remote sensing

Review

A Systematic Review on Advancements in Remote Sensing for Assessing and Monitoring Land Use and Land Cover Changes Impacts on Surface Water Resources in Semi-Arid Tropical Environments

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Abstract: This study aimed to provide a systematic overview of the progress made in utilizing remote sensing for assessing the impacts of land use and land cover (LULC) changes on water resources (quality and quantity). This review also addresses research gaps, challenges, and opportunities associated with the use of remotely sensed data in assessment and monitoring. The progress of remote sensing applications in the assessment and monitoring of LULC, along with their impacts on water quality and quantity, has advanced significantly. The availability of high-resolution satellite imagery, the integration of multiple sensors, and advanced classification techniques have improved the accuracy of land cover mapping and change detection. Furthermore, the study highlights the vast potential for providing detailed information on the monitoring and assessment of the relationship between LULC and water resources through advancements in data science analytics, drones, web-based platforms, and balloons. It emphasizes the importance of promoting research efforts, and the integration of remote sensing data with spatial patterns, ecosystem services, and hydrological models enables a more comprehensive evaluation of water quantity and quality changes. Continued advancements in remote sensing technology and methodologies will further improve our ability to assess and monitor the impacts of LULC changes on water quality and quantity, ultimately leading to more informed decision making and effective water resource management. Such research endeavors are crucial for achieving the effective and sustainable management of water quality and quantity.

Keywords: arid environment; land cover assessment and monitoring; machine learning; satellite data; water quality and quantity; water resources management

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1. Introduction

Freshwater is a valuable natural resource that sustains biodiversity, carbon and nutrient cycles, food provision, and ecological functions [1]. Globally, freshwater resources offer significant socio-economic and ecological benefits, serving industrial, agricultural, and domestic needs. Semi-arid regions, covering about 15% of the Earth's surface [2], are characterized by unpredictable weather, long dry seasons, and erratic rainfall [3]. In the global semi-arid tropical regions, particularly Southern Africa, renewable freshwater resources are estimated to be around 2300 cubic kilometers [4]. Around seventy percent of the available water resources are in transboundary rivers, with the remaining thirty percent distributed between lakes and groundwater [5]. Any modifications or fluctuations in the water supply can have significant consequences for vital economic sectors, especially agriculture, and the overall natural capital. Scientific research has demonstrated that alterations in seasonal and inter-annual rainfall patterns, climate change effects, droughts, floods, and human activities have collectively influenced water systems, increasing their vulnerability [5,6].

Thus, it is crucial to manage these delicate freshwater resources carefully. Sub-Saharan African countries heavily rely on freshwater resources for agriculture and residential use, intensifying the pressure on ensuring water security and sustainable management [7]. Uneven rainfall distribution and external influences on water resources highlight the importance of water conservation and effective management. Extensive research had revealed that changes in land use and land cover (LULC), climate change impacts, and the proliferation of invasive alien species make water resources vulnerable [8,9]. The study of LULC change gained prominence in the mid-20th century [10], influencing water resources, human livelihoods, and ecosystem health. Human activities, such as agriculture, mining, and urbanization, significantly drive LULC transformation. These changes affect hydrological processes, climate variability, ecosystem services, drainage systems, and increase vulnerability to floods [11–13] Consequently, they directly impact the quantity and quality of water resources. For instance, studies have demonstrated how LULC changes contribute to a declining water quality in rivers and lakes, adversely affecting ecology and water quality [7,14,15]. Therefore, identifying effective methods to assess and monitor the impacts of LULC dynamics on water quality and quantity is vital for efficient water resource management.

Remote sensing has proven to be a cost-effective and efficient tool for providing spatially explicit data on various ecosystems, including surface water resources [16]. Earth observation techniques, such as modern UAVs, balloons, multispectral, and hyperspectral sensors, can help monitor semi-arid tropical environments and potentially address water scarcity, pollution, and the conservation of water quality. Understanding the relationship between LULC and water resources is essential for effective watershed management, policymaking, future LULC development considerations, and freshwater protection. Giri and Qui [17] provide a detailed review addressing land use and water quality in the 21st century. The study also provides insights into the factors that contribute to water quality problems, the indices used to evaluate water quality, techniques for identifying suitable explanatory variables for water quality, and the processing methods needed to capture spatial effects. Moreover, the study explores the modelling of water quality, using the identified explanatory variables to gain insights. Ullah et al. [18] reviewed the impacts of land use on surface water quality using a statistical approach. They indicated that each statistical method has a unique purpose, application and assumptions aimed at providing solutions to different problems. Meanwhile, Ozbay et al. [19] reviewed the relationship between land use and water quality and its assessment, using hyperspectral remote sensing in the mid-Atlantic estuary. Their main goal was to provide research findings on the application of hyperspectral remote sensing in order to monitor specific LULC and water quality. Meanwhile, previous studies have explored this relationship and the application of remote sensing in monitoring water quality, quantity, and specific LULC changes. However, bibliometric analyses of comprehensive systematic reviews on the use of remote sensing in global semi-arid tropical environments to understand LULC changes and their impacts on water resources are lacking.

This study aims to bridge this research gap by providing a comprehensive systematic overview of the progress, challenges, and opportunities related to the use of remote sensing applications in order to assess and monitor LULC changes and their effects on water quality and quantity in semi-arid tropical environments. This study aims to address the following key questions: (i) Which water quality and quantity parameters can be detected using remote sensing? (ii) What role does remote sensing play in understanding the relationship between LULC changes and water quality and quantity? (iii) Which methods have been utilized to assess and monitor these changes? (iv) What challenges have been encountered in these endeavors? (v) What can be achieved in the future to improve our understanding and monitoring of LULC changes and their impacts on water resources? Through these efforts, the study seeks to offer valuable insights into the potential of remote sensing technologies and provide suggestions with which to better assess and monitor LULC changes and their impacts on water resources in semi-arid tropical regions.

2. Research Method and Literature Search

This study conducted a systematic literature review that aimed to establish progress and identify existing gaps, using remotely sensed data to map and monitor LULC changes and their effects on water quality. This study also aimed to further outline the challenges and opportunities associated with remote sensing applications for assessing and monitoring the impacts of LULC change on surface water resources.

Literature Search and Data Extraction

The literature searches for this study utilized the Google Scholar, Scopus, and Web of Science databases, targeting peer-reviewed international journals related to remote sensing, hydrology, ecology, geographical information systems (GIS), and water resources. The search strategy involved defining appropriate search strings and identifying relevant keywords, phrases, and terms. To identify relevant keywords, phrases, and terms, we used the most cited literature reviews. Initial searches included terms such as "land use and land cover change", "impacts", and "water quality and quantity", resulting in a total of 18,187 publications being retrieved (17,500 from Google Scholar, 411 from Scopus, and 276 from Web of Science).

The retrieved articles underwent further screening using level 2 search criteria, including keywords such as "remote sensing", "tropical semi-arid", and the years 2001–2021. This process yielded a total of 1248 articles from Google Scholar, 121 articles from Scopus, and 95 articles from Web of Science. In the level three screening, additional keywords such as "catchment scale", "sub-catchment scale", "algorithms", "riparian buffers", "land cover land use classifications", "land use land cover monitoring challenges", "machine learning", "freshwater resources", "deep learning", "hydrological model", "spatial pattern", "ecosystem services", "change detection", "multi-spatial scale", "catchment management", "buffer zone" and "water pollution" were used. This resulted in a final compilation of 197 articles in EndNote for further screening, eliminating duplications and excluding non-English papers, gray literature, extended abstracts, conference proceedings, fee articles, and those not published between 2001 and 2021 (Figure 1). The remaining 197 articles were captured in Microsoft Excel and used to comprehensively outline the progress, gaps, challenges, and opportunities related to using remote sensing to assess and monitor land use and land cover changes and their impacts on surface water resources in semi-arid environments. Bibliometric analysis was employed to assess the published articles and identify key terms related to mapping and monitoring LULC changes and their impacts on surface water quality.

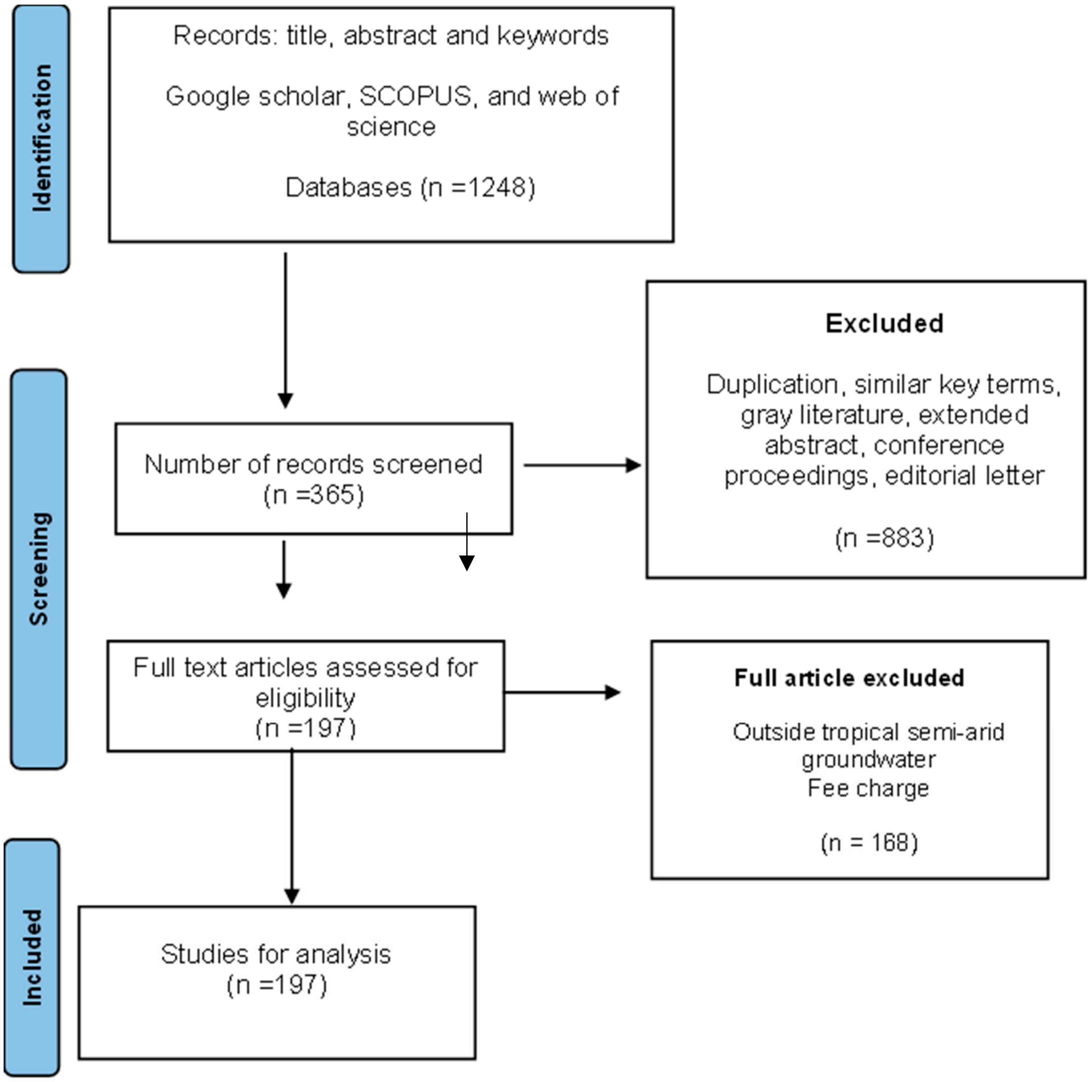


Figure 1. Methodology undertaken for selection of articles considered in the review.

3. Results

3.1. Progress of Remote Sensing in Assessment and Monitoring Land Use and Land Cover Changes

Land use and land cover (LULC) change examines the transformation and alteration of Earth's land surface, including changes in land use patterns and the conversion of natural land cover to human-modified landscapes. The assessment and monitoring of LULC changes using remote sensing have made significant progress over the years. Remote sensing technologies have advanced in terms of data acquisition, spatial resolution, spectral coverage, and temporal frequency, enabling the more accurate and detailed analysis of LULC dynamics. Some key areas of progress in the remote sensing assessment and monitoring of LULC changes include data availability, fine-scale mapping, the integration of multisource data, classification algorithms, change detection techniques, and web-based platforms and open data initiatives.

3.1.1. Data Availability and Integration of Multisource Data

The availability of satellite imagery data from platforms such as Landsat, Sentinel, and other commercial satellites has greatly improved. These datasets provide consistent seasonal and long-term coverage, allowing for the analysis of LULC changes over time. Advances in remote sensing have enabled the mapping and monitoring of LULC changes at finer spatial scales. High-resolution imagery and data fusion techniques have enhanced our ability to capture detailed LULC information, including urban areas, agricultural fields, and small-scale changes [20]. The integration of multisource remote sensing data, such as optical, radar, and LiDAR, has expanded the capabilities of LULC change assessment. Combining data from different sensors enhances our understanding of LULC dynamics and provides valuable information regarding vegetation structure, terrain characteristics, and three-dimensional mapping. Remote sensing has progressed in the development of change detection techniques, enabling the identification and quantification of LULC changes. These techniques include image differencing, spectral indices, time series analysis, and object-based change detection, enabling more accurate and efficient change assessment.

3.1.2. Classification Algorithms

The repetitive practice of using a multi-sensor image system to capture information provides valuable data for managing land-based resources. Remote sensing also offers the standardized data collection procedure, data integration, and analysis within a geographic information system [21,22]. Remote sensing satellites have proven valuable in employing various classification techniques to map LULC changes within watersheds such as supervised, unsupervised classification, and object-based image analysis (Table 1).

Table 1. Classification algorithms for mapping LULC classification.

Algorithm/Techniques	Sensor Used	Performance Range	References
Supervised Classification			
Support Vector Machine (SVM)	Landsat OLI, ETM+, TM, Terra ASTER, Hyperion Hyperspectral imagery and Quickbird	88–98%	[23–25]
Random Forest (RF)	Synthetic Aperture Radar (SAR) Sentinel 2 MSI, Landsat 8, SPOT, RapiEye, LiDAR	88–95%	[20,26,27]
Convolutional Neural Network (CNN)	Aerial photograph	91–98%	[28]
Classification and Regression Tree (CART)	Sentinel 2 and Landsat OLI, LiDAR	85–90%	[29,30]
Deep Neural Network (DNN)	Landsat TM and OLI, Sentinel 2	92–95%	[31]
Decision Tree (DT)	Landsat TM and ETM+, Sentinel 2	85–90%	[20,32]
Spectral Angle Mapper	Landsat 8, hyperspectral, RapidEye	89–90%	[24,33,34]
Recurrent Neural Network (RNN)	Very High Spatial Resolution (VHSR)	75–86%	[35]
Artificial Neural Network (ANN)	Landsat ETM+	70–85%	[32]
Maximum Likelihood (MLC)	Landsat TM	67–72%	[20,36,37]
Unsupervised Classification			
ISODATA	MODIS	54–69%	[38]
K-Nearest neighbor	Landsat TM and ETM+, Sentinel 2	87–91%	[39]
Object-Based Image Analysis			
Object-based image analysis (OBIA)	Lidar, Sentinel 2	87–91%	[40]

Unsupervised classification is a computer-automated process that groups pixels that are statistically similar into categories using a clustering algorithm, such as K-means [41] or ISODATA [38]. Unsupervised classification is valuable when the field data are lacking or knowledge about the study area is unavailable [20,42]. However, the spectral properties change over time with the image data, atmospheric condition, and the sun's angle at the time the image was captured; hence, detailed spectral knowledge of different features may be required. In contrast, supervised classification allows the analyst to select training samples for each land cover class and guide the computer to identify the spectral features of similar areas for each class [43]. This is particularly achievable using classification algorithms such as maximum likelihood (MLC), support vector machine (SVM), an artificial neural network (ANN) and random forest (RF), among others. Based on the finding (Figure 2), classification techniques such as MLC have been widely employed in studying LULC change in water resources. For example, the study by Ding et al. [44] derived the LULC change map from the Landsat TM using the MLC algorithm for classification and achieved an overall accuracy of 88% and a Kappa coefficient of 0.85%. Similarly, the study by Tadesse et al. [45] derived the LULC change from Landsat TM, ETM+ and OLI using MLC and achieved overall accuracies of 87%, 89%, and 93%, respectively, and Kappa coefficients of 0.83, 0.83, and 0.88, respectively. The MLC considers spectral variation within each category and the overlap covering the different classes. However, this method is time-consuming since it requires more pixels in each training dataset to specify each class [20] The MLC technique also produces lower classification accuracy results when compared to other classification techniques such as ANN, SVM, and RF [20,30,46].

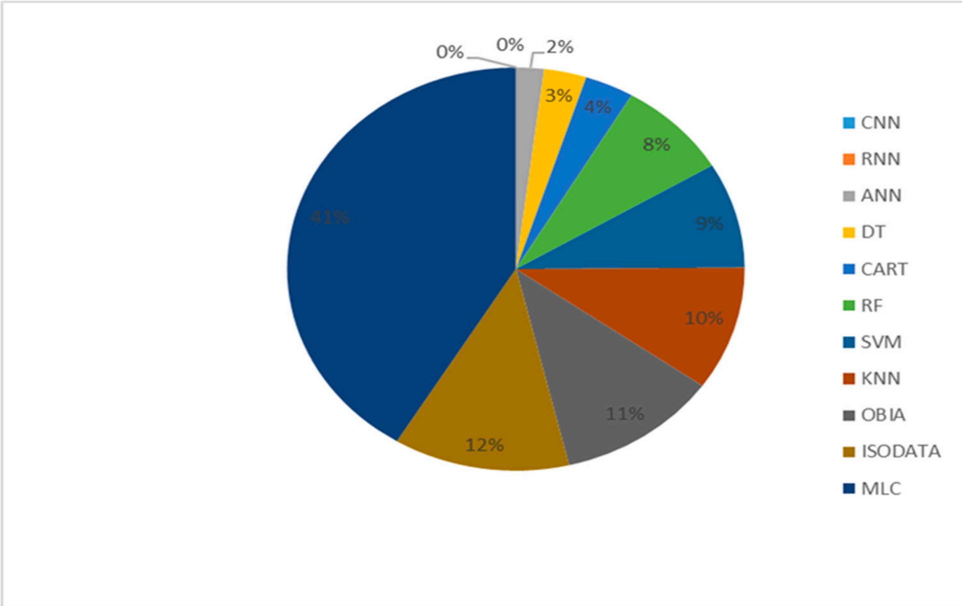


Figure 2. Classification algorithms (%) used to detect and map LULC using multi-sensors.

Thus, ANN, SVM, and RF machine learning (ML) algorithms are more robust and effective for classification techniques [20,47,48]. Supervised classification requires labelled training data to learn and understand the patterns associated with each category. Once the training data are labelled, these ML techniques can build models based on the labelled examples and use this knowledge to categorize new, unseen text accurately and efficiently, which is a challenge with MLC. However, the challenges associated with these methods are that they require extensive training (data hungry), require human supervision (expertise), and are computationally extensive when producing accurate LULC change maps [49]. Although individual classifiers achieve better accuracy results, they often fail to predict true classes with high accuracy. Therefore, studies have combined different classifiers to boost performance and reduce the classification error [50–52]. However, the ensemble fails on new data when individual classifiers are too complex for the training data present or their training error becomes too large quickly [49,53]. The problem associated with the ensemble is finding the right balance between the individual models' complexity and their fit to the data. Thereby, performing more ensemble iterations can reduce the error of the combined classifier on the training data.

Obtaining high-quality and sufficient reference datasets, as is required in most of these machine learning algorithms, is still an enormous task in most of the sub-Saharan African countries [54]. Acquiring reference data through field surveys is still challenging due to the inaccessibility of some areas, costs associated with travel and the time investment needed. To counter this limitation, other studies have adopted the migration of reference data from a specific time (year) to another time (target year) in order to address the lack of accurate and reliable current data. Likewise, good training data combined with the high spatial resolution of an image, together with an ensemble ML, often provide a high classification accuracy [55]. For instance, the study by Zhou [40] used Light Detection and

Ranging (LiDAR) to map LULC change using object-based image analysis classification and achieved an overall accuracy of 91% and a Kappa coefficient of 0.87%; additional examples are provided in Table 1.

Deep Learning (DL) algorithms have the capacity to extract automatic and hierarchical features from a large dataset, which makes them able to work with remote sensing data [31,56]. CNNs are one DL algorithm that are used to solve problems associated with spatial data. CNNs outshine other algorithms when aiming to capture spatial features such LULC patterns, textures, and shapes. They can also handle both multispectral and hyperspectral data. They can automatically learn and extract meaningful representations from the image data, leading to a high classification accuracy [28]. CNN transfer learning enables the learned features to be leveraged and reduces the need for extensive labelled training data. Meanwhile, RNNs are best at processing temporal and spatial dependencies in sequential remote sensing data, such as time series and spatial data in a sequential structure. RNNs are also able to flexibly work with hyperspectral imagery because they can handle data in which the number of spectral bands may vary across different samples [35]. Understanding the different spectral bands can be valuable for the classification of LULC. This provides opportunities to classify complex contextual images and improve the classification accuracy. However, these techniques have never been used to assess and monitor the impacts of LULC on water resources in semi-arid tropical environments. The major drawback of using these algorithms is the requirement for extensive datasets during the training process, particularly when dealing with large amounts of data. The computation involved in training and testing can be costly. RNNs can struggle to capture long-term dependencies effectively with remote sensing data, especially when analyzing time series with a large time lag. CNNs are prone to overfitting, where the model becomes excessively specialized to the training data and fails to generalize to unseen data.

3.1.3. Spectral Classification

Band Based Classification

Band-based classification is performed using the individual spectral bands of the remote sensing image [57]. This method relies solely on the spectral information captured by the different bands of the remote sensing image. They cannot effectively enhance specific features of interest, as the classification is based on the raw spectral values of each band. The results of band-based classification may be more straightforward to interpret since they directly correspond to the individual spectral bands [58]. This method can be more sensitive to atmospheric effects, such as haze or aerosols, which may impact the accuracy of the classification [57,58]. It is relatively straightforward and simple to implement, as it involves using each band independently for classification.

Index Based Classification

Classification using different spectral indices in remote sensing is a common approach used to extract valuable information from satellite imagery. Spectral indices combine specific spectral bands to highlight various land cover characteristics, such as vegetation health, water content, and soil properties. Index-based classification and specific spectral indices, which are combinations of different spectral bands, are used to perform the classification [59]. Instead of using individual bands, index-based classification uses spectral indices that combine bands in specific ways to highlight certain features of interest. By using spectral indices, this method can enhance specific features, such as vegetation, water bodies, or soil, making it more effective in certain applications [59]. Index-based classification can be more robust against atmospheric effects since the spectral indices can mitigate some of the atmospheric influences. Implementing index-based classification may require more pre-processing steps to calculate the spectral indices, adding some complexity to the process. The commonly used indices are the normalized vegetation index (NDVI), the normalized difference water index (NDWI), the normalized difference built-up index (NDBI), and the soil adjusted vegetation index (SAVI). Integrating spectral indices with other data sources, such as ancillary data and ground truth information, can enhance the accuracy and reliability of LULC change classification results.

3.1.4. Change Detection

Change detection is the process of identifying and quantifying areas of change in the LULC, or other environmental variables over time. Change detection provides a means by which to monitor and understand the dynamics of environmental changes [60]. It helps identify the magnitude, location, and patterns of changes, enabling researchers and decision makers to gain insights into ecosystem dynamics, urban growth, deforestation, agricultural expansion, and other changes affecting the environment [27]. It facilitates a better understanding of the dynamic nature of the Earth's surface and enables informed decision making for sustainable development and environmental protection. The accuracy of change detection relies on factors such data quality, spatial and temporal resolution, methodology and reference, or ground truth data [61]. The accuracy of the quality input data used for change detection plays a significant role. High-quality, well-calibrated data with minimal noise and distortions contribute to better levels of accuracy. Possessing reliable reference data or ground truth information is crucial for evaluating the change detection accuracy. Ground truth data, obtained via field surveys or high-accuracy sources and remote sensing technology, are used to verify the detected changes, and assess the method's performance [62,63].

Techniques such as pixel-by-pixel differencing, image ratioing, and image thresholding are used to identify and highlight differences between images. Time series analysis involves studying data collected over a period of time to detect patterns or trends. Statistical methods, such as regression analysis, seasonal decomposition, and moving averages, are employed to reveal changes in temporal data [64]. Remote sensing technologies, including satellite and aerial imagery, play a crucial role in monitoring LULC. Geographic Information Systems (GIS) aid in spatially analyzing and visualizing the detected changes. With the advent of machine learning and artificial intelligence, change detection has seen significant advancements. Supervised and unsupervised learning algorithms, such as SVM, RF, and CNNs, can be trained to automatically detect changes in various data types [27,65]. Light Detection and Ranging (LiDAR) technology utilizes laser pulses to measure distances to the Earth's surface and generate high-resolution 3D maps [29]. It is especially useful in detecting changes in topography, vegetation, and infrastructure. Radar-based change detection employs microwaves to penetrate clouds and vegetation, making it an all-weather and day-and-night imaging technique. It is useful for monitoring land subsidence, urban growth, and natural disasters. Data mining techniques can be applied to large datasets to discover hidden patterns or anomalies that are indicative of changes. This technology is widely used in fraud detection, network intrusion detection, and more. Time-of-flight cameras use light signals to measure distances, enabling real-time 3D imaging and change detection applications, such as object tracking and gesture recognition [66]. The challenges associated with the technique include spatial and temporal resolution, spectral heterogeneity, spectral similarity, radiometric variation, scale and context, computational resources and processing, and data availability.

3.1.5. Web-Based Platforms and Open Data Initiatives

The emergence of web-based platforms, such as Google Earth Engine (GEE) and Sentinel Hub, has facilitated easy access to remote sensing data and analysis tools [67]. Open data initiatives promoted by space agencies and governments have further promoted the sharing of remote sensing datasets, enabling broader participation in LULC change monitoring. These advancements in remote sensing technology and techniques have significantly improved the assessment and monitoring of LULC changes. They provide a more comprehensive understanding of the dynamics and impacts of human activities on the Earth's surface. Continued progress in remote sensing, along with ongoing research and development, will further enhance our ability to monitor and manage LULC changes effectively.

3.2. Water Quality and Quantity

Water quantity refers to the various aspects that contribute to the overall measurement and understanding of water availability and supply. Some common components that can be measured using remote sensing technology include precipitation, evapotranspiration, runoff and streamflow, groundwater, reservoir and lake monitoring, and soil moisture. Remote sensing can estimate precipitation patterns and distribution by measuring cloud properties, rainfall rates, and storm characteristics using sensors such as radar or microwave radiometers [22,68]. Remote sensing can quantify the amount of water lost from the land surface through evaporation and plant transpiration. It involves estimating energy fluxes and vegetation indices using optical or thermal sensors in order to assess evapotranspiration rates [69,70]. It can also help to estimate runoff and streamflow by monitoring changes in water levels and river discharge using altimeters, radar sensors, or optical imagery [71,72]. This enables the water movement in river networks to be assessed. More insights into groundwater resources can be obtained by monitoring changes in the land surface elevation using satellite-based radar interferometry (InSAR) or gravity data from the Gravity Recovery and Climate Experiment (GRACE) mission [48,73]. The soil moisture content can be estimated by measuring the microwave radiation emitted or reflected by the Earth's surface [68,74]. This information helps to assess water availability in the root zone and supports agricultural water management. In reservoir and lake monitoring, remote sensing enables the monitoring of water levels, surface area, and volume changes in reservoirs and lakes using radar or optical imagery [75]. This information is crucial for water supply management and flood control.

Remote sensing data may have limitations regarding its spatial and temporal resolution, sensitivity to atmospheric conditions, calibration and validation, complex terrain and land cover heterogeneity, and limited data accessibility for specific parameters. Therefore, it is important to consider these limitations when using remote sensing for water quantity assessments. Integrating remote sensing with other data sources, utilizing complementary techniques, and incorporating appropriate modelling approaches can help to mitigate these limitations and improve the accuracy and reliability of water quantity assessments. In addition, by leveraging remote sensing data, scientists and water resource managers can assess and monitor these components of water quantity on various scales, providing valuable insights into water availability, distribution, and movement.

Water quality refers to the chemical, physical, biological, and radiological characteristics of water that determine its suitability for various uses and its impact on the environment and human health [28]. The water quality parameters that can be assessed using remote sensing include the chlorophyll-a concentration, water turbidity, dissolved organic matter (DOM), water temperature, total suspended solids (TSS), water pH, and harmful algal blooms (HABs) [76]. For further details, the study by Gholizadeh et al. [77] elaborates more on the water quality parameters and limitations of remote sensing for assessing water quality. However, most studies monitoring water quantity have focused more on water balance (evapotranspiration) and monitoring water (reservoir and lakes), with little attention paid to runoff, ground water recharge and soil moisture. Water quality parameters such as pH, TSS, temperature, and DO are commonly evaluated in water quality assessments [78]. Meanwhile, HABs and the chlorophyll-a concentration have received little attention.

3.3. Impacts of LULC Changes on Water Resources

Rapid population growth, socioeconomic factors and a lack of natural resource conservation policies are major contributing factors to LULC changes worldwide. According to Dwarakish and Ganasri [43], slope, the distance from the river, soil erosion, altitude, and built-up areas are significant contributing factors to LULC changes. Nonetheless, they are not considered in most studies when assessing and monitoring the impact of LULC on water resources. Changes in LULC can have a wide-ranging impact on various aspects of the environment. These LULC changes can alter landscape patterns, hydrological processes (surface flow), physical factors (stream morphology and temperature increase), biology (biodiversity and ecosystems) and water quality and quantity (nutrients and pollution increase). Semi-arid tropical climates are characterized by erratic climate change. The semi-arid tropical climatic conditions need to be frequently monitored for effective watershed or catchment management, and sustainable water resources. LULC changes, such as agriculture, urbanization, and mining, are likely to improve livelihoods, contribute towards local and national economic development, facilitate food security and advance biofuel energy, making them a priority for the development of countries. Yet, these are the most substantial factors causing negative environmental modification. Agriculture is directly associated with the removal of natural vegetation, increased soil erosion [79], algal bloom [80], increased greenhouse gas emissions and nutrient imbalances. Natural vegetation, such as riparian vegetation, can act as an important habitat for a variety of species and can trap sediments and pollutants in water. Therefore, alterations in the natural vegetation affect the ecosystem services provided by the streams, which are important for reducing flood streams, managing runoff, and preventing erosion [64,79,81]. Ultimately, these changes affect the water storage provided by aquifers, ecological processes, functions and services, and hydrological factors. This will have implications for hydrological factors, thus affecting water supply and availability [26]. This will lead to changes in the drainage network, which is important for surface runoff and drainage patterns. Ecosystem services play an important role in watershed and water management. However, they are often overlooked in water resources management.

Urbanization and mining are associated with impervious surfaces, urban heat islands, the increased susceptibility of areas to floods, the loss of drainage systems and changing hydrological systems [82,83]. These artificial surfaces often result in increased runoff, and further generate a path for the transportation of pollutants into water bodies [84]; this reduces the infiltration into and storage capacity of water in shallow aquifers and increases the chances of severe floods occurring [85]. Urban heat islands can be aggravated by a warming climate, particularly during heat waves, which change the water balance (evapotranspiration) and hydrological factors of the catchment. These changes affect the timing and magnitude of evaporation loss and the water yield, which govern the soil moisture content and the flow patterns of hydrological regimes. At the end, increased streamflow and precipitation occur, and the frequency of large floods and larger sedimentation increases [85]. To better manage LULC and water resources effectively, it is important to assess hydrological components by using advanced tools, with which it is very important to attain sustainable water resources at a catchment scale. Land cover changes are located within the spatial representation of landscape. Modeling LULC patterns offers a better understanding of past and future LULC and its related implications and guides future land use policies. Taking these studies in semi-arid tropical areas into account will ensure the sustainability of the catchment via the planning and management of the watersheds.

Consequently, these LULC changes have a serious impact on a wide range of ecological processes and result in several global environmental problems, such as land degradation, desertification, biodiversity loss, habitat loss, and species transfer. These impacts affect the water supply, irrigation, fishing, and power generation, reduce food production and land productivity, and decrease many countries' Gross Domestic Products (GDP). Contaminated surface water results in health risks for humans, increases the financial cost of purification and human consumption, and affects economic development. The impact of LULC on water resources is caused by a lack of proper management strategies and land use planning surrounding water resources. A lack of awareness regarding water pollution, especially in Sub-Saharan countries, further compromises water quality. The enforcement of policies and regulations regarding the discharge of pollutants from agricultural sectors, urbanization, waste-water treatments, and industries needs to be strengthened. This will promote sustainable water quality, watershed management and improve global economies.

3.4. The Role Played by Remote Sensing Platforms in Assessing and Monitoring LULC Changes and Their Impacts on Water Resources

Seasonal and Long-Term Monitoring

The effects of LULC changes on water quality differ spatially and temporarily due to climatic conditions (e.g., temperature and rainfall), and topography (e.g., slope and landscape patterns). The hydrological factors (e.g., flow) also play an important role in the movement and transportation of the pollutants into rivers and the degree to which they disrupt the ecosystems. Remote sensing platforms, with different image acquisitions (Table 2), offer an opportunity for the seasonal and long-term monitoring of the effects of LULC changes on water resources. Long-term monitoring offers the important data needed to measure the changes in natural water resources over time and predict trends; this is in order to implement, plan, monitor and manage water quality. The tabulated information below is helpful in designing an assessment evaluating the effects of LULC changes on water resources and may be used in the selection of appropriate sensors.

Table 2. Available sensors that can be applied for assessing and monitoring the effects of LULC changes on water resources.

Sensor/Platform	Resolution (m)	Spectral Bands	Swath Width (km)	Revisit Time (days)	Acquisition Cost
AVHHR	1100	5	2900	1	Free
IKONOS	4	5	11	1–2	High
ASTER	15, 30, 90	144	60	16	Free
GRACE				10	Free
Hyperspectral	<1		>100		Very high
Landsat ETM+	30	8	185	16	Free
Landsat TM	30	7	185	16	Free
Landsat OLI	30	11	185	16	Free
LIDAR	0.45	5	1–2		Very high
MODIS	500, 1000	7	2330	1	Free
MERIS	300	15	1150	3	Free
Radar	0.3, 0.56	2			Very high
Rapid Eye	5	5	77	5.5	High
Sentinel 1 SAR	5, 5 × 20, 20 × 40	4	20, 80, 250, 400	6–12	Free
Sentinel 2 MSI	10, 20, 60	13	290	5	Free
SPOT	10, 20	4	120	26	High
Quickbird	2.4	5	16.5	1–3.5	High
Worldview	<1	8	16.4	1–3.7	Very high

The long-term monitoring of the effects of LULC changes on water resources has used aerial photographs due to their long period of existence. For example, the study by Schilling et al. [86] used aerial photographs to map LULC, and the results indicated that the change in grassland to row crop increased nitrate levels up from 8.0 to 11.6 mg L in two Squaw creek subbasins in the USA for a period of ten years. Aerial photographs offer a high spatial resolution and are very good for analyzing ground surface events and detecting different LULC [87]. However, they are limited to a smaller scale compared to satellite data, and the images lack repeatable acquisition. They require qualified and experienced personnel to interpret the image [88], and interpretating the images is costly and time-consuming.

Landsat ((Thematic Mapper (TM), Multispectral Scanner System (MSS), Enhanced Thematic Mapper (ETM)) multispectral sensors have been widely used to conduct long-term monitoring of the impacts of LULC changes on water quality at regional and local scales. The study by Kibena [89] used Landsat TM to map the effects of LULC change on water quality from the year 1995 to 2012. They observed that the LULC, namely grassland, forest and bare land, had been converted into settlement and agricultural land, which had increased pollution in Lake Chevero in Zimbabwe. The results showed that the total phosphorus (TP) increased from 130 to 376 kg/day, the total nitrogen (TN) increased from 290 to 494 kg/day, the DO increased from 0.1 to 6.8 mg/L, the chemical oxygen demand (COD) increased from 11 to 569 mg/L, the biochemical oxygen demand (BOD) increased from 5 to 341 mg/L, Phosphate Phosphorus (PO_4-P) increased from 0.01 to 4.45 mg/L, Ammonia Nitrogen (NH_3-N) increased from 0.001 to 6.800 mg/L and the electrical conductivity (EC) increased from 38 to 642 mg/L. Similarly, Zhang et al. [90] further observed that grassland, forest, water, and bare land were converted into farmland and constructed land from 1990 to 2016, which increased the level of chemical oxygen demand, manganese variant (COD_{MN}) from 0.92 to 1.09 mg/L, BOD from 0.63 to 0.85 mg/L, TP from 0.006 to 0.007 mg/L, and TN from 0.12 to 0.20 mg/L. The temporal range of the Landsat images provided the researchers with the ability to predict the effects of LULC on water quality; hence, there are still challenges related to the use of the Thematic Mapper (TM) and Multispectral Scanner (MSS), in that they are no longer operating, and with the Enhanced Thematic Mapper Plus (ETM+) images, which are persistent with the Scan Line Corrector (SLC). The malfunctioning of the sensor's SLC leads to a data loss of approximately 22% of the normal scene area [91]. Therefore, these medium-resolution sensors (i.e., Landsat TM and MSS) fail to deliver real-time images; in addition, the loss of data for the operational ETM+ sensor has resulted in considerable challenges regarding the estimation of the impacts of LULC change on water quality.

In 1986, the French government launched the Satellite Pour L'Observation de la Terra (SPOT), and it was the first earth resource satellite to have a pointable optic with high resolution, which increases the high opportunity of the imaging areas [92]. The SPOT sensor has the ability to obtain information every day at any time due to the frequency revisit time, and can map LULC change, ranging from the regional scale to global scale [93]. Plessis et al. [94] used Landsat TM and SPOT for classification and successfully predicted the future concentration of the water quality for the years 2015, 2020, 2030 and 2050, which increased with changes in the LULC. However, SPOT imagery is costly, which often hinders the adoption of its products in many studies.

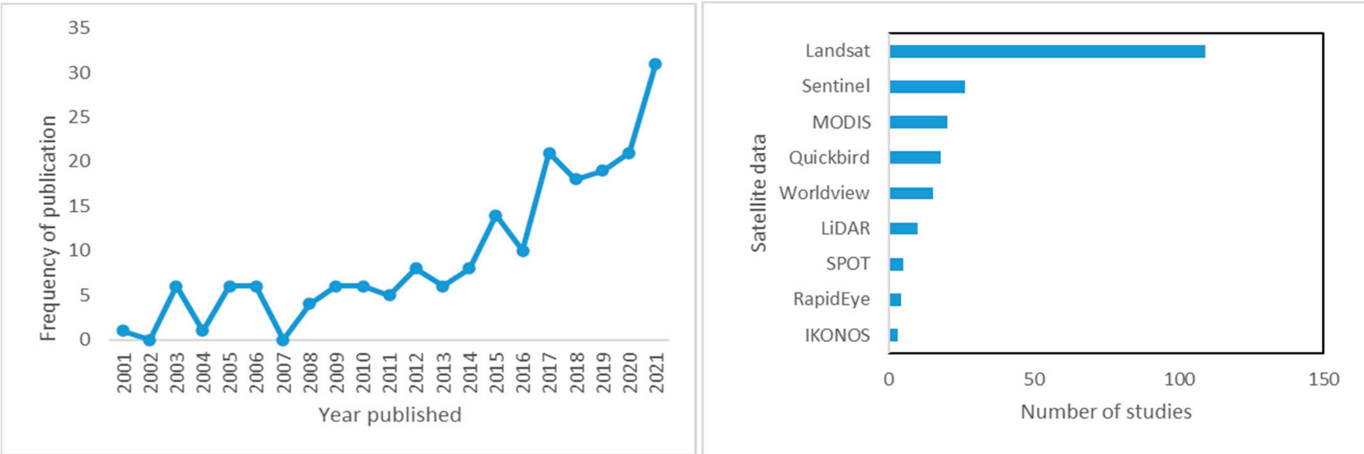
Moderate-Resolution Imaging Spectroradiometer (MODIS) instruments use NASA Aqua and Terra satellites, thus providing nearly daily repeated coverage of the Earth's surface with 36 spectral bands and a swath width of approximately 2330 km [87]. MODIS plays a significant role in mapping LULC change and dynamics at a coarse spatial resolution [88]. The sensor is freely available and presents an opportunity for the long-term and seasonal monitoring of LULC changes at a large scale due to its long period of existence and its revisit time [93]. For example, the study by Juma [95] used MODIS to map LULC change and demonstrated an increase in agriculture and residential growth due to population growth from 1990 to 2008. The results showed that Nitrate Nitrogen (NO_3-N) increased from 10 μg^{-1} to 98 μgL^{-1}, PO_4-P increased from 4 μgL^{-1} to 57 μgmL^{-1} and chlorophyll also increased due to poor practices in agriculture, which resulted in the proliferation of an alien invasive water hyacinth species. However, the limitation of using the MODIS sensor is the difficulty involved in linking the coarse spatial resolution with field data, and the difficulties involved in monitoring small areas using the sensor.

On the other hand, the Advanced Very High-Resolution Radiometer (AVHRR) is freely available and has a high probability of obtaining a cloud-free view of the land surface compared to multispectral sensors (e.g., Landsat) [96], and is very useful for long-term monitoring. The coarse spatial resolution of AVHRR can cover large areas and fails to distinguish the earth's features. This makes it difficult to detect or view detailed information about features. However, AVHRR has not been used at a national or global scale because of the difficulties involved in linking coarse spatial resolution data and field measurement [97]. Still, not all LULC changes affect water quality, as demonstrated by the study by Kaushal [98]. The authors found that the transformation of row crop cover to perennial grassland decreased the amount of NO_3-N. Also, Khare et al. [99] indicated that between 1974 and 2007, residential areas increased from 10% to 21%, while agriculture decreased from 36% to 19%, and forest decreased from 13% to 8%. This conversion decreased the TN from 2 mg/L to 1.5 mg/L. In addition, the expansion of residential areas may cause an increase in fecal coliform in water bodies since they pave the way for the entry of pollutants into rivers. On the contrary, the expansion of forest cover decreases the number of pollutants entering into rivers, although it increases dissolved oxygen, which is important for the lives of fish and macroinvertebrates [100]. Therefore, many studies agree that the expansion of forest and grassland cover is important an mitigation strategy for improving water quality [101,102].

The seasonal monitoring of the river catchment plays a substantial role in evaluating the temporal variations in river pollution due to LULC changes for effective land use management and watershed management. This is important for developing proper management strategies for water resources. The seasonal monitoring of the quality of pollution can further indicate the current, ongoing, and emerging problems. Most studies, for instance those by Tahiru et al. [7], Namugize et al. [14] and Beck et al. [71], have observed that built-up areas are positively correlated with most of the water quality parameters; this is due to increased surface runoff caused by impervious surfaces, which create paths for the transportation of contaminants including TP, TN, NH_3-N. Thus, policies pertaining to land use planning, especially in urban areas, should be implemented and enforced in order to sustain water resources. Forests and grasslands have a relationship with DO, and cultivated land/agriculture are positively associated with TN, TP, turbidity, and pH due to various farming practices, such as the use of pesticides, herbicides, and fertilizers. As such, most concentrations of these contaminants are higher during the dry season than in the wet season. However, DO is higher in the wet season than the dry season, while TP and TN are higher in both seasons (dry and wet). The high quantities of contaminants observed in the dry season may be driven by high water discharge and low water retention [71].

For instance, Pullanikkatil et al. [103] seasonally monitored the impacts of LULC on the Likangala river catchment in Malawi and found that turbidity increased in the wet season, with 190.5 NTU downstream in the area dominated by wetland and settlement. Meanwhile, the pH increased during the dry season, with 880.83 mg/L, and decreased by 218.72 mg/L in the wet season downstream, which was dominated by wetland and settlements where people nearby practice fishing. The EC varied from 4 to 466 µs cm^{-1} during the wet season and between 40 and 3520 µs cm^{-1} in the dry season in the upstream and downstream, respectively. The TDS varies from 20 to 1760 mg^{-1} in the dry season and from 2 to 233 mg^{-1} during the wet season. Similarly, the study by Zhang [101] seasonally monitored the effect of land use on water quality and observed that water quality parameters such NH_3-N and CODmn were higher in the dry season (7.29 mg/L and 7.8 mg/L) and lower in the wet season (0.048 mg/L and 2.2 mg/L) in built-up areas (dominated by urban areas). Meanwhile, the DO was lower in the wet season (3 mg/L) in the built-up area and higher in the dry season (12.9 mg/L) in the forest–grassland area. However, the TP was higher both seasons, with (0.28 mg/L) in the wet season and (0.29 mg/L) in the dry season. The study concluded that the high levels of NH_3-N and COD_{mn} were influenced by urban areas, which increased the surface runoff of contaminants into the water bodies. Meanwhile, studies such as those by Kaushal et al. [98] and Rothenberger et al. [97] found that NO_3-N and NH_4-N, respectively, are higher in the wet season than in the dry season. The high concentration of pollutants in the wet season may be attributed to an increased run-off that washes off the soil, releasing a large amount of sediment, nutrients, and pesticides into surface water. An in-depth understanding of LULC change and seasonal factors can help to implement effective catchment management strategies for the protection of these water resources.

Progress has been noted in detecting, mapping, and monitoring LULC change and its effects on water quality using remotely sensed data over the years (Figure 3a). The use of satellite remote sensing in mapping and modelling the impact of LULC change on water quality has recently attracted increased attention, as evidenced in the number of publications between the years 2001 and 2021 (Figure 1). According to our analysis, extensive research has been conducted mostly using multispectral sensors; these include a range of Landsat sensors (TM, MSS, ETM+), and a few studies have used Sentinels, SPOT and MODIS (Figure 3b).



(**a**) (**b**)

Figure 3. (**a**) Progress of remote sensing publications, and (**b**) sensors that were used in monitoring the effect of land use and land cover change on water quantity and quality.

The advancement of this research could be attributed to the significant increase in earth observation technologies, their relatively low cost and their time efficiency when managing large areas [9]. For instance, remote sensing has the ability to perform the spatiotemporal monitoring of LULC change, water quality, and natural resources, which is also important for assessing water quality and quantity in terms of river pollution. However, Landsat TM, MSS and ETM+ have been the most used sensors [104,105]. This could be attributed to the fact that Landsat is the longest mission (since 1972) that has been supplying remotely sensed data for a wide variety of applications without charges. However, the Landsat sensors have been useful for assessing and monitoring the impacts of LULC change on water quality. It cannot be denied that medium- and low-spatial-resolutions can limit the detection and mapping of LULC and water quality when the area affected is smaller than the pixel size [91].

Advances in earth observation technology with improved image acquisition characteristics have progressively expanded our ability to distinguish features of the earth. Platforms such as Sentinel 1 synthetic aperture radar (SAR) provide an opportunity to integrate optical and radar data to improve the mapping capacity on cloudy days [50]. This is necessary for monitoring areas such as semi-arid environments, which receive most of their rainfall seasonally (wet season). Therefore, Sentinel 1 uses multiple sensors and sensing periods to accurately map heterogeneous LULC [51]. Schulz et al. [51] and Hu et al. [106] combined an ensemble Sentinel 1 and 2 Multispectral Instrument (MSI) to map LULC at a local to regional scale and achieved improved results compared to using only the optical sensor exclusively. The water quality parameters that were assessed using sentinel 1 were TN, TSS, COD and TP. Munthali et al. [66] and Chen et al. [78] used Sentinel 2 and normalized the vegetation index to monitor the TSS concentration at various buffer scales and showed that a 300 m scale most effectively explained the variation in TSS concentrations (R^2) of 0.83, $p < 0.001$). Sentinel (SAR and MSI) sensors are freely available and have successfully monitored LULC and water quality separately. However, they have not been used to their full capacity in assessing and monitoring the relationship between LULC and water resources [77]. Other studies have used the LULC prototype supplied by the European space agency (ESA) for instance, Copernicus global land cover (100 m × 100 m pixel size) [107] and Globcover (300 m × 300 m pixel size) [32]. Although the LULC prototypes provide useful data, they are need to be updated frequently for effective management since the LULC changes over time. The development of hyperspectral sensors presents a unique opportunity for the extraction of the LULC [108], biological and physicochemical parameters of water quality [77,109].

Specifically, hyperspectral remote sensing provides several narrow and quasi contiguous bands that enhance discrimination among different land uses and land covers. Thus, the narrow band of hyperspectral sensors provides an opportunity to generate spectral reflectance curves for each pixel, which are unique in order to differentiate different classes of LULC, including water and pollutants [17,110]. Hyperspectral sensors have been reported in the literature to capture unique spectral signatures of water quality indicators, such as salinity, chlorophyll content (chla), turbidity, TSS and colored dissolved organic matter (CDOM) [21]. This may help us to understand and quantify the relationships among the spatial, structural, biological, and chemical processes occurring in the natural water ecosystem. The narrow bands of the sensors have allowed researchers to develop and implement water quality indices that have been effective in estimating water quality, thus including the Maximum Chlorophyll Index (MCI), Normalized Difference Turbidity Index (NDTI), and Green Normalized Difference Vegetation Index (GNDVI). The study by Elhag et al. [111] used water quality parameter indices to estimate water quality, including MCI, NDTI and GNDVI. They achieved an outstanding coefficient of correlation (R) result of 0.96 with MCI, an R of 0.94 with NDTI, and an R of 0.94 with GNDVI. Although water quality indices are effective for monitoring water, they have been widely used in semi-arid tropical environments. The lack of robust and reliable water and quantity data needed to parameterize models remains a challenge.

The optimal spectral and spatial resolution remains a major challenge to the remote sensing community since not all water quality parameters can be detected and monitored using remotely sensed data because they are not optically active. Hyperspectral image analysis has not been fully explored due to its high cost and complex pre-processing procedure [109]. Regardless of their outstanding performance, only a few studies have attempted to use hyperspectral sensors to assess and monitor the relationship between LULC and its associated impacts on water resources. Advanced modern technologies such as Unnamed Aerial Vehicles (UAVs), commonly known as drones, have emerged as a potential alternative for mapping and monitoring LULC and water resources at a local scale [112,113]. They are flexible, affordable, and offer a very high spatial resolution. However, drones are limited to small areas and many of the affordable drones exclusively cover the true color (RGB) section, which does not offer sufficient data for extensive application in areas such as characterizing water quality [113,114]. These have never been fully explored in understanding the relationship between LULC and water quality. Based on the findings of this study, the growing interest in assessing and mapping the relationship between LULC and its impact on water resources in semi-arid areas has focused on using the Landsat image platform. Meanwhile, advanced earth observation platforms such as sentinels, UAVs, and hyperspectral technology have not been fully explored in assessing and monitoring the relationship between LULC changes and their impact on water quality and quantity. The use of advanced earth observation could be viable in monitoring the impacts of LULC on water resources in semi-arid tropical environments.

3.5. Algorithms Used for Quantifying the Effects of LULC Changes on Water Resources (Quality and Quantity)

Different algorithms are available for estimating the effects of LULC change on water quality using remotely sensed data. The techniques use different statistical modelling approaches that provide relatively accurate results and are easier to understand when compared to hydrological water quality modelling approaches. Most machine learning (ML) algorithms developed for remotely sensing the effect of LULC changes on water quality can be categorized as parametric or non-parametric. The most frequently used methods by researchers for modelling the relationship between LULC change and water quality parameters are the parametric machine learning algorithm (PMLA), which assumes the linear relationship between variables. Parametric algorithms, such as linear [115], multilinear [7,116] and Stepwise multilinear (SML) regression [117], have shown satisfactory performance. However, PMLA, such as linear and multilinear regression, have the limitations of multicollinearity and the overfitting of large data. Although the SML regression algorithm attempts to reduce the collinearity problems, it also eliminates variables that are ecologically and statistically important [117]. Seilheimer [118] used the linear mixed-effect model (LMEM) algorithm approach, which enables the robust simultaneous evaluation of the association and environmental gradient. Meanwhile, it accounts for the repeated measures embedded in the data structure and indicates a better prediction performance when compared to multiple linear regression. The LMEM assumes that observation with the cluster is always positively correlated and that some individuals competing in the cluster for the scarce resources are negatively correlated. Thereby, it ignores a small negative correlation, resulting in a deflated type-1 error, and an invalid standard error and confidence interval in regression analysis [119].

Researchers have introduced more advanced non-parametric machine learning algorithms (NPMLA), including Partial Least Square Regression (PLSR) and multivariate statistics, which have been reported to be robust and efficient when aiming to overcome the problems of overfitting and multicollinearity with high accuracy. The algorithms include Principal Component Analysis (PCA) [120,121], Discriminant analysis (DA) [122], Cluster analysis (CA), Redundancy Analysis (RDA) [123] and Hierarchical cluster analysis [122] (Figure 4). The NPMLA works well with large volumes of data. Singh et al. [124] reported that multivariate statistical techniques (CA, DA, and PCA) are important for evaluating and interpreting large and complex datasets and obtaining better information regarding water quality and the design of monitoring. Besides the robustness of the NPMLA, there are limitations associated with some of the machine learning (ML) algorithms.

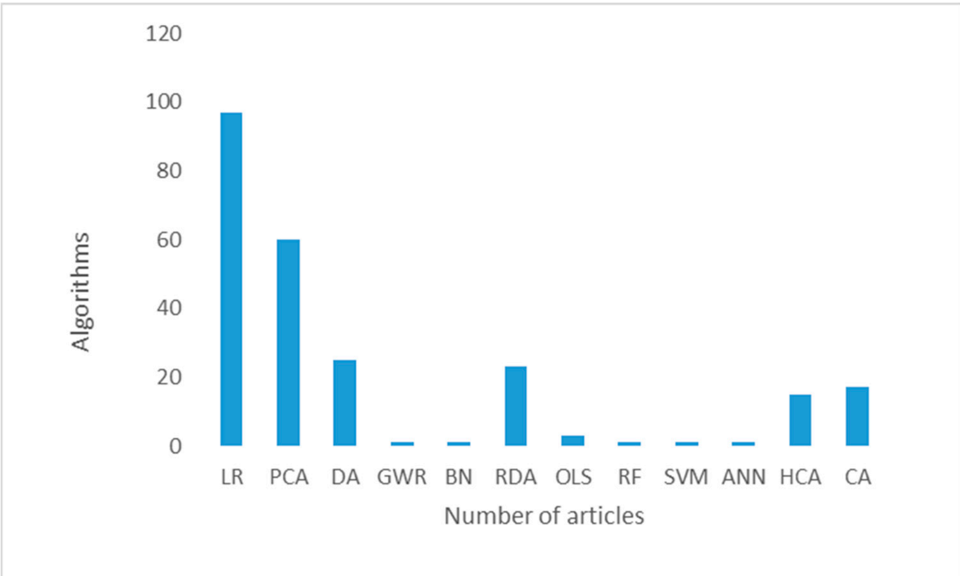


Figure 4. Algorithms used to assess and monitor the relationship between impacts of LULC and water quality.

The limitation of these multivariate statistical methods shows an existing relationship between water quality and LULC pattern, which may neglect some of the important spatial characteristics and hide local variation [101,125]. ML algorithms, including Ordinary Least Squares (OLS) and Geographically Weighted Regression (GWR), were introduced to address spatial non-stationary issues and to examine spatial autocorrelation, which is neglected by multivariate algorithms [122,125]. OLS is important for developing a relationship between independent LULC and water quality variables at a large scale by selecting the most significant variables in the regression [18]. The coefficient from the OLS model provides the most influential parameter of different water quality parameters. However, OLS requires a large dataset to obtain reliable results [126]. The GWR considers the spatial variation and determines the relationship by incorporating the coordinates of location into the regression equation. The GWR model uses a single land use indicator as the independent variable and excludes the selection model because of the high potential of multicollinearity among different land-use variables; this would result in an invalid GWR model when variables experiencing multicollinearity are selected [127]. However, GWR statistical analysis is limited to small scales. Therefore, the implementation of models that cover large areas is required. Bayesian Network (BN) is an effective method for spatiotemporal analysis as it enables the interaction of variables in space and time [18], and is suitable for handling missing data prediction [18,128]. The model is essential for evaluating the complicated LULC change in water quality at various scales. However, the model is too complicated, too difficult to automate, requires specific software to run the model and qualified statistical expertise, and is sensitive to probabilities [129].

On the other hand, Artificial Intelligence (AI) has gained considerable attention because of its potential to leverage big data and solve the problems faced in traditional techniques (mathematical models). AI refers to the simulation of human intelligence in machines that are programmed to think, reason, learn, and perform tasks that typically require human intelligence [130]. The goal of AI is to create machines or systems that can mimic human cognitive functions, such as problem solving, pattern recognition, language understanding, and decision making [131]. Moreover, AI encompasses a broad range of techniques, algorithms, and methodologies to enable machines to perform intelligent tasks. AI computing technologies are on the edge of becoming the prevalent alternative to conventional data processing techniques [131]. Some of the key subfields of AI that are used in remote sensing include ML and DL. ML developed for earth observation data can support the challenges of spatial and temporal realm adaptations, hyperspectral data, the integration of multisource information and large-volume data analyses [132,133]. Advances in ML technology have created a unique opportunity for the development of accurate large-scale prediction and prescriptive models [134]. DL is used to improve results due to its accuracy in classification and prediction when trained with extremely big data; in addition, it can extract features from raw data. DL helps to capture the potential relationship between environmental variables for remote sensing retrieval, fusion, downscaling and superiority in multiscale and multilevel feature extraction. However, it is not clear how to best use ML or DL for expanding the range of increasingly accessible satellite data for LULC change research, particularly under environmental and socioeconomic impacts.

3.6. Multi-Spatial Scale Relationship between LULC Changes and Water Quality and Quantity

Water quality monitoring often relies on the conventional methods of conducting in situ measures using a handheld multiparameter instrument and laboratory analysis. However, the accuracy and precision of collected in situ data may be questionable due to human error in the field and laboratory [77]. The use of in situ data provides an accurate measure; therefore, integrating them with remote sensing data provides accurate measurements for the cost- and time-effective management of water pollution. Therefore, remote sensing has been widely used to assess and monitor the environmental effects had by LULC change on water quality at both the local and global scales [89,93,135,136]. However, when determining the relationship between LULC change and water quality, it is important to consider scale (spatial and temporal). Scale plays an important role in reflecting the different impacts of LULC changes on water quality. Therefore, in order to better manage the impacts of LULC changes on water resources, it is essential to consider streams as a complex ecosystem that operate at different spatial and temporal scales [136]. Three types of spatial scale, namely the buffer, sub-catchment, and catchment scale, have been used to estimate the impacts of LULC changes on water quality. However, there is no consensus regarding which of the abovementioned spatial scales explains a better relationship between LULC changes and their impacts on water quality and quantity.

Buffer zones are strongly influenced by water from the upslope, which is divided into three categories: surface flow and shallow subsurface flow [137,138]. When choosing a buffer scale, one should consider the structure and the function of the catchment, since there are two types of buffer scale; these include a circular and riparian buffer [135]. Riparian buffers are determined by the soil, vegetation and hydrology characteristics of the buffer and the interaction with the upslope and downslope. Meanwhile, circular buffers are effective for the diversity of water bodies such as lakes, streams, and dams in the lakeshore areas [139]. Most studies use a riparian buffer rather than a circular buffer to measure the influence of LULC change on water quality and quantity. For example, the study by [139] observed that many impacts came from all land uses, such as constructed land (CL), wetland (WL), original forest (OF), artificial forest (AF), and original land (OL), which reflected TN at 2 km; meanwhile, WL and CL continued to affect TN at the 4 km buffer. Moreover, Song et al. [135] found that urban areas influenced TN in all buffers from 500 m to 1000 m. Similarly, Li et al. [140] further indicated that a 300 m buffer is the strongest for the land use type to affect COD. Riparian buffers are storage areas that can be both the source and the sink of pollutants if no degradation process exists in the buffer zone. However, the drawback of using riparian buffers is that there is no uniform way of defining the width of a riparian zone [84]. Overcoming this problem requires a wider use of a riparian buffer to maximize its effectiveness in improving the water quality. The other problem with using a riparian buffer is the inability to address all water-related problems, since they are only effective in buffer areas that are not degraded. In the case of a degraded buffer zone, the scale may fail to reflect some of the impacts of land use on water quality and quantity.

Meanwhile, Gyawali et al. [141] indicated that the sub-catchment scale is more effective in reflecting the impacts of land use on water than the buffer and the whole catchment. Their results indicated that agriculture influenced dissolved oxygen (DO), and that urban and water bodies influenced dissolved solids (DS), biological oxygen dissolve (BOD), and temperature at the sub-catchment scale. Wan et al. [96] further revealed that LULC showed varied impacts of the same LULC category over different sub-catchments. However, other LULCs that are not nearby sub-catchments may have an influence on or contribute to impacts on the water quality, because pollutants from LULC in the upper catchment may be transported downstream. The scale of the stream reach might be improper as the pollutants are diluted by the flow or absorbed by plants [38,142]. Other studies propound that the whole catchment plays an important role in influencing the impacts of LULC on the water quality [12,136,143]. However, it is difficult to sample larger catchments at an appropriate spatial and temporal resolution. In addition, the spatial scale between LULC change and water quality differs spatially, and the characteristics of the stream, human disturbance and data accuracy all have different degrees of influence in multi-scale studies [135]. Therefore, for the better management of pollution, the application of different spatial scales may provide an effective method by which to understand the relationship between LULC and its impacts on water quality and quantity. Gyawali et al. [141] revealed that all LULCs, i.e., agriculture, forest, urban, and water bodies, affect temperature, DO, BOD, solid sediments (SS), DS, Fecal Coliform (FC) and EC at all three spatial scales. Similarly, Tanaka et al. [143] also confirmed that water quality indicators have a different response to LULC patterns when evaluated at different spatial scales.

4. Discussion

The findings based on the search keywords indicate that the use of remote sensing in assessing and monitoring land use and land cover (LULC) changes has been significant. Remote sensing techniques have undergone significant advancements, particularly with the introduction of advanced algorithms such as machine learning (ML) and deep learning (DL), which offer increased opportunities to explore and effectively manage environmental issues. Numerous studies [33,39,66,70] have focused on accurately mapping and detecting LULC changes using remote sensing. However, the utilization of machine learning and deep learning classifiers remains relatively limited compared to the traditional use of methods like maximum likelihood classification (MLC). Over the decades, the assessment and monitoring of LULC changes have extensively employed geographic information systems (GIS) and remote sensing. Earlier methods involved the use of aerial photographs and field observations for the interpretation of LULC to produce maps. With time, there have been notable advancements in LULC classification techniques, leading to improved mapping accuracy facilitated by advanced satellite imagery. Accurate LULC maps play a crucial role in informing decision-making processes for the planning and management of natural land resources.

4.1. Challenges in Remote Sensing the Effects of LULC Changes on Water Resources

Identifying the non-point source of pollution is still a challenging task due to an ongoing discussion and varying thoughts regarding the scale. Some studies argue that sub-catchment influences can be used [141], others suggest that the whole catchment would be the most optimum to use [116], and others have supported that riparian buffer [101] play an important role in influencing the water quality. Therefore, separating the impacts of LULC on water resources remains problematic, due to the extensive time scale over which impacts from LULC spread through the hydrologic system. The confounding effects of climate and weather, as well as large-scale observation field studies, often lack control, thus making it difficult to assign the temporal changes to causal mechanisms [144]. Thus far, most of the remote sensing techniques have been applied to LULC changes using a statistical model that links the relationship to in situ water quality parameters. However, the statistical models do not consider physically based hydrologic models, which are important in representing hydrological processes using spatially distributed data such as climate parameters (e.g., precipitation, temperature, and evapotranspiration), vegetation and soil moisture, and slope distribution [145]. The data contain crucial information about surface water flow and the integration of surface and ground water and can be used to describe the land surface topography characteristics [43]. Hydrological process models, such as the soil and water resources tool (SWAT), have been presented by many reviewers as an effective management tool for watershed models, simulating the stream flow better than other models [75,145,146]. The integration of these models with remote sensing data will provide effective management for monitoring the impacts of land use on water resources in semi-arid tropical environments. The reviews by Dwarakish and Ganasri [43], as well as Dong et al. [147], elaborate more on integrating remotely sensed data and hydrological models in LULC and water resources.

Efficient and accurate LULC using remote sensing therefore requires a high spatial detailed image for the classification method [125]. However, it is important to note that factors such as image resolution, radiometric conditions, and atmospheric effects can impact the effectiveness and accuracy of classification algorithms in remote sensing. Radiometric and atmospheric corrections play a crucial role in mitigating these challenges. However, performing accurate corrections can be complex, particularly due to the dynamic and spatially varying nature of atmospheric conditions. To address this issue, it is essential for users to have access to suitable atmospheric correction software that aligns with the specific requirements of their study and the chosen approach. Selecting the correct or appropriate atmospheric correction method is crucial in order to ensure reliable and accurate results in remote sensing analyses. By carefully considering the data needs and research objectives, users can make informed decisions and choose the most suitable atmospheric correction software for their specific study [108]. The accurate assessment of LULC change is crucial, particularly when it comes to capturing small classes such as roads and built-up areas, as they can have significant impacts on water quality. Achieving precise results for these classes requires the use of sensors with a very high spatial resolution, typically less than 5 m. While sensors like LiDAR, WorldView-2, and Quickbird offer the required level of detail for accurate LULC mapping, their utilization in studies has been limited. The main challenges associated with these sensors are their cost and low temporal resolution. Acquiring data from these sensors for long-term studies can be expensive, and their restricted availability may limit their use to smaller study areas. To conduct the effective long-term monitoring of LULC change, it is necessary to analyze time series of remotely sensed imagery. However, obtaining and analyzing consistent time series data from multiple sensors pose challenges. It is essential to ensure that the acquired images are captured under similar environmental conditions, such as the same time of the year, sun angle, and spectral bands, to minimize errors and maintain data consistency. Overcoming these challenges in acquiring and analyzing time series and multi-sensor data is crucial for improving our understanding of LULC change and its impact on water resources. Efforts should be made to address these limitations and develop methodologies that enable the accurate and consistent analysis of LULC change over time [60,148]. To minimize errors, the accuracy of a fraction of a pixel must be attained, meaning that variations in solar illumination atmospheric scattering and absorption and detector performance must be normalized, i.e., the radiometric properties of each image must adjust to those of the reference image [60,148].

One drawback of minimizing the issue of radiometric calibration is that any errors identified in the classification maps of individual dates will also be present in the final change detection map. To validate the results, it is important to compare the classified maps with ground-truth data. Researchers often utilize a confusion matrix as the preferred method for validation, which includes metrics such as overall accuracy, user accuracy, producer accuracy, and the Kappa coefficient. However, the Kappa coefficient has been criticized for its limitations in accurately assessing the results. It fails to convert the sample confusion matrix into an estimated population matrix, which can affect the reliability of the assessment [149,150]. To perform this hardware, software and qualified personnel are required for processing and analyzing the dataset. This hinders the application of remote sensing in monitoring the effects of LULC on water quality. Moreover, open-source software solutions, such as R-software, QuantumGIS or GRASS [151], are freely available to manipulate remote sensing products. However, these open-source software lack clear documentation and steep learning curves that hinder their adoption and use. Therefore, offering training across the discipline could potentially increase the adoption of these software [152]. The lack of reliability in ground-truth data has also inhibited the progress of classification in remote sensing.

Different algorithms have different strengths and require different input parameters [18]. Many factors, such as the spatial resolution of the remotely sensed data, the scale of the study area, the availability of software, the capacity of the analyst skills and knowledge, affect the modelling approach [149]. The developed model from remote sensing data requires adequate calibration and validation using in situ measurement and can only be used in the absence of clouds [149]. ML algorithms rely on a large number of training samples, which are difficult to obtain in the real world. However, remote sensing big data may provide significant solutions to the lack of data, although they often cause computational challenges, for instance, the need for scalable data storage, dynamic workflow management, and flexible computing resource provisioning [149].

The Google Earth Engine (GEE) [153], which is a cloud-based semi-automated platform that offers basic calculation functions for both raster and vector data, can successfully handle remote sensing big data on the cloud [153,154]. These advancements offer new possibilities for integrating and combining techniques to assess and monitor the connection between LULC change and water resources. However, the Google Earth Engine (GEE) platform has its limitations. It does not support the execution of deep learning algorithms due to computational constraints and the unavailability of such algorithms on the platform. Consequently, users can only gather the data on the platform and perform deep learning algorithms outside of the GEE platform. Additionally, using the platform requires a robust internet connection, which can be challenging in developing countries and may result in limited adoption [155,156]. GEE can cause an error with large computation complexity because of the memory limitation [146]. Remote sensing data are often multimodal, which requires the development of a novel ML model to extract joint features from the heterogeneous spectral, spatial, and temporal information. The integration of hydrologists, statisticians and expert remote sensing analysts is limited, leading to satellite remote sensing data regularly being underutilized and undervalued [152]. The limited sharing of data, particularly in Sub-Saharan Africa, significantly hampers our capacity to examine land function changes beyond land use and land cover alterations. Understanding the spatial variability in the land's ability to offer unintended services and identifying the factors influencing it are crucial for regional policy and spatial planning. Despite these challenges, this review emphasizes the need to shift towards adopting satellite data applications in assessing and monitoring the connection between LULC changes and water resources. This shift involves leveraging multiple data sources and employing advanced data processing techniques to enhance our comprehension of these complex systems.

4.2. Progress and Future Direction on Remote Sensing of LULC Changes on Water Resources

Progress has been made regarding the utility of remote sensing in semi-arid tropical environments, particularly in long-term monitoring, with a limited number of studies on seasonal monitoring. There is still a gap in the real-time use of modern earth observation techniques, such as Sentinels, which are freely available. Sentinels, with improved spectral resolution and revisit time (5 days), bring new opportunities for the biweekly and seasonal monitoring of the effect of LULC on water quantity and quality. The assessment and monitoring of LULC changes and their impacts on water resources using hyperspectral, drones and balloons has not attracted much attention. Only a few studies have attempted nonparametric machine learning algorithms [149,154]. Numerous researchers have found that LULC change correlates with water quantity and quality; still, there is no clear understanding of how LULC changes affect water quantity and quality. The quantification of the relationship between LULC change and water resources is a complex system. Understanding the relationship between LULC and water resource dynamics cannot be solely based on a single factor. Therefore, factors such as hydrology, spatial patterns and ecosystem services are often overlooked when assessing and monitoring the impact of LULC changes on water resources. Research efforts need to be promoted to evaluate the relationship between LULC and spatial patterns, ecosystem services and hydrological processes, particularly in semi-arid tropical environments that are susceptible to climate variability. This research could be crucial to supporting LULC planning, effective watershed management, and making informed decisions regarding water resource management in order to ensure the sustainable management of landscape composition and configuration, ecosystem services and hydrological factors.

Multispectral sensors such as Sentinel 2 and Landsat images tend to be limited by clouds and a relatively coarser spatial and temporal resolution [112,113]. Drone images are not affected by clouds because they are flown at a lower altitude and can be used to collect data over some inaccessible and remote areas [157]. As the fourth industrial revolution is progressing, the adoption of drones is advised in future studies as an innovative source of near real-time spatial data for mapping and monitoring the relationship between LULC and water resources. Thus far, no studies have been conducted using drones and comparing satellite sensors and drones in monitoring the impacts of LULC change on water quantity and quality in semi-arid tropical environments. Balloons equipped with a digital camera also have capabilities with regard to filling the gap between satellites and aircraft on the earth observation platform. Balloons filled with helium gas can be flown at lower altitudes than airplanes when detecting relatively small objects (small rivers, roads) with minimal expense [158]. The limitations associated with balloons are that they need to be appropriately used to avoid the geometrical distortion of images [158]. Geometrically distorted images provide false locations for the objects detected. Due to minimal expense, there is a need to also test this platform.

More research is needed to find the best variable and prediction model that can be integrated with a free multispectral dataset [108]. Different algorithms have weaknesses and strengths. Thus far, using an ensemble of different individual sensors and classifiers has been the most effective approach regarding the advance of LULC mapping. The use of more advanced non-parametric algorithms in estimating the effects of LULC on water quantity and quality has also been underutilized, despite their higher predictive accuracy, when compared to parametric algorithms, even when using broadband multispectral sensors. The application of the GWR and BN statistical model is robust; therefore, the use of this model should be adopted in future studies since the algorithms alone could not determine the physical processes of water resources. Integrating remotely sensed data with physical-based hydrologic models is recommended in future studies for effective management and decision making in watershed management. More research is needed to develop advanced models using multi-source data, and improved algorithms and applications are vital and required. The water quality parameter indices also showed effectiveness in estimating water quality; therefore, integrating them with ML algorithms in future might improve the models. There is also a need to assess the spatial pattern since it provides an understanding of the spatial processes underlying the distribution. The use of AI capabilities enables ML approaches to draw the complex nonlinear relationship between the land surfaces variable and water quality parameters [47,49]. AI has shown much promise for a wide range of physical environmental problems, from identifying critical situations, to aiding human interpretation, to discovering new relationships in large datasets [49]. This provides new opportunities with which to speed up the analysis process of large datasets, improve models and successfully transform the exploitation of environmental data in the future. In this regard, the use of multispectral sensor and parametric analysis in characterizing the impacts of LULC on surface water is required if the sustainable utilization of water management is to be achieved when aiming to address the rapidly growing population and its water needs. This information holds great importance for water managers, catchment managers, and land planners as it enables them to tailor their land and water management strategies according to the spatial variability and seasonal changes in the impacts of LULC on water quality and quantity. By understanding these relationships, it becomes feasible to implement local to regional framework policies that promote the sustainable utilization of land and water resources, thus facilitating effective land and water management practices.

5. Conclusions

The objective of this study was to conduct a systematic review to assess and monitor the progress of remote sensing applications in mapping land use and land cover (LULC) changes and their impacts on surface water quality and quantity. The literature indicates that the use of remote sensing in this field has gained significant attention in recent years. However, most studies have used multispectral Landsat images, while the potential of other sensors with an improved revisit time, a medium spatial resolution, and enhanced radiometric capabilities (e.g., Sentinel 1 and 2) has received less attention. These sensors offer opportunities for seasonal monitoring. Additionally, the integration of multisource remote sensing data, such as Sentinel 1, Worldview, radar, Quickbird, and LiDAR, has expanded tour ability to obtain, although their limitations need to be assessed. Combining data from different sensors enhances our understanding of the impact of LULC dynamics on water resources. Platforms like drones and helium-filled balloons enable the near-real-time acquisition of fine-resolution data, which can enhance the accuracy of LULC mapping via improved training and validation processes. The use of advanced classification algorithms, namely ML (e.g., SVM, ANN, RF, BN) and DL algorithms (e.g., RNN, CNN, DNN), which improve the accuracy and efficiency of land cover classification, is recommended. Moreover, the underutilization of advanced machine learning and deep learning algorithms in tropical semi-arid regions and globally suggests the potential for adopting these approaches in order to accurately estimate the effects of LULC changes on water resources. The use of artificial intelligence (AI) technology can enhance the data processing capabilities of big data analysis, thereby improving the quality of outcomes in future studies. The GEE platform, known for its capacity to handle remote sensing big data, could be a valuable and time-efficient tool for mapping LULC changes. To effectively manage water pollution resulting from different LULC patterns and improve water quality at local and regional scales, it is crucial to fully embrace these innovative technologies and methodologies. These advancements have enhanced our ability to assess and monitor the effects of land use changes on water resources, enabling more effective planning and management strategies. The progress made in remote sensing applications contributes to a better understanding of the complex interactions between LULC and water resources, thus supporting sustainable water management and environmental conservation efforts.

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