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To cite this article: Maria Sigopi, Cletah Shoko & Timothy Dube (2024) Advancements in remote sensing technologies for accurate monitoring and management of surface water resources in Africa: an overview, limitations, and future directions, Geocarto International, 39:1, 2347935, DOI: [10.1080/10106049.2024.2347935](https://doi.org/10.1080/10106049.2024.2347935)

To link to this article: <https://doi.org/10.1080/10106049.2024.2347935>



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Published online: 16 May 2024.



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Advancements in remote sensing technologies for accurate monitoring and management of surface water resources in Africa: an overview, limitations, and future directions

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ABSTRACT

This review presents a comprehensive examination of recent advancements in utilizing multi-date satellite data to analyze spatial and temporal variations in seasonal and inter-annual surface water dynamics within arid environments of Africa. Remote sensing offers continuous, precise, and long-term datasets for surface water research. Various sensors with differing spatial resolutions are discussed, with high-resolution multispectral sensors providing superior spatial resolution but at higher costs. Conversely, dual-sensor approaches, including optical sensors (Sentinel-2 and Landsat), radar satellites (Sentinel-1 and RADARSAT) and UAVs were investigated. The review further examines the efficiency and applicability of traditional algorithms such as the modified normalized difference water index (MNDWI), normalized difference water index (NDWI), and automated water extraction index (AWEI) in detecting and delineating surface water resources. Additionally, machine learning (ML) algorithms, including support vector machines (SVM), Random Forest (RF), deep learning and emerging methodologies like recurrent transformer networks, have been explored. Therefore, we recommend that future research endeavours focus on leveraging high-resolution satellite imagery and integrating physical models with deep learning techniques, artificial intelligence, and online big data processing platforms to improve surface water mapping capabilities.

ARTICLE HISTORY

Received 23 January 2024

Accepted 22 April 2024

KEYWORDS

Aridity; big data; climate change; data extraction and integration; multi-date satellite data; surface water dynamics; water scarcity

1. Introduction

In Africa, surface water plays a crucial role in supporting various environmental and socio-economic activities. Africa's freshwater systems, including iconic rivers like the Nile and Congo, as well as significant lakes such as northern Lake Victoria, southern Lake Tanganyika, and southern Lake Malawi, play a pivotal role in sustaining human

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populations. For example, the Nile River, one of the world's longest rivers, traverses several African countries, including Egypt, Sudan, and Ethiopia, whereas the Lake Victoria, the largest lake in Africa, serves as a vital resource supporting the livelihoods of millions of people residing in the surrounding region. The Nile Basin sustains millions of people and serves as a vital source of water for agriculture, industry, and domestic use (Fielding et al. 2018). Both water bodies are vital for the livelihoods of over 238 million people, highlighting their critical importance (Dile et al. 2018).

However, challenges such as pollution, over-extraction, and inefficient management pose significant threats to water quality and availability, even in regions with abundant water resources. The imperative to address these challenges becomes more apparent given water's essential role in supporting various human activities such as food production, energy generation, and agriculture (Frenkel-Pinter et al. 2021; Saturday et al. 2021). Fluctuations in the surface water dynamics, including variations in water levels and shoreline erosion, can have profound impacts on local communities, ecosystems, and economies (Saturday et al. 2021). These changes may affect various socio-economic activities such as fishing, agriculture, and tourism, which are heavily reliant on the lake's resources (Olowoyeye and Kanwar 2023). Monitoring and assessing changes in these surface water resources can therefore provide valuable insights into water availability and distribution patterns, helping to inform water management strategies and ensure sustainable use of this critical resource.

Through the utilization of multi-date satellite data, researchers can systematically monitor and analyze surface water dynamic and processes over time, facilitating informed decision-making in water resource management and conservation efforts (Seaton et al. 2020). Moreover, such data-driven assessments contribute to the development of adaptive strategies to mitigate the impacts of environmental changes on local communities and ecosystems, thereby promoting the sustainable use and preservation of Lake Victoria's valuable resources (Lin et al. 2020). Advanced remote sensing methods, such as machine learning algorithms and data fusion techniques, offer additional capabilities for extracting valuable information from satellite imagery (Bhaga et al. 2020). For instance, researchers can use machine learning algorithms to classify surface water features and identify changes in water extent with high accuracy. Additionally, data fusion techniques allow researchers to combine information from different satellite sensors to improve the spatial and temporal resolution of surface water datasets, enabling more detailed and comprehensive analysis of water dynamics in semi-arid regions.

In recent decades, profound alterations in the quantity and quality of surface water have occurred globally, driven by the compounding effects of drought, climate change processes and anthropogenic activities (Bhaga et al. 2020). Sub-Saharan Africa, home to some of the world's most significant freshwater systems, faces the repercussions of these changes. Factors such as agricultural practices, industrialization, climate variability, and population growth pose imminent threats to water resources in the region (Molekoa et al. 2021; Turyasingura et al. 2022). The intricate nexus between these stressors and the resultant spatial-temporal variability of surface water is further underscored by the documented impacts of climate change on extreme weather events, as observed in the unprecedented changes affecting Lake Victoria (Wu et al. 2023).

In some regions, e.g. the Okavango River Basin (ORB), escalating water demands driven primarily by agricultural activities pose challenges for communities reliant on surface water resources in the Okavango Delta region (Mbaiwa 2004). Anticipated exponential growth in surface water demand further underscores the pressing need for a comprehensive understanding of surface water resources variations to inform effective decision-making

(Mosepele et al. 2019). Moreover, arid and semi-arid regions face mounting challenges in water resource management due to climate-induced complexities, presenting a formidable obstacle to water security, particularly evident in sub-Saharan Africa, where approximately 300 million people lack access to safe water sources, amplifying the stress on rural regions and exacerbating the pressure on water resources (Braune and Xu 2008).

Against the backdrop of Africa's vast and diverse climatic zones, coupled with its burgeoning population, estimated at 1.4 billion in 2022, urgent attention is warranted to comprehend and address the escalating challenges impinging upon the availability and contamination of surface water. Despite the existing mapping and exploration of surface water in African regions, some researchers express reservations regarding the significance, accuracy, reliability, and consistency of the data, particularly scrutinizing the 30-meter resolution global surface water maps (Hamunyela et al. 2022). Scientific investigations have revealed notable gaps in detailed information pertaining to climate, vegetation, and river discharge characteristics within various African regions (Mfundisi et al. 2022; Moses et al. 2022). For instance, Dile et al. (2018) underscored the limitations imposed by data scarcity on water resources research in the Upper Blue Nile basin. The consequent lack of reliable and consistent information accentuates the urgency of accurately assessing, monitoring, and managing small surface water bodies in Sub-Saharan Africa. Additionally, Sheffield et al. (2018) posits that attaining water security necessitates a profound comprehension of water resource dynamics at the basin scale, a crucial consideration in the hydrological study of African river basins, which remains a globally understudied feature (Rodell et al. 2018). This deficiency hampers the formulation of appropriate and sustainable water resource management strategies, highlighting the imperative for urgent action in monitoring surface water to ensure the establishment of effective and sustainable water management practices.

The timing and accurate detection and quantification of surface water resources have significant implications for water resource management in Africa (Prigent et al. 2016). Various approaches have been employed to monitor surface water resources in arid environments, particularly in Africa, including ground-based measurements and remote sensing techniques (e.g. empirical and physical-based approaches) (Tulbure and Broich 2019; Gong et al. 2023). While in-situ measurements are considered direct and accurate, they are also costly, time-consuming, and labor-intensive, making them challenging to implement effectively across large areas and ungauged catchments (Folwell and Farquharson 2006; Pekel et al. 2016). Therefore, there is a growing consensus that remote sensing approaches play a crucial and irreplaceable role in monitoring surface water resources in Africa, mainly due to the scarcity of in-situ data (Mashala et al. 2023).

Remote sensing provides valuable information on the condition, distribution, and state of water resources, enabling the monitoring of surface water resources at both local and regional scales (Smith 2019; Wang et al. 2020). The frequent availability of remote sensing data in a spatially distributed manner, with varying resolutions, offers a complementary data source and opportunity to monitor surface water resources compared to in-situ measurements (Barnieh et al. 2020; Peter et al. 2020). Furthermore, advancements in remote sensing technology over the years have significantly enhanced the ability to detect and quantify surface water resources, thereby expanding monitoring capabilities (Govender et al. 2022; Koffi et al. 2023). Table 1 presents selected studies conducted on surface water dynamics, outlining key findings, future suggestions, and limitations. With the emergence of remote sensing, the potential for monitoring surface water at different resolutions has become increasingly evident, providing valuable insights into surface water dynamics in Africa's arid regions.

Table 1. Selected studies focusing on surface water variation and impacts.

Region/country	Reference of study	Key findings	Future suggestions and limitations
Algeria	Rouibah and Belabbas (2022)	Found that the dam's surface area has consistently declined between 2015 and 2018, with two-thirds of its surface water area lost during this period.	The study should be complemented by future research on the environmental impact of water shortage.
Botswana	Mokgedi et al. (2019)	Satellite imagery was found to be an effective tool in monitoring of lake surface dynamic.	Since the floods of 2009, the precipitation in the Angola Highlands has a major influence in the surface dynamics of Lake Ngami.
Democratic Republic of Congo	Frappart et al. (2021)	The resulting time series exhibit temporal variations in agreement with the hydrological regime of the study area in terms of temporal variations and annual amplitude.	Future studies are recommended to expand the river stretch coverage with additional sampling locations for comprehensive time-series water quality analysis. Also, the study recommends investigating both point and non-point pollutant sources.
East Africa	Seka et al. (2022)	A significant correlation was found between total water storage (TWS) and precipitation in the East Africa region and basins.	Future studies should prioritise estimating the impact of extreme climate events on water storage in lake basins.
Ethiopia	Asfaw et al. (2020)	The study concluded that lake levels, lake surface area and lake volume gradually decreased and since 2009 the lake has lost 12.75 % of its water storage volume.	The research proposed innovative methods for lake monitoring, advocating using alternative data sources to address the limitations posed by in-situ data.
Malawi	Tadeyo et al. (2020)	The study found that the eastern part receives more rainfall than the western part of the country. As a result, spatial pattern of rainfall may be attributed to the high topographical diversity of the study area.	The study recommended further investigations of the mechanisms that influence the spatio-temporal trends and periodicity of rainfall in Malawi.
West Africa	Herndon et al. (2020)	Global surface water datasets effectively minimise positives but greatly underestimate the existence and extent of smaller and more turbid water bodies.	Additional datasets (Sentinel-2) and other sources of high-resolution optical data, such as Planet, are recommended.
Northern Africa	Belhassan (2022)	The study concluded that limited water reserves, growing population and droughts are the main factors resulting in increased consumption of freshwater.	Future studies should consider a balance between water demand and supply by managing drought and water stress in the region.
Rwanda	Ndayisaba et al. (2017)	The study noted that inhabiting waterbodies have been subject to enormous instability due to invasive species.	Future researchers should use advance remote sensing technologies such as aerial photographs and/or unmanned imaging systems, such as drones to monitor wetlands and investigate water hyacinths.
Senegal	Ogilvie et al. (2020)	The study suggests that integrating coarser MODIS observations into long-term surface water datasets is crucial for accurately monitoring flood dynamics, especially for events missed by Landsat data before 2013.	Combining multi-sensors over different periods is the future direction. Additionally, combining Landsat and Sentinel-2 data offers modest improvements in flood monitoring, particularly after 2015.

(continued)

Table 1. Continued.

Region/country	Reference of study	Key findings	Future suggestions and limitations
South Africa	Chiloane et al. (2020)	Pan inundation varied significantly ($\alpha = 0.05$) from season to season. Moreover, rainfall and temperature variations were also observed to influence pan inundation spatially.	Additional research using high-resolution data is essential, considering the impact of cloud cover, particularly during the wet season. Moreover, Landsat-8 has a low revisit frequency, with two monthly images, and has challenges, especially in rapidly changing conditions.
South Africa	Molekoa et al. (2022)	Water quality parameters complied with the WHO (2011) and South African guidelines (1996) except turbidity, which is above the limit.	Continuous monitoring of water quality in Limpopo is crucial for future pollution control and ensuring health safety.
Tanzania	Makaka et al. (2021)	This study assessed water quality parameters in the maritime and coastal zones of the lake, which varied with time and space.	Scientific research studies should account for seasonal variations (wet and dry) to enhance effectiveness in surface water mapping. Also, priority intervention areas should target the polluted littoral zones.
Uganda	Nsubuga et al. (2017)	The study found that surface water area fluctuation was linked to rainfall variability. Moreover, it was observed that Lake Kyoga sub-basin experienced an increase in surface water area in 2010 compared to 1986.	Future research should conduct impact assessment studies.
West-central Africa	Mahamat et al. (2021)	Lake Chad is believed to be suffering from catastrophic complication of drought crisis, which arose as a result of climate change and global warming.	Integrated management and planning should be implemented, considering not only various socio-economic sectors but also factors such as transhumance and migration, which exert significant pressure on available resources.
Zimbabwe	Chisadza et al. (2022)	The sub-catchment is undergoing degradation due to a decline in its water retention capacity.	Future studies should examine the hydrological response of the sub-catchment to the potential influence of climate, variability, change, and land use land cover (LULC) changes.

The study thus intends to examine and assess the progress in utilizing multi-date satellite data for monitoring and evaluating surface water resources. It also aims to assess the potential and limitations of employing advanced remote sensing methods for water extraction, while suggesting future research directions and management strategies for surface water resources. As a result, the review offers a comprehensive and detailed overview of the advancements in utilizing multi-date satellite data to study surface water dynamics in the semi-arid environments of Africa.

2. Materials and methods

2.1. Literature search

The study utilized Google Scholar, Scopus, web of science and other freely accessible search engines to construct a comprehensive literature database, utilizing specific keywords and phrases abstracted from the research topic. Additionally, keywords from the

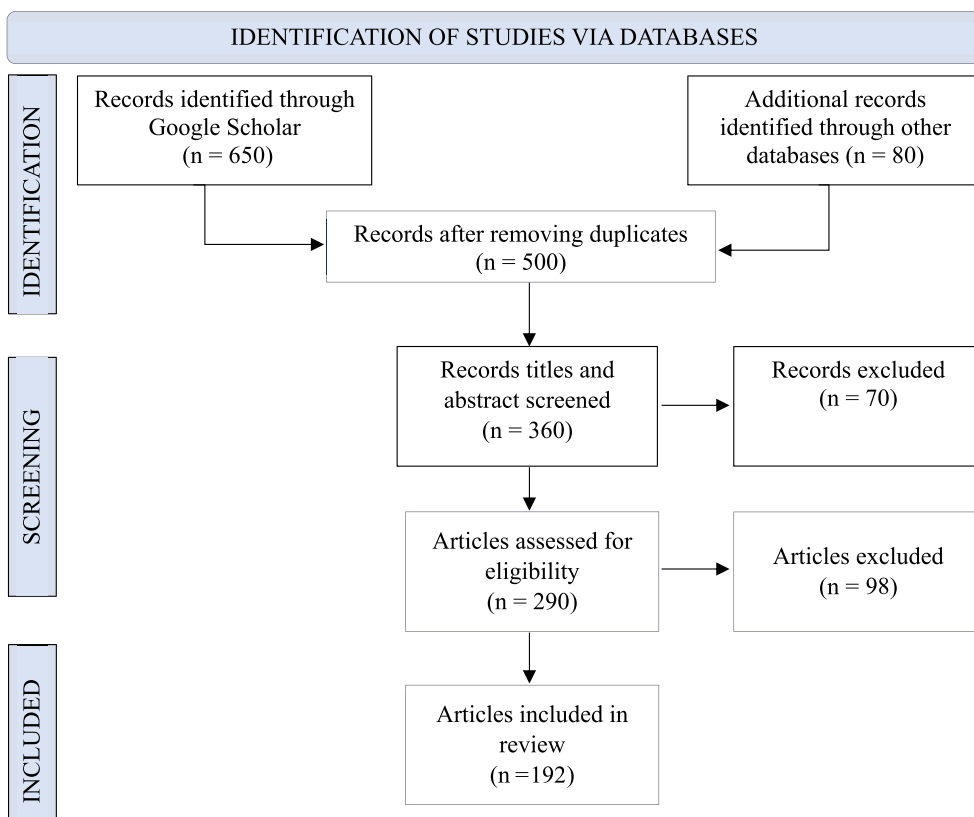


Figure 1. Graphical representation of the literature review search process adopted from PRIMSA flowchart methodology (Page et al. 2021).

study by Dube et al. (2023) were incorporated to enhance the breadth of remote sensing applications on surface water dynamics. Emphasis was placed on geographical location, publication year, and high-value publications in scientific journals. The search criteria targeted studies published between 1990 and 2024. Figure 1 illustrates the workflow employed to retrieve literature from the search engines, resulting in $n=192$ reviewed publications from Google Scholar and other databases. The focus was on internationally recognized peer-reviewed journals addressing climate variability, surface water resources, spatio-temporal dynamics, and multi-date satellite data, with Boolean operators ensuring the inclusion of all relevant publications.

3. The evolution of remote sensing systems in detecting surface water resources

The use of remote sensing systems, particularly satellite imagery, for surface water resource monitoring has increased rapidly in the past 30 years. The history of remote sensing goes back to the 1960s when the first satellite to carry out remote sensing was launched in 1972 (Albertini et al. 2022). Satellite remote sensing, including optical, radar, and thermal imagery, has been increasingly employed in water-related studies. These data sources are known for their comprehensive coverage and for improving spatial and temporal resolutions (Jiang and Wang 2019). Moreover, airborne remote sensing sensors,

particularly UAVs have also evolved in capturing high-resolution imagery compared to satellite sensors (Sibanda et al. 2021).

3.1. Coarse spatial resolution sensors

Coarse spatial resolution sensors in remote sensing are instruments designed to capture images of the Earth's surface with lower detail levels than high-resolution sensors. These sensors are typically used for applications where broad coverage or monitoring large-scale phenomena is more critical than fine-grained details. For example, the Moderate Resolution Imaging Spectroradiometer (MODIS) is the primary sensor aboard NASA's Terra and Aqua satellites, launched in December 1999 and the Aqua satellite in May 2002, with a coarse spatial resolution (Table 2) (Albertini et al. 2022). The swath width of MODIS is 2330 km and provides moderate spatial resolution ranging from 250 m to 1000 m, with 36 spectral bands and a revisit period of 1–2 days (Table 2) (Mashala et al. 2023). This historical data is well-suited for mapping surface water dynamics over large areas, assessing trends, and studying seasonal water variations. MODIS detects surface water bodies at 500 m spatial resolution, making it well-suited for large-scale surface water dynamic analysis due to its short return cycle and medium spatial resolution (Rao et al. 2018). However, this resolution may not be sufficient for detailed monitoring of small water bodies such as rivers and lakes smaller than 4 km² or fine-scale changes in water dynamics (Table 2) (Che et al. 2015). Papa et al. (2023) stressed the importance of accurately tracking the size and changes in small water bodies, especially in arid and semi-arid African regions. These water bodies are widespread and vital in supporting the rural population. Furthermore, MODIS instruments are affected by cloud cover, which can obscure the Earth's surface and limit data acquisition. MODIS cloud mask accounts for 67% of the Earth's sky, with land experiencing a cloud cover of 55% (King et al. 2013; Xu et al. 2019; Lin et al. 2020). This highlights the high sensitivity of optical and infrared satellites to clouds and shadows (Fernandez-Moran et al. 2021). The presence of cloud cover can also be particularly problematic in regions with frequent cloud cover or during the rainy season when cloud cover is more prevalent, especially in the African areas where most surface water bodies are measured at a small scale. Several studies have used MODIS data to monitor changes in surface water bodies and flooding at regional and global scales (Carroll et al. 2009; Sun et al. 2011; Thito et al. 2016). For example, a study conducted by Tong et al. (2016) used Terra/MODIS Level-3 8-day products at 500 m resolution to estimate the lake surface area from 2000 to 2012. The results were validated using Landsat images, achieving an overall accuracy of 97.83%. Another study by d'Andrimont and Defourny (2018) used MODIS to monitor surface water bodies covering the entire African continent from 2004 to 2010, using time series daily observations. The study employed a surface water detection method to derive 10-day indicators describing the location of intra and inter-annual variability and the temporal characterisation of water bodies. More importantly, the study estimated a commission error of less than 6%. Pham-Duc et al. (2020) used a times series of the surface water extent of Lake Chad derived from multi-spectral MODIS images. The results indicated that Lake Chad remained constant over the last two decades with variations in surface water extent. The information mentioned above makes it evident that MODIS has been detecting surface water bodies over a large scale.

The Advanced Very High-Resolution Radiometer onboard National Oceanic and Atmospheric Administration satellites (NOAA/AVHRR) is a remote sensing instrument used for several Earth's observation applications such as weather forecasting, drought

Table 2. Summary of coarse spatial resolution sensors discussed.

Satellite/sensor	Number of bands	Spectral range (μ)/frequency	Swath width at nadir (km)	Spatial resolution (m)	Temporal resolution (Days)	Data availability	Limitations	
Terra/Aqua MODIS	36 with 7 bands for Land/Cloud properties	0.620–0.670 (Blue) 0.841–0.876 (Green) 0.459–0.479 (Red) 0.545–0.565 (NIR) 1.230–1.250 (SWIR) 1.628–1.652 (SWIR) 2.105–2.155 (SWIR) 0.590–0.670 (PAN)	2330	Red, Near-infrared (NIR) (250 m) Blue, Green, IR (500 m) Thermal (1 km)	1–2	1999 Terra 2002 Aqua	MODIS instruments are affected by cloud cover, and it is difficult to detect small surface water bodies due to low spatial resolution.	
	Band 1	0.58–0.68 (VIS)	2900	1100	0.5	1978–2009	Suffers from cloud contamination.	
	Band 2	0.725–1.00 (VIS)						
	Band 3	3.55–3.93 (IR)						
	Band 4	10.3–11.3 (IR)						
	Band 5	11.5–12.5 (IR)						
	MERIS	Band 1	0.412–0.452	1150	300	3	2002–2012	Course spatial resolution Images are limited for precise monitoring of small or narrow water bodies (about 1 km2) such as rivers and pans, and Limited data availability for long-term monitoring.
		Band 2	0.443–0.503					
Band 3		0.491–0.531						
Band 4		0.509–0.549						
Band 5		0.619–0.664						
	Band 6; Band 7	0.664–0.690; 0.753–0.779						
	Band 8; Band 9	0.761–0.789; 0.843–0.877						
	Band 10; Band 11	0.884–0.900; 1.240–1.260						
	Band 12; Band 13	1.628–1.652; 2.105–2.155						
	U.S. Geological Survey (USGS) EarthExplorer data portal : https://earthexplorer.usgs.gov/ (accessed on 6 March 2024)							
Dataset source	DigitalGlobe data portal : https://evwhs.digitalglobe.com/ (accessed on 9 March 2024)							

detection, climate monitoring and surface water monitoring. NOAA/AVHRR instrument has provided daily data since the early 1980s, at a spatial resolution of 1100 m and a temporal resolution of 0.5 days (Table 2) (Asam et al. 2023). Initially, the sensor was designed to monitor the ocean and atmosphere but was later found effective in detecting large-scale flood events (Barton and Bathols 1989; Huang et al. 2018). Although just like other optical sensors, NOAA/AVHRR suffers from cloud contamination (Table 2). Several studies used NOAA/AVHRR to observe flood inundation and other land cover features. For example, Henchiri et al. (2020) used the normalised difference vegetation index (NDVI) generated from AVHRR to produce a land cover for North and West Africa between 1982 and 2015. The study demonstrated that the land cover 2015 map was 76%, 2% higher than the MODIS map for the same year. McCarthy et al. (2003) employed NOAA/AVHRR data from 1985 to 2000 to analyse flood patterns in Botswana's Okavango wetlands. They conducted this study by classifying one AVHRR image taken every ten days into either land or water areas. A study by Mahe et al. (2011) examined NOAA/AVHRR data between the years 1990 and 2000 to estimate the flooded size of Mali's Inner Delta of the Niger River. Their study focused on distinguishing between open water surfaces and vegetation to derive helpful information for predicting flooded surface areas weeks ahead in the delta.

The Medium Resolution Imaging Spectrometer (MERIS) imagery was made available through the European Space Agency (ESA) for the Envisat polar orbit mission since the year 2002. As an imaging spectrometer for visible and near-infrared wavelengths, MERIS provides 300-meter spatial resolution in the visible and near-infrared (VNIR) spectrum spectral range from 400 to 900 nm. MERIS has 15 spectral bands and a temporal resolution of 3 m (Table 2) (Bangira et al. 2017). The products provide valuable data for monitoring large surface water bodies like Lake Victoria and Malawi. However, the satellite's operational lifespan spans only 10 years (2002–2012), restricting its ability to monitor water resources over the long term (Table 2) (Bhaga et al. 2020). A study by Makaka et al. (2021) used MERIS to assess the spatial and temporal variation of water quality for Lake Victoria in Tanzania. Their results demonstrated that water quality parameters varied significantly between pelagic and littoral zones. Vundo et al. (2019) used MERIS data from the years 2003–2011 to analyse water transparency status and spatiotemporal variation in Lake Malawi. Their results showed that the lake is dominated by waters with SD values larger than 6 m (>95%).

3.2. Medium spatial resolution sensors

Landsat is the oldest and longest optical satellite data launched to monitor the Earth's surface, including surface water. The main factors contributing to this are spatial resolution, radiometric quality, consistency, and long-term continuous records (Mishra et al. 2020). The Landsat satellites are grouped into three according to their sensors and platform characteristics. Landsat-1, 2, and 3 use Multispectral Scanner sensors and RBV cameras to monitor the Earth's resources. However, they are limited to detecting small surface water bodies due to their low spatial resolution (Table 3). In contrast, Landsat-4 and 5 use MSS and Thematic Mapper, and Landsat-7 includes Enhanced Thematic Mapper Plus (ETM+) (Table 3) (Chander et al. 2009). The Landsat-1 program started 23 July 1972, providing medium spatial resolution imagery, followed by Landsat-2 in 1975 and Landsat-3 in 1978 (Table 3). Henceforth, the Thematic Mapper (TM) sensors consisting of Landsat-4 followed in 1982 and Landsat-5 in 1984. Landsat-6 started in 1993 with eight bands and a spatial resolution ranging from 15 to 30 m; however, the satellite failed to orbit (Table 3)

(Bhaga et al. 2020). Landsat-7 Enhanced Thematic Plus (ETM+) was launched in 1999, with similar spectral bands as TM and a spatial resolution of 30 m, a Thermal band of 60 m, and a 15 m panchromatic band (Table 3). All these satellites were equipped with different instruments placed in orbit, the most recent satellite missions and still in operation being Landsat-8 (2013) and Landsat-9 (since 2021, with OLI-2) (Table 3) (Albertini et al. 2022). Although remote sensing data with higher spatial resolution (e.g. Landsat-8 OLI and Landsat-9 OLI-2) can delineate smaller water bodies, its long repeating time (16 days) limits it from catching rapid water dynamic due to seasonal or extreme weather events, such as heavy rainfall (Che et al. 2015). Moreover, these images are affected by cloud and shadow, hence water bodies smaller than 0.09 ha may not be mapped accurately by 30 m resolution Landsat data due to mixed pixel problems (Table 3) (Ogilvie et al. 2018). Masocha et al. (2018) used Landsat-8 OLI to map surface water bodies in Zimbabwe using multiple water indices. The results demonstrated that the OLI images are suitable for mapping land surface water bodies nationally. Mishra et al. (2020) used Landsat-8 compared to Planet data to detect smaller water bodies over West Africa. The study found that the Planet images could detect nearly 95% of the water bodies, whereas Landsat could identify only 32% at the water fraction threshold $>40\%$.

On the other hand, the Sentinel missions provide a robust dataset with better spatial and temporal resolutions for environmental monitoring. Sentinel-1 is a polar-orbiting radar mission equipped with a C-band SAR sensor capable of observing Earth in any weather condition throughout the day (Barasa and Wanyama 2020). Sentinel-2 is a polar-orbiting, multispectral, high-resolution imaging mission launched in 2015 and 2017 for land monitoring (Chaves et al. 2020). They provide images that can detect surface water and consist of 13 spectral bands with a spatial resolution of 10 m in four bands, 20 m for six bands, and 60 m for three bands (Table 3) (Slagter et al. 2019; Shirmard et al. 2022). Moreover, Sentinel-2A and Sentinel-2B with Multi-Spectral Instruments (MSI) offer advanced opportunities to study acceptable scale surface water extent variations (Drusch et al. 2012). However, historical SAR data is limited when monitoring long-term surface water bodies. Also, although SAR images can provide information on shallow water and shadow areas, their coherent speckle noise cannot be avoided (Li et al. 2022). Consequently, they are affected by the mixed-pixel problem (Hamunyela et al. 2022). Spectral unmixing techniques have been proposed to address the challenge of inaccurate extraction caused by mixed pixel problems in pixel-based classification (Quintano et al. 2012). Barasa and Wanyama (2020) used Sentinel-1 SAR images to investigate freshwater lake inundation, demonstrating the effective monitoring of inundation coverage and lake basin features. Another study by Cherif et al. (2021) used Sentinel-1 data to improve water bodies detection in South Africa.

Combining optical and radar satellites in a dual-sensor approach has proven to be the most efficient method for large-scale national and regional surface water mapping. For example, Bhaga et al. (2023) used Landsat-8 OLI and Sentinel-2 MSI data to monitor surface water availability and drought impacts in the Western Cape Province, achieving an overall accuracy of 77.27%. Similarly, Seaton et al. (2020) used both Landsat-8 and Sentinel-2 datasets from 2016 to 2017 to detect and monitor the dynamics of water surface areas of pools along three non-perennial rivers and one perennial river in the Western Cape, South Africa. It was found that Sentinel-2 TOA reflectance datasets were most suitable for mapping pools with an average accuracy of 60–86%. The Sentinel-3 satellite is a multi-instrument platform with three instruments: the Sea and Land Surface Temperature Radiometer (SLSTR), the Ocean and Land Colour Instrument (OLCI), as well as the Synthetic Aperture Radar Altimeter (SRAL) and a

Table 3. Summary of medium to high course remote sensing satellites: Landsat 1–3, Landsat 4- and 5-Thematic Mapper (TM), 7-Enhanced Thematic Mapper plus (ETM+), 8-Operational Land Imager (OLI), Sentinel-2 multispectral instrument (MSI), Sentinel-3 OLCI, Sentinel-4-5, Aster & SPOT.

Satellite/sensor	Number of bands	Swath width at nadir (km)	Spatial resolution (m)	Temporal resolution (Days)	Data availability	Limitations
Landsat 1–3	4	185	78	18	1972–1983	There's a significant barrier when detecting small surface water bodies.
Landsat 4-, 5-TM	7	185	30–120	16	1982–2013	Limited data for Landsat-4 due to transmitter failure.
Landsat 6-ETM	8	185	15–30	16	1993	Landsat-5 data loss due to transmitter failure in 1987.
Landsat 7-ETM+	8	185	15–30	16	Since 1999	Failed on Launch.
Landsat 8-OLI	9	185	15–30	16	Since 2013	Images are hindered by cloud cover. Water bodies smaller than 0.09 ha may not be mapped accurately by 30 m resolution Landsat data due to mixed pixel problems.
Landsat 9-OLI 2	11	185	15–30	16	Since 2021	This may result in Cloud contamination, which results in a series of missing data.
Sentinel-1 SAR	1	400	5	6–12	Since 2014	Spatial resolution may not adequately detect small surface water bodies. Identifying water bodies covered by vegetation, particularly during floods, can be challenging. Coherent speckle noise is unavoidable.
Sentinel-2 MSI	13	290	10–60	5	Since 2015	Affected by the mixed-pixel problem, cloud cover during the wet season.
Sentinel-3 OLCI	21	1270	300 m	1–2	Since 2016	Spatial resolution may include a lot of mixed pixels around boundaries. Also, spectral bands are sensitive to surface water bodies.
Sentinel-4	3	8	0.5nm-0.2nm	0.1	Since 2019	They are designed for large-scale atmospheric monitoring; hence, their spatial resolution may not be suitable for fine, small-scale mapping.
Sentinel-5	7	2670	5.5–7	16	Since 2017	
Aster	14	60	15–90		Since 1999	The satellite may lead to misclassification of other landscape elements, such as water.
SPOT 1–7	4–5	60	2.5–20	26	1986 – 2014	Data is not immediately available for use. Able to detect small water bodies.
Dataset source	U.S. Geological Survey (USGS) EarthExplorer data portal: https://earthexplorer.usgs.gov/ (accessed on 6 March 2024) DigitalGlobe data portal: https://ewhhs.digitalglobe.com/ (accessed on 9 March 2024) Sentinel Scientific Data Hub: https://www.copernicus.eu/en/access-data (accessed on 9 March 2024)					

Microwave Radiometer (MWR) (Table 3) (Xu et al. 2024). In contrast, Sentinel-3A and Sentinel-3B launched in February 2016 and April 2018, offer the best possible approach for mapping surface water bodies in real-time due to their high temporal resolution (e.g. one day), which facilitates annual or monthly monitoring of water bodies. However, they are often limited by their low spatial resolution (Table 3) (Wang et al. 2019; Kittel et al. 2021). Consequently, the revisit period for Sentinel-3 OLCI is not sufficient to identify real-time variations in water bodies, due to rapid water body changes caused by, for example, flooding and drought (Wang et al. 2022). The Advanced Spaceborne Thermal Emission and Reflection Radiometer (ASTER) images are collected at a high spatial resolution of 15 m (Table 3). Sensors in the Visible and Near Infrared bands, however only the ASTER sensor operates in three spectral bands including the visible and near infrared (VNIR), the short-wave infrared (SWIR), and the thermal infrared (TIR). ASTER images detect surface water bodies more accurately, especially those with small surface areas (Sivanpillai and Miller 2010). However, they are acquired on request hence there is limited access at a regional scale. Also, using ASTER satellite may lead to misclassification of other landscape elements, such as water bodies (Table 3).

3.3. High spatial resolution sensors

Launching commercial Earth Observation satellites has changed remote sensing and geospatial technology. These high spatial resolution sensors, such as IKONOS, QuickBird, WorldView, GeoEye, RapidEye and RADARSAT, contributed significantly to compacting global challenges by capturing finely detailed geospatial information (Brisco et al. 2009; Gašparović and Singh 2023). They have a high spatial resolution which have great advantage of detecting small water bodies (Table 4) (Ogilvie et al. 2018). Although the sensors above yielded favourable results, they exhibit certain limitations. For example, they have smaller image footprints and are more expensive than sensors with slightly lower spatial resolutions (Dube et al. 2015; Van Niekerk et al. 2018; Ngwenya and Marambanyika 2021). Moreover, their small scene coverage limits them from detecting larger water bodies. Lastly, the presence of shadows, especially in urban and mountainous areas can affect water body detection (Huang et al. 2018). IKONOS sensor was launched in 1990 with a high spatial resolution imagery that is valuable for environmental monitoring. The satellite carries a panchromatic sensor with a resolution of 0.82 m and a multispectral sensor with a spatial resolution of 3.2 m (Table 4). QuickBird was launched in 2001, offering even higher spatial resolution (Panchromatic: 0.61 m and Multispectral: 2.44 m), suitable for various applications.

Another satellite sensor (WorldView-1 (WV-1)) was launched in 2007, capturing detailed black and white panchromatic imagery with a spatial resolution of 0.31 m and a multispectral spatial resolution of 1.24 m (Table 4) (Shirmard et al. 2022). The next breakthrough was the launch of WorldView-2 (WV-2) in 2009, providing a high resolution of 1.84 m panchromatic data at 16.4 km swath width (Table 4) (Adetoro et al. 2022). Currently in orbit is WorldView-3 (WV-3), launched in 2014 (Park et al. 2020). Compared to WorldView-2, WV-3 is capable of detecting eight SWIR bands (1.2–2.33 μm) with a spatial resolution of 3.7 m, along with eight VNIR bands (0.42–1.04 μm) at a spatial resolution of 1.2 m (Table 4) (Shirmard et al. 2022). WorldView-4 is the latest addition to the commercial high spatial resolution satellite constellation, launched in 2016 (Cavallo et al. 2021). It was designed to enhance the constellation's data gathering capabilities. However, shortly after its launch, it encountered an unexpected issue with its control

Table 4. Spatial and spectral resolution of very highly selected remote sensing satellites: IKONOS, QuickBird, WorldView 1-4, RapidEye, RADARSAT-1 SAR & RADARSAT-2 SAR.

Satellite/sensor	Number of bands	Spectral range (μ)/frequency	Spatial resolution (m)	Swath width (km)	Year of launch/data availability	Limitations
IKONOS (Optical Sensors Assembly OSA)	5	0.45–0.90 (PAN) 0.45–0.52 (Blue) 0.52–0.60 (Green) 0.63–0.69 (Red) 0.76–0.90 (NIR)	0.82–4	11 (PAN) 13.3 (MS)	1999–2015	A limited number of spectral bands could sometimes limit its environmental monitoring applications. Moreover, shadow problems which could also affect surface water detection
QuickBird (Ball's Global Imaging System sensor)	5	0.45–0.90 (PAN) 0.45–0.52 (Blue) 0.52–0.60 (Green) 0.63–0.69 (Red) 0.76–0.90 (NIR)	0.61–2.88	16.5 (PAN) 20 (MS)	2001–2014	Satellites are affected by cloud cover, adverse weather conditions, and limited MS Bands.
WorldView 1-4	4-28	0.45–0.90 (PAN) 0.45–0.510 (Blue) 0.510–0.580 (Green) 0.630–0.690 (Red) 0.705–0.745 (Red Edge) 0.770–0.895 (NIR1) 0.860–1.040 (NIR2) 1.57–1.65 (SWIR) 400–450 (Coastal) 0.40–0.85 (Blue) 0.45–0.51 (Green) 0.52–0.59 (Red) 0.63–0.69 (Red Edge) 0.69–0.76 (NIR)	0.31–3.7	17.6 (PAN) 16.4 (PAN) 13.1 (PAN) 15.1 (MS)	WorldView-1: 2007 WorldView-2: 2009 WorldView-3: 2014 WorldView-4: 2016	They are greatly affected by clouds and shadows during water recognition.
RapidEye	5 (MS)		5.0	77		Lack of high spatial resolution data for developing countries at a regional scale. The VHR sensors have smaller image footprints and are significantly more expensive. It might not be sufficient to detect smaller water bodies.
RADARSAT-1, SAR RADARSAT-2, SAR Dataset source	C-band C-band U.S. Geological Survey (USGS) EarthExplorer data portal: https://earthexplorer.usgs.gov/ (accessed on 6 March 2024) DigitalGlobe data portal: https://ewwhs.digitalglobe.com/ (accessed on 9 March 2024)	5.3 GHz 5.405 GHz	10–100 3–100	~100 ~50	1995 2007	

moment gyros. The launch of RADARSAT-1 (1995), and RADARSAT-2 (2007) is a collaborative effort between the Canadian Space Agency (CSA) and Maxar Technologies Ltd (Table 4) (Shirmard et al. 2022). RADARSAT-2 can penetrate through clouds, although it might not be able to detect smaller surface water bodies (Olthof and Tolszczuk-Leclerc 2018). These high-resolution commercial satellites have been used to study surface water bodies, determine their extent, and produce more detailed maps of small freshwater areas in arid and semiarid regions of Africa.

Water resource management have long depended on a combination of *in situ* measurements and satellite remotely sensed data for research. However, the breakthrough of Unmanned Aerial Vehicles (UAVs) in 2015 marked a significant milestone, being widely recognized as a valuable platform for acquiring remote sensing imagery. The UAVs, also known as drones, are now filling the gaps between spaceborne and ground-based observations with enhanced spatial and temporal resolution coverage (Ridolfi and Manciola 2018). Therefore, offering potential alternative and enabling a more comprehensive monitoring and analysis of water resources at local scales (Acharya et al. 2021). They are more cost-effective compared to high resolution satellites (QuickBird, RapidEye, WorldView and IKONOS), and flexible option for obtaining high-resolution real-time data (Ruwaimana et al. 2018; Nhamo et al. 2020). Moreover, UAVs can efficiently capture images at low altitudes which was not feasible with traditional aerial imagery platforms. The most common used flight platforms in hydrology and water management studies are the Rotary-wing and Fixed-wing UAVs. The sensors are useful under low visibility weather conditions such as cloud cover (Torres-Sánchez et al. 2014). Moreover, they are easy to integrate with different platforms when monitoring flood and water quality. Although the technology above yields good results like any other emerging technology, UAVs come with their own repercussions. For example, it was reported that UAVs pose a threat to safety, privacy, and security within civilian air space (Haula and Agbozo 2020). Moreover, UAVs are constraints by limited flight duration and battery lifespan. Likewise, they are affected by environmental weather conditions such as lightning, wind, and air humidity (Acharya et al. 2021). UAV adoption in the Africa is still in its early phase, with a few implemented cases primarily focusing on engineering and agriculture. Hence, their application in monitoring water resources remains limited in Africa (Sibanda et al. 2021). It was suggested that artificial intelligence, machine learning, and algorithm should be explored to correct noise in images and reduce possible (Arroyo-Mora et al. 2019). Moreover, although small UAVs acquire high resolution images, advance research is warranted to improve sensors, automate flights, and increase flight duration (Becker et al. 2019).

3.4. Satellite-based remote sensing products for water variation and climate variability

Remote sensing technology has offered a cost-effective way of monitoring global surface water (Huang et al. 2018). Traditionally, monitoring surface water variability was based on *in situ* earth observations that quantified the movement and quality of water in major river channels, lakes and wetlands (Papa et al. 2023). They used gauge stations to collect hydrological data for various water features such as lakes, rivers, and reservoirs. Gauge stations measured hydrological information such as precipitation, evapotranspiration (EAT), and water variability. However, it was observed that historical records of *in situ* networks are limited, sparse and unevenly distributed, especially in most parts of Africa (Alsdorf et al. 2007; Chawla et al. 2020). Consequently, this contributed to the challenge

of measuring accurate hydrological information such as rainfall. Thus, satellite-based rainfall products are now increasingly used as an alternative measure or a supplement to station observations. It was reported that most of these long-term products suffer from coarse and spatial resolution (Dinku et al. 2018). Some prominent rainfall products include the Climate Hazards Group Infra-Red Precipitation with Stations (CHIRPS), Tropical Rainfall Measuring Mission (TRMM), Precipitation Estimation from Remotely Sensed Information using Artificial Neural Networks (PERSIANN), Global Satellite Mapping of Precipitation (GSMAP), Tropical Applications of Meteorology using Satellite data and Ground-based observations (TAMSAT), as well as the Global Precipitation Climatology Centre (GPCC) (Gebrechorkos et al. 2018; Wang et al. 2021; Dube et al. 2023). These rainfall products are widely used due to their flexibility to integrate several satellites and ground-based datasets, resulting in detailed and reliable information. The CHIRPS-v2 product utilizes both rain gauge and satellite data to create a complete spatio-temporal rainfall distribution, especially in regions with limited data availability (Dube et al. 2023). For example, Muthoni et al. (2019) used CHIRPS-v2 satellite data to analyse long-term trends and variability of rainfall (1981–2017) over Burundi, Kenya, Malawi, Rwanda, Tanzania, Uganda and Zambia, and the results indicated that CHIRPS-v2 satellite rainfall estimated high skill for estimating gauge observations in ESA region.

Alternatively, water resource variation and climate variability are highly influenced by the process of evapotranspiration. In regions characterized by arid and semi-arid climates, such as Africa, a significant amount of surface water is lost through the process of evapotranspiration, thereby influencing the overall flow of surface water (Aguilar et al. 2018; Banda et al. 2022; Raza et al. 2023). Hence, understanding how EAT affects surface water availability, is important for managing water resources, responding to climate change and ecosystem activities (Leal Filho et al. 2022). Commonly used evapotranspiration product in the context of water resources and climate variability include MODIS (MOD16) (Ramatsabana et al. 2019). MOD16 AET product has an 8 day, monthly, and yearly temporal and 1 km spatial resolution (Khan et al. 2018). This product is also widely used for monitoring water fluxes over large areas (Palmer et al. 2020).

The Gravity Recovery and Climate Experiment (GRACE) product is used to monitor variation terrestrial water storage (TWS), especially over the Southern and Central African regions, which are recognized as strong climatic hotspots (Kalu et al. 2021). GRACE data products offer insights into long-term trends and interannual variability in water resources and climate change (Khaki and Awange 2019). Moreover, the product offers great opportunities to measure total water storage (TWS) in lakes, rivers and reservoirs, providing insights into water storage variations (Seka et al. 2022; Papa et al. 2023). For example, Nigatu et al. (2021) investigated the GRACE product and land surface models to estimate changes in water storage components of the Nile River Basin. The study found that the Nile River Basin's groundwater and soil moisture trend showed a potential depletion in water storage. A more extensive study by Ahmed and Wiese (2019) integrated GRACE product with rainfall, temperature, evapotranspiration and altimetry remote sensing datasets to monitor the short-term trends in terrestrial water storage (TWS) over the African hydrogeologic systems. The study found that short-term trends over the African continent are driven by natural variability, such as changes in rainfall, evapotranspiration, and associated variations in lake levels. Moreover, Bigot et al. (2021) used CHIRPS and GRACE (2003–2016) data to study hydroclimatic variability in Mahajunga province, Madagascar. The study resulted in a negative trend in continental rainfall and water content, also a time lag was observed in the linear variations and trends

of the Water Equivalent Height. Hence it is important to study and intergrade this product for improved water resource management.

4. Image processing and water extraction methods

Image processing and water extraction methods are the primary techniques used to extract information on surface water using remote sensing images. Using spectral indices make it possible to accurately extract surface water from remote sensing images. Over the years, they have been employed to monitor and quantify water resources at various scales ranging from local to global (Mishra et al. 2020). Water extraction method is divided into two categories: threshold segmentation and image classification (Li et al. 2022). Thresholding methods are mainly applied using a single pixel value for water characterisation (Su et al. 2021). This method uses spectral knowledge to assess and distinguish water from land based on their respective classification models. Moreover, there has been a growing trend in using machine learning algorithms to increase the accuracy of surface water extraction (Li et al. 2022). Machine Learning is derived from artificial intelligence (AI) and has been considered reliable since its development. This approach enables accurate and efficient classification of remotely sensed imagery. Machine learning (ML) techniques and classical algorithms such as Support Vector Machine (SVM), Random Forest (RF), Decision Tree (DT), and Deep Learning (DL) are widely used in processing and classifying surface water dynamics (Mountrakis et al. 2011; Donmez et al. 2015; Shetty et al. 2023). Moreover, the methods effectively measure spectral and ground truth against noise and uncertainties (Shirmard et al. 2021). The recent machine learning (ML) trend has brought about a transformative phase in analysing remote sensing data, consistently demonstrating impressive performance in various computer vision tasks across multiple domains (Shirmard et al. 2022).

4.1. Remote sensing techniques for surface water monitoring: traditional algorithms

The traditional methods of applying several spectral indices have been developed, each composing of different band combinations (Albertini et al. 2022). The spectral index method is extensively used to extract surface water extent. Over the years, water extraction indices, such as the normalised difference vegetation index (NDVI) developed by Rouse et al. (1974), normalised difference water index (NDWI), modified normalised difference water index (MNDWI), water index (WI), automated water extraction index (AWEI), water ratio index (WRI), normalised difference vegetation index (NDWI), enhanced water index (EWI), revised normalised difference water index (RNDWI) and others, have been proposed and used to map pools of surface water bodies (Sisay 2017; Masocha et al. 2018; Seaton et al. 2020). For example, the NDWI was developed by McFEETERS (1996) to delineate open water features and enhance their visibility in Landsat imagery. However, the results sometimes lead to misclassification of buildings as surface water bodies. The method prompted Xu (2006) to develop the MNDWI, which enhances the distinction and identification of surface water. The MNDWI employed Mid-Infrared (MIR) or Shortwave (SWIR) bands which minimises the classification of built-up features as open water (El-Asmar et al. 2013). Similarly, Deng et al. (2019) proposed a multiple water index rule (MIWDR) for extracting surface water bodies. MIWDR was suitable for long-term and large-scale extraction of water bodies from Landsat. Other methods, such as the automated water extraction index (AWEI), which uses two modes:

shaded images with dark surfaces (AWEIsh) and non-shadow (AWEInsh) regions, were also developed to improve the accuracy of surface water mapping (Feyisa et al. 2014). These methods can suppress background noise from shadow and non-water dark surfaces. Spectral bands such as the NDVI, NDWI, MNDWI, AWEIsh, and AWEInsh were tested for their robustness under different environmental conditions to evaluate their accuracy (Table 5). Multiband methods applied to Landsat datasets have been extensively used for surface water mapping and monitoring at local and regional scales. Using satellite imagery, Singh et al. (2015) applied the rule-based classification algorithm to delineate water features. The study compared the accuracy of NDWI and MNDWI in extracting waterlogged areas in the Sri Muktsar Sahib district of Punjab, India. The MNDWI achieved an overall accuracy of 96.9% with a Kappa coefficient of 0.89 for retrieving waterlogged areas.

Several studies also attempted to compare the accuracy of multiband methods in mapping surface water, by primarily using Landsat datasets (Soti et al. 2009; Jones et al. 2017). For example, Wang et al. (2021) used Landsat images to map the spatiotemporal characteristics of the Xiaolangdi reservoir. They adopted the MNDWI, enhanced vegetation index (EVI), and normalised difference vegetation index (NDVI) for accuracy assessment. All the spectral indices combined had a reasonable accuracy of 98.86% and a kappa coefficient of 0.96 for water body extraction. Rad et al. (2021) introduced a more robust water index that compared NDWI, MNDWI, AWEI, and WI with augmented NDWI (ANDWI) and incorporated the Otsu algorithm to enhance its performance. However, the combination of ANDWI and Otsu-thresholding yielded better results with an accuracy of 0.98 and Kappa of 0.96. Shetty et al. (2023) recently used Landsat imagery, AWEI, MNDWI, EVI, and NDWI to map open-surface water. However, the results noted that the AWEI method outperformed the MNDWI and EVI. Similarly, Deoli et al. (2022) used Landsat data, multiband indices NDWI, MNDWI, and water ratio index (WRI) to analyse the dynamic change in Eutrophic Lake. The study conducted a physical GPS survey of the lake to verify the accuracy of these indices and found that NDWI was the most accurate approach, with an accuracy of 96.94%.

Extensive research was conducted by Bhaga et al. (2020), providing a detailed overview of studies conducted using a variety of remotely sensed and in-situ datasets to monitor drought and climate variability in Sub-Saharan Africa. The study revealed that the most effective drought and water indices were the SPI, PDSI, NDVI, VCI, NDWI, MNDWI, MNDWI + 5, automated water extraction index for shadowed (AWEIsh), and non-shadowed (AWEInsh) (Table 5). However, the results suggested that Landsat-8 and Sentinel-2 satellite data were likely more suited for the study. Moreover, Herndon et al. (2020) conducted a study in Nigerien Sahel and evaluated two global dynamic surface water datasets with fifteen spectral indices to classify surface water extent. Their results found that three (NDMI, TCW, and AWEIsh) of fifteen spectral indices used exhibited high accuracy and threshold stability when observed during different seasons and areas. Similarly, Seaton et al. (2020) compared six multiband methods ((NDWI, MNDWI, NDVI, AWEIsh, AWEInsh, and the multiband water index (MBWI)) across two sensors, namely, Landsat-8 and Sentinel-2 to monitor change in non-perennial and perennial rivers. The result suggested that the NDWI computed from Sentinel-2 datasets proved the most suitable for mapping water pools, achieving an overall accuracy ranging from 60% to 86%. A recent article by Ekpeter et al. (2023) integrated satellite imagery and ground-based Measurements using a machine learning approach (RF) to delineate lake area extent over a Semi-Arid Region. The results showed that the GSL area extent declined significantly by more than 50% between 1999 and 2021. In contrast, the land cover showed more

Table 5. Selected surface waterbody indices and their performance in previous studies.

Water index	Formula	Reference of study	Key findings	Limitations of index
NDVI	$NDVI = NIR - R / NIR + R$	Ondari et al. (2023)	The study examined Landsat and CHIRPS data, which achieved a strong correlation between precipitation, fluctuating water levels, and floating island formation.	Vegetation poses challenges in distinguishing floating islands from water hyacinth.
		Bhaga et al. (2023)	This study used Landsat-8 OLI and Sentinel-2 MSI images to detect surface water bodies and monitor drought impacts in the Western Cape, South Africa. The Sentinel-2-derived NDVI proved most effective, achieving an overall accuracy of 77.27%.	Landsat-8 OLI NDVI has a spatial resolution of 30 meters, which is coarser than Sentinel-2 NDVI. This may limit its ability to capture fine-scale variations in water extent.
NDWI	$NDWI = (Green - NIR) / (Green + NIR)$	Maswanganye et al. (2022)	The study used random forest classifier and Sentinel-1 SAR in mapping pool dynamics in semi-arid environment of South Africa.	Methods failed to detect and map small pools (<400 m ²).
		Seaton and Dube (2021)	Used Sentinel-1 and Sentinel-2 to monitor non-perennial river water availability in Tankwa Karoo of the Western Cape and achieved an overall accuracy of 85% for Sentinel-2 and 38% for Sentinel-1.	The study failed to detect connectivity between pools and the index sometimes misclassifies buildings as water.
		Asfaw et al. (2020)	Merged satellite data to estimate water storage variations in Lake Ziway, Ethiopia. The indices used for extracting lake surface area from images demonstrated an overall accuracy of 91–99%.	It showed limitations in uniquely detecting the water body from some land features since some urban areas with higher reflectance were misclassified as water bodies.
		Mishra et al. (2020)	The PlanetScope (PS) images detected nearly 95% of the WBs, whereas Landsat could identify only 32% at the water fraction threshold > 40%.	Known to underperform in semi-arid to arid regions.
		Herndon et al. (2020)	NDWI, a commonly used index, had relatively poor performance and low threshold stability, along with W2015, band ratios, and the NIR band.	The study failed to detect many smaller and more turbid water bodies.
		Sathianarayanan (2018)	The findings indicated a significant and consistent decline in surface area for Cheleleka, Kiroftu, Lake 1, and Lake 3 from 1984 to 2017.	Limitation on soil and built-up area.
MNDWI	$MNDWI = (Green - SWIR) / (Green + SWIR)$	Molekoa et al. (2022)	The study used Landsat-8 and Sentinel-2 data to map variations in surface water quality for the Doorndraai Dam in South Africa.	There is a decreasing trend in the water area due to encroachment.
		Thamaga and Shoko (2021)	Used Sentinel-2 data to assess wetland dynamics from July 2020 to June 2021 in the Maungani wetland of the Limpopo Transboundary Basin of South Africa. They achieved an overall accuracy classification ranging from 70.83%–98%.	They are affected by cloud cover during the wet season.

(continued)

Table 5. Continued.

Water index	Formula	Reference of study	Key findings	Limitations of index
		Herndon et al. (2020)	The results demonstrate that existing global surface water datasets are not sufficient to address the limited availability of surface water in the Nigerien Sahel.	The index confused vegetation areas with water bodies.
		Slagter et al. (2019)	The study used Landsat-1 and Landsat-2 to map St. Lucia wetlands in South Africa, achieving 87.1% for mapping surface water dynamics.	Found poor classifications in high-vegetated areas.
		Ogilvie et al. (2018)	Used Landsat combined observations with 10 m pansharpened Sentinel-2 imagery, reducing RMSE to 5200 m2, displaying the increased opportunities for surface water monitoring in small water bodies after 2015.	Experienced difficulties in shallow water and flooded vegetation.
		Malahlela (2016)	Mapped inland water bodies using the SWI in Pretoria, South Africa and performed an accuracy SWI showed the highest overall accuracy of 91.9% ($\kappa = 0.83$) over the MNDWI.	Classified shadows as water.
		Feyisa et al. (2014)	Tested the accuracy of the new method using Landsat-5 TM images of several water bodies in Denmark, Switzerland, Ethiopia, South Africa and New Zealand.	Produced noisy results. Also performance is unsatisfactorily when the image has a mixture of built-up areas, shadows, and waterbodies.
Simple Water Index (SWI)	$SWI = 1 / (BLUE - SWIR1)$, values < 5 are classified as water	Malahlela (2016)	The SWI approach reduces the thresholding problem by 50% over the conventional MNDWI and AWEI by achieving an overall accuracy of 91.9% ($\kappa = 0.83$).	SWI algorithm classifies paddy rice farms as waterbodies.
Land Surface Water Index (LSWI + 5)	$LSWI = (NIR - SWIR) / (NIR + SWIR)$	Masocha et al. (2018)	The study observed an overall accuracy of 86%, kappa statistic of 0.70, and a reliability accuracy of 89%.	There is a weakness of LSWI in detecting waterbodies.
		Bhaga et al. (2023)	Used Landsat-8 OLI and Sentinel-2 MSI satellite data to assess the extent of water in the Western Cape, South Africa, using multiple indices.	Misclassify built-up and mountainous areas as surface water bodies.
(AWEIsh)	$AWEIsh = BLUE + 2.5 \times GREEN - 1.5 \times (NIR + SWIR1) - 0.25 \times SWIR2$	Chisadza et al. (2022)	The study used Landsat Detecting land surface water changes in the Upper Mzingwane sub-catchment (Zimbabwe).	Failed to discriminate water edges, very small dams and ponds effectively.
(AWEInsh)	$AWEInsh = 4 \times (GREEN - SWIR1) - (0.25 \times NIR + 2.75 \times SWIR1)$	Acharya et al. (2018)	Used the Landsat-8 scene of Nepal to evaluate index methods used for surface water estimation based on a threshold value.	AWEI is unable to reject snow cover and shadows in optimum thresholding.
		Buma et al. (2018)	Used Landsat-7 and 8 images in to estimate area changes around Lake Chad.	Misclassify some water pixels as non-water features.
		Malahlela (2016)	Mapped inland surface water bodies in South Africa, and Pretoria and observed validation data set at $p = 0.041$ and $p = 0.013$.	Classified shadows as water.

significant fluctuations with a relatively minor decline in its area extent, around 30% during the same period.

Although the combination of spectral indices yields good results, there has yet to be a single water index that has proven to be the best approach universally in remote sensing, as discussed in the literature by Fisher et al. (2016). The accuracy of specific indices depends on the scale of features, the spatial and spectral resolution of remote sensing data, and the geographical area. For example, Bhaga et al. (2020) and Huang et al. (2018) emphasised that most of the drought monitoring and water detection indices were developed for specific satellite data, encouraging the development and testing of new indices across diverse environments to enhance their effectiveness.

4.2. Applications of multiband methods for small surface area water bodies

Small water bodies like shallow, natural, and artificial water impoundments such as fishponds, pans, reservoirs, and inland lakes are characterised by their relatively small surface area. The size of small water bodies varies geographically, ranging from less than one hectare to over 10 hectares and, at most, 50 hectares (Perin et al. 2021; El Bilali et al. 2022). While multiband methods effectively distinguish large water bodies, they often encounter challenges when identifying and monitoring small water bodies over extensive geographical regions. These challenges primarily arise due to the complexities associated with the surrounding land features, including built-up areas, vegetation, and cloud shadows. For example, Li et al. (2020) emphasised the importance of monitoring small wetlands in arid, semi-arid, and Mediterranean regions for ecosystem conservation. Bie et al. (2020) compared the accuracy of index composition and HSI (hue, saturation, and intensity) with MNDWI and EWI using Sentinel-2 data. The HSI approach exhibited superior performance, achieving an overall accuracy of 97%, a producer's accuracy of 96%, and a user's accuracy of 98% in test regions. However, optical imagery faces accuracy issues when differentiating water features from low-albedo surfaces like tree shadows (Prošek et al. 2020).

Comparisons between multiband methods and machine learning algorithms with Earth observation systems, provided the potential for accurate results across diverse regions and landscapes, thereby providing optimal solutions for water index mapping. Notably, Dong et al. (2022) introduced the small water bodies mapping (SWM) algorithm, which employed Landsat and Sentinel-2 optical remote sensing images. The SWM algorithm outperformed several other water extraction methods, achieving an overall accuracy of 97%. Wang et al. (2022) proposed an automated and hierarchical surface water fraction mapping (AHSWFM) approach for mapping small water bodies (SWBs). They used self-trained regression with scalable algorithms and random forest based on Sentinel-2 images, leading to increased accuracy. Moreover, Prošek et al. (2020) integrated hyperspectral data with LiDAR using object-based classification (Support Vector Machine), successfully eliminating shadows. Hyperspectral and LiDAR data integration significantly improved the mapping of small surface water bodies.

4.3. Remote sensing techniques for surface water extraction: machine learning algorithms

Deep learning (DL) methods have played a significant role in recent applications of remote sensing studies, particularly in the field of water resource management (Sit et al. 2020). Combining precise deep-learning techniques and readily available high-resolution aerial or satellite imagery yielded significant results across diverse fields despite challenges

such as background noise, limited datasets, and missing data (Bhaga et al. 2020; Kseňak et al. 2022). They are composed of a wide range of methods, including graph deep learning techniques, Bayesian deep learning, artificial neural networks (ANN), convolutional neural networks CNN, variational autoencoders, and emerging approaches like recurrent transformer networks, which are for remote sensing retrievals of corresponding variables (Mas and Flores 2008; Shirmard et al. 2022; Dimitrovski et al. 2023). Several studies adopted these methods to increase prediction accuracy. Hence, a significant contribution involves image-scene classification, particularly in identifying land-use and land-cover (LULC) patterns. Most research articles stated that efforts centred around analysing, characterising, and categorising changes in the landscape caused by either human activities or natural factors. Developing research highlighted that processing data using deep learning techniques demonstrates their effectiveness in handling large and complex multi-date satellite datasets while accounting for spectral and ground truth measurements, noise, and uncertainties (Sit et al. 2020; Camps-Valls et al. 2021; Shirmard et al. 2022; Tariq and Qin 2023). For example, De Oliveira e Lucas et al. (2020) employed three CNNs with different structures to forecast evapotranspiration time series. They further developed four ensemble models of the three CNNs, producing high accuracy and low variance predictions. Furthermore, Sit et al. (2020) indicated that CNNs are the most applied architectures in deep learning reviewed papers. Song et al. (2019) introduced a method of deep learning using fully convolutional networks (FCN) to detect changes in surface water. O'Neil et al. (2020) performed deep learning using physically informed input data for wetland identification, which resulted in accurate wetland predictions of 91% and 57% precision. The artificial neural network (ANN) is among the earliest and most applied machine learning algorithms. It has primarily been employed to retrieve biophysical variables and other domain applications (Ali et al. 2015). A study by Li et al. (2022) provides an overview of the prevailing methods for water extraction from optical and radar images, such as threshold segmentation, support vector machine, decision tree, object-oriented extraction, and deep learning. Furthermore, the study discussed the strengths and limitations of each approach and found that all models yielded reliable results. The study further concluded that the threshold segmentation technique using the normalised difference water index (NDVI) demonstrated higher resilience than the other methods. Further recommendations included producing automatic, extensive, and high-precision water extraction methods. Zheng et al. (2022) investigated Aeolian dunes and found that the extensive use of change detection algorithms, particularly COSI-Corr, offers valuable knowledge regarding dune migration. However, investigating interactions between dunes is still in its preliminary stages. There remains a dearth of extensive research focused on applying these techniques to process the latest generation of remote sensing data. Therefore, scientists are encouraged to consider applying deep learning methods to detect and measure the extent of surface water dynamics in Africa.

Ensemble learning algorithms such as the Random Forest (RF), Support Vector Machine (SVM), and Spectral Angular Mapper (SAM) are employed for the classification of surface water and other field studies (Lary et al. 2015; Wang et al. 2022; Jan et al. 2023). Ensemble methods combine multiple machine learning models to solve classification or regression problems, and they generally yield better results than individual methods (Breiman 2001; Sagi and Rokach 2018). For example, Zhang et al. (2022) studied ensemble algorithms, a machine learning algorithm in remote sensing. The article, supported by other studies, revealed that support vector machines (SVM) and random forests (RF) are the two most recognised nonparametric machine learning algorithms (Mountrakis et al. 2011; Belgiu and Drăguț 2016; Sheykhmousa et al. 2020). RF is a

specific type of ensemble method that follows the bagging approach and decision trees (Rokach 2010). Meanwhile, SVM gained significance due to its capability of handling high-dimensional data and achieving good performance with limited training samples, among other advantages (Ma et al. 2019). SVM is a powerful machine-learning tool for data classification and prediction (Cortes and Vapnik 1995; Cristianini and Ricci 2008; Wilson 2008; Belmahdi et al. 2023).

The contributions of applying machine learning algorithms span a wide range of science fields, including agriculture, ecology, geology, meteorology, urban mapping and planning, and archaeology. For example, Tao et al. (2023) investigated the application of ML algorithms to predict the spatiotemporal distribution of air pollution at a high resolution using meteorological and soil parameters. The study used ML models to predict high-resolution air particulate matter PM_{2.5} concentration. Meanwhile, Shirmard et al. (2022) demonstrated a high capability of merging remote sensing data and machine learning methods to map different geological features. Another study by Son et al. (2022) used Sentinel-2 imagery to predict rice crop yields. The study adopted three models (RF, SVM, and ANN) to investigate the study on yield prediction. As a result, the study concluded that the SVM produced slightly more accurate predictions than the other two models. Baker et al. (2023) employed machine learning (ML) techniques to identify collagen peptide biomarkers in archaeological fish remains for taxonomic classification purposes. The study specifically investigated the efficacy of machine learning methods, including RF algorithms, in this identification process. However, despite efforts, the study concluded that isolating significant biomarkers solely through these methods posed challenges.

Various studies used Landsat datasets to assess the ML algorithm's performance (Li and Xu 2021). For example, Hamunyela et al. (2022) used the random forest algorithm (RF) to compute the probability of surface water in the Cuvelai Etosha basin, Namibia using Landsat spectral bands and six indices to predict surface water dynamics. The study found that the overall surface water extent mapped resulted in $91.5 \pm 2.5\%$, whereas the producer's accuracies resulted in $91.1 \pm 6\%$. Gidey and Mhangara (2023) used random forest (RF) classifier and remote sensing models to explore the implications of the changing land-use diversity on surface water resources in Gauteng Province, South Africa. The study found that nine land-use diversity classes had increased and decreased tendencies, which resulted in high F-score values ranging from 72.3% to 100%.

Moreover, Zurqani et al. (2018) highlighted that the random forest (RF) approach gives modelling flexibility when using various data sources to classify images and accurately identify the Savannah River basin's heterogeneous land cover. Similarly, compared to other ML algorithms, the Random Forest (RF) was the most adopted method for earth observation applications (Zhang et al. 2022). Moreover, studies revealed that the random forest (RF) approach gives modelling flexibility to resolve classification and regression problems observed when processing remote sensing images (Zurqani et al. 2018; Zhang et al. 2022).

5. Challenges and future recommendation

The evolution of remote sensing technologies has advanced in monitoring and detecting surface water over a long period and across global and regional scales. However, knowledge of the advancements and scientific studies in remote sensing technologies and data processing methods remains poorly documented in Africa. In the past, monitoring surface water variability was based on *in situ* earth observations using rain gauges. However, it was observed that historical records of *in situ* networks are limited, sparse

and unevenly distributed, especially in most parts of Africa. Consequently, this contributed to the challenge of measuring accurate hydrological information such as precipitation, soil moisture and groundwater. Thus, satellite-based rainfall products (e.g. CHIRPS & TRMM) were developed and used as an alternative or a supplement to station observations and to improve surface water resource management. Satellite products offer excellent opportunities to measure surface water storage (SWS) in lakes, rivers and reservoirs, providing insights into water storage variations, mainly using GRACE data (Seka et al. 2022; Papa et al. 2023). However, it was reported that most of these long-term products suffer from coarse and spatial resolution (Dinku et al. 2018). Using high-resolution images (e.g. Sentinel-2) has limitations of images dating only from 2015. This limits studies from extracting long-term high-resolution data on surface water. Furthermore, sensors like WorldView and QuickBird are not easily accessible in large quantities due to high purchase costs and smaller footprints. However, combining optical and radar satellites in a dual-sensor approach has proven to be the most efficient method for national and regional surface water mapping. Researchers are increasingly using UAVs (Unmanned Aerial Vehicles) platforms to fill the gaps in both spatial and temporal resolution (Acharya et al. 2021). However, this sensor is restricted to acquiring images over large spatial scales and under different environmental weather conditions. It was suggested that artificial intelligence should be explored to improve UAVs images. Overall, remote sensing sensors suffer from high incidence cloud and shadow occurrences caused by physical limitations in sensor imaging systems. This motivates future studies to consider spatial data integration techniques, radar data, precipitation, cloud computing, and machine learning or artificial intelligence (AI) techniques to improve water resources across various scales (Bhaga et al. 2020). Moreover, the cloud-based high-performance Google Earth Engine (GEE) Platform offers a centralised and standardised interface for handling earth observation data. GEE enables efficiency when processing massive and complex satellite data (Wang et al. 2019). However, the platform is limited in executing deep learning algorithms due to computational constraints and the unavailability of such algorithms on the platform. Hence, users are restricted to acquiring data on the platform and implementing deep learning algorithms externally. As sub-Saharan Africa emerges as the next hotspot for water scarcity (Baggio et al. 2021), addressing these challenges becomes imperative for sustainable development and the well-being of its communities.

6. Conclusion

Remote sensing technology's ability to provide global, continuous, accurate, and long-term data on the earth's surface and its dynamics makes it an indispensable tool to address global challenges, particularly in Africa. It offers practical ways to monitor surface water dynamics at various spatial and temporal scales. Furthermore, it supports scientific research, informs decision-making, and helps societies globally understand and address challenges about Earth observation. This literature review chapter provides a foundation for the subsequent research conducted in the study, highlighting the knowledge gaps and research opportunities in the spatiotemporal analysis of surface water extent and dynamics in the Okavango basin using multi-date satellite data. Synthesising the existing literature sets the stage for developing novel methodologies and generating valuable insights into the hydrological processes in the regions. Coarse spatial resolution sensors such as NOAA/AVHRR, MODIS and MERIS monitors surface water variations, climate and environment disasters for over three decades. In addition, they are well-suited for

mapping surface water dynamics over large areas due to their low spatial resolution (Table 2). However, this resolution may not be sufficient for detailed monitoring of small water bodies such as rivers and lakes smaller than 4 km² or fine-scale changes in water dynamics. Optical sensors with very high spatial resolution, such as WorldView, QuickBird, GeoEye and IKONOS, provide detailed mapping of small water bodies. In contrast, they are greatly affected by the presence of shadows, especially in mountainous and urban areas (Table 4). The Multispectral Scanner System (MSS), Thematic Mapper (TM), Enhanced Thematic Mapper Plus (ETM+), and Sentinel data have all been used to extract information about land surface water bodies. However, they are highly affected by cloud cover and temporal resolution in high-resolution optical imagery, which results in a series of missing data (Table 3). Image processing and water extraction methods such as traditional (MNDWI, AWEI and NDWI) and machine learning (e.g. SVM, RF and DL) algorithms are presented in the review. Surface water resources play a significant role in sustaining human life and terrestrial ecosystems. With increased population, ongoing global climate change and human activities, surface water's spatial and temporal dynamics have drastically changed. Consequently, understanding these dynamics becomes imperative for monitoring and enhancing the accuracy of surface water resources.

Disclosure statement

No potential conflict of interest was reported by the author(s).

Ethical approval

All ethical practices have been followed in relation to the development, writing, and publication of the article.

Data availability statement

No known competing financial interests and data used for this study.

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