remote sensing

Review

Multispectral Remote Sensing of Wetlands in Semi-Arid and Arid Areas: A Review on Applications, Challenges and Possible Future Research Directions

Siyamthanda Gxokwe *, Timothy Dube and Dominic Mazvimavi

Department of Earth Science, Institute for Water Studies, University of the Western Cape, Private Bag X17, Bellville 7535, South Africa; tidube@uwc.ac.za (T.D.); dmazvimavi@uwc.ac.za (D.M.)
* Correspondence: 3050512@myuwc.ac.za; Tel.: +27-219-594-130

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Abstract: Wetlands are ranked as very diverse ecosystems, covering about 4–6% of the global land surface. They occupy the transition zones between aquatic and terrestrial environments, and share characteristics of both zones. Wetlands play critical roles in the hydrological cycle, sustaining livelihoods and aquatic life, and biodiversity. Poor management of wetlands results in the loss of critical ecosystems goods and services. Globally, wetlands are degrading at a fast rate due to global environmental change and anthropogenic activities. This requires holistic monitoring, assessment, and management of wetlands to prevent further degradation and losses. Remote-sensing data offer an opportunity to assess changes in the status of wetlands including their spatial coverage. So far, a number of studies have been conducted using remotely sensed data to assess and monitor wetland status in semi-arid and arid regions. A literature search shows a significant increase in the number of papers published during the 2000–2020 period, with most of these studies being in semi-arid regions in Australia and China, and few in the sub-Saharan Africa. This paper reviews progress made in the use of remote sensing in detecting and monitoring of the semi-arid and arid wetlands, and focuses particularly on new insights in detection and monitoring of wetlands using freely available multispectral sensors. The paper firstly describes important characteristics of wetlands in semi-arid and arid regions that require monitoring in order to improve their management. Secondly, the use of freely available multispectral imagery for compiling wetland inventories is reviewed. Thirdly, the challenges of using freely available multispectral imagery in mapping and monitoring wetlands dynamics like inundation, vegetation cover and extent, are examined. Lastly, algorithms for image classification as well as challenges associated with their uses and possible future research are summarised. However, there are concerns regarding whether the spatial and temporal resolutions of some of the remote-sensing data enable accurate monitoring of wetlands of varying sizes. Furthermore, it was noted that there were challenges associated with the both spatial and spectral resolutions of data used when mapping and monitoring wetlands. However, advancements in remote-sensing and data analytics provides new opportunities for further research on wetland monitoring and assessment across various scales.

Keywords: data integration; inundation; multispectral imagery; semi-arid; seasonal wetlands; vegetation dynamics

1. Introduction

There are several definitions of wetlands and most of these definitions include abiotic and biotic factors, hydrological regime, geomorphology and vegetation factors controlling the existence of wetlands. The Ramsar convention definition which includes these factors is widely used. However, the Ramsar convention excludes areas with marine water greater than 6 m at low tide. Wetlands exist where soils are saturated or inundated with water for a varying duration and frequencies [1]. The Ramsar convention definition of wetlands includes not only those systems falling within the traditional concept of wetlands such as mangrove swamps, peat bogs, tidal flats and water meadows, but also many other natural and man-made features like flooded gravel peats, reservoirs, rice paddies and coastal beaches [2]. While the Ramsar definition does not refer to the hydrological system, the definition includes components of natural inland systems, and predates the recent conceptual developments and management of coastal and water systems [3].

In North America, wetlands are defined as "lands that are either inundated by shallow water less than 2 m deep during low water events or have soils that are saturated long enough during the growing season to become anoxic and support specialized wetland plants (hydrophytes)" [4]. Unlike the Ramsar convention definition, the North American definition takes into consideration the fact that wetland water can be at the soil surface or below at some season. Several definitions of wetlands are used in South Africa, such as the one in the National Water Act (36 of 1998) and another by SANBI (South African National Biodiversity institute). The South African National Water Act (SANWA) (36 of 1998) defines wetlands as "areas which are transitional between terrestrial and aquatic systems where the water table is usually at or near the surface or the land is periodically covered with shallow water and which in normal circumstances supports or would support vegetation typically adapted to life in saturated soils" [5]. For the purpose of this review, the Ramsar definition of wetlands will be used, as this is globally accepted. Since different countries have different wetlands definitions, some ecosystems that are not considered as wetlands based on the Ramsar definition will be included.

Wetlands are ranked among very diverse ecosystems that cover a proportion of about 4–6% of the land surface [6,7], and provide an array of ecosystem services, which are categorised as provisioning, regulating, and cultural services. The provisioning services include the provision of water for livestock and domestic use, raw material as well as genetic resources, and production of wild foods and medicine [8]. The regulating services include carbon sequestration, flood attenuation, groundwater replenishment, sediment retention, waste treatment and regulation of pests and pathogens [1]. Cultural services include providing opportunities for cultural activities and heritage, recreational use as well as social interactions [9,10].

Globally, wetlands have been undergoing changes resulting from natural and human anthropogenic causes [11]. The natural causes include severe droughts experienced in certain parts of the world leading to drying and degradation of wetlands [11]. Anthropogenic causes include the conversion of wetlands to agricultural lands and pollution. However, there are uncertainties regarding the extent of wetland loss globally [12]. These uncertainties are caused by inconsistencies in data sets on spatial changes in wetlands and sizes of the studied systems [13]. Liu et al. [14] reported that in semi-arid China, natural wetlands have been lost over the past 50 years, and about 30% of these systems disappeared between 1990 and 2000, mostly due to anthropogenic causes. In Africa, wetlands are considered among threatened and degraded ecosystems [15]. In semi-arid South Africa, at least 50% of wetlands have been eradicated in some catchments [1]. Riddell et al. [16] highlighted that about 30–60% of wetland losses in South Africa were experienced in several major catchments due to poor land use management practices which is also the case across sub-Saharan Africa. Oluocha and Okeke [17] reported that in semi-arid Nigeria, wetlands that previously were recharging groundwater systems had been undergoing degradation at an alarming rate, and without measures to protect these systems.

Given the significance of ecological services provided by wetlands, it is imperative that they are sustainably managed. One of the key elements of sustainable management of wetlands is continuous monitoring of changes in their ecohydrological dynamics [18]. This is a challenge for wetlands in semi-arid and arid areas as most wetlands are seasonal or temporary and inaccessible because of their remoteness [7,19]. Remote sensing offers unique opportunities for providing information about wetlands in a spatially explicit manner where monitoring programs are not available [20], with input data from various satellite sensors ranging from multispectral to hyperspectral sensors. However, there are concerns regarding whether the spatial and temporal resolutions of some of the remote-sensing data enable accurate monitoring of wetlands of varying sizes especially in semi-arid and arid areas [21].

A significant number of reviews on the remote sensing of wetlands have been published. These reviews highlight the major progress on the use of remote-sensing data ranging from low spatial resolution to hyperspectral imagery for inventorying wetland in different climatic zones [22–30]. Although these reviews are showing progress on the use of various remotely sensed data for wetlands of different types, geographical location and climatic zones, these reviews did not only focus on the applications of freely available multispectral data on remote sensing of wetlands in semi-arid and arid areas. Guo et al. [22] and Dronova [24] incorporated semi-arid and arid studies in their reviews; which included wetlands in humid and sub-humid areas. In addition, the reviews by Guo et al. [22] and Dronova [24] also included studies on hyperspectral remote sensing of wetlands. These reviews also focused on either one aspect of wetland ecosystem, type or the application of one multispectral data set. The reviews by Adeli et al. [27], Wohlfart et al. [28] focused on the application of the Synthetic Aperture Radar (SAR) on the remote sensing of different wetland types. Kuenzer et al. [30], and Klemas [29] focused on the remote sensing of one specific wetland type which is the coastal marsh. Adam et al. [31] provided a comprehensive review on the status of remote sensing applications in differentiating and mapping biochemical and biophysical parameters of wetland vegetation. Owing to that background, this paper sought to provide a comprehensive review on the progress and development of remote sensing in the detection and monitoring of semi-arid and arid wetlands. Attention is drawn to the new insights in detection and monitoring of all wetland types located within the semi-arid and arid regions using freely available multispectral images.

Literature Search

A literature search was conducted using search engines such as Google Scholar, Scopus, and Web of Science to gain an overview of the remote-sensing application on wetlands. The targeted journals were internationally recognised peer reviewed journals covering geographical information system (GIS), remote sensing and water resource science. Information in journals was supplemented with that in books and reports from the European Union (EU), South African Water Research Commission (WRC), International Union for Conservation of Nature (IUCN), African Union (AU) and South African National Biodiversity Institute (SANBI) amongst others. The search criteria were used to find studies that were published between the years 2000 and 2020. For level-one search criteria, the key words "remote sensing" and "wetlands" were used to search for publications within the specified time frame. A total of 32,500 publications were retrieved. These included 17,500 from Google Scholar, 8500 from Scopus and 6500 from the Web of Science. The articles collected were further subjected to level 2 search or screening using key words "multispectral sensors", "semi-arid wetlands" and "arid", and the years 2000–2020. A total of 6380 were retrieved from the Google Scholar articles, 3870 from Scopus and 3200 from Web of Science. Further screening was conducted on these articles using the keywords, "wetlands inundation and extent", "wetlands vegetation cover", "wetlands degradation extent", "land-use land-cover changes" "wetlands monitoring challenges" and "wetlands classification", "Sentinel ", "SAR", "Landsat", "MODIS" and "radar" on level 3, and a total of 196 articles within the scope of this review were retrieved.

2. Semi-Arid and Arid Wetlands Characteristics and Key Monitoring and Management Challenges

The semi-arid and arid areas (Figure 1) host a diverse range of perennial to non-perennial wetlands with most of them being visible during the wet season [11]. These wetlands include swamps, peatlands, marshes and floodplains [1,6,32]. The existence of wetlands in semi-arid and arid areas is controlled by the positive surface water balance for the whole or part of the year, and inundation is mostly due to frequent rainfall from the upper humid basins. Groundwater also contributes to inundation of wetlands [6,31]. Outflows from wetlands are usually higher, due to high evaporation rates experienced over prolonged dry periods in the semi-arid and arid regions [31]. The dominating vegetation species characterising the semi-arid and arid wetlands vary with the locality of each wetland. In semi-arid South Africa, common wetland vegetation species include the short grasses family species such as *Cynodon dyctolon*, and the common reeds, *Phragmites australis*. These species are able to adapt to inundation, drying and sediments deposition. The semi-arid and arid wetlands soils tend to be oxygenated in some seasons due to the episodic inundation nature. For that reason, these wetlands tend to host more animal species than other wetlands that are permanently inundated [7,33,34].

Despite the ecological significance of semi-arid and arid wetlands, their conservation is not prioritized [35]. This is due to their ephemeral nature and small sizes [7], thus resulting in poor management, wetland degradation and loss of species and ecosystem services [20]. Gebresllassie, et al. [36] reported that in semi-arid Ethiopia, lack of policies to protect wetlands resulted in the loss of socio-economic services. Regular monitoring of their ecohydrological dynamics [14] is critical for formulating appropriate management measures. Frequent monitoring of semi-arid and arid wetland systems presents some challenges associated with the methods used and types of wetlands. Traditional field monitoring methods provided baseline information about semi-arid and arid wetlands. However, due to the cost of these methods, regular monitoring has not been possible, which creates problems for tracking changes occurring within wetlands [32].

Remote sensing from satellite sensors such as the Landsat and MODIS provides cost-effective data sets for wetland monitoring in both space and time. However, these sensors have a limitation based on their spatial resolution, since most semi-arid and arid wetlands are fairly small, <10 and 2500 ha [7], and confined to small depressions with no definite boundaries. These wetlands merge with the surrounding terrestrial ecosystem [1] posing challenges when mapping their spatial extent using optical sensors, especially during the dry period when the surrounding and wetland vegetation are not very healthy, resulting in similar spectral reflectance of soils and other land-cover classes. Rapinel et al. [37] reported that inventorying and characterization of wetlands in semi-arid and arid areas are limited to mostly small basins. Furthermore, Cape et al. [38] reported that the semi-arid wetlands are lost over a short period of time because of the anthropogenic activities including overexploitation of their water for irrigation. This necessitates the development of a cost-effective integrated monitoring and management approach, which will enable the generation of wetland information for wetlands of different sizes thus informing management strategies of wetlands in the semi-arid and arid areas.

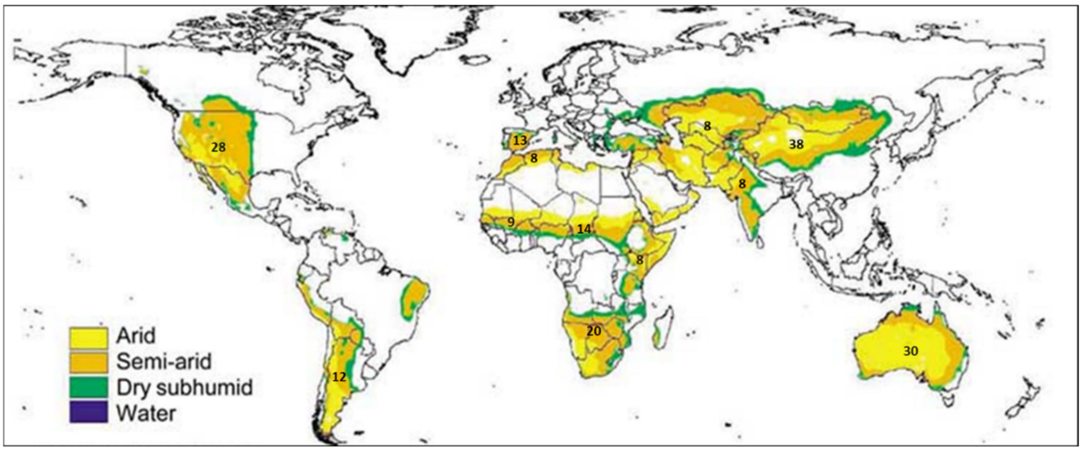

Figure 1. Global extent of semi-arid and arid areas with number of studies in each region [39].

3. Commonly Used Freely Available Multispectral Sensors for Semi-Arid and Arid Wetland Inventories

Over the last decades different types of wetlands ranging from inland freshwater marshes, coastal tidal marshes, mangrove ecosystems and forested wetlands or swamps have been studied using remotely sensed data sets of different spatial, spectral and temporal resolutions [40]. The number of studies conducted in semi-arid and arid areas on the application of freely available multispectral data sets for inventorying wetlands has increased exponentially as is evident in the number of publications between 2000 and 2020 (R^2 = 0.76) (Figure 2a). A significant increase was noted between the 2008 and 2020, with the highest number of publications in 2020. An analysis of the number of publications per region reveals that, most publications were from the semi-arid Australia and China (Figure 1) with a total of 30 and 38 publications respectively, while the semi-arid India and North Africa had the lowest number of publications (Figure 1). In all these studies, the commonly used data sources were Landsat Thematic Mapper (TM), Landsat Enhanced Thematic Mapper Plus (ETM+), Landsat Operational Land Imager (OLI), Moderate Resolution Imaging Spectroradiometer (MODIS), Landsat Multispectral Scanner System (MSS) and Synthetic Aperture Radar in the form of Sentinel-1 and Advanced Land Observing Satellite-1- The Phased Array type L-band Synthetic Aperture Radar (ALOS PALSAR). There was an increase in the use of Landsat OLI in mapping different aspects of semi-arid and arid wetlands. The justification is that Landsat 8 OLI uses the push broom feature which has improved noise to signal ratio, and that is an advantage when compared to Landsat TM and ETM+. The most studied wetland aspects were characterization, which include wetland classification and mapping as well as inundation (Figure 2b).

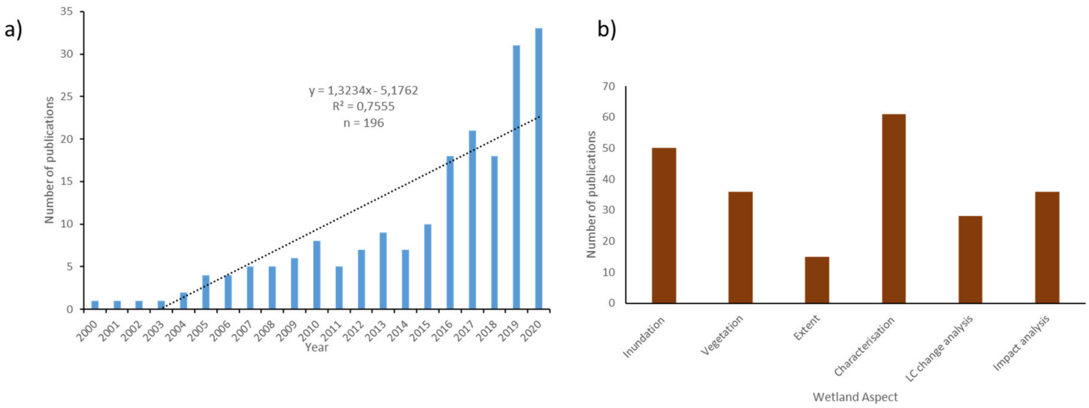

Figure 2. Number of remote-sensing publications on semi-arid and arid wetlands (**a**) and number of publications per area of focus (**b**). Characterization include studies on classification and wetland mapping, impact analysis includes studies focusing of both climatic and anthropogenic impacts on wetlands, and Land cover analysis refers to all studies on wetland cover change analysis (n = 196).

The earliest remote-sensing studies on wetlands utilised colour infrared aerial photographs, and orthophoto quads to examine different aspects of wetlands such as the spatial extent, wetlands vegetation (types, changes and growth), wetlands classification types and water quality [41]. Although aerial photographs provided useful information about wetlands, it is not feasible to map and monitor different wetlands at regional scale using aerial photograph, because of cost and time required to process aerial photographs [41,42]. Currently, a variety of remotely sensed products are available at different spatial, temporal and spectral resolutions for wetlands inventories, by a range of spaceborne and airborne sensors from multispectral sensors and hyperspectral sensors. These sensors operate at different optical spectrum. Amongst these sensors are the commonly used Landsat (Multispectral Scanner: MSS, Thematic Mapper: TM and Enhanced Thematic Mapper: ETM+, Operational Land Imager: OLI), Moderate Resolution Imaging Spectroradiometer: MODIS, Sentinel 2 and SAR (Table 1). Although, there are other satellite products like HALOS-2, the Second Advanced Earth Observation satellite (ADEOS), Satellite Pour I'Observation de la Terre (SPOT), QuickBird, IKONOS and Hisaki amongst other, the current review focuses on the commonly used products in Table 1.

Table 1. Commonly used freely available sensors specifications for wetlands inventories modified from Ozesmi and Bauer, [40].

Resolution	Landsat MSS	Landsat TM	Landsat ETM+	Landsat OLI	Sentinel-1	Sentinel-2	MODIS
Spectral bands (μm)					C-band (3.75–75 cm)		
Band 1		0.45–0.52	0.45–0.515	0.43–0.45		0.443	0.62–0.67
Band 2		0.52–0.62	0.525–0.605	0.45–0.51		0.49	0.841–0.876
Band 3		0.63–0.69	0.63–0.69	0.53–0.59		0.56	0.459–0.479
Band 4	0.5–0.6	0.76–0.90	0.775–0.90	0.64–0.67		0.665	0.545–0.565
Band 5	0.6–0.7	1.55–1.75	1.55–1.75	0.85–0.88		0.705	1.23–1.25
Band 6	0.7–0.8	10.4–12.5	10.4–12.5	1.57–1.65		0.74	1.628–1.652
Band 7	0.8–1.1	2.08–2.35	2.08–2.35	2.11–2.29		0.783	2.105–2.155
Band 8			0.52–0.9	0.50–0.68		0.842	
Band 8A						0.865	
Band 9				1.36–1.38		0.945	0.438–0.448
Band 10				10.6–11.19		1.375	
Band 11				11.5–12.5		1.61	
Band 12						2.19	
Band 19							0.915–0.965
Band 31							10.78–11.28
Band 32							11.77–12.27
Temporal	180 days	16 days	16 days	16 days	12 days	5 days	1–2 days
Spatial (pixel-sizes)	80 m	30 m & 120 for Band 6	30 m, 15 m B8 & 60 m B6	30 m B1–7 & 9 15 m B8 100 m B10–11	5 m × 5 m	60 m B1,9,10 10 m B2,3,4,8 20 m-B5,6,7,11,12	250 m B1–2, 500 m B8–36 1000 m B8–36
Period	1972–1992	1982–Present	2003–Present	2013–Present	2014–present for 1A 2016–present For 1B	2015–Present For 2A and 2017 for 2B	2000–present for Terra 2002–present for Aqua

Although multispectral sensors in Table 1 have been providing crucial information on wetlands at no cost and repeated coverage over the larger areas, fine detail wetland detection is still a major challenge [43,44], especially the fairly small semi-arid and arid wetlands (<10 ha) with varied vegetation and other land-cover characteristics. This results in some of the wetlands being missed or confused with other land-cover classes during classification. Various studies have been undertaken to establish the utility of these sensors in understanding different dynamics of wetlands in semi-arid and arid areas. These studies include [7,15,32,45] amongst others. The study by Powell et al. [32] demonstrated the utility of Landsat TM and ETM+ data sets coupled with digital elevation and light detection and ranging (LIDAR) data sets to classify and map land-cover classes of the semi-arid wetland in Barwon-Darling River system using stochastic gradient boasting algorithm and fractional cover model. The study deduced 5 land-cover classes which included tree-dominated forest and woodlands, shrub lands, vegetated swamps and non-flood dependent terrestrial communities with an overall accuracy of 88%. However, the study failed to distinguish between certain types of wetland located at the boundaries of the drier wetlands from the Landsat TM and TM+ images used. The study by Li et al. [7] evaluated the utility of MODIS spectral indices in monitoring hydrological dynamics of a small seasonally flooded wetland (1364 ha) in semi-arid southern Spain. An analysis of the relationship between the MODIS inundation area and field measured water levels showed a positive linear relationship between the two variables with a R^2 determinant of 0.96, suggesting the success of MODIS data set in monitoring hydrological dynamics of seasonal wetlands. However, the study focused on a single seasonal wetland with only varying soil characteristics. The other semi-arid and arid seasonal wetlands have other diverging characteristics e.g., marshes with dense emergent vegetation, and are even smaller, and comprise only a few MODIS pixels.

Chen et al. [45] utilised a 250 m resolution MODIS data set coupled with daily field water levels to investigate the applicability of MODIS time series data set in monitoring wetlands cover dynamics overtime. Four land-cover classes which are water, mudflats, submerged and emergent vegetation were identified with the overall accuracy of 80.18% and Kappa coefficient of 0.734. There were, however, omission errors of about 30% where water was confused with other classes such as mudflats and emergent vegetation. Much of this water was located at the interface of mudflats and other classes. Landmann et al. [15] also utilised MODIS coupled with topographical landform data set to map basic wetland classes in semi-arid Burkina Faso and Mali. The results showed a total of 5 wetland classes with a total area of 9350 km^2. The results demonstrated low accuracies of mapped land cover classes. Although the studies demonstrated the success of these freely available data sets in detecting and mapping different wetland cover classes, the fine detailed differentiation between the wetland classes was a major challenge. The use of pixel and sub-pixel-based approaches offer a great opportunity to improve the accuracy in wetland cover detection and monitoring from freely available multispectral data. These approaches provide the analysis of spectral characteristics of each class within a pixel, as such pixels with the same spectral characteristics are grouped together as one object. This has the potential to minimize the spectral confusion between classes. However, the challenge in the case of wetlands is that wetlands vary spatially and temporally; the inner wetland may be permanently inundated when compared to the seasonally inundated edges of the same wetland but the temporal pattern of the entire system is what distinguishes it from other landscapes. As such, using the pixel-based approach will not permit the capture of that temporal pattern [46]. In addition, wetlands have similar spectral characteristics to other landscapes i.e., flooded wetland may resemble shadows from trees, hills and other features since these have low surface reflectance.

The use of object-based image analysis (OBIA) offers an opportunity to improve wetlands detection and classification, despite the inherent computational costs higher than pixel-based approach. The introduction of cloud computing systems such as Google Earth Engine (GEE), National Aeronautics and Space Administration (NASA) Earth Exchange and Amazon web services amongst other presents an opportunity to simplify the use of OBIA approach in wetlands mapping and thus improving the accuracy of the classification. In addition, the use of fine spatial resolution images from commercial sensors may also assist in improving the classification accuracy.

4. Mapping Semi-Arid and Arid Wetland Vegetation Using Freely Available Multispectral Images

Wetland vegetation provides a habitat to a variety of aquatic animal species [26]. Changes in the conditions of wetland vegetation can be used as a proxy for early signs of any chemical and physical wetland degradation [41]. The assessment of wetlands vegetation is considered an important aspect for evaluating the ecological status of a particular wetland [47–49], and management of wetland biodiversity relies heavily on accurate assessment of wetland vegetation [33]. The assessment of wetland vegetation includes an understanding of wetland vegetation components such as structure, species type and composition. The use of optical freely available multispectral remote-sensing data in understanding wetland vegetation components is a common practice for semi-arid and arid wetland inventories, and most studies have successfully mapped wetland vegetation using these types of data set e.g., [48,50,51]. The challenge however lies with the spatial resolution of these data sets which are often too coarse to accurately map mixed vegetated and small semi-arid and arid wetlands.

The spectral reflectance of vegetation types in a mixed vegetated wetland are similar, and usually combined with spectral reflectance from the underlying soils, water and top of the atmospheric effects resulting in complications during the classification process [44]. In addition, steep environmental gradients cause short ecotones and sharp demarcations between vegetation species in the wetlands resulting in high spectral and spatial variability, thus presenting difficulties in identification of boundaries between vegetation communities and types during the optical mapping [26,44]. As such, the use of optical freely available multispectral imagery may present challenges in separating and understanding wetland vegetation components such as different species types, composition and structure due to their low to medium spatial and spectral resolution. McCarthy, et al. [52] mapped eco-regions of the Okavango Delta in Botswana, from the Landsat TM imagery using maximum likelihood classification (MLC) and rule-based classification (RBC) with 6 and 10 classes. The results showed overall accuracy of 46% and Kappa co-efficient of 0.37 for all the 10 classes based on MLC, overall accuracy of 63% and Kappa co-efficient of 0.59 based on RBC for the 10 classes, and an overall accuracy of 74% and Kappa co-efficient of 0.67 based on the RBC 6 class map. Based on these findings, the study deemed Landsat TM as unsatisfactory in the classification of the land cover classes including the wetland vegetation in the Okavango Delta.

Carreño et al. [53] utilised Landsat TM and ETM+ to assess the spatiotemporal changes in the area and internal components of the Mar Menor coastal wetland in semi-arid Spain from 1984 to 2001. The results for classification of land cover classes showed three natural vegetation sub-classes, which included salt steppe, salt marsh and reed bed. The user accuracy of 90% for the salt marshes, and 80% for both the reed beds and salt marshes based on the 1984 image were achieved, and based on the 1997 image the user accuracies of 62% for salt steppe, 96.5% for salt marshes and 76.92% for reed beds were reported respectively. The study reported high commission errors for salt steppe (37.5%) based on the 1997 image, which were attributed to the spatial resolution of the Landsat images used. Mazzarino [54] used Landsat 5 TM-derived NDVI to investigate multi decadal (1985–2010) vegetation dynamics of the Andean wetland system in the Nuñoa watershed. The classification results showed 2 classes named wetland (characterised by wetland vegetation) and non-wetland with an accuracy of 93% for wetland systems and 87% for non-wetland systems respectively. Although the Landsat 5 TM used in the study proved to be successful in the separation of non-wetland areas from wetlands area, the images used were representing dry season when the wetland is not inundated and wetland vegetation classes can be identified easily.

Literature [52–54] showed the successfulness of the application of multispectral images in mapping vegetation of the semi-arid wetland, however mapping vegetation communities and specific species to the finest detail is still a major gap requiring the use of high spatial-resolution satellite images. In attempting to resolve this issue, the fusion of different data sets which combines strengths of different sensors has the potential to improve mapping of wetland vegetation. Data fusion may however cause information distortion resulting from mismatch in pixels of different sizes of the fused data thus lowering the quality of the produced image.

5. Mapping Wetlands Inundation Using Freely Available Multispectral Images

Inundation plays a critical role in expressing the hydrological dynamics of the wetlands [7]. Understanding of this process plays a key role in water management, ecosystems assessment and biodiversity conservation [55]. Use of in situ gauge data set has been the backbone for the current understanding of surface water dynamics including wetlands inundation [56]. The use of in situ measurements presents challenges because most wetlands in semi-arid and arid areas are not gauged due partly to their episodic nature [7,34]. The advancement in remote-sensing approaches and products improves mapping surface water features including changes of inundation. The most utilized products include Landsat 5 TM and Landsat ETM+, as well as MODIS. The use of freely available medium spatial resolution products like MODIS presents difficulties in mapping inundation from heterogeneous seasonal flooded wetlands whose water is beneath the vegetation, small in size and with very dynamic eco-hydrological changes, especially during dry season [45]. This is evident in the studies by Klein et al. [55], Xie et al. [57] and Moser et al. [58].

Moser et al. [58] used a MODIS time-series data set to establish the spatio-temporal variability of water coverage of a semi-arid wetland in sub-Sahara West Africa. The coverage of surface water was slightly over-estimated from MODIS. Klein et al. [55] evaluated the spatial extent of seasonal water bodies in semi-arid central Asia from 1968–2001 using the coupled Advanced Very High Resolution Radiometer (AVHRR) and MODIS multispectral data. The accuracy assessment showed overall classification accuracy of 0.83 based on the AVHRR data, and 0.91 based on MODIS data. Lower accuracies were observed for the month of April in the northern region of the basin including the Tengiz-Kolgalzhyn lake system and was attributed to the presence of lake ice and snow. In addition, water masks were over-estimated due to the coarse spatial resolutions of the data sets particular at the interface of land and water surfaces.

Xie et al. [57] used Landsat (TM, ETM+ and OLI) coupled with gravity recovery and climate experiment data sets to investigate hydrological dynamics and ecosystems functioning of the Coongie Lake in the arid central Australia over a 24-year period. The analysis of flooding extent indicated a variable water regime with episodes of long-term drought and short periods of flooding over the Coongie Lake. Although the study successfully mapped the inundation dynamics of the Coongie Lake, there were uncertainties regarding the magnitudes of monthly inundation derived from the Landsat images. Literature [55,57,58] demonstrated the capabilities of the freely available multispectral data set in mapping and understanding inundation of the semi-arid and arid wetlands, however, it was noted that the presence of other wetland features influenced the level of accuracy when mapping inundation using coarse spatial resolution images such as MODIS. In addition, the issue of spectral confusion between water and soils at their boundaries remained unresolved, as such water pixels were overestimated. In attempting to resolve the issue of spectral mixing between wetland water and soils at the boundaries of these two classes, the use of high spatial-resolution images is likely to improve the latter. Moreover, the use of the SAR data set has the potential of improving the detection of inundation patterns since the sensor has the ability to penetrate wetland vegetation canopy.

6. Mapping Land-Use and Land-Cover Changes Impacts on Semi-Arid and Arid Wetland Systems Using Freely Available Multispectral Images

An understanding of land-use and land-cover changes (LULC) assists in developing effective environmental management strategies for the degradation and loss of wetlands [59,60]. In addition, to better understand land dynamics, LULC change analysis is pertinent [61]. Studies have revealed that changes in LULC are significant drivers for wetland degradation. Alam et al. [62] reported that a continuous inflow of sediment loads and nutrients in the Hokar Sar wetlands in India led to their degradation. Inflows of sediments were attributed to the changes of LULC due to the anthropogenic activities during 1986–2005 in the upper basin. Martínez-López et al. [49] also highlighted that the expansion of irrigated lands in semi-arid Mediterranean catchments has altered inputs of water and nutrients to lowland wetlands resulting in their degradation. Regular monitoring of LULC is necessary for developing measures for managing degradation of wetlands [63]. The use of data sets from different satellite sensors such as the multispectral MODIS and Landsat has been widely recognised as a powerful tool for studying and monitoring the dynamic impacts of LULC changes on wetlands in semi-arid and arid environments. The challenge, however, is the detection of these impacts with adequate precision [43].

Peter, et al. [64] used four decades of Landsat data set to assess the impact of anthropogenic activities and climate variability on the spatiotemporal pattern of Lake Babati in Tanzania. The study achieved an overall classification accuracy of 87%. The extent of water surface area was not accurately captured. This was due to the unavailability of usable continuous Landsat data set caused by significant cloud cover for most of the year. Wang et al. [65] investigated the shrinkage and fragmentation of marshes in the West Songnen in China for the period between 1954 and 2008 using Landsat data set coupled with topographical land cover maps. The study reported an overall classification accuracy of 90%. Mwita, [66] utilized Landsat MSS, TM, ETM and ETM+ over a 30-year period with a sequence of 10 years (1976–2003) to assess land-use and land-cover dynamics of the Rumuruti and Malindi wetlands in Kenya and Tanzania. The classification achieved an overall accuracy ranging between 88.28% and 95.17% for both wetlands. Although the overall accuracy results were higher, the producer's accuracy for open water class for the 1976 scene was low (33.3%) for both the wetlands. This was attributed to the spatial resolution of the Landsat MSS used for 1976. Although other studies [64–66] reported high classification accuracies, there were challenges associated with the type of data used in these studies. In an attempt to avoid the issues of cloud cover as reported by Peter, et al. [64], the use of SAR data set proved to be a solution as the sensor can penetrate through the cloud cover.

7. Low- to Medium- vs. High-Resolution Remote Sensing for Wetland Monitoring and Assessment

Low to medium spatial resolution remote-sensing data sets are characterised by pixel sizes ranging between 30 and >200 m. These data sets have been successfully used in many wetland inventories in different climatic zones globally. This is because they are readily available at no cost and mostly provide timely data sets thus providing the opportunity to monitor changes in wetlands over longer time periods. Despite the highlighted advantages of low to medium spatial-resolution data, their applications are somehow challenging especially on wetlands with an aerial extent less than 1-ha [24,27]. The advancements in satellite technological developments have led to the introduction of new generation multispectral sensors both spaceborne and airborne sensors with high spatial-resolution data sets (<10 m pixel size; Table 2). The sensors are uniquely characterised with improved sensing characteristics, which include the presence of strategically positioned spectral bands e.g., red-edge, near-infra red II as well as improved signal-to-noise ratio, amongst others [67]. The sensors are freely available and come in fine spatial resolution with strategically organised bands, which can finely detect wetland features similarly to the high spatial-resolution commercial sensors. These sensors have been explored in vegetation monitoring, biomass and surface water mapping studies and the findings were commendable [67]]. It is upon this premise that these datasets are likely to improve the monitoring and understanding of wetlands and wetland dynamics in semi-arid and arid areas, a previously challenging task with broadband sensors as the majority have an aerial extent below 1 ha [27]. However, the challenges are the cost implications for some of these datasets because most of these are available at a cost. For example, high spatial-resolution data sets from sensors such as Worldview-2, QuickBird and RapidEye amongst other are very costly to acquire thus making it difficult to map semi-arid and arid wetlands distributed in resource-limited environments.

Table 2. Selected low to high spatial-resolution sensors for wetland monitoring and assessment (highlighted bold are freely available data sensors).

Sensor	Pixel Size (m)	Bands	Revisit Time	Acquisition Cost	Scale of Application	Spatial Resolution
AVHRR	**1100**	**5**	**1**	**Readily available**	**Regional to global**	**Low**
Hyperspectral	<1	>100	-	Very expensive	Plot	High
IKONOS	4	5	1–2	Expensive	Local	High
Landsat TM	**30**	**7**	**16**	**Readily available**	**Local to regional**	**Medium**
Landsat ETM+	**30**	**8,11**	**16**	**Readily available**	**Local to regional**	**Medium**
Landsat MSS	**80**	**4**	**180**	**Readily available**	**Local to regional**	**Low**
Landsat OLI	**30**	**11**	**16**	**Readily available**	**Local to regional**	**Medium**
MERIS	**300**	**15**	**3**	**Readily available**	**Regional**	**Low**
MODIS	**500, 1000**	**7**	**1**	**Readily available**	**Regional to global**	**Low**
QuickBird	2.4	5	1–3.5	Expensive	Local	High
RapidEye	5	5	5.5	Expensive	Local	High
Sentinel-2	**10, 20, 60**	**13**	**5**	**Readily available**	**Local to regional**	**High/medium**
SPOT	**10, 20**	**4**	**26**	**Readily available**	**Local to regional**	**High**
Worldview-2	<1	8	1	Very expensive	Local	High
Sentinel-1	**5m**	**1**	**12**	**Readily available**	**Local to regional**	**High**

8. Available Satellite Image Processing Techniques for Accurate Wetland Monitoring

There are challenges in mapping wetlands from optical sensors since wetlands have a heterogenous mixture of land-cover classes, which may produce similar spectral reflectance resulting in complications during the classification process [44,67]. In addition, wetlands are highly dynamic with regards to presence of both water, plants and land surface which alters their reflectance and energy back-scattering properties. The classification of wetlands can be achieved through the pixel-based or OBIA approaches. In pixel-based classification, pixels are analysed by their spectral information and require imagery that extend beyond the visible spectrum [68]. Although the pixel-based classification has long been used [67], the approach does not fully utilise the spatial information of the multispectral imagery.

Unlike pixel-based classification, OBIA aggregates pixels with similar characteristics into objects or segments, which are then classified using analyst rules, machine-learning algorithms and statistical approaches [46]. One of the advantages of using OBIA over the pixel-based approach is that additional features such as shape, size and context are considered during the classification process, and reduces the within class spectral variation, thus improving the accuracy of classification [69]. Although OBIA is the preferred approach, one of the limitations in wetland mapping is that there is no clear standard for pre-classification assessment of segmentation effects on the final outcomes in either wetlands or other heterogeneous landscapes [24].

Different machine-learning algorithms are available for classifying wetlands using remotely sensed data. These include supervised machine learning algorithm such as the K-nearest neighbor (KNN), support vector machine (SVM), maximum likelihood classification (MLC), random forest (RF), artificial neural network and classification and regression tree (CART), as well as the unsupervised K-means, and Iterative Self-Organizing Data Analysis Technique ISODATA. The selection of the appropriate algorithm to use depends on the objective of the classification. A number of studies have used these algorithms in studying wetland systems in the semi-arid and arid areas. The supervised machine-learning algorithms have proved to be better performing than the unsupervised classification algorithms (Table 3). However, despite the better performance these algorithms have some limitations. For example, ANN and SVM were reported to be too difficult to automate and require an adjustment of a large number of parameters [70], RF sometimes tends to overfit and for every data set the size of a tree can take up memory [71]. The availability of image-processing techniques such as Google Earth Engine and image processing on cloud simplifies the use of supervised machine-learning algorithms. However, according to the literature, these platforms have been under-utilised in remote sensing of semi-arid and arid wetlands using the freely available multispectral sensors.

Table 3. Available algorithms for wetlands remote sensing.

Algorithm	Remote Sensing Data	Performance Range	Reference
RF	Landsat TM, Sentinel 1A, 2A, MODIS, LiDAR, SAR, ALOS-PALSAR, RADARSAT	80–98%	[70,72–77]
CART	Landsat TM, Sentinel-1A, 2A, PALSAR, Landsat ETM+	89.2–92%	[71,78–80]
MLC	Landsat TM, MODIS, Landsat MSS, Landsat ETM+	83.6–94%	[71,72,80–82]
SVM	Sentinel-2,1A, Landsat OLI	75–87%	[78,80,83–86]
ANN	Sentinel-2, Landsat TM, ETM+, OLI	90–96%	[72,78,86,87]
KNN	Sentinel-2, Landsat TM, ETM+, OLI, RADARSAT-2, Sentinel-1	83–97%	[77,78,84,87]
Unsupervised classification	Landsat TM, ETM+, MSS, Sentinel-2	82–96%	[71,78,81]

9. Summary of Key Challenges and Future Research Directions

Although the semi-arid and arid wetland systems tend to host most invertebrate and vertebrate species that would not survive in the surrounding landscape, they are still overlooked. Remote-sensing approaches have been offering an opportunity to understand these wetlands from aspects ranging from wetland characterisation, inundation, vegetation, extent and land-cover changes. The majority of these studies utilised the freely available multispectral sensors such as Sentinel-2 MODIS and Landsat (MSS, TM, ETM+, OLI). Although progress has been made regarding the utility of freely available multispectral sensors in understanding the dynamics of wetlands in semi-arid and arid areas, it is still challenging to map these wetlands to the finest precision due to their complex edaphic and small hydrological gradients. Moreover, the spatial resolution of these freely available multispectral sensors limits the detection and monitoring of these wetlands.

Wetlands are complex systems, and understanding their ecohydrological dynamics cannot be solely based on a single data source and or validation using the in situ measured data. In most arid and semi-arid environments, the in situ data set is limited. In addition, in most of these regions sharing of such data among different institutions is poor particularly in sub-Saharan Africa. The availability and free access to numerous spatial data sources with varying sensing characteristics e.g., global mapper Landsat series, Sentinel Copernicus and freely available radar and weather data set products, improves the mapping of wetlands where in-situ data are limited. This provides new opportunities for monitoring and assessment of fairly small semi-arid and arid wetlands, which were previously ignored due to the lack of requisite spatial data. This challenge or knowledge gap can easily be addressed by exploring different spatial data set integration techniques—a previous challenging task with broadband and coarse spatial resolution multispectral data set. Furthermore, improvements in data analytical techniques such as the introduction of advanced computer-processing methods provide new opportunities for the detection and monitoring of wetlands.

Literature shows that the introduction of advanced machine-learning algorithms and cloud computing such as GEE, artificial intelligence (AI) and Petascale image-processing techniques provide new avenues for multisource data integration and fusion [88]. Although few studies have explored the applicability of these techniques in vegetation monitoring and other related field of study, there is need for future studies to shift towards embracing the methods to enhance wetlands detection and monitoring particularly in data poor regions. One advantage of these techniques is the fast processing of large data sets. However, challenges such as inadequate network and internet connectivity as well as lack of high-performance computing systems for cloud computing and the lack of skilled personnel limit the application of such techniques especially in developing countries, mostly in sub-Saharan Africa, and other parts of the world. Despite some of the highlighted challenges, this review advocates for a paradigm shift in satellite data applications in wetland monitoring by embracing multi-data and advanced data processing techniques to improve our understanding of these systems.

10. Conclusions

The current review was aimed at providing a comprehensive overview on the progress and development of multispectral remote sensing in detection and monitoring of the semi-arid and arid wetlands. The literature search showed that there is a great improvement on the use of freely available multispectral data set in monitoring semi-arid and arid wetlands but more is required for smaller wetlands monitoring and assessment in these regions. This is evident in the number of studies that were published between the period of 2000–2020, with a significant increase between 2008 and 2020. Although there is a significant increase in the number of published papers focusing on the use of freely available multispectral data set on remote sensing of semi-arid and arid wetlands, it was noted that monitoring of key wetland aspects presented some challenges mainly due to spectral mixing and poor data quality for determining inherent wetland characteristics. These challenges include mapping inaccuracies which were either attributed to poor spatial resolution versus wetland, inadequate validation data or the classification method used. The introduction of advanced machine-learning algorithm and cloud computing systems such Google Earth Engine and Petascale thus provide a great opportunity to improve monitoring and assessment of wetlands particularly in data poor regions and in semi-arid or arid environments. So far, the use of these machine-learning algorithms and cloud computing techniques as well as data integration methods in semi-arid and arid wetlands is still in its infancy but the increased applications of these methods provide a new window of hope. Further investigations are thus required to test the utility of these programs and platforms in understanding the distribution, dynamics and the status of wetlands in semi-arid and arid regions to enhance their management and conservation as well as to safeguard ecosystems goods and services and, above all, livelihoods.

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