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REVIEW

Advances in satellite remote sensing of the wetland ecosystems in Sub-Saharan Africa

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ABSTRACT
Wetlands are highly productive systems that act as habitats for a variety of fauna and flora. Despite their ecohydrological significance, wetland ecosystems are severely under threat from global environmental changes as well as pressure from anthropogenic activities. Such changes results in severe disturbances of plant species composition, spatial distribution, productivity, diversity, and their ability to offer critical ecosystem goods and services . However, wetland degradation varies considerably from place to place with severe degradation in developing countries, especially in sub-Saharan Africa due to poor management practices that leads to underutilization and over reliance on them for livelihoods. The lack of monitoring and assessment in this region has therefore led to the lack of consolidated detailed understanding on the rate of wetland loss. For example, the lack of up-to-date and reliable spatial explicit information further complicates the management of wetland ecosystems in semi-arid tropical environments. To monitor, understand and document wetland degradation rate, the use of remote sensing for accurate estimation and precise mapping of present and historic information remains imperative. Similarly, there is a need to develop robust methodologies to precisely assess and monitor wetland degradation, ecohydrological processes and wetland condition over space and time. This work thereof, provides a comprehensive overview of remote sensing applications in monitoring and mapping the wetland ecosystem. It also highlights the strength and challenges associated with the use of satellite data for purposes of wetland monitoring. Spatial explicit and periodic information offered by satellite remote sensing demonstrate a unique opportunity for documenting and understanding of wetlands, their ecohydrological processes, and environmental conditions.

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Human influence; remote sensing; satellite data; spatial resolution; species diversity; wetland degradation; wetland productivity

1. Introduction

Wetlands are distinctive, complex ecohydrological systems that occur within a wide range of climatic and topographic environments. They constitute one of the world's most

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productive and important natural resources. Wetlands fall centrally under public management and they are recognized as an integral part of the productive ecosystem capable of supporting the 2030 UN Agenda on Sustainable Development Goals (SDGs) (Kakuba and Kanyamurwa 2021). Wetland hydrophytic vegetation species, hydromorphic soil and hydrology are a critical part of wetland ecosystems, contributing towards the provision of fundemental goods and services. Wetlands, for instance, offer food and habitat for species, maintain water quality, recharge of aquifers, control soil erosion, climate regulation and carbon storage (McCartney et al. 2010; Adam et al. 2012; Wood et al. 2013; Meli et al. 2014; Scott et al. 2014; Sieben et al. 2016). They also provide a wide variety of goods for local communities including reeds for weaving, grazing for domestic stock, and services to downstream consumer facilities, such as flood attenuation and nutrient retention (Mutanga et al. 2012; Dadson et al. 2017; Mahdavi et al. 2017). In sub-Saharan Africa, wetlands are predominantly significant sources of forage for livestock, which supports the livelihoods for most rural communities, as well as for the vast wildlife populations (Marambanyika and Beckedahl 2016). Despite their 6% coverage of the earth's surface, wetlands offer about 40% of regulatory services (Marambanyika and Beckedahl 2016; Reis et al. 2017). However, not all wetland ecosystems provide regulatory services; unique wetland services depend on the type of wetland and locational positioning within a catchment (Hu et al. 2017; Slagter et al. 2020). Due to the response to climate variability, precipitation, evapotranspiration and anthropogenic activities, surface-water levels and groundwater recharge in wetland ecosystems vary seasonally.

Despite the associated echohydrological benefits, wetlands are vulnerable to change in quantity and quality and they continue to face challenges as a result of intensified anthropogenic and natural changes globally (Sieben et al. 2016; Sutton et al. 2016; Xie et al. 2017; Bhaga et al. 2020; Novoa et al. 2020), due to the ongoing landscapes transformation and alterations (e.g. global warming, urban development, agricultural expansion), which significantly affect the ecological attributes of wetlands. For example, the Ngiri-Tumba-Maindombe in the western Congo Basin in the Democratic Republic of the Congo is under apparent threat due to pressure from rapid population growth and illegal activities which have led to overexploitation of the wetland resources (Xu et al. 2019). On the other hand, land use land cover changes alter hydrological processes, thus influencing flow regimes, aquifer recharge, and water storage within the catchment (de Medeiros et al. 2019). The remaining wetland portion are exposed to a wide range of stress inducing changes, e.g. infrastructure development, hydrologic changes, excess nutrient inputs and invasive species (Oliver-Cabrera and Wdowinski 2016; Hu et al. 2017). These cause a dramatic reduction and deterioration of the natural landscapes, which in turn complicate wetland functionality, with significant repercussions amplified on the ecological, socio-economic, and cultural benefits (Hu et al. 2017). Therefore, it is critical to understanding threats to wetland ecosystems, characteristics, species diversity (richness and evenness), productivity, soil, and hydrology to safeguard the ecohydrological system.

There is a growing interest in developing new operational frameworks, as well as spatial explicit and sound tools to assess wetland health conditions. Accurate information and monitoring of wetland status is therefore the first step in determining wetland ecological integrity. Dennison et al. (1993) highlighted that wetland vegetation remains an exceptional indicator for the first signs of any biophysical or chemical degradation in wetland environments. However, characterization of the spatial patterns of wetland extent is often challenging due to their heterogeneous nature (Szantoi et al. 2013). Previously, studies used traditional methodologies based on ground-based measurements, in assessing and monitoring wetland ecosystems, such as wetland hydrology, soil, species richness and evenness, species composition and aboveground biomass (Luo et al. 2017). These measurements were recognized as the most direct and accurate method of assessing and monitoring wetland ecosystems and diversity. Although the traditional approaches provide the most accurate results, these methods are generally not effective due to limited spatial representation. Similarly, the inherent heterogeneous species distribution and their compositions (Szantoi et al. 2013) are very difficult to capture. In addition, these techniques are time-consuming, labor-intensive, and costly, besides being difficult to carry out effectively in assessing the spatial extent of wetlands, especially across large areas over time (Psomas et al. 2011; Adam et al. 2012; Han et al. 2015; Orimoloye et al. 2018). Therefore, derived wetland information lacks the requisite spatial and temporal representation, hence there is limited understanding on the dynamics of soil, water as well as wetland vegetation within these ecosystems. It is important to track wetland ecosystems on a spatial and periodic basis as it offers comprehensive information that can lead to the sustainable conservation of ecosystem services.

Availability of automated, reliable and near-real-time remotely sensed data has emerged as the most critical data source for gathering spatial explicit information on the condition, distribution, and spatial configuration of wetland ecosystems, from local to a global scale. The spatial distribution of wetlands varies at different times and can be analysed with the aid of multi-spectral and hyperspectral remote sensing satellite images such as Landsat, MODIS, SPOT, and RapidEye. Some of these images have high spectral and spatial characteristics, which enable enhanced monitoring and mapping of wetland ecosystem characteristics. When compared to conventional labor-intensive field investigation, remote sensing information not only saves time but also enhances the prospect of characterizing wetland species through spectral and texture analytics (Vasconcelos et al. 2002; Kokaly et al. 2003; Roberts et al. 2003). Recently, advances in remote sensing data have shown high potential to examine land use land cover changes threatening wetland ecosystem functioning and services (Pettorelli et al. 2017). In addition, advances in sensor technologies have contributed towards the acquisition of freely available satellite imagery, such as Sentinel dataset. For example, Sentinel-2 is characterized by finer spatial (10 m) and higher spectral (13 spectral bands including red edge strategic bands) resolution, essential for extraction of wetland ecosystem characteristics, with varying geographical coverage (285 km) for the evaluation of wetland dynamics (Truus 2011; Adelabu et al. 2014; Orimoloye et al. 2018). Remote sensing technology allows repetitive image acquisitions over the same area, that are required for the detection of temporal changes and pattern of wetland ecosystems. For instance, Sentinel-2 offers remotely sensed data at high revisit frequency of between 5 and nineteen days.

In the light of the advantages associated with the use of remotely sensed data, in Sub-Saharan Africa, researchers have used both passive, optical sensors and active sensors to map and delineate the spatial distribution of wetlands in order to understand their status under the changing environmental and anthropogenic pressure. Knowing the past and current distribution of wetlands in sub-Saharan Africa could ease the understanding of the developments in wetlands or trends and improvements, as well as their contribution to ecosystem goods and services. In addition, it is critical to obtain the status of degradation, vegetation cover, species diversity, water level, erosivity, and rates of sedimentation in order to ensure informed decision-making for proper wetland protection and restoration programs (Davidson et al. 2018; Gxokwe et al. 2020). However, major attempts are now being made to integrate geospatial data products (e.g. water, soil moisture and vegetation) into various land surface models to enhance wetland ecosystems monitoring and evaluation.

This work provides a comprehensive overview of remote sensing applications in monitoring and mapping wetland ecosystems (wetland vegetation, species diversity, productivity, hydrology, soil etc.), as well as highlights the strengths and challenges associated with the use of satellite data. To meet the above-mentioned aim, related literature information was acquired from wetlands, ecology, water, and remote sensing journals. Numerous keywords and expressions were used, and these included: 'wetland', 'water level monitoring', 'wetland hydrological processes', 'wetland-catchment linkage', 'hydrological modeling', 'hydrophytic vegetation', 'vegetation diversity', 'biodiversity', 'Species richness and evenness', 'wetland productivity', 'wetland plant species', 'aboveground biomass (AGB)', 'remote sensing', 'satellite data', 'Synthetic Aperture Radar'.

To retrieve information during literature search, articles published in international peer-reviewed journals were selected via relevant search engines. These include: 'ISI Web of Science', 'Google Scholar', 'Photogrammetric Engineering and Remote Sensing', 'GIScience and Remote Sensing', 'Applied Earth Observation and Geoinformation', 'IEEE Applied Earth Observations and Remote Sensing', 'SCOPUS', 'Wetland Ecology', 'Hydrology', 'Ecology', 'Ecohydrology and Hydrobiology', 'African Ecology' and other internationally recognized remote sensing, as well as wetland science journals. Due to a limited number of studies on remote sensing applications, particularly in the sub-Saharan region, the review was not limited to a specific criterion. Consequently, all studies that utilized remote sensing for wetland monitoring and assessment were considered.

2. Geographical distribution of wetland ecosystems

Globally, wetlands occupy an area of nearly 9.2 million km^2 with 1.3 million km^2 of these found in Africa (Melendez-Pastor et al. 2010; Rebelo et al. 2010; Kabiri et al. 2020). Finlayson et al. (2011) also showed that estimates of wetland spatial extent across the world including Africa differ across studies due to the different definitions of wetlands and approaches used to delineate them. The common types of wetlands found in sub-Saharan Africa include Dambos, Lakes, Reservoirs, Freshwater marshes, floodplains, Swampy forests, flooded forests, Coastal wetlands, Pans, Brackish/saline wetlands, and Intermittent wetlands (Gxokwe et al. 2020). These wetlands vary with topography or landscape characteristics and climatic regimes, which supports diverse and unique wetland habitats (Space Applications Centre (SAC) 2011, Rebelo et al. 2017). Xu et al. (2019) mentioned that about 2,303 of global wetlands are designated under Ramsar convention, which are referred to as wetlands of international importance (Ramsar Secretariat 2013) and these wetlands are unevenly distributed in different parts of the world (Figure 1). As shown in Figure 1, Europe has the largest number of sites with a total of 1004, occupying 44% of Ramsar sites, 397 (17%) in Africa, 146 (6%) in South America, 368 (16%) in Asia, 309 (13%) in North America, and 79 (4%) in the Oceania region (Rebelo et al. 2010; Ramsar Secretariat 2013; Davidson et al. 2018; Gardner et al. 2018; Xu et al. 2019). Despite the number of wetlands designated under the Ramsar, there are many other small wetlands (unprotected) performing potentially incredible functions to the neighboring communities but they are continuously ignored in the policy process. As a result, some of these wetlands are already threatened, degraded, and lost due to uncontrolled activities, both natural and anthropogenic activities. According to the National Biodiversity Assessment for South Africa (NBASA) carried out in 2011, wetlands occupy only 2.4% of the country's total area. However, 48% of these ecosystems are critically endangered, 12% are endangered, 5% vulnerable while 35% are least affected (Macfarlane et al. 2014).

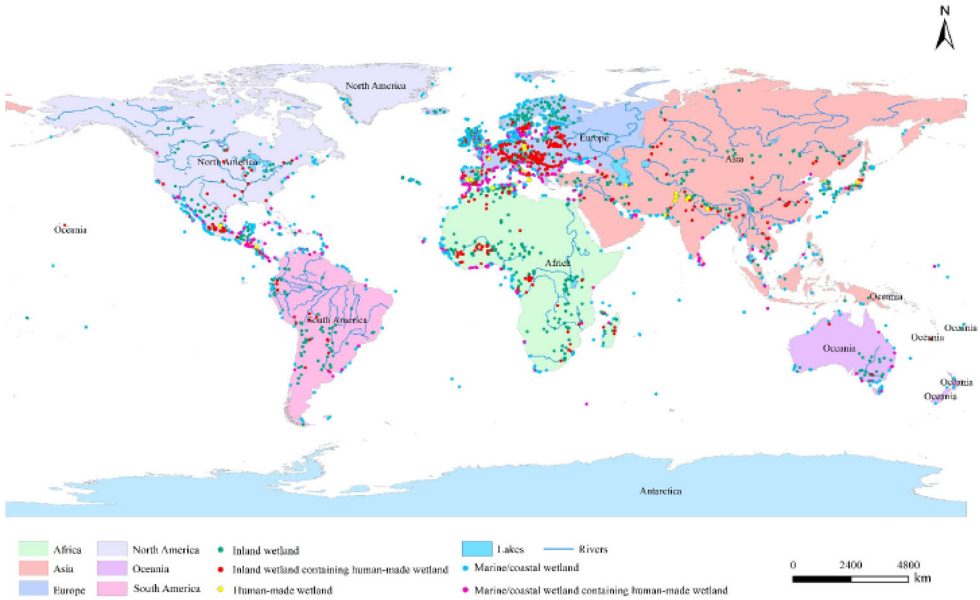

Figure 1. Global wetland distribution designated under Ramsar (Xu et al. 2019).

3. Factors influencing wetland degradation

Wetlands have a long history of transformation, destruction, and degradation. Globally, estimates suggest that about 50% of the global wetland areas have been degraded in the 20th century (Jogo and Hassan 2010; van Dam et al. 2013; . The remaining wetlands are under threat from anthropogenic activities and impacts of climate change, despite robust regulations for their protection and conservation or restoration (TEEB 2013). Literature demonstrates that there are multiple factors that degrade wetland ecosystems and maintain their survival. Anthropogenic factors include agriculture, reclamation, water use, infrastructure development, environmental pollution, and unsustainable use of wetland resources (Ramsar Convention Secretariat (RCS) 2010; Vörösmarty et al. 2010; Van Asselen et al. 2013; Gardner et al. 2018; Xu et al. 2019). Such factors affect wetland hydrology, soil, species diversity, productivity, and composition (Klemas 2013).Gardner et al. (2018) stated that pollution caused by population growth and socio-economic development is a major factor leading to degradation and loss of wetlands. Rebelo et al. (2010) showed that gradual cause of wetland destruction is primarily the need for flat, fertile land with water supply for agricultural purposes (both cultivation and livestock production). These studies concur with the work by Slagter et al. (2020) demonstrated that South Africa has lost and continue to lose wetlands due to dam construction, overgrazing, pollution, crop production, urbanization, erosion, developments, and poor management of land resources. Loss of connective rivers further contributes to the rate of wetland degradation (IPCC 2013; Tiner et al. 2015; Oliver-Cabrera and Wdowinski 2016).

Climate change is also a major threat to wetlands, particularly, changes in rainfall patterns and global warming (Boon et al. 2016). These changes result in significant biodiversity configurations and wetland biochemical processes and this is quite variable over space and time, from local to global scales (Dawson et al. 2011; Bellard et al. 2012). The rising temperatures may aid the invasion of warmer-water species into older zones and these species outcompete dominant species. Climate change is also considered as a cause for habitat destruction, a shift in species composition and habitat degradation in existing wetlands (Titus et al. 2009). Moreover, acute pollution and siltation have exaggerated these sensitive systems in recent times (Van Asselen et al. 2013; Li et al. 2014).

Since the early 1900s, it was estimated that wetland acreage from the existing inland and coastal marshes have been lost, with about 56% to 65% through conversion to agricultural production in Europe and North America, 27% in Asia and 6% in South America (Prigent et al. 2012). While China lost about 23% of its freshwater swamps, 16.1% of its lakes, 15.3% of its rivers, and 51.2% of its coastal wetlands (Niu et al. 2012). In Africa, a notable decrease in wetland areas has also been observed. For example, in Tanzania, wetland extent shrunk by 18% (Nguyen et al. 2017). In other parts of the African continent, estimates of degraded wetland acreage is a challenge and still rudimentary, due to the lack of historical documentation and monitoring of these ecosystems (Marambanyika and Beckedahl 2016; Grenfell et al. 2019; Xu et al. 2019; Stephenson et al. 2020). The decrease in wetland extent and quality has caused the species population to decline in many wetland-dependent species (Zhang et al. 2020). Although other strategies are in place to protect wetlands, many wetland ecosystems still suffer from degradation through eutrophication, reduced water availability, as well as impacts from weeds and pests (Gopal 2016). Other major causes of wetland destruction more specifically in sub-Saharan Africa are precisely due to the lack of awareness by planners, natural resource managers and wetland users (Ellery et al. 2003). Lack of conformity between government policies in the areas of economics, environment, biodiversity conservation, development planning is one of the reasons for the continued degradation of these systems (Turner et al. 2000). Lack of action taken to conserve wetlands, poor governance, and management further complicates management strategies (Kumar et al. 2013). Monitoring of wetland hydrology, soil and vegetation is becoming a major concern, due to the rise in anthropogenic activities on wetlands.

4. Role of remote sensing applications in wetland ecosystems mapping

Since the 1960s, remote sensing observations, in particular satellite imagery, serves as the most useful tool for gathering information such as in land cover change or mapping features in wetland regions, climate warming in wetland ecosystems, species diversity and productivity, hydrological processes in wetlands (O'Grady and Leblanc 2014; Prospere et al. 2014; Brisco et al. 2015; Tiner et al. 2015; Guo et al. 2017). Remotely sensed datasets and approaches provide frequent data with varying footprints and resolutions, which are more practical and economical means to address issues of wetland identification, delineation, classification, hydrophytic vegetation or biomass, hydromorphic soil, hydrology and vegetation characteristics, productivity, and density (Mansour et al. 2013). Literature gathered from peer-reviewed remote sensing journals shows that remote sensing applications have progressed remarkably over the years, with technological advances that have led to efficient data processing (Figure 2) in mapping and quantifying wetland ecosystems (i.e. forested wetlands or swamps, marshes etc.) in sub-Saharan Africa. Most of these studies have mainly focused on wetland ecosystems that are designated under Ramsar Convention, neglecting small or unprotected wetlands, which serve the neighboring communities. There is an increase in application of remote sensing for wetlands under Ramsar (r^2 = 0.884) than non-Ramsar sites (r^2 = 0.6545). These highlight that there are limited studies that use remote sensing for small wetland ecosystems that provide a life line to rural communities, particularly in sub-Saharan Africa (Guo et al. 2017; Osorio et al. 2020; White et al. 2020). This is because in most cases the smaller sizes of wetlands

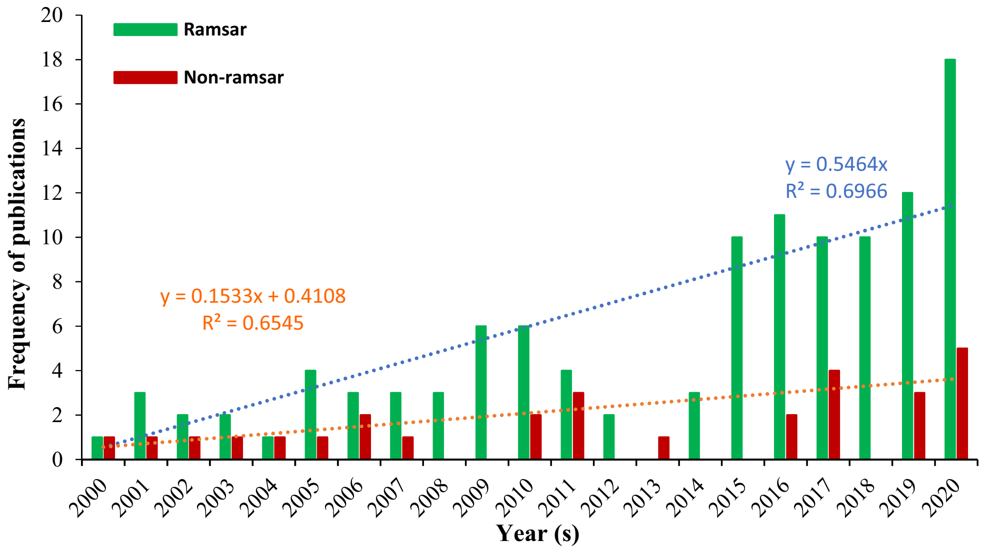

Figure 2. Progress of remote sensing publications in mapping wetland ecosystems in Africa.

when compared to image spatial resolutions, largely result in spectral mixing hence the failure to derive accurate and highly informative information particularly from coarse resolutions or broadband satellite images like MODIS etc. Progress in remote sensing data usage (from aerial photography to multispectral scanners) in mapping and monitoring wetlands ecosystems is thus linked to the availability of freely accessible satellite images (e.g. Landsat, Sentinel, etc.) as well as the recent technological capabilities (improved spatial, spectral and temporal resolution) that can rapidly detect and map wetlands over large scales. Most of the studies conducted in Africa used multispectral remote sensing dataset. These new cutting-edge technologies substitute the use of aerial photographs, which are not practically possible in acquiring information for large areas (Thamaga and Dube 2019). Therefore, based on the literature examined, most of the wetland studies used aerial photographs, Landsat and MODIS datasets (Landmann et al. 2010; Adam et al. 2012; Hladik and Alber 2012; Mutanga et al. 2012; Tiner et al. 2015; Guo and Guo 2016; Gxokwe et al. 2020). These sensors (Figures 3 and 4) were mainly applied in mapping, monitoring wetland extent, LULC impacts as well as wetland classification. Wetland vegetation, soil and hydrology remain understudied using remote sensing.

Previous studies have confirmed the effectiveness of satellite remote sensing tools for wetland monitoring and classification (Berlanga-Robles et al. 2011; Rapinel et al. 2015; Mahdianpari et al. 2018). These approaches have effectively addressed large-scale historical challenges in managing wetlands synoptically and mapping using conventional approaches (e.g. accessibility and repeatability) as they are time-consuming and labor-intensive, particularly in relatively small areas. Given the sensors' capability to collect synoptic observations more often remote sensing techniques have become effective in studying, identifying and quantifying wetland ecosystems (i.e. plant species, diversity and productivity, hydrological estimation) (Li et al. 2013; Han et al. 2015; Lou et al. 2016; Pande-Chhetri et al. 2017; Chen et al. 2018), from small to large-scale projects with spatially continuous coverage from several satellite datasets (Kuenzer et al. 2011; Tiner et al. 2015). Nevertheless, remotely sensed satellite datasets (Table 1) with varying spatial resolution of less than 10 m to several kilometers have been used globally to detect wetland ecosystems (Laba et al. 2010; Betbeder et al. 2015; Liu and Abd-Elrahman 2018).

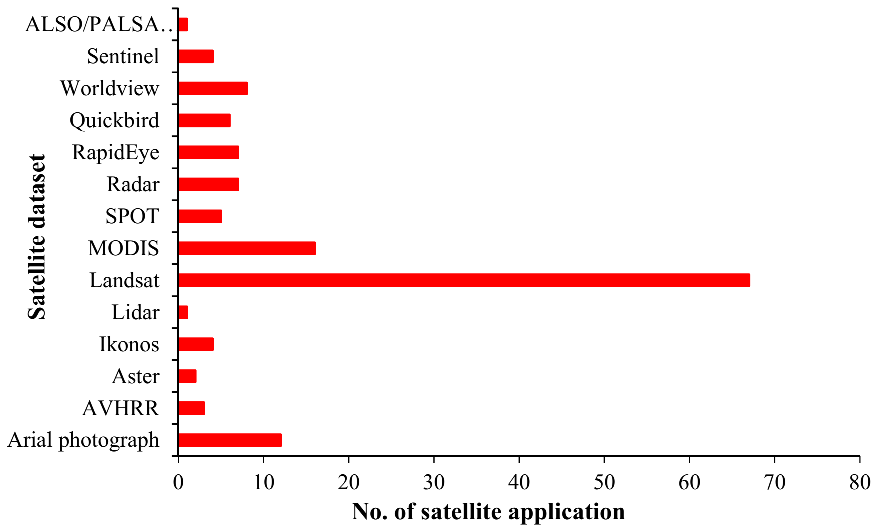

Figure 3. Number of satellite images used to study wetland ecosystem.

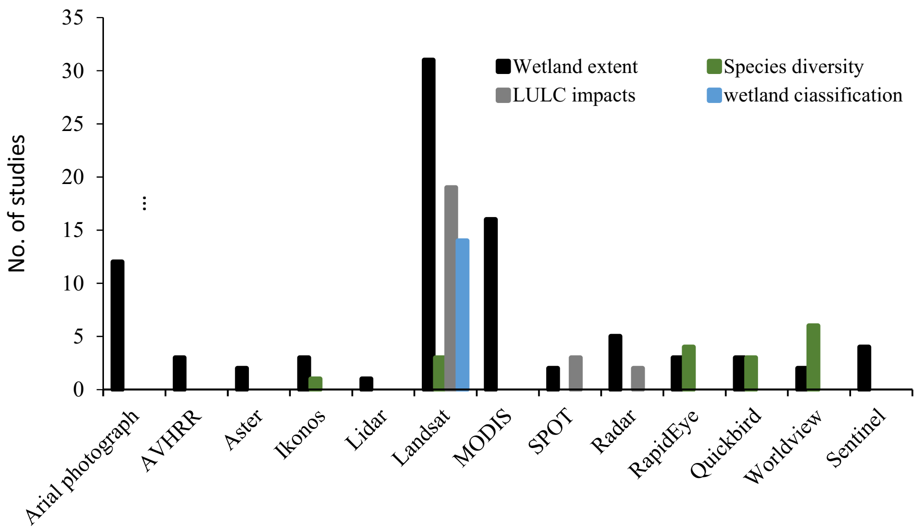

Figure 4. Monitoring and mapping wetlands using remotely sensed data.

Broadband multispectral and hyperspectral images are acquired in different characteristics providing new insights or approaches in assessing wetlands. The availability of remote sensing at affordable and freely accessible means marked the new beginning of continuous mapping and comprehensive monitoring of wetland ecosystem. For instance, Landsat with long history of spatial data archival was used in a variety of wetland studies; including wetland classification, mapping, and change detection (Guo et al. 2017). Long-term change detection enables researchers to better understand the trends and gradual changes of wetlands, analyse change dynamics, and protect wetlands. Rebelo et al. (2010), Adam et al. (2012) and Gxokwe et al. (2020) have provided comprehensive reviews of remote sensing datasets and methods for wetland characterization. Overall, previous studies also showed that the probability of satellite remote sensing for detecting permanently flooded

Table 1. Remote sensing sensor specifications and associated acquisition cost per square meter.

Sensor	Spectral bands	GSD (m)	Description	Swath-width (km)	Frequency (days)	Cost of image acquisition (US $/km^2)
Landsat Thematic Mapper (TM)	7	30 120	Band (1-5 & 7) Band 6	185	26	Free
Landsat Enhanced Thematic Mapper plus (ETM+)	8	30 15	Band (1-7) Band 8	185	18	Free
MODIS	36	250 500 1000	Band (1-2) Band (3-7) Band (8-36)	2330	1-2	Free
Sentinel-2	13	10 20 60	Band (2,3,4 & 8) Band (5, 6, 7, 8a, 11 and 12) Band (1,9 & 10)	290	5	free
RapidEye	5	5	All bands	77	1 (off nadir) / 5.5 (nadir)	US $1.28
Système Pour l'Observation de la Terre 5 (SPOT 5) High-Resolution Stereoscopic (HRS) High Resolution Geometric (HRG) Vegetation (VGT)	5	10	Band (1-3)	60	2.5	US $5.15
Quickbird	5	20 2.40	Band 4 All multi-spectral bands	16.8	1-3.5	US $24
World View-2	8	2 0.48	All multi-spectral bands Panchromatic band	16.4	1.1	US $28.5
World View-3	8	1.24 0.31	All multi-spectral bands Panchromatic	13.1	1	US $29

or intermittently exposed open water surfaces information is critical, but knowledge gaps still exist, particularly on mapping and monitoring small wetlands (unprotected wetlands).

5. Remotely sensed applications on wetland hydrology and soil

Hydrology and hydromorphic soil sustain wetland ecosystems, but wetlands have been drained for irrigation purposes and dam construction for drinking water. On the other hand, pollution in wetland ecosystems has affected soil fertility, moisture, carbon sequestration as well as water quality thereby exerting pressure on these systems (Van Asselen et al. 2013; de Klein and van der Werf 2014; Xiaolong et al. 2014; Zhang et al. 2015; Were et al. 2019). Remote sensing data provide effective and efficient tool to detect water bodies and soil extent and quality. MODIS with high temporal resolution showed its significant advantages in mapping wetland extent and change over time (Ordoyne and Friedl 2008). In the North-Central Namibia, Mizuochi et al. (2017) to identified surface water distribution using modified normalised difference water index (MNDWI) of MODIS image and normalized difference polarization index (NDPI) of Advanced Microwave Scanning Radiometer Observing System (AMSR-E). On the other hand, Zoffoli et al. (2008) used AVHRR NDVI to analyse seasonal and annual wetland changes over-time and showed that NDVI can provide useful information for wetland surface water. Klein et al. (2015) mapped daily open water bodies using MODIS time series data and threshold technique, the technique depicts annual water changes. Frazier et al. (2003) used Landsat images to assess before and after flood occurrence to describe the relationship between flow regulation and inundation of flood plain wetlands. Results from their study, highlighted that river regulation could reduce the duration and frequency of inundation. Other sensors, such as Sentinel, SPOT, have been employed to examine wetland hydrological regimes and mapping wetlands extent at various scales with satisfactory results (Davranche et al. 2010, 2013; Muro et al. 2016; Xing et al. 2018; Bhatnagar et al. 2020; Slagter et al. 2020). Indices such as Land Surface Water Index (LSWI), NDWI, NDWI they have been extensively used to improve accuracies. For instance, LSWI is known to be sensitive to the total amount of liquid water in vegetation and associated soil background. Using hydrological models such as soil water assessment tool (SWAT), HEC-RAS, Geo-rus together with satellite data, soil and climatic information seem to be promising in assessing wetland hydrology as well as soil quality and quantity.

6. Wetland plant species characterization

Remote sensing has the capabilities to analyse, map, and monitor wetland plant species at all scales, using various satellite datasets. Ecological based studies have demonstrated the benefits of using multi-remote sensing sensors (both active and passive) providing a wide range of data at varying resolutions with the abilities to extract various physiological, chemical and phenological characteristics of species for determining wetland plant species (Ustin and Gamon 2010; Pau et al. 2013). The retrieved information using remotely sensed data provides spatially explicit data on wetland species dynamics, structure, annual precipitation, hydrological pathways, and local physiological cycle (Gallant 2015). Additionally, remote sensing techniques provide information from inaccessible areas that cannot be accessed during field surveys. These contribute to enhanced estimation of wetland plant species, understanding and identifying key factors impacting on wetland biodiversity and biomass. Methods for estimating vegetation in wetland ecosystems by remote sensing have not been treated in much detail especially in developing countries. The detection, delineation and mapping of wetland plant species remains a challenge with multispectral satellite imagery due to the lack of spatial resolution of most satellites with respect to the small and sharp vegetation units present within wetland ecosystems (Brisco et al. 2017). Therefore, with multispectral imagery spectral mixing of several vegetation species in various proportions remains a challenge (Zomer et al. 2009). Moreover, the use of wide spectral bands from coarse multispectral imagery for mapping wetland species remains difficult, due to the spectral overlap among species since healthy vegetation species typically show similar spectral responses in the visible and near-infrared region due to similarities and limited basic components that contribute to their spectral reflection.

6.1. Mapping of wetland vegetation using remote sensing data

Wetland vegetation can be used to reflect the status of wetland ecosystems and biomass estimates can provide basic information about a particular wetland. Knowledge on wetland plant species types, productivity, and diversity is key in terms of planning, conservation, and protection of ecosystem functions. Wetland vegetation spatial explicit information retrieved from satellite imagery serves as the baseline evidence that is needed for monitoring and assessment of wetland status and health. Wilen et al. (2002) noted that satellite remote sensing images offers much better results of wetland plant species. Hence, these could be critically used for the prioritization of different purposes including planning, environmental impact assessments, wetland assessment, and monitoring, detection of alien plant species, water flow, and level, rehabilitation and analysis of trends in wetland status, to enhance conservation of wetland ecosystems (Wilen et al. 2002; Zheng et al. 2014). Mutanga and Skidmore (2004); Zheng et al. (2014) and Wu et al. (2018) highlighted that estimation, monitoring, and mapping of wetland species biomass (aboveground biomass) is required for studying nutrient allocation, species diversity, productivity, and the carbon cycle. Furthermore, Mutanga and Skidmore (2004) and Adam et al. (2012) emphasized that despite wetlands exhibiting discrete light-reflectance characteristics centred in the visible or infrared region of the Electromagnetic Spectrum Radiation (EMR), achievements in estimating biochemical and biophysical parameters in some ecosystems revealed that the remaining challenges are strongly affected by water, atmospheric conditions and soil. The use of vegetation indices such as NDVI, EVI and NDWI offers opportunities that can supersede the effects of soil background, atmospheric composition and zenith angle effects while improving the vegetation signal, when estimating wetland plant species (Mutanga et al. 2012; Ramoelo et al. 2015; Sibanda et al. 2015). High-resolution vegetation mapping of wetland complexes, with accurate distribution and population estimates for different functional plant species can be used to analyse vegetation dynamics, quantify the spatial patterns of vegetation evolution, analyse the effects of environmental changes on vegetation and predict the spatial configuration of species diversity.

6.2. Mapping species diversity in wetland environments

Many predominantly upland regions encompass small patches of wetland habitats, which hold great potential for biological diversity conservation, however, these areas have received little recognition (Nicolet 2003; de Meester et al. 2005). These wetlands can contribute disproportionately to landscape-level diversity since they often have high levels of species richness (alpha diversity) and spatial variations in community composition (beta diversity) (Tiner 2003; de Meester et al. 2005). Wet habitation patches surrounded by uplands support unique species assemblages, different from those of large-scale wetlands (Nicolet 2003; de Meester et al. 2005). These communities often include regionally rare species, and they can serve wetland specialists in landscapes where major wetlands are being destroyed, degraded, or absent (Nicolet 2003). Few studies on species diversity of small wetlands have focused on a single wetland category, such as seasonal pools with mineral soils , riparian areas in headwater streams (Hagan et al. 2006), or groundwater seepage . The snapshots from a single image lackdetails. However, these wetlands often defy simple classification the distinctions among wetland types remain largely arbitrary and inconsistent, from inherent differences in wetland vegetation species often result in spectral overlaps. To understand how small wetlands contribute to regional species plant diversity, we need to consider all the wet areas within a landscape and identify them based on the vegetation composition. Different indices for determining species diversity have been developed. These included the widely used Shannon-Wiener Index (H'), Simpson diversity index (1-D), Fisher's alpha - a diversity index (a), Menhinink richness index (DMn), Margalef richness index (DMg) and Sheldon (Buzas and Gibson) evenness index (E_3) (Kent and Cocker 1992; Barajas-Gea 2005; Mitchell et al. 2006; Janišová et al. 2014; Caranqui et al. 2016; Yaranga et al. 2018). These indices thus can be used in quantifying species diversity within a wetland. Integrating diversity indices with remotely sensed data i.e. Landsat, Sentinel, Worldview etc provide a better understanding of wetland conditions and their functioning in general.

6.3. Wetland productivity and assessment

Wetland productivity is a positive increase in vegetation species biomass per unit. This does not only reflect vegetation, condition, but it is a central variable for carbon cycling (Luyssaert et al. 2007). It was revealed in different studies (Cramer et al. 2001; Klemas 2013; Yin et al. 2017) that wetland productivity changes in volume and measures of prospective resource products receive attention from a rising number of researchers in the context of global change. Wetland productivity is also a function of climate variability and hydrological fluctuations. For example, the fluctuations in water table provide a better understanding of wetland conditions and their functioning in general with increased climate variability strongly affect wetland vegetation productivity. Work by Rivera-Monroy et al. (2019) highlighted that Louisiana wetland in Gulf of Mexico lost 4900 km^2 of wetland area since the early 1930s. Furthermore, the study mentioned that despite the relevance of wetland biomass and net primary productivity procedures in wetland ecosystems assessment, there is a lack of vegetation simulation models forecasting the trends of biomass and productivity. Long-term overview of the wetland simulation models with remote sensing dataset provide a better understanding of wetland plant productivity.

7. Analytical algorithms for evaluating wetland ecosystems and conditions using remote sensing

Several algorithms and remotely sensed datasets offer opportunities to classify and quantify wetland ecosystems. These algorithms can be broadly categorized into the threshold method, unsupervised and supervised classification, object-based classification, principal component analysis and hybrid classification (Dronova et al. 2015; Villa et al. 2015; Liu and Abd-Elrahman 2018). Artificial neural network (ANN) (Kumar et al. 2013), decision tree (DT) (Khosravi et al. 2017), Random Forest (RF), CART, and Support Vector Machine (SVM) (Xie et al. 2017) are also non-parametric supervised machine learning techniques commonly used for land cover classification. Additionally, digital data from satellite imagery enable efficient and rapid classifications through automated methods that have been shown to improve accuracy than simple aerial photo interpretations (Tiner et al. 2015). The use of remote sensing techniques has been explored over large regions of wetlands. For instance, it has been applied in species and cover type assessment, canopy density or Leaf Area Index (LAI) estimation (Wang et al. 2012), biomass monitoring (Mutanga et al. 2012; Byrd et al. 2014), or on quantities related to plant productivity and stress (Amani et al. 2017). The newly advanced methodologies such as drones, Google Earth Engine cloud-based platform, and artificial intelligence have been adopted to understand wetland ecosystems around the world (Alonso et al. 2016; Xie et al. 2019). Wu et al. (2019) stated that moderate resolution satellite imagery cannot be used as standalone for wetland delineation; however, they integrated automated approach to delineate wetland inundation extent at the watershed scales using Google Earth Engine. Outcomes of the algorithm did not only delineate the current state of the wetland but also demonstrated critical information on hydrological dynamics. Other studies used the drone technology to assess wetland ecological integrity . Díaz-Delgado et al. (2019) demonstrated that derived thematic maps from drone data are a very valuable input to assess wetland hydrology, soil, habitat diversity, wetlands health, dynamics, and wetland productivity as frequently as desired by wetland related managers or researchers. These advanced algorithms are scalable for mapping and quantifying wetland inundation from small to larger geographical scales. The integration of multispectral remote sensing imagery together with automated algorithms enhance image classification and further, provide practical, frequent, and requisite framework, which plays a critical role in delineating wetland inundation dynamics.

The increase in the use of remote sensing data in mapping wetland ecosystems is linked to its ability to offer a variety of new applications that can quickly and synoptically monitor and manage large areas. In Table 2, recent studies have indicated that the use of satellite imagery provide the most reliable primary data for the detection, monitoring, and mapping of wetland ecosystems. For example, Nhamo et al. (2017) mapped wetlands in Mpumalanga using Landsat 8 and MODIS-based NDVI and found that thewetland extent declined by 19%. Nineteen percent of degraded land has been mainly replaced by urban and agricultural development, which affected the ecohydrological processes and functions. In a different study, Orimoloye et al. (2018) assessed the potential of Landsat data to understand the status of Isimangaliso wetland in South Africa. Results obtained from the study showed that the extent of the wetland shrunk from 655.416 km^2 (1987) to 429.489 km^2 (2017) and, achieved an overall classification accuracy of 97.55% and kappa coefficient of 0.941. Berhane et al. (2019) showed that integration of machine learning techniques, Landsat and Pléiade-1B improved mapping of the wetland ecosystems, obtaining an overall classification accuracy of 93% with a Kappa coefficient of 0.92.

8. Implications of remote sensing of wetland vegetation and productivity mapping

Despite the robust advanced remote sensing techniques and modeling algorithms, spatial assessment of wetland ecosystems at various spatial scales remains a challenging task. This is primarily due to the heterogeneity nature of wetland ecosystems that are difficult to capture especially when using broadband and coarse spatial resolution sensors. In addition, high similarity of vegetation spectral characteristics due to wetland fragmentation, have been noted, which contributes to confusion in species mapping (Corcoran et al. 2013; Peimer et al. 2017; Wu et al. 2018). A major reason for this difficulty is that although each of the wetland species has several distinctive characteristics, they share some ecological and phenological similarities (Boon et al. 2016), with non-wetland plant species (Henderson & Lewis 2008). Therefore, this makes it difficult to spectrally distinguish some of the wetland plants from non-wetland plant species using remote sensing imagery (Amani et al. 2017). Furthermore, the accuracy of monitoring and assessing LULC change impacts on wetland ecosystems is mainly limited by the imaging characteristics of remotely sensed data as well as the algorithms used, which have been developed by different studies or for a specific application scale.

Previously, studies treated all vegetation communities as one single type, or they focused only on a short period (Dronova et al. 2012; Chen et al. 2014; Han et al. 2015). Vegetation species vary and these variations influence their functions within a wetland. In this regard, they generally view these species as a single type which then masks considerable information that is critical in understanding the dynamics of wetland ecosystems. Wetland vegetation varies over time; hence focusing on a particular period is inadequate for the implementation of sustainable regulations and policies for their conservation. Nevertheless, other researchers have attempted to adopt the long-term monitoring of wetland species. For example, Ballanti et al. (2017) used Landsat imagery to identify change

Table 2. Summary of recent remote sensing applications in mapping wetland ecosystems.

Sensor(s)	Study	Image analysis technique(s)	Major findings	Reference
Pléiade-1B, Landsat-8	Wetlands along the Etrix River in North Xinjiang, China	Random forest Normalized Difference Vegetation Index (NDVI)	RF classifier achieved an overall accuracy of 93% with a Kappa coefficient of 0.92.	Tian et al. (2016)
Landsat TM, Landsat 8 OLI, Landsat 8 TIRS,	Isimangaliso Wetland – Kwa Zulu Natal, South Africa	Normalized Difference Water Index (NDWI)	Wetland extent shrunk from 655.416 Km^2 (1987) to 429.489 Km^2 (2017) during the study period. The study revealed that other land cover features increased from 2149.911 Km^2 to 2375.838 Km^2 in 1987 and 2017. The classified imagery managed to achieve an overall classification accuracy of 97.55% and a Kappa coefficient of 0.941. NDWI revealed that there is a depletion of water in the study area mainly due to environmental and human interferences.	Orimoloye et al. (2018)
RADARSAT-2, TerraSAR-x ALOS-1 & 2 Sentinel-1	Newfoundland and Labrador (NL) Wetlands of Canada	Random Forest classifier	RADARSAT-2 was superior to the other sensors used in terms of accuracies except for TerraSAR-x for which the user accuracy was higher than that of RADARSAT-2.	Mahdavi et al. (2017)
MODIS Landsat 8	Witbank Dam Catchment in Mpumalanga Province	NDWI	The delineated wetlands show a declining extent from 2000 to 2015, which could worsen in the coming few years if no remedial action is taken. Current efforts to demarcate wetland extent varied time-series trend analysis. The wetland area declined by 19% during the period of study.	Nhamo et al. (2017)
WorldView-2	South American	Object-based Image Analysis approach,	Overall classification accuracy was 81%, and the Kappa index was 78.1%.	Gonzalez et al. 2019
WorldView-2	Selenga River Delta of Lake Baikal, Russia	Nonparametric machine-learning	RF classification outperformed both	Berhane et al. (2019)

(*continued*)

Table 2. Continued.

Sensor(s)	Study	Image analysis technique(s)	Major findings	Reference
		algorithms (DT, RB, and RF)	the DT and RB methods, achieving overall classification accuracy of more than 81%.	
RapidEye	Peninsula, Newfoundland and Labrador, Canada.	Random Forest and Support Vector Machine	The top three convnets (ResNetV2, ResNet50, and Xception), provide high classification accuracies of 96.17%, 94.81%, and 93.57%, respectively. The classification accuracies obtained using Support Vector Machine (SVM) and Random Forest (RF) is 74.89% and 76.08%. InceptionResNetV2 found to be superior over all other convnets. It can be suggested that the integration of Inception and ResNet are efficient for classifying complex remote sensing scenes such as wetlands.	Mahdianpari et al. (2018)

within the watershed and wetland ecosystems for 58 years in Nisqually River Delta. Their findings revealed that emergent marsh wetlands increased by 79% (188.4 ha) as a result of rehabilitation strategies implemented in 2009. Furthermore, it was mentioned that despite wetland gains in 2009, 35% of marsh wetland was lost between 1957 and 2015 due to river shifting and erosion patterns. The study by Son et al. (2015) used the Landsat dataset, dating from 1979 to 2013 (34 years) in Vietnam. Results indicated that 16% of the wetland ecosystems was lost because of anthropogenic activities. In assessing vegetation characteristics of the wetland, the study found that alien plant species were dominating the wetland areas. The study further demonstrated the critical role of remote sensing in wetland change detection, as well as future monitoring. Although long-term data have been used in some studies to identify different vegetation communities, the phenological disparities between different years that are associated with inter-annual water level changes were not considered (Chen et al. 2014; Gallant 2015; Hu et al. 2017; Wu et al. 2018). The transition of different vegetation communities within a wetland, over the years, remains largely unknown. Similarly, the processes or causes of these drastic changes are poorly documented. Consequently, high vegetation fragmentation is observed when classifying these wetland ecosystems (Henderson and Lewis 2008).

In summary, wetlands have high intra-class and low inter-class variability, which makes their classification challenging. The use of advanced remote sensing images with improved resolutions coupled with modeling techniques can enhance the classification of wetland ecosystems. Further, wetlands lack a defined boundary and their border is almost fuzzy since they gradually transit from wetland to other land cover classes, such as upland or open water, or even other types of wetlands (Dronova 2015). In addition, the ecotone proximity to wetlands is sometimes very narrow, which makes their detection or discrimination from wetlands difficult (Gallant 2015). Therefore, the quality of image interpretation and feature extraction methodologies in assessing wetlands should be considered (Dronova 2015). Remote sensing satellite images are also restricted to a specific spatial resolution, which might limit the detection of small wetlands (Ozesmi and Bauer 2002). Despite these limitations, there have been some notable research efforts that investigated applications of remote sensing data for regular wetland monitoring. There is a need to use freely available sensors such as Landsat and Sentinel with high time revisit, covering large swath-width and improved resolutions that are authoritative in solving noted limitations related to monitoring, estimation, and mapping of wetland ecosystems.

9. Future investigation for improved wetland ecosystem conservation

Significant progress has been made in the application of remote sensing techniques in wetland ecosystems research. Remote sensing techniques play a critical role in detecting and mapping areas impacted by different forms of anthropogenic and natural activities. Hence, the use of remote sensing to detect and map wetland ecosystems across sub-Saharan Africa has gained attention in the last decade. While several studies have successfully utilized remotely sensed data in wetland research, there are still challenges that still need to be addressed. Spatial studies of these ecosystems require versatile and robust computational methods to help deal with non-linear relationships, high-order interactions, and missing data. Despite these difficulties, the methods used for mapping the distribution of wetlands should be clear to understand and easy to interpret . Wetland ecosystems are important to society and there is a need to establish digital efforts for wetland conservation. Furthermore, wetlands resources surveys, legislation, management, and research need to be revised since there is still much work to be done to protect future wetlands.

10. Conclusion

Several scholars have studied various characteristics and functions of the wetland ecosystem, impacts of land use land cover changes, delineation, and degradation of these ecosystems. Most studies have been focusing on estimating and mapping biophysical and biochemical parameters of vegetation in wetlands recognized under the Ramsar convention, although little emphases have been placed on small wetlands (unprotected wetlands), which also play a critical role in adjacent communities. There is therefore little attention given towards wetland hydrology, soil, vegetation quantification, species characteristics, species diversity and productivity. Quantification and frequent mapping and monitoring of these wetlands across diverse landscapes is required for sustainable and effective wetland management control, formulation of governmental policies that promote ecological preservation under increased pressure from human interference and climate change. However, long-term ecological studies revealed that human activities continue to affect wetlands water levels, vegetation composition, structure, productivity, diversity, and functioning of the ecosystems, for decades after the activity has ceased. A new crop of robust satellite sensors e.g. Landsat with improved spatial resolutions and high record of archival data provides the most needed spatial tool for detecting, monitoring, and understanding wetland status at low costs. There is a data gap or undocumented information on the state of wetlands in developing countries, which further complicates management strategies and policy development. This review, therefore, provides the insights for wetland-related managers emphasizing on the urgent need to shift towards the use of cheap and readily available techniques for assessing and controlling wetland degradation, especially small wetlands dotted across under-resourced countries. Further, there is a need for future studies to utilize new advanced satellite imagery coupled with the use of robust machine learning algorithms such as GEE, principle component analysis, to improve modeling for well-informed management decisions of wetland ecosystems.

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