing*, 11(24), 2951. <https://doi.org/10.3390/rs11242951>
- UNECE. (2021). *Progress on transboundary water cooperation – 2021 update*. Retrieved January 30, 2023, from <https://www.unwater.org/publications/progress-transboundary-water-cooperation-2021-update>

- United Nations. (1997). *Convention on the law of the non-navigational uses of international watercourses*.
- United Nations. (2015). *A/RES/70/1 – Transforming the world: The 2030 agenda for sustainable development*. <https://sdgs.un.org/>
- Varis, O., Rahaman, M. M., & Stucki, V. (2008). The rocky road from integrated plans to implementation: Lessons learned from the Mekong and Senegal River basins. *International Journal of Water Resources Development*, 24(1), 103–121. <https://doi.org/10.1080/07900620701723307>
- Velpuri, N. M., Senay, G. B., Singh, R. K., Bohms, S., & Verdin, J. P. (2013). A comprehensive evaluation of two MODIS evapotranspiration products over the conterminous United States: Using point and gridded FLUXNET and water balance ET. *Remote Sensing of Environment*, 139, 35–49. <https://doi.org/10.1016/j.rse.2013.07.013>
- Vinukollu, R. K., Wood, E. F., Ferguson, C. R., & Fisher, J. B. (2011). Global estimates of evapotranspiration for climate studies using multi-sensor remote sensing data: Evaluation of three process-based approaches. *Remote Sensing of Environment*, 115(3), 801–823. <https://doi.org/10.1016/j.rse.2010.11.006>
- Voss, K. A., Famiglietti, J. S., Lo, M., De Linage, C., Rodell, M., & Swenson, S. C. (2013). Groundwater depletion in the middle east from grace with implications for transboundary water management in the Tigris-Euphrates-Western Iran region. *Water Resources Research*, 49(2), 904–914. <https://doi.org/10.1002/wrcr.20078>
- Wahr, J., Swenson, S., Zlotnicki, V., & Velicogna, I. (2004). Time-variable gravity from GRACE: First results. *Geophysical Research Letters*, 31(11). <https://doi.org/10.1029/2004GL019779>
- Wang, X., & Yang, W. (2019). Water quality monitoring and evaluation using remote sensing techniques in China: A systematic review. *Ecosystem Health and Sustainability*, 5(1), 47–56. <https://doi.org/10.1080/20964129.2019.1571443>
- Weerasinghe, I., Bastiaanssen, W., Mul, M., Jia, L., & Van Griensven, A. (2020). Can we trust remote sensing evapotranspiration products over Africa? *Hydrology and Earth System Sciences*, 24(3), 1565–1586. <https://doi.org/10.5194/hess-24-1565-2020>
- Wheeler, K. G., Jeuland, M., Hall, J. W., Zagana, E., & Whittington, D. (2020). Understanding and managing new risks on the Nile with the Grand Ethiopian Renaissance Dam. *Nature Communications*, 11(1), 1–9. <https://doi.org/10.1038/s41467-020-19089-x>
- Xu, H., Bailey, J. O., Barrett, E. C., & Kelly, R. E. J. (1993). Monitoring snow area and depth with integration of remote sensing and GIS. *International Journal of Remote Sensing*, 14(17), 3259–3268. <https://doi.org/10.1080/01431169308904440>
- Yalew, S., Kwakkal, J., & Doorn, N. (2021). Distributive justice and sustainability goals in transboundary rivers: Case of the Nile basin. *Frontiers in Environmental Science*, 8, 590954. <https://doi.org/10.3389/fenvs.2020.590954>
- Zhang, K., Kimball, J. S., & Running, S. W. (2016). A review of remote sensing based actual evapotranspiration estimation. *WIREs Water*, 3(6), 834–853. <https://doi.org/10.1002/wat2.1168>
- Zhang, X., Qu, Y., Ma, M., Liu, H., Su, Z., Lv, J., Peng, J., Leng, G., He, X., & Di, C. (2020). Satellite-based operational real-time drought monitoring in the transboundary Lancang–Mekong river basin. *Remote Sensing*, 12(3), 376. <https://doi.org/10.3390/rs12030376>