Journal of Water & Health

PUBLISHING

 Journal of Water and Health Vol 22 No 7, 1162 doi: 10.2166/wh.2024.102

The application of satellite sensors, current state of utilization, and sources of remote sensing dataset in hydrology for water resource management

Daniel Abegeja [a,b,c]

[a] Africa Center of Excellence for Water Management (ACEWM), Addis Ababa University, Addis Ababa, Ethiopia
[b] Oromia Agricultural Research Institute, Addis Ababa, Ethiopia
[c] Sinana Agricultural Research Center, Soil and Water Conservation, and Watershed Management Research Team, Bale Robe, Oromia
E-mail: aredodani@gmail.com; daniel.abegeja@aau.edu.et

DA, 0000-0002-2971-0466

ABSTRACT

Hydrologists rely heavily on satellite sensors because they provide useful information for tracking, evaluating, managing water resources, aiding provision of safe drinking water, help preventing waterborne diseases, and address the challenges posed by climate change. Water conservation and the collection of hydrologic data have made remote sensing (RS) an invaluable tool. As a result, there are fewer hydrologic stations globally in terms of space because of various topography landforms, human limitations, and financial limits. A thorough examination of the RS satellite products' hydrological applications is essential to finding a solution to this issue. By doing this, academicians, researchers, and conservationists in various professions can better understand the products and obtain the data needed for conservation. This paper primarily focuses on the following two objectives: 1). To synthesize the scientific information on satellite remote sensing application for hydrology, and 2). To explain the RS dataset sources for hydrologic parameters. Extensive literature search from reputable journal publishers. This review article synthesized vital sources of information for academicians, researchers, and government agencies involved in hydrology and water resources management. It is recommended that RS can be used as a data source for scarce, sparsely gauged, and inaccessible regions.

Key words: hydrological parameters, remote sensing, satellite, sensors, water resources

HIGHLIGHTS

- Satellite sensors for hydrology.
- Satellite sensors for water resource management.
- Familiarity with satellite products.
- Ease of hydrological data collection.
- Monitoring, assessment, and management of water resources.

1. INTRODUCTION

Using satellite data to observe hydrological processes is crucial for the sustainable management of water resources across a wide area. The process of remotely sensing water resources entails producing data on a variety of topics, including the routine inventory of surface water bodies and the evaluation of precipitation, soil moisture, evapotranspiration (ET), ground water, and snowmelt runoff (Singh 2018). These days, hydrological cycle components such as precipitation, evaporation, lake and river levels, surface water, soil moisture, snow, and total water storage may all be measured directly or indirectly using satellite-based sensors (McCabe *et al.* 2017). For precise and dependable data on Earth observations, satellite remote sensing (RS) is a valuable resource in atmospheric and environmental science. Hydrological modeling finds it attractive due its seamless availability throughout ungauged regions, boosting spatial and temporal resolution. Earth observation data have already proven to be immensely beneficial to the field of hydrology sciences (Tang *et al.* 2016; McCabe *et al.* 2017; Alfieri *et al.* 2020).

Quantifying the hydrological budget over large spatial domains and lengthy time periods by direct observation is relatively difficult because *in situ* observations are expensive and labor-intensive. This is particularly true in ungauged basins, where stream flow measurements are either nonexistent or insufficient, and little to no observations of spatially variable hydrological parameters are made. Hydrological modeling for water resource estimates is, therefore, quite difficult. Satellite RS provides a method to address these issues with broad spatial coverage and reproducible temporal coverage. Hydrological studies are hampered in ungauged basins because they do not have the calibration and validation data needed to employ land surface models. Therefore, it is necessary to make use of satellite data (Lakshmi 2018).

Currently, little is known about these satellite sensors in developing countries such as East Africa, particularly Ethiopia. Therefore, it has been an urgent issue to conduct a review of these satellite sensors and thereby work on the adoption of such technologies in universities and research institutions. Many research works have been done extensively on validating these satellite sensors. However, it is not designed to be easily understood by users. In addition, they focused on only a few satellite sensors. On the contrary, this review paper covers various satellites and sensors with their spatial and temporal resolutions, which are suitable for hydrological modeling, and gives valuable information on satellites and sensors for the modeling to academicians and researchers who are not familiar with satellite-derived data. It is much preferable to review all hydrologic response units and store them in a simple form on a single paper that paves the way for easier access to input data on water conservation, which is the ultimate goal of this article. On the other hand, many developing countries in the world do not have hydrology and water resource data centers at an acceptable distance. Meanwhile, these hydrological and water resource data are in high demand in relation to climate change. Obtaining data on hydrology and water resource parameters from existing gage stations in the required quantity and timeliness has been a constraint. So, where do we find these clues? From which website can we get it in the shortest time without spending money? Is it a question that awaits an answer? In this regard, this article is intended to play an important role in answering these questions in a concise manner.

In this research, the function of satellite RS in hydrology and water resource management is reviewed, along with its possible applications in the future. This review paper primarily focuses on the following two objectives: (1) to synthesize the scientific information on satellite RS applications for hydrology and water resources and (2) to explain the RS dataset sources for hydrological parameters.

2. METHODOLOGY

2.1. Description of satellite sensors

Remote sensors are devices that receive and respond to a signal or stimulus and convert any type of energy into electrical energy (Al-Aubidy 2007). RS satellites are equipped with various sensors designed to capture different types of data about the Earth's surface, atmosphere, and other phenomena. These sensors gather information across the electromagnetic spectrum, ranging from visible light to microwaves and beyond.

Passive microwave sensors: These sensors measure microwave radiation emitted or scattered by the Earth's surface and atmosphere. They are particularly useful for estimating soil moisture and detecting precipitation. Examples include the Advanced Microwave Scanning Radiometer and the Soil Moisture and Ocean Salinity satellite.

Active microwave sensors: These sensors emit microwave pulses toward the Earth's surface and measure the reflected signal. They are used for measuring surface water extent, soil moisture, and snow cover. Synthetic-aperture radar sensors, such as those on the European Space Agency's (ESA) Sentinel-1 satellites, are examples of active microwave sensors.

Optical sensors: Optical sensors capture images of the Earth's surface using visible and infrared light. They are used for monitoring vegetation health, land cover changes, and snow cover extent. Examples include the Moderate Resolution Imaging Spectroradiometer (MODIS) and the Visible Infrared Imaging Radiometer Suite.

LiDAR (*Light Detection and Ranging*): LiDAR sensors emit laser pulses and measure the time it takes for the pulses to return after reflecting off the Earth's surface. LiDAR data can be used to measure river and lake levels, as well as terrain elevation. The Ice, Cloud, and Land Elevation Satellite mission and the Global Ecosystem Dynamics Investigation aboard the International Space Station are examples of LiDAR missions.

Gravimetric sensors: Gravimetric sensors measure variations in the Earth's gravitational field, which can provide information on changes in water storage, such as groundwater depletion and changes in surface water storage. The Gravity Recovery and Climate Experiment (GRACE) and its successor, GRACE Follow-On, are examples of gravimetric missions.

Multispectral sensors: Multispectral sensors capture data in several discrete spectral bands within the visible and near-infrared (NIR) portions of the electromagnetic spectrum (Light 1990).

Hyperspectral sensors: These sensors measure a wide range of wavelengths across the electromagnetic spectrum, providing detailed information about the composition and properties of the Earth's surface. They are used for tasks such as identifying different types of vegetation and detecting water quality parameters. Examples include the Hyperspectral Infrared Imager and the Environmental Mapping and Analysis Program.

2.2. Aspects of satellite sensors

2.2.1. Positive aspects of satellite sensors

Satellite sensors used in hydrology are designed to capture various aspects of the Earth's surface and atmosphere relevant to the water cycle (Azarderakhsh *et al.* 2011). Several key aspects are essential for these sensors to effectively monitor and study hydrological processes:

Global coverage: Satellite sensors can observe remote and inaccessible regions by providing comprehensive coverage. This allows for monitoring water resources in diverse environments, including remote areas, mountainous regions, and polar regions, where ground-based observations may be limited or unavailable.

Cost and time-saving: Satellite sensors enable non-invasive RS of the Earth's surface and atmosphere, allowing for continuous monitoring of hydrological parameters over large spatial scales. This capability reduces the need for costly and time-consuming fieldwork, making it possible to assess water resources in areas with challenging terrain or limited accessibility.

Multi-sensor integration: Satellite missions often include multiple sensors with complementary capabilities, such as optical, microwave, and infrared sensors. Integrating data from different sensors allows for a more comprehensive understanding of hydrological processes, including the estimation of soil moisture, precipitation, ET, and surface water extent.

Large-scale monitoring: Satellite sensors can monitor large-scale hydrological phenomena, such as river basins, watersheds, and continental-scale water cycles. This ability to observe broad spatial extents facilitates the assessment of water availability, distribution, and movement across different regions, supporting regional water resource management and transboundary water management efforts.

Real-time and near real-time data: Many satellite missions provide real-time or near real-time data, allowing for timely monitoring and response to hydrological events such as floods, landslides, and water quality changes. Rapid access to satellite data supports early warning systems, emergency response planning, and disaster management activities, helping to mitigate the impacts of water-related hazards.

Long-term monitoring: Satellite sensors have enabled long-term monitoring of hydrological parameters, facilitating the analysis of historical trends and the detection of long-term changes in water resources. Long-term satellite datasets contribute to climate change studies, water resource planning, and ecosystem management by providing insights into the impacts of climate variability and human activities on water availability and quality.

Spatio-temporal resolution: Many satellite sensors offer high temporal resolution, capturing frequent observations of hydrological processes over time. This temporal continuity allows for monitoring changes in precipitation patterns, snowmelt dynamics, soil moisture levels, and water body dynamics, facilitating the detection of trends, seasonal variations, and extreme events, such as floods and droughts. Spatial resolution refers to the level of detail in an image captured by a satellite sensor. Higher spatial resolution sensors can distinguish smaller features on the Earth's surface, which are important for tasks such as monitoring small water bodies, river networks, and urban areas. Different hydrological applications may require sensors with varying spatial resolutions to meet specific monitoring needs. Temporal resolution refers to how frequently a satellite revisits the same location on Earth. Hydrological processes, such as precipitation, snowmelt, and vegetation growth, can exhibit rapid changes over time. Sensors with high temporal resolution can capture these dynamic processes more frequently, allowing for better monitoring and forecasting of hydrological events like floods and droughts.

Spectral bands: Satellite sensors are equipped with different spectral bands to capture electromagnetic radiation across the spectrum. Each spectral band is sensitive to specific features of the Earth's surface and atmosphere. For hydrological applications, sensors with bands sensitive to water-related parameters, such as NIR and microwave bands, are crucial for tasks like estimating soil moisture, detecting water bodies, and monitoring vegetation health.

Radiometric accuracy: Radiometric accuracy refers to the precision with which a satellite sensor measures the intensity of electromagnetic radiation. Accurate radiometric measurements are essential for quantifying surface properties related to hydrology, such as land surface temperature, vegetation indices (VIs), and water reflectance. Calibration and validation procedures are employed to ensure the radiometric accuracy of satellite data, enabling reliable hydrological analysis and modeling.

Data accessibility and availability: The accessibility and availability of satellite data are critical for operational hydrological monitoring and research. Open-access satellite missions, such as those provided by space agencies, such as NASA, ESA, and National Oceanic and Atmospheric Administration (NOAA), enable researchers and water resource managers to access a wealth of satellite data for various hydrological applications. In addition, data archives and distribution platforms facilitate easy access to historical and real-time satellite data for ongoing hydrological studies.

Integration with ground-based observations: Satellite sensors are often used in conjunction with ground-based observations, such as weather stations, stream gauges, and groundwater monitoring networks, to validate and supplement satellite-derived data. Integrating satellite observations with ground-based measurements improves the accuracy and reliability of hydrological models and enhances our understanding of local-scale processes.

By considering these important aspects, satellite sensors can effectively contribute to hydrological research, water resource management, and environmental monitoring efforts worldwide.

2.2.2. Negative aspects of satellite sensors

The use of satellite precipitation products (SPPs) in environmental applications has been limited by their accuracy and spatial resolution (Beyene 2023). While satellite sensors offer numerous advantages for hydrological monitoring, they also have some limitations and disadvantages.

Spatial resolution: Many satellite sensors have limited spatial resolution, particularly for freely available data. This can be a drawback when monitoring small-scale features such as small rivers, wetlands, or urban water bodies. Higher spatial resolution data may be available from commercial satellites, but often at a higher cost.

Temporal resolution: Sensors have varied revisit times to a specific location depending on their satellite's orbit and mission design (Barsi *et al.* 2019). For instance, Sentinel 2 has slow revisit times to the same location (in the order of 1 or 2 weeks). Images are often obstructed by clouds, which, together with slow revisit times, cause extended periods without any data (Guillermo *et al.* 2022).

Cloud cover and weather conditions: Satellite sensors reliant on optical imagery are hindered by cloud cover and adverse weather conditions, which can obscure the Earth's surface and limit data availability. Persistent cloud cover in tropical regions or during the rainy season can pose challenges for consistent monitoring of hydrological processes.

Atmospheric interference: Atmospheric conditions, such as aerosols, water vapor, and atmospheric scattering, can introduce errors in satellite-derived measurements, particularly in the case of optical sensors. Corrections for atmospheric interference are necessary to ensure the accuracy of hydrological data derived from satellite observations.

Data processing and interpretation: Processing satellite data requires specialized expertise and computational resources, including algorithms for image correction, calibration, and interpretation. In addition, integrating satellite data with ground-based observations and hydrological models can be complex and may introduce uncertainties in the analysis.

Cost: While some satellite data sources offer free or low-cost access to data, high-resolution or specialized satellite imagery may come at a significant cost, particularly for commercial data providers. This can be a barrier for researchers and organizations with limited budgets, especially in developing regions where funding for RS applications may be scarce.

Data validation and accuracy: Satellite-derived hydrological data require validation against ground-based observations to ensure accuracy and reliability. *In situ* measurements are essential for calibrating and validating satellite observations, but establishing and maintaining ground-based monitoring networks can be resource-intensive and challenging in remote or inaccessible areas.

Limited sensitivity to subsurface processes: Satellite sensors primarily observe surface water and moisture dynamics, but they have limited sensitivity to subsurface processes, such as groundwater recharge, aquifer depletion, and soil moisture at deeper depths. Integrating satellite observations with ground-based measurements and hydrological models is necessary for a comprehensive understanding of the water cycle.

2.3. Review method and data collection

The library research method, which includes (i) analyzing historical records (recording of notes and analysis) and (ii) analyzing documents (statistical compilations and manipulations, references, and abstract guides), was done. An extensive literature search was conducted. Secondary data that are relevant to the preset objectives were collected and compiled from recent literature.

3. RESULTS AND DISCUSSIONS

3.1. Satellite sensors for hydrological parameters

3.1.1. Precipitation

Earth's precipitation is measured using multiple satellite sensors. These sensors use a variety of methods to monitor and quantify precipitation in various forms (rain, snow, sleet, etc.) in various parts of the world (Table 1).

3.1.2. Evapotranspiration

In order to estimate the combined processes of water evaporation from the Earth's surface (such as water bodies, soil, and vegetation) and transpiration from plants, ET from space is measured using a variety of satellite sensors and techniques (Table 2).

3.1.3. Vegetation

Satellite sensors for monitoring vegetation health and dynamics gather information about plant health, growth, and environmental conditions using various wavelengths of light. Different sensors are used to measure certain elements of vegetation (Table 3). Satellite products of VIs have been widely used for various purposes, including vegetation change monitoring (Zhang *et al.* 2017; Zeng *et al.* 2020), vegetation phenology extraction (Buyantuyev & Wu 2012; Pastor-Guzman *et al.* 2018), terrestrial carbon circulation modeling (Tucker & Sellers 1986; Guan *et al.* 2019), dynamic environmental simulations (Tong *et al.* 2017; Zhao *et al.* 2020), and land coverage and change detection (Jia *et al.* 2014; Hu 2021). Among them, the normalized difference vegetation index (NDVI) calculated from the NIR band and the visible red band (RED) obtained by optical satellites is one of the most popular indices (Holben *et al.* 1980). Similar to the NDVI, the enhanced vegetation index (EVI) minimizes the canopy background variations and maintains its sensitivity under dense vegetation conditions. The EVI also uses the blue band (BLUE) to remove residual atmospheric contamination caused by smoke and thin subpixel clouds (Huete *et al.* 2002).

The ratio vegetation index is calculated by simply dividing the reflectance values of the NIR band by those of the red band. The result clearly captures the contrast between the red and infrared bands for vegetated pixels, with high index values being produced by combinations of low red (because of absorption by chlorophyll) and high infrared (as a result of leaf structure) reflectance. The perpendicular vegetation index (PVI) is the parent index from which the entire group of distance-based VIs is derived. The PVI uses the perpendicular distance from each pixel coordinate to the soil line. The main objective of the PVI is to cancel the effect of soil brightness in cases where vegetation is sparse and pixels contain a mixture of green vegetation and soil background.

3.1.4. Soil moisture

Satellite sensors for measuring soil moisture (Table 4) are critical tools in environmental monitoring, agriculture, hydrology, and climate studies. These sensors work by sensing microwave radiation emitted or reflected by the Earth's surface.

3.1.5. Surface temperature

Satellite sensors developed for surface temperature measurements (Table 5) work by absorbing thermal radiation released by the Earth's surface using various technologies and spectral bands. These sensors aid in the monitoring and analysis of temperature differences in landscapes, oceans, and cities.

3.2. Satellite sensors for water resource management

3.2.1. Water storage

Satellite sensors are critical for monitoring and quantifying water storage in a variety of environments, including oceans, lakes, rivers, and subsurface reservoirs. These sensors estimate water storage levels (Table 6) using various methodologies and wavelengths.

3.2.2. Surface water level

Several technologies and satellite-based sensors are used to measure and monitor surface water levels across oceans, lakes, rivers, and reservoirs (Table 7).

Table 1 | Satellite products for precipitation

Satellite sensor	Spatial resolution	Temporal frequency	Temporal interval	Access/source	Hydrological model	References
TMPA	0.25°	3 h	1998–2019	https://gpm.nasa.gov/missions/trmm	SWAT, CREST	Huffman *et al.* (2007)
CHIRPS v2.0	0.05°	Daily	1981 to present	https://data.chc.ucsb.edu/products/CHIRPS-2.0/ https://climateserv.servirglobal.net/ https://developers.google.com/earth-engine/datasets/catalog/UCSB-CHG_CHIRPS_DAILY		Funk *et al.* (2015)
Climate Prediction Center morphing technique (CMORPH) –30 min	0.07°	30 min	1998 to present	https://www.ncei.noaa.gov/products/climate-data-records/precipitation-cmorph https://www.ncei.noaa.gov/data/cmorph-high-resolution-global-precipitation-estimates/access/30min/	SWAT	Joyce *et al.* (2004)
PERSIANN	0.25°	1 h	2000 to present	https://chrsdata.eng.uci.edu/		Hsu *et al.* (1997), Sellars *et al.* (2013), Sorooshian *et al.* (2000)
PERSIANN –CCS	0.04°	1 h	2003 to present			Hong *et al.* (2012)
PERSIANN –CDR	0.25°	Daily	1983 to present		SWAT	Ashouri *et al.* (2015)
PERSIANN –CONNECT	0.25°	1 h	1983 to present			Sellars *et al.* (2013)
GSMaP	0.1°	1 h	2003–2015	http://sharaku.eorc.jaxa.jp/GSMaP/index.htm http://sharaku.eorc.jaxa.jp/GSMaP_crest/	SWAT	Kubota *et al.* (2009); Chen *et al.* 2020
GPM/IMERG	0.1°	30 min	Mar 2014–Dec 2021	https://pmm.nasa.gov/data-access/downloads/gpm	DRYP, SWAT	Aonashi *et al.* (2009), Quichimbo (2021)
MSWEP	0.1°	3 h	1979 to present	http://www.gloh2o.org	XAJ, SWAT, DRYP	Beck *et al.* (2016), Beck *et al.* (2017)
GPCC	1° global	3 months	1891 to present	https://psl.noaa.gov/data/gridded/data.gpcc.html	SWT, XAJ, VIC	Rudolf & Schneider (2005), Ma & Sun (2018)
GPCC-daily	1.0° × 1.0°	Daily	1982 to present	GPCC	HBV, SWMM	Schamm *et al.* (2014), Bergström (1992)
CRU	0.5° × 0.5°	Monthly	1901–2018	The CRU of the University of East Anglia		New *et al.* (2000), Harris *et al.* (2014)
GHCN-M	5° × 5°	Monthly	1998–2014	National Climatic Data Center	TOPMODEL	Peterson & Vose (1997), Naz *et al.* (2020)
PREC/L	0.5° × 0.5°, 1.0° × 1.0°,	Monthly	1948 to present	NCEP/NOAA		Chen *et al.* (2011)
UDEL	0.5° × 0.5°,	Monthly		University of Delaware		Willmott & Matsuura (1995)

(*Continued.*)

Table 1 | Continued

Satellite sensor	Spatial resolution	Temporal frequency	Temporal interval	Access/source	Hydrological model	References
CPC-Global	0.5° × 0.5°,	Daily	1979 to present	https://www.cpc.ncep.noaa.gov/		Xie *et al.* (2010)
SM2RAIN	1° global	Monthly	1998–2021	https://opendata.dwd.de/climate_environment/GPCC/html/download_gate.html.		Mosaffa *et al.* (2023)

TMPA, Tropical Rainfall Measurement Mission Multi-Satellite Precipitation Analysis; CFSR, Climate Forest System Reanalysis system; CHIRPS, Climate Hazards Group InfraRed Precipitation with Station data; CMORPH, Climate Prediction Center morphing technique; CRU, Climate Research Unit; GHCN-M, Global Historical Climatology Network monthly; GPCC, Global Precipitation Climatology Centre; GPCP 1dd, GPCP one-degree daily precipitation analysis; GPCP, Global Precipitation Climatology Project; GPM, Global Precipitation Measurement; GSMaP, Global Satellite Mapping of Precipitation; MSWEP, Multi-Source Weighted-Ensemble Precipitation; version PERSIANN, Precipitation Estimation from Remotely Sensed Information using Artificial Neural Networks; PREC, Precipitation reconstruction; PRECL, Precipitation reconstruction over land; Tropical Rainfall Measuring Mission (TRMM); SWAT, Soil and Water Assessment Tools; TOPMODEL, TOPography-based hydrological MODEL; XAJ, Xinanjiang Model; DRYP, distributed, integrated, hydrological model; CREST, coupled routing and excess storage model; SWMM, Storm Water Management Model; HBV, Hydrologiska Byrans Vattenbalansavdelning; VIC, Variable Infiltration Capacity.

Table 2 | Satellite products for the estimation of ET

Satellite sensor	Spatial resolution	Temporal frequency	Temporal interval	Access/source	Hydrological models	References
RS-PM	0.5°	Daily		Princeton University		Vinokullo *et al.* (2011)
MOD16 ET	1 km	8 days	2001–2015	http://www.ntsg.umt.edu/project/modis/mod16.php		Mu *et al.* (2011)
PT-JPL	1–0°	Monthly		https://lpdaac.usgs.gov/products/eco3etptjplv001/		Fisher *et al.* (2008)
GLEAM	0.25°	Daily	1980–2022	https://www.gleam.eu		Martens *et al.* (2017), Senay *et al.* (2013)
ALEXI-DisALEXI	30 m (Landsat), 1 km (MODIS)	Hourly/daily		Atmosphere-Land Exchange Inverse Model (ALEXI)		Anderson *et al.* (2007)
ESI	0.05°	4 and 12 weeks		https://servirglobal.net/Global/Evaporative-Stress-Index		Anderson *et al.* (2011)

RS-PM, Remote Sensing Penman Montheith; MOD16 ET, MODIS Global Evapotranspiration Project; PT-JPL, Priestly-Taylor Jet Propulsion Laboratory; GLEAM, Global Land Evaporation Amsterdam Model; FEWS, Famine Early Warning system; ALEXI, Atmosphere-Land Exchange Inverse Model; DisALEXI, Disaggregated ALEXI algorithm; ESI, Evaporative Stress Index.

3.2.3. Surface water extent

Various types of satellite sensors (Table 8) are used to detect and track surface water extent in oceans, lakes, rivers, and reservoirs.

3.2.4. Stream flow

Stream flow is monitored using a variety of satellite sensors and technology (Table 9). Satellite sensors play an important role in stream flow monitoring by providing vital data on water levels, surface water extent, and other characteristics.

3.2.5. Discharge

Monitoring river discharge with satellite sensors entails determining the amount of water flowing through a river or stream at a specific spot (Table 10). While the direct measurement of discharge from space is difficult, data from multiple satellite sensors can be utilized to estimate discharge indirectly.

Table 3 | Satellite products for vegetation

Satellite sensor	Spatial resolution	Temporal frequency	Temporal interval	Access/source	Hydrological model	References
Landsat	15 m	16 days	1985 to date	https://landsat.usgs.gov		NASA (2001), Chaves *et al.* (2020)
AVHRR/ GIMMS	1 km	7-/14-day composites	1980–2015	https://catalog.data.gov/ dataset/	W3RA	Khaki *et al.* (2020), Pinzon & Tucker (2014)
MODIS	250 m, 1 km, 0.05°	16-day, monthly	2017–2019	https://modis.gsfc.nasa.gov/		Huete *et al.* (2002)
VIIRS	375 m (swath), 500 m	Daily and 8-day composite	2012–2021	https://modis.gsfc.nasa.gov/ data/dataprod/mod13.php		Vargas *et al.* (2013)
Sentinel-2	10–60 m	5/10 days	2015–2020	https://sentinel.esa.int/web/ sentinel/sentinel-data-access		ESA (2013)

VIIRS, Visible Infrared Imaging Radiometer Suite; AVHRR, Advanced Very High-Resolution Radiometer; SWE, snow water equivalence; MODIS, Moderate Resolution Imaging Spectroradiometer; ECOSTRESS, ECOsystem Spaceborne Thermal Radiometer Experiment on Space Station; W3RA, World-Wide Water Resources Assessment model.

Table 4 | Satellite products for soil moisture

Satellite sensor	Spatial resolution	Temporal frequency	Temporal interval	Access/source	Hydrological model	References
AMSR-E	25 km	1-day revisit	2002–2011	https://nsidc.org/data/ae_ land3	W3RA	Khaki *et al.* (2020), Njoku (2004)
AMSR2	25 km	1-day revisit	2012–2021	http://nsidc.org/data/au_land	SHEELS	Owe *et al.* (2008), Koike (2013)
SMOS	15, 25, and 50 km	1- to 3-day revisit; daily, 9-day and monthly products	2018–2021	https://earth.esa.int/ eogateway/catalog		Kerr *et al.* (2012)
SMAP SMAP L4 Root zone Soil moisture	36 km, 9 km	1- to 3-day revisit 3 h	2015 to present 2015–2021	https://smap.jpl.nasa.gov/data/		Entekhabi *et al.* (2010), Reichle *et al.* (2016)
Sentinel-1	< 1 km^2	8 days	2016 to date	https://sentinel.esa.int/web/ sentinel/sentinel-data-access		Paloscia *et al.* (2013)
ASCAT	0.1°	1–3 days revisit time	2007–2018	https://land.copernicus.eu/ global/products/swi		Wagner *et al.* (1999)
FY3-B	25 km		2011–2018	http://satellite.nsmc.org.cn/ PortalSite/Default.aspx		Shi *et al.* (2006)

AMSR2, Advanced Microwave Scanning Radiometer 2; AMSR-E, Advanced Microwave Scanning Radiometer for the Earth Observing System; SMAP, Soil Moisture Active Passive; SMOS, Soil Moisture and Ocean Salinity; ASCAT, Advanced Scatterometer; FY3-B, Fengyan; SHEELS, Simulator for hydrology and energy exchange at the land surface.

3.2.6. Water budget

Satellite RS can be used to examine the important terms in the water balance equation. Retrievals of all components of the terrestrial water cycle have evolved in recent years, and there is now the possibility of performing continuous worldwide observations of the terrestrial water cycle in real time (Alsdorf & Lettenmaier 2003). The terrestrial water budget can be defined as the balance between the change in water storage (ΔS) and the difference between the incoming water fluxes of

Table 5 | Satellite products for surface temperature

Satellite sensor	Spatial resolution	Temporal frequency	Temporal interval	Access/source	Hydrological models	References
CHIRTS; CHIRTS-daily	60°S–70°N	Daily, monthly	1983–2016	https://cds.climate.copernicus.eu/cdsapp#!/home		Verdin *et al.* (2020)
Landsat	30 multispectral ***(Landsat-8)*** 100 m thermal ***(Landsat-9)***	16 days	1972 to date	https://landsat.usgs.gov		NASA (2001)
AVHRR	1 km	1 day		https://lta.cr.usgs.gov/AVHRR		Gao *et al.* (2012), Gao (2019)
ASTER	90 m	16 days	1999 to date	https://asterweb.jpl.nasa.gov/data.asp		NASA (2001)
MODIS	1 km/6 km	1 day, 8 days	2000–2017	https://modis.gsfc.nasa.gov/data/dataprod/mod11.php	CLM	Gao *et al.* (2012), Naz *et al.* (2020)
VIIRS	375–750 m	1 day	2012–2021	https://www.nesdis.noaa.gov/our-satellites/currently-flying/joint-polar-satellite-system/visible-infrared-imaging-radiometer-suite-viirs		Su (2002), Kustas *et al.* (1995)
Sentinel-3	1 km	<2 days	2017 to date	https://sentinel.esa.int/web/sentinel/sentinel-data-access		ESA (2018)
ECOSTRESS	38×69 m	4 days				Hulley *et al.* (2017)

AVHRR, Advanced Very High-Resolution Radiometer; VIIRS, Visible Infrared Imaging Radiometer Suite; ASTER, Advanced Spaceborne Thermal Emission and Reflection Radiometer; MODIS, Moderate Resolution Imaging Spectroradiometer; ECOSTRESS, ECOsystem Spaceborne Thermal Radiometer Experiment on Space Station; CLM, Community Land Model.

Table 6 | Satellite products for water storage

Satellite sensor	Spatial resolution	Temporal frequency	Temporal interval	Access/source	Hydrological model	References
GRACE	500,000 km^2	30 days	2006 to present	https://grace.jpl.nasa.gov/data/get-data/	W3RA	Han *et al.* (2009), Muskett & Romanovsky (2009), Rodell *et al.* (2009), Khaki *et al.* (2020)
SWOT	10 km (larger waterbodies) 250 m^2 (lakes, reservoirs, wetlands)	11 days	2000–2019	https://directory.eoportal.org/web/eoportal/satellite-missions/s/swot https://dahiti.dgfi.tum.de/en/		Fjørtoft *et al.* (2014), Schwatke *et al.* (2019)

precipitation (P) and outgoing fluxes of ET and discharge (Q) at the Earth's surface in the following equation:

$$\Delta S = P - \mathrm{ET} - Q \tag{1}$$

Each water budget component in Equation (1) has different temporal dynamics. For example, precipitation has faster dynamics than storage change. Irrespective of the different temporal dynamics of each flux, Equation (1) holds at any time interval. There are several products from previous and continuing satellite missions that measure these components at various time and space scales, either separately or as an aggregate. By combining microwave and infrared satellite observations, global precipitation is retrieved with very high spatial and temporal resolution (Sorooshian *et al.* 2000; Kummerow *et al.*

Table 7 | Satellite products for the surface water level

Satellite sensor	Spatial resolution	Temporal frequency	Temporal interval	Access/source	Hydrological models	References
Jason-2/3	Lakes > 100 km^2	10 days	2003–2016	https://ipad.fas.usda.gov/cropexplorer/global_reservoir/ https://www.jpl.nasa.gov/missions/jason-3		Lambin *et al.* (2010)
Sentinel-3	350 m along the track	27 days	2017 to date	https://sentinel.esa.int/web/sentinel/sentinel-data-access		ESA (2018)
ENVISAT		10 days		https://earth.esa.int/eogateway/missions/envisat		Resti *et al.* (1999)
Topex/Poseidon		10 days	1992–2001	https://sealevel.jpl.nasa.gov/missions/topex-poseidon/summary/		Resti *et al.* (1999)
SWOT	10 km (larger waterbodies) 250 m^2 (lakes, reservoirs, wetlands)	11 days		https://directory.eoportal.org/web/eoportal/satellite-missions/s/swot https://dahiti.dgfi.tum.de/en/		Fjørtoft *et al.* (2014), Schwatke *et al.* (2019)

Table 8 | Satellite products for surface water extent

Satellite sensor	Spatial resolution	Temporal frequency	Temporal interval	Access/source	Hydrological models	References
Landsat	30 multispectral ***(Landsat-8)*** 100 m thermal ***(Landsat-9)***	16 days	1985–2019	https://landsat.usgs.gov		Landsat 8 Data Users Handbook (2020)
MODIS	500 m	Daily		https://floodmap.gsfc.nasa.gov		Radočaj *et al.* (2020)
Sentinel-2	10–60 m	5/10 days	2016 to date	https://sentinel.esa.int/web/sentinel/sentinel-data-access		Sentinel-2 User Handbook (2020)

Table 9 | Satellite products for stream flow

Satellite sensor	Spatialresolution	Temporal frequency	Temporal interval	Access/source	Hydrological models	Reference
SWOT	10 km	11 days		https://swot.jpl.nasa.gov/		Alsdorf & Lettenmaier (2003)

SWOT, Surface Water Ocean Topography.

Table 10 | Satellite products for discharge

Satellite sensor	Spatial resolution	Temporal frequency	Temporal interval	Access/source	Hydrological models	Reference
GRDC	Global	Daily		https://www.bafg.de/GRDC/EN/01_GRDC/13_dtbse/database_node.html		Dai *et al.* (2012)

GRDC, Global Runoff Data Center.

2001; Joyce *et al.* 2004; Huffman *et al.* 2007). Satellite sensors play an important role in monitoring various components of the water budget, which includes tracking the transport and distribution of water throughout the Earth's hydrological cycle (Table 11). They give statistics on various crucial characteristics that help to understand the water budget.

3.2.7. Groundwater

Groundwater monitoring is more difficult than monitoring surface water bodies such as rivers or lakes. Satellite sensors, on the other hand, play a role in indirectly assessing and analyzing groundwater by observing numerous surface indicators related to groundwater levels, land surface changes, and hydrological processes (Table 12).

3.3. Bias correction methods

Accuracy assessments determine the quality of the information derived from remotely sensed data (Congalton & Green 2009; Beyene 2023). Some correction methods (atmospheric correction, topographic correction, geometric correction, and radiometric correction) need to be applied for obtaining high-quality data. Atmospheric corrections are methods used to convert the radiance measured at the satellite to the outgoing radiance measured at the ground (Lu *et al.* 2002). It considers that selective scattering and absorption of light alter reflectance (Silleos *et al.* 2006). Radiometric correction takes into account sensor calibration, illumination, and view angle (Carlson & Ripley 1997). Geometric correction uses careful Ground Control Point selection, which is required for satellite images. Accurate and consistent georeferencing is especially important for automatic land cover change algorithms because change detection is performed by overlaying images from different sources (Russ 1995). Radiometric corrections include correcting the data for sensor irregularities and unwanted sensor or atmospheric noise and converting the data, so they accurately represent the reflected or emitted radiation measured by the sensor. Geometric corrections include correcting for geometric distortions due to sensor-Earth geometry variations and converting the data to real-world coordinates (e.g., latitude and longitude) on the Earth's surface (Jain 1989; Lillesand & Kiefer 1994).

In order to reduce the position errors, Hoffman & Grassotti (1996) proposed a feature correction and alignment technique (FCA), which used a variational approach to solve a nonlinear least squares estimation problem with side constraints to vary the displacement and amplification errors of the prior background field until usable observations were available (Hoffman & Grassotti 1996). Based on the FCA method, Grassotti fused radar and satellite precipitation estimates and performed the ideal experiment for Typhoon Andrew, using the precipitation observed by radar to adjust the precipitation estimates from Special

Table 11 | Satellite products for water budget

Satellite sensor	Spatial resolution	Temporal frequency	Temporal interval	Access/source	References
GRACE	500,000 km^2	30 days	January 2004–December 2015	https://grace.jpl.nasa.gov/data/get-data/	Swenson & Milly (2006), Syed *et al.* (2007), Awange *et al.* (2008), Jiang *et al.* (2014)
SWOT	10 km	11 days		https://swot.jpl.nasa.gov/	Crowley *et al.* (2008)

GRACE, Gravity Recovery, and Climate Experiment; SWOT, Surface Water Ocean Topography.

Table 12 | Satellite products for groundwater

Satellite sensor	Spatial resolution	Temporal frequency	Temporal interval	Access/source	Hydrologic models	References
GRACE	500,000 km^2	30 days	2002–2017	https://grace.jpl.nasa.gov/data/get-data/	MODFLOW	Rodell *et al.* (2009), Durand *et al.* (2016), Tapley *et al.* (2004), Frappart *et al.* (2015), Azarderakhsh *et al.* (2011), Yeh *et al.* (2006)
GRACE FO	500,000 km^2	30 days	2018 to date	https://gracefo.jpl.nasa.gov/		Niu & Yang (2006)

GRACE, Gravity Recovery, and Climate Experiment; GRACE FO, GRACE Follow-On.

Sensor Microwave/Imager (SSM/I). The adjusted SSM/I precipitation estimates can better fit radar observations and satisfy other constraints (Grassotti *et al.* 1999).

Systematic errors and random errors are common in satellite rainfall products (Goshime 2020). Error sources are mostly related to the imperfection of the retrieval algorithm, data source, and postprocessing procedures (Dubovik *et al.* 2021; Zhang *et al.* 2021). Compared to some meteorological variables like temperature, which has a steadier geographical and temporal pattern, bias correction of satellite rainfall data is thought to be the most difficult (Soo *et al.* 2020). From the available methods, distribution mapping tends to address bias by correlating patterns of different rainfall magnitudes (Valdés-Pineda *et al.* 2016; Katiraie-Boroujerdy *et al.* 2020).

Many previous studies have shown that the assimilation of hydrological parameter data from satellite sensor products and gauges could complement each other and achieve good performance with sufficient ground observations (Tan & Yang 2020; Zhou *et al.* 2021, 2022). Tian & Peters-Lidard (2010) corrected the CMORPH and TRMM data by reducing the error by 47–63% based on rain gauges in the USA. Stisen & Sandholt (2010) improved hydrological simulation efficiency by correcting the SPPs in the Senegal River Basin in West Africa. Zhou *et al.* (2021, 2022) employed statistical and dynamic bias correction to correct Global Satellite Mapping of Precipitation (GSMaP) and Global Precipitation Measurement (GPM) series data in the Fuji River Basin, Japan. The results showed that the corrected SPPs significantly improved and benefited the efficiency of runoff simulation. Recently, Liu *et al.* (2023) addressed a three-step bias correction method incorporating the statistic and dynamic bias correction method, the cumulative distribution function matching method and the inverse error variance weighting method for SPPs by correcting the bias of SPPs in regions with limited gauge data, which poses a significant challenge, especially when aiming for reliable precipitation data for hydrological simulations, particularly in near-real-time scenarios.

4. CONCLUSION AND RECOMMENDATIONS

The use of satellite sensors and RS data in hydrology is critically important to the water and health sectors. It enhances the ability to monitor, manage, and protect water resources, thereby ensuring the provision of safe drinking water and aiding in the prevention of waterborne diseases and the challenges posed by climate change. The continuous advancement and utilization of these technologies are essential for promoting public health and achieving sustainable water resource management.

Hydrological observations and modeling utilizing satellite data are critical for the long-term management of water resources across wide areas. Water resource RS entails gathering data ranging from a regular inventory of surface water bodies to an assessment of rainfall, soil moisture, ET, groundwater, and snow melt runoff (Singh 2018). Satellite RS is increasingly being utilized as a supplement to in-person monitoring networks, and in many situations, it is the only viable source. Satellite-based sensors can now measure nearly all components of the hydrological cycle, both directly and indirectly (Flechtner *et al.* 2015; Lettenmaier *et al.* 2015). These include precipitation, evaporation, lake and river levels, surface water, soil moisture, snow, and total water storage (surface and subsurface water). As a result, these sensors are capable of providing crucial information in support of water management and monitoring the evolution of hazards and their repercussions (Van Dijk & Renzullo 2011).

The authors recommend satellite sensors for several advantages in monitoring hydrologic parameters, providing a wealth of information that can be invaluable for understanding and managing water resources as follows:

- *Wide coverage and frequent monitoring:* Satellites can cover large and remote areas, including regions that are otherwise inaccessible or difficult to monitor regularly. This capability allows for the comprehensive and consistent monitoring of hydrological parameters over vast areas, such as entire watersheds or river basins. Satellites can monitor hydrological parameters globally, making them valuable for studying water resources on a worldwide scale and facilitating international collaboration and understanding of water-related issues. Satellites provide frequent and repetitive observations over time. This allows for the assessment of temporal changes in hydrological conditions, enabling the detection of trends, seasonal variations, and sudden changes such as floods or droughts.
- *Multispectral and multi-temporal data*: Satellite sensors can capture data in various spectral bands, including visible, infrared, and microwave wavelengths. This multispectral data allow for the analysis of different hydrological parameters, such as soil moisture, ET, snow cover, and surface water bodies.
- *Consistency and standardization*: Satellite data are consistent and standardized, providing a continuous record that facilitates comparison and analysis over different spatial and temporal scales. This consistency is crucial for assessing long-term trends and changes in hydrological parameters.

- *Integration with geographic information systems (GISs)*: Satellite data can be easily integrated with GIS technology, allowing for the creation of spatially explicit maps and models. This integration enables better decision-making in water resource management, land use planning, and disaster risk reduction.
- *Timely and rapid response*: Satellites can provide near-real-time data, enabling rapid response to hydrological events such as floods or droughts. This information is valuable for early warning systems and emergency management.
- *Cost-effectiveness*: While there are initial costs associated with satellite systems, they can be cost-effective in the long run compared to traditional ground-based monitoring, especially in remote or inaccessible regions where establishing and maintaining ground stations might be challenging.
- *Monitoring water quality and quantity*: Satellite sensors play a crucial role in monitoring various water quality parameters, such as turbidity, chlorophyll concentration, and harmful algal blooms. By providing continuous and large-scale data, RS helps detect and track pollution sources, monitor the extent of contamination, and assess the overall health of water bodies. This information is vital for ensuring safe drinking water and managing water resources effectively.
- *Early warning systems for water-related health hazards*: RS datasets are essential for developing early warning systems for water-related health hazards such as floods and likely associated waterborne disease outbreaks. Satellite data can predict extreme weather events and their impact on water resources, allowing for timely interventions to mitigate health risks. For instance, flood prediction can lead to the evacuation of at-risk populations and exposures to contaminated water.
- *Addressing climate change impacts on water resources*: Climate change poses significant challenges to water availability and quality, affecting public health. Satellite sensors offer insights into changing precipitation patterns, melting glaciers, and shifting river flows. Understanding these changes helps in developing adaptive strategies to ensure reliable water supplies and mitigate health impacts related to water scarcity and quality degradation.
- *Supporting research and policy development*: The integration of satellite sensor data into hydrology and water resource management research supports evidence-based policy-making. It enables researchers and policymakers to analyze trends, evaluate the effectiveness of interventions, and make informed decisions to protect public health. This data-driven approach fosters the development of robust water management policies that safeguard communities against water-related health issues.

In summary, satellite sensors offer a powerful and versatile tool for monitoring hydrological parameters, providing valuable data that support water resource management, environmental conservation, disaster mitigation, mitigating health impacts related to water scarcity, and scientific research. Therefore, it is advisable to use RS data for sparsely gauged stations for water resource assessment and management at all levels.

DATA AVAILABILITY STATEMENT

All relevant data are included in the paper or its Supplementary Information.

CONFLICT OF INTEREST

The authors declare there is no conflict.

REFERENCES

Al-Aubidy, K. 2007 *Sensor Characteristics: Advanced Measurement Systems & Sensors (0640732)*, Lecture 2, p. 19, Philadelphia University-Jordan.

Alfieri, L., Lorini, V., Hirpa, F. A., Harrigan, S., Zsoter, E., Prudhomme, C. & Salamon, P. 2020 A global streamflow reanalysis for 1980–2018. *Journal of Hydrology X* **6**, 100049. https://doi.org/10.1016/j.hydroa.2019.100049.

Alsdorf, D. A. & Lettenmaier, D. P. 2003 Tracking fresh water from space. *Science* **301**, 1491–1494.

Anderson, M. C., Norman, J. M., Mecikalski, J. R., Otkin, J. A. & Kustas, W. P. 2007 A climatological study of evapotranspiration and moisture stress across the continental U.S. based on thermal remote sensing: 1. Model formulation. *Journal of Geophysical Research* **112**, D10117. https://doi.org/10110.11029/12006JD007506.

Anderson, M. C., Hain, C. R., Wardlow, B., Mecikalski, J. R. & Kustas, W. P. 2011 Evaluation of a drought index based on thermal remote sensing of evapotranspiration over the continental U.S. *Journal of Climate* **24** (8), 2025–2044. https://doi.org/10.1175/ 2010JCLI3812.1.

Aonashi, K., Awaka, J., Hirose, M., Kozu, T., Kubota, T., Liu, G., Shige, S., Kida, S., Seto, S., Takahashi, N. & Takayabu, Y. N. 2009 GSMap passive microwave precipitation retrievals: Algorithm description and validation. *Journal of Applied Meteorology* **87A**, 119–136.

Ashouri, H., Hsu, K. L., Sorooshian, S., Braithwaite, D. K., Knapp, K. R., Cecil, L. D., Nelson, B. R. & Prat, O. P. 2015 PERSIANN-CDR: Daily precipitation climate data record from multisatellite observations for hydrological and climate studies. *Bulletin of the American Meteorological Society* **96** (1), 69–83. https://doi.org/10.1175/BAMS-D-13-00068.1.

Awange, J. L., Sharifi, M. A., Ogonda, G., Wickert, J., Grafarend, E. W. & Omulo, M. A. 2008 The falling Lake Victoria water level: GRACE, TRIMM and CHAMP satellite analysis of the lake basin. *Water Resources Management* **22**, 775–796.

Azarderakhsh, M., Rossow, W. B., Papa, F., Norouzi, H. & Khanbilvardi, R. 2011 Diagnosing water variations within the Amazon Basin using satellite data. *Journal of Geophysical Research* **116**, D24107. https://doi.org/10.1029/2011JD015997.

Barsi, Á., Kugler, Z., Juhász, A., Szabó, G., Batini, C., Abdulmuttalib, H., Huang, G. & Shen, H. 2019 Remote sensing data quality model: From data sources to lifecycle phases. *International Journal of Image and Data Fusion*. https://doi.org/10.1080/19479832.2019.1625977.

Beck, H. E., van Dijk, A. I. J. M., Levizzani, V., Schellekens, J., Miralles, D. G., Martens, B. & de Roo, A. 2016 MSWEP: 3-hourly 0.25° global gridded precipitation (1979–2015) by merging gauge, satellite, and reanalysis data. *Hydrology and Earth System Sciences* **21**, 589–615.

Beck, H. E., Vergopolan, N., Pan, M., Levizzani, V., Van Dijk, A. I. J. M., Weedon, G. P., Brocca, L., Pappenberger, F., Huffman, G. J. & Wood, E. J. 2017 Global-scale evaluation of 22 precipitation datasets using gauge observations and hydrological modeling. *Hydrology and Earth System Sciences* **21** (12), 6201–6217. doi: 10.5194/hess-21-6201-2017.

Bergström, S. 1992 *The HBV Model – Its Structure and Applications*. Swedish Meteorological and Hydrological Institute, Norrköping, Sweden.

Beyene, T. D. 2023 Evaluation of a multi-staged bias correction approach on CHIRP and CHIRPS rainfall product: A case study of the Lake Hawassa watershed. *Journal of Water and Climate Change* **14** (6), 1847–1867. https://doi.org/10.2166/wcc.2023.457.

Buyantuyev, A. & Wu, J. G. 2012 Urbanization diversifies land surface phenology in arid environments: Interactions among vegetation, climatic variation, and land use pattern in the Phoenix metropolitan region, USA. *Landscape and Urban Planning* **105**, 149–159.

Carlson, N. T. & Ripley, D. A. 1997 On the relation between NDVI, fractional vegetation cover, and leaf area index. *Remote Sensing of Environment* **62**, 241–252.

Chaves, M. E. D., Picoli, M. C. A. & Sanches, I. D. 2020 Recent applications of Landsat 8/OLI and sentinel-2/MSI for land use and land cover mapping: A systematic review. *Remote Sensing* **12** (18), 3062. https://doi.org/10.3390/rs12183062.

Chen, F., Crow, W. T., Starks, P. J. & Moriasi, D. N. 2011 Improving hydrologic predictions of a catchment model via assimilation of surface soil moisture. *Advances in Water Resources* **34**, 526–536. https://doi.org/10.1016/j.advwatres.2011.01.011.

Chen, J., Li, Z., Li, L., Wang, J., Qi, W., Xu, C. & Kim, J. 2020 Evaluation of multi-satellite precipitation datasets and their error propagation in hydrological modeling in a Monsoon-Prone Region. *Remote Sensing* **12** (21), 3550.

Congalton, R. G. & Green, K. 2009 *Assessing the Accuracy of Remotely Sensed Data –Principles and Practices* 2nd edn.. CRC Press, Taylor & Francis Group, Boca Raton, FL.

Crowley, J. W., Mitrovica, J. X., Bailey, R. C., Tamisiea, M. E. & Davis, J. L. 2008 Annual variations in water storage and precipitation in the Amazon Basin. *Journal of Geodesy* **82**, 9–13.

Dai, L., Che, T., Wang, J. & Zhang, P. 2012 Snow depth and snow water equivalent estimation from AMSR-E data based on a priori snow characteristics in Xinjiang, China. *Remote Sensing of Environment* **127** (December), 14–29.

Dubovik, O., Schuster, G. L., Xu, F., Hu, Y., Bösch, H., Landgraf, J. & Li, Z. 2021 Grand challenges in satellite remote sensing. *Frontiers in Remote Sensing* **2**, 619818.

Durand, M., Gleason, C. J., Garambois, P. A., Bjerklie, D., Smith, L. C. & Roux, H. 2016 An intercomparison of remote sensing river discharge estimation algorithms from measurements of river height, width, and slope. *Water Resources Research* **52**, 4527–4549. https://doi. org/10.1002/2015WR018434 Earth Observation for Water Resources Management. (n.d.). Earth Observation for Water Resources Management. (n.d.).

Entekhabi, D., Njoku, E. G., Njoku, E. G., Kellogg, K. H., Kellogg, K. H. & Edelstein, W. N. 2010 The Soil Moisture Active Passive (SMAP) mission. *Proceedings of the IEEE* **98** (5), 704–716. https://doi.org/10.1109/JPROC.2010.2043918.

ESA 2013 *The Operational Copernicus Optical High-Resolution Land Mission*. Available from: www.esa.int/copernicus.

ESA 2018 Sentinel-1 {level-1} products. Available from: https://earth.esa.int/web/sentinel/ technical guides/sentinel-1-sar/products-algorithms/level-1-algorithms/products.

Fisher, J. B., Tu, K. P. & Baldocchi, D. D. 2008 Global estimates of the land–atmosphere water flux based on monthly AVHRR and ISLSCP-II data, validated at 16 FLUXNET sites. *Remote Sensing of Environment* **112** (3), 901–919.

Fjørtoft, R., Gaudin, J. M., Pourthié, N., Lalaurie, J., Mallet, A., Nouvel, J., Martinot-Lagarde, J., Oriot, H., Borderies, P., Ruiz, C. & Daniel, S. 2014 KaRIn on SWOT: Characteristics of Near-Nadir Ka-band interferometric SAR imagery. *IEEE Transactions on Geoscience and Remote Sensing* **52**, 2172–2185. doi:10.1109/TGRS.2013.2258402.

Flechtner, F., Christoph, K. N. & Gu, A. 2015 What Can be Expected from the GRACE-FO Laser Ranging Interferometer for Earth Science Applications? 88090. https://doi.org/10.1007/978-3-319-32449-4.

Frappart, F., Papa, F., Malbeteau, Y., León, J. G., Ramillien, G., Prigent, C., Seoane, P., Seyler, F. & Calmant, S. 2015 Surface freshwater storage variations in the Orinoco floodplains using multi-satellite observations. *Remote Sensing* **7**, 89–110. https://doi.org/10.3390/rs70100089.

Funk, C., Peterson, P., Landsfeld, M., Pedreros, D., Verdin, J., Shukla, S., Husak, G., Rowland, J., Harrison, L., Hoell, A. & Michaelson, J. 2015 The climate hazards infrared precipitation with stations – A new environmental record for monitoring extremes. *Scientific Data* **2**, 150066. https://doi.org/10.1038/sdata.2015.66.

Gao, Q. 2019 *Estimation of Water Resources on Continental Surfaces by Multi-Sensor Microwave Remote Sensing*, pp. 1–3.

Gao, H., Birkett, C. & Lettenmaier, D. P. 2012 Global monitoring of large reservoir storage from satellite remote sensing. *Water Resources Research* **48**, W09504. https://doi.org/10.1029/2012WR012063.

Goshime, D. 2020 *Integration of Satellite and Ground-Based Rainfall Data for Water Resources Assessment in Central Rift Valley Lakes Basin, Ethiopia*. CY Cergy Paris Université, Paris.

Grassotti, C., Iskenderian, H. & Hoffman, R. N. 1999 Calibration and alignment. *Journal of Applied Meteorology* **38**, 677–695.

Guan, X. B., Shen, H. F., Li, X. H., Gan, W. X. & Zhang, L. P. 2019 A long-term and comprehensive assessment of the urbanization-induced impacts on vegetation net primary productivity. *Science of the Total Environment* **669**, 342–352.

Guillermo, J., Pedreros, G. & Ospina-noreña, J. E. 2022 Remote sensing applications: Society and environment spatial distribution model of terrestrial radiation imbalance measured by means of orbiting radiometers. *Remote Sensing Applications: Society and Environment* **28** (October), 100857. https://doi.org/10.1016/j.rsase.2022.100857.

Han, S., Kim, H., Yeo, I., Yeh, P., Oki, T., Seo, K., Alsdorf, D. & Luthcke, S. 2009 Dynamics of surface water storage in the Amazon inferred from measurements of inter-satellite distance change. *Geophysical Research Letter* **26**, L09403. doi:10.1029/2009GL037910.

Harris, I., Jones, P. D., Osborn, T. J. & Lister, D. H. 2014 Updated high-resolution grids of monthly climatic observations – The CRU TS3.10 dataset. *International Journal of Climatology* **34** (3), 623–642.

Hoffman, R. N. & Grassotti, C. 1996 A technique for assimilating SSM/I observations of marine atmospheric storms: Tests with ECMWF analyses. *Journal of Applied Meteorology and Climatology* **35**, 1177–1188.

Holben, B. N., Tucker, C. J. & Fan, C. J. 1980 Spectral assessment of soybean leaf-area and leaf biomass. *Photogrammetric Engineering and Remote Sensing* **46**, 651–656.

Hong, Y., Chen, S., Xue, X., Hodges, G., 2012 Global precipitation estimation and applications. In: *Multiscale Hydrologic Remote Sensing: Perspectives and Applications* (Chang, N. & Hong, Y., eds). CRC Press, Boca Raton, FL, pp. 371–386.

Hsu, K.-l., Gao, X., Sorooshian, S. & Gupta, H. 1997 Precipitation estimation from remotely sensed information using artificial neural networks. *Journal of Applied Meteorology* **36** (9), 1176–1190.

Hu, T. X. 2021 Mapping fine-scale human disturbances in a working landscape with Landsat time series on Google Earth Engine. *Isprs Journal of Photogrammetry and Remote Sensing* **176**, 250–261.

Huete, A. R., Didan, K., Miura, T., Rodriguez, E. P., Gao, X. & Ferreira, L. G. 2002 Overview of the radiometric and biophysical performance of the MODIS vegetation indices. *Remote Sensing of Environment* **83**, 195–213.

Huffman, G. J., Bolvin, D. T., Nelkin, E. J., Wolff, D. B., Adler, R. F., Gu, G., Hong, Y., Bowman, K. P. & Stocker, E. F. 2007 The TRMM multisatellite precipitation analysis (TMPA): Quasi-global, multiyear, combined-sensor precipitation estimates at fine scales. *Journal of Hydrometeorology* **8**, 38–55.

Hulley, G., Hook, S., Fisher, J. & Lee, C. 2017 ECOSTRESS, a NASA earth-ventures instrument for studying links between the water cycle and plant health over the diurnal cycle. In: *International Geoscience and Remote Sensing Symposium (IGARSS) 8128248*, pp. 5494–5496.

Jain, A. K. 1989 *Fundamentals of Digital Image Processing*. Prentice-Hall, New Jersey.

Jia, J., Deng, P., Zhang, M., Guo, H., Xu, C. & Bing, J. 2014 Land cover classification of finer resolution remote sensing data integrating temporal features from time series coarser resolution data. *Isprs Journal of Photogrammetry and Remote Sensing* **93**, 49–55.

Jiang, D., Wang, J., Huang, Y., Zhou, K., Ding, X. & Fu, J. 2014 The review of GRACE data applications in terrestrial hydrology monitoring. *Advances in Meteorology* **2014**. https://doi.org/10.1155/2014/725131.

Joyce, R. J., Janowiak, J. E., Arkin, P. A. & Xie, P. 2004 CMORPH: A method that produces global precipitation estimates from passive microwave and infrared data at high spatial and temporal resolution. *Journal of Hydrometeorology* **5** (3), 487–503. https://doi.org/10.1175/ 1525-7541(2004)005 < 0487: CAMTPG > 2.0.CO;2.

Katiraie-Boroujerdy, P.-S., Rahnamay Naeini, M., Akbari Asanjan, A., Chavoshian, A., Hsu, K.-L. & Sorooshian, S. 2020 Bias correction of satellite-based precipitation estimations using quantile mapping approach in different climate regions of Iran. *Remote Sensing* **12**, 2102.

Kerr, Y. H., Waldteufel, P., Richaume, P., Wigneron, J. P., Ferrazzoli, P., Mahmoodi, A., Bitar, A., Cabot, F., Gruhier, C., Juglea, S. E., Leroux, D., Mialon, A. & Delwart, S. 2012 The SMOS soil moisture retrieval algorithm. *Geoscience and Remote Sensing* **50**, 1384–1403.

Khaki, M., Franssen, H. J. H. & Han, S. C. 2020 Multi-mission satellite remote sensing data for improving land hydrological models via data assimilation. *Scientific Reports* **0123456789**, 1–23. https://doi.org/10.1038/s41598-020-75710-5.

Koike, T. 2013 Description of the GCOM-W1 AMSR2 Soil Moisture Algorithm. Technical Report NDX-120015A: Chapter 8. Japan Aerospace Exploration Agency Earth Observation Research Center Bulletin.

Kubota, T., Ushio, T., Shige, S., Kida, S., Kachi, M. & Okamoto, K. 2009 Verification of high-resolution satellite-based rainfall estimates around Japan using a gauge-calibrated ground-radar dataset. *Journal of the Meteorological Society of Japan* **87A**, 203–222.

Kummerow, C., Hong, Y., Oleson, W. S., Yang, S., Adler, R. F., Mccollum, J., Ferraro, R., Petty, G. & Shin, D. 2001 The evolution of the Goddard profiling algorithm (GPROF) for rainfall estimation from passive microwave sensors. *Journal of Applied Meteorology* **40**, 1801–1820.

Kustas, W. P., Humes, K. S., Norman, J. M. & Moran, M. S. 1995 Single-and dual-source modeling of surface energy fluxes with radiometric surface temperature. *Journal of Applied Meteorology* **35**, 110–121.

Lakshmi, V. 2018 Use of satellite remote sensing in hydrological predictions in ungaged basins. In: Department of Geological Sciences, University of South Carolina, Columbia SC 29208.

Lambin, J., Morrow, R., Fu, L.-L., Willis, J. K., Bonekamp, H. & Lillibridge, J. 2010 The OSTM/Jason-2 mission. *Marine Geodesy*, 33 (supp1), 4–25. https://doi.org/10.1080/01490419.2010.491030.

Landsat 8 Data Users Handbook 2020. Available from: https://www.usgs.gov/media/files/landsat-8-data-usershandbook.

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**, 7309–7342. https://doi.org/10.1002/2015WR017616.

Light, D. L. 1990 Characteristics of remote sensors for mapping and earth science applications. *United States Geological Survey* **56** (12), 1613–1623.

Lillesand, T. M. & Kiefer, R. W. 1994 *Remote Sensing and Image Interpretation*. John Wiley and Sons Inc., New York.

Liu, X., Yong, Z., Liu, L., Chen, T., Li, J. & Zhou, L. 2023 Improving hydrological simulation accuracy through a three-step bias correction method for satellite precipitation. *MDPI: Water* **15**, 3615.

Lu, D., Mausel, P., Brondízio, E. & Moran, E. F. 2002 Assessment of atmospheric correction methods for Landsat TM data applicable to Amazon Basin LBA research. *International Journal of Remote Sensing* **3**, 487–503.

Ma, J. U. N. & Sun, W. 2018 Hydrological analysis using satellite remote sensing big data and CREST model. *IEEE Access* **6**, 9006–9016. https://doi.org/10.1109/ACCESS.2018.2810252.

Martens, B., Miralles, D. G., Lievens, H., van der Schalie, R., de Jeu, R. A. M., Fernández-Prieto, D., Beck, H. E., Dorigo, W. A. & Verhoest, N. E. 2017 GLEAM v3: Satellite based land evaporation and root-zone soil moisture. *Geoscientific Model Development* **10**, 1903–1925. https://doi.org/10.5194/gmd-.

McCabe, M. F., Rodell, M., Alsdorf, D. E., Miralles, D. G., Uijlenhoet, R., Wagner, W., Lucieer, A., Houborg, R., Verhoest, N. E. C., Franz, T. E., Shi, J., Gao, H. & Wood, E. F. 2017 The future of earth observation in hydrology. *Hydrology and Earth System Sciences Discussions* **21**, 3879–3914.

Mosaffa, H., Filippucci, P., Massari, C., Ciabatta, L. & Brocca, L. 2023 SM2RAIN-Climate, a monthly global long-term rainfall dataset for climatological studies. *Nature Scientific Data* 1–14. https://doi.org/10.1038/s41597-023-02654-6.

Mu, Q., Zhao, M. & Running, S. W. 2011 Improvements to a MODIS global terrestrial evapotranspiration algorithm. *Remote Sensing of Environment* **115**, 1781–1800. https://doi.org/10.1016/j.rse.2011.02.019.

Muskett, R. R. & Romanovsky, V. E. 2009 Groundwater storage change in Arctic permafrost watersheds from GRACE and in situ measurements. *Environmental Research Letter* **4**. doi:10.1088/1748-9326/4/4/045009.

NASA 2001 *National Snow and Ice Data Center Distributed Active Archive Center*. https://doi.org/10.5067/AMSR-E/AE_LAND3.002.

Naz, B. S., Kollet, S., Franssen, H.-J. H., Montzka, C. & Kurtz, W. 2020 A 3 km spatially and temporally consistent European daily soil moisture reanalysis from 2000 to 2015. *Nture: Scientific Data* 1–14. https://doi.org/10.1038/s41597-020-0450-6.

New, M., Hulme, M. & Jones, P. 2000 Representing twentieth-century space–time climate variability. Part II: Development of 1901–96 monthly grids of terrestrial surface climate. *Journal of Climate* **13**, 2217–2238.

Niu, G. Y. & Yang, Z. L. 2006 Assessing a land surface model's improvement with GRACE estimates. *Geophysical Research Letters* **33**, L07401. doi:10.1029/2005GL025555.

Njoku, E. G. 2004 AMSR-E/Aqua Daily L3 surface soil moisture, interpretive parameters, & QC EASE-Grids, Version 2. Boulder, Colorado, USA.

Owe, M., de Jeu, R. & Holmes, T. 2008 Multisensor historical climatology of satellite-derived global land surface moisture. *Journal of Geophysical Research* **113**, F01002. https://doi.org/10.1029/2007JF000769.

Paloscia, S., Pettinato, S., Santi, E., Notarnicola, C., Pasolli, L. & Reppucci, A. 2013 Soil moisture mapping using Sentinel-1 images: Algorithm and preliminary validation. *Remote Sensing of Environment* **134**, 234–248.

Pastor-Guzman, J., Dash, J. & Atkinson, P. M. 2018 Remote sensing of mangrove forest phenology and its environmental drivers. *Remote Sensing of Environment* **205**, 71–84.

Peterson, T. C. & Vose, R. S. 1997 An overview of the global historical climatology network temperature database. *Bulletin of the American Meteorological Society* **78** (12), 2837–2849.

Pinzon, J. E. & Tucker, C. J. 2014 A non-stationary 1981-2012 AVHRR NDVI3g time series. *Remote Sensing* **6**, 6929–6960. https://doi.org/10.3390/rs6086929.

Quichimbo, E. A. 2021 *Modelling Water Partitioning in Dryland Regions: A Multiscale Analysis*. Cardiff University, Cardiff.

Radočaj, D., Obhodaš, J., Jurišic, M. & Gašparovic, M. 2020 Global open data remote sensing satellite missions for land monitoring and conservation: A review. *Land* **9**, 402. doi:10.3390/land9110402.

Reichle, R., De Lannoy, G., Koster, R., Crow, W. & Kimball, J. 2016 SMAP L4 9km EASE grid surface and root zone soil moisture geophysical data. Version 2. [Indicate subset used]. Boulder, Colorado, USA: NASA National Snow and Ice Data Center Distributed Active Archive Center. https://doi.org/10.5067/YK70EPDHNF0L.

Resti, A., Benveniste, J., Roca, M., Levrini, G. & Johannessen, J. 1999 The Envisat radar altimeter system (RA-2). *ESA Bulletin* **98**, 94–101.

Rodell, M., Velicogna, I. & Famiglietti, J. S. 2009 Satellite-based estimates of groundwater depletion in India. *Nature* **460**, 999–1002. https://doi.org/10.1038/nature08238.

Rudolf, B. & Schneider, U. 2005 Calculation of gridded precipitation data for the global land–surface using in-situ gauge observations. In: *Proceedings of the 2nd Workshop of the International Precipitation Working Group IPWG, Monterey October 2004*, pp. 231–247. EUMETSAT92-9110-070-6 ISSN 1727-432X.

Russ, J. C. 1995 *The Image Processing Handbook*, 2nd edn. CRC Press, Baca Raton, FL.

Schamm, K., Ziese, M., Becker, A., Finger, P., Meyer-Christoffer, A., Schneider, U. & Stender, P. 2014 Global gridded precipitation over land: A description of the new GPCC first guess daily product. *Earth System Science Data* **6** (1), 49–60.

Schwatke, C., Scherer, D. & Dettmering, D. 2019 Automated extraction of consistent time-variable water surfaces of lakes and reservoirs based on Landsat and Sentinel-2. *Remote Sensing* **11** (9), 1010. doi:10.3390/rs11091010, 2019.

Sellars, S., Nguyen, P., Chu, W., Gao, X., Hsu, K. & Sorooshian, S. 2013 Computational earth science: Big data transformed into insight. *EOS Transactions American Geophysical* **94** (32), 277–278.

Senay, G. B., Bohms, S., Singh, R. K., Gowda, P. H., Velpuri, N. M., Alemu, H. & Verdin, J. P. 2013 Operational evapotranspiration mapping using remote sensing and weather datasets: A new parameterization for the SSEB approach. *Journal of the American Water Resources Association* **49**, 577–591. https://doi.org/10.1111/jawr.12057.

Sentinel-2 User Handbook 2020. Available from: https://earth.esa.int/documents/247904/685211/Sentinel-2_User_Handbook.

Shi, J., Jian, L., Zhang, L., Chen, K. S., Wigneron, J. P., Chanzy, A. & Jackson, T. J. 2006 Physically based estimation of bare-surface soil moisture with the passive radiometers. *IEEE Transactions on Geoscience and Remote Sensing* **44**, 3145–3152. https://doi.org/10.1109/TGRS.2006.876706 (2006).

Silleos, N. G., Alexandridis, T. K., Gitas, I. Z. & Perakis, K. 2006 *Advances Made in Biomass Estimation and Vegetation Monitoring in the Last 30 Years*.

Singh, R. P. 2018 Satellite Based Hydrology and Modeling. Land Hydrology Division Geosciences, Hydrology, Cryosphere Sciences and Applications Group (EPSA) Space Applications Centre, ISRO Ahmedabad.

Soo, E. Z. X., Jaafar, W. Z. W., Lai, S. H., Othman, F., Elshafie, A., Islam, T., Srivastava, P. & Hadi, H. S. O. 2020 Evaluation of bias-adjusted satellite precipitation estimations for extreme flood events in Langat River basin, Malaysia. *Hydrology Research* **51**, 105–126.

Sorooshian, S., Hsu, K. L., Gao, X., Gupta, H. V., Imam, B. & Braithwaite, D. 2000 *Evaluation of PERSIANN System Satellite-Based Estimates of Tropical Rainfall*. The University of Arizona, Tucson.

Stisen, S. & Sandholt, I. 2010 Evaluation of remote-sensing-based rainfall products through predictive capability in hydrological runoff modelling. *Hydrology Research* **24**, 879–891.

Su, B. 2002 The surface energy balance system (SEBS) for the estimation of turbulent heat fluxes. *Hydrology and Earth System Sciences* **6** (1), 85–99.

Swenson, S. C. & Milly, P. C. D. 2006 Climate model biases in seasonality of continental water storage revealed by satellite gravimetry. *Water Resources Research* **42**, W03201. doi:10.1029/2005WR004628.

Syed, T. H., Famiglietti, J. S., Zlotnicki, V. & Rodell, M. 2007 Contemporary estimates of Pan-Arctic freshwater discharge from GRACE and reanalysis. *Geophysical Research Letters* **34** (19), 1–6. https://doi.org/10.1029/2007GL031254.

Tan, M. L. & Yang, X. 2020 Effect of rainfall station density, distribution and missing values on SWAT outputs in tropical region. *Journal of Hydrology* **584**, 124660.

Tang, Q., Zhang, X., Duan, Q., Huang, S., Yuan, X., Cui, H., Li, Z. & Liu, X. 2016 Hydrological monitoring and seasonal forecasting: Progress and perspectives. *Journal of Geographical Sciences* **26** (7), 904–920.

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**, L09607. https://doi.org/10.1029/2004GL019920.

Tian, Y. & Peters-Lidard, C. D. 2010 A global map of uncertainties in satellite-based precipitation measurements. *Geophysical Research Letters* **37**, L24407.

Tong, X. W., Wang, K., Yue, Y., Brandt, M., Liu, B., Zhang, C., Liao, C. & Fensholt, R. 2017 Quantifying the effectiveness of ecological restoration projects on long-term vegetation dynamics in the karst regions of Southwest China. *International Journal of Applied Earth Observation and Geoinformation* **54**, 105–113.

Tucker, C. J. & Sellers, P. J. 1986 Satellite remote-sensing of primary production. *International Journal of Remote Sensing* **7**, 1395–1416.

Valdés-Pineda, R., Demaría, E., Valdés, J. B., Wi, S. & Serrat-Capdevilla, A. 2016 Bias correction of daily satellite-based rainfall estimates for hydrologic forecasting in the Upper Zambezi, Africa. *Hydrology and Earth System Sciences Discussions* **10**, 1–28.

Van Dijk, A. I. J. M. & Renzullo, L. J. 2011 Water resource monitoring systems and the role of satellite observations. *Hydrology and Earth System Sciences* **15** (1), 39–55. https://doi.org/10.5194/hess-15-39-2011.

Vargas, M., Miura, T., Shabanov, N. & Kato, A. 2013 An initial assessment of Suomi NPP VIIRS vegetation index EDR. *Journal of Geophysical Research: Atmospheres* **118**, 1–16. https://doi.org/10.1002/2013JD020439.

Verdin, A., Funk, C., Peterson, P., Landsfeld, M., Tuholske, C. & Grace, K. 2020 Development and validation of the CHIRTS-daily quasi-global high-resolution daily temperature data set. *Scientific Data* **7** (1), 1–14. https://doi.org/10.1038/s41597-020-00643-7.

Vinokullo, R. V., Meynadier, R., Sheffield, J. & Wood, E. F. 2011 Multi-model, multi-sensor estimates of global evapotranspiration: Climatology, uncertainties and trends. *Hydrological Procedure*. https://doi.org/10.1002/hyp.8393.

Wagner, W., Lemoine, G. & Rott, H. 1999 A method for estimating soil moisture from ERS scatterometer and soil data. *Remote Sensing of Environment* **70**, 191–207. https://doi.org/10.1016/S0034-4257(99)00036-X.

Willmott, C. J. & Matsuura, K. 1995 Smart interpolation of annually averaged air temperature in the United States. *Journal of Applied Meteorology* **34**, 2577–2586.

Xie, P., Chen, M. & Shi, W. 2010 CPC global unified gauge-based analysis of daily precipitation, Preprints. In: *24th Conferences on Hydrology*, Atlanta, GA. American Meteorological Society, p. 2.

Yeh, P. J. F., Swenson, S. C., Famiglietti, J. S. & Rodell, M. 2006 Remote sensing of groundwater storage changes in Illinois using the Gravity Recovery and Climate Experiment (GRACE). *Water Resources Research* **42**, W12203. doi:10.1029/2006WR005374.

Zeng, L. L., Wardlow, B. D., Xiang, D. X., Hu, S. & Li, D. R. 2020 A review of vegetation phenological metrics extraction using time-series, multispectral satellite data. *Remote Sensing of Environment* **237**, 20.

Zhang, Y. L., Song, C. H., Band, L. E., Sun, G. & Li, J. X. 2017 Reanalysis of global terrestrial vegetation trends from MODIS products: Browning or greening? *Remote Sensing of Environment* **191**, 145–155.

Zhang, Y., Ye, A., Nguyen, P., Analui, B., Sorooshian, S. & Hsu, K. 2021 Error characteristics and scale dependence of current satellite precipitation estimates products in hydrological modeling. *Remote Sensing* **13**, 3061.

Zhao, J., Huang, S., Huang, Q., Wang, H., Leng, G. & Fang, W. 2020 Time-lagged response of vegetation dynamics to climatic and teleconnection factors. *Catena* **189** (12), 6911.

Zhou, L., Rasmy, M., Takeuchi, K., Koike, T., Selvarajah, H. & Ao, T. 2021 Adequacy of near real-time satellite precipitation products in driving flood discharge simulation in the Fuji River Basin, Japan. *Applied Science* **11**, 1087.

Zhou, L., Koike, T., Takeuchi, K., Rasmy, M., Onuma, K., Ito, H., Selvarajah, H., Liu, L., Li, X. & Ao, T. 2022 A study on availability of ground observations and its impacts on bias correction of satellite precipitation products and hydrologic simulation efficiency. *Journal of Hydrology* **610**, 127595.

First received 2 January 2024; accepted in revised form 15 May 2024. Available online 17 June 2024