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Progress in the remote sensing of groundwater-dependent ecosystems in semi-arid environments

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ABSTRACT

Remote sensing of groundwater-dependent ecosystems (GDEs) has increased substantially in recent years. Of significant prominence, is the delineation and mapping of groundwater-dependent vegetation (GDV), species diversity, and water quality in these ecosystems. Groundwater-dependent ecosystems provide several ecological services such as habitat for wildlife fauna, carbon sequestration and water purification. The recent technological advancements and readily accessibility of new satellite sensors with improved sensing characteristics have resulted in numerous state-of-the-art applications for GDEs assessment and monitoring. These studies were done at varying scales, essentially in light of global climate change and variability. In this study, we review and assess the progress on the remote sensing of GDEs in semi-arid environments. We present the key trends in GDEs remote sensing that underpin many of the recent scientific research milestones and application developments. In addition, we observed a considerable shift towards the use of advanced spatial modelling techniques, using high-resolution remotely sensed data to further improve the characterisation and understanding of GDEs. Thus, literature shows the successful use of freely available remotely sensed data in mapping GDEs. We conclude that the advancement in remote sensing provides unique opportunities for the assessment and monitoring of GDEs in environments currently influenced by climate change and other anthropogenic impacts. Although remarkable progress has been made, this review revealed the need for further remote sensing and geospatial analysis studies to map other GDEs aspects including water quality and species diversity. Furthermore, the mapping and characterizing of the seasonal and yearly variability and changes in GDEs is required, mainly in the face of climate change and human impacts as well as water scarcity, particularly in data-limited tropical environments.

1. Introduction

Groundwater plays a vital role as source of water for humans and maintains various ecosystems such as rivers, lakes, wetlands, and terrestrial systems particularly in semi-arid environments (Howard and Merrifield, 2010; Eamus et al., 2015; Pérez Hoyos et al., 2016). Ecosystems which rely on groundwater on a temporary or permanent basis to sustain their growth and productivity are considered groundwater-dependent ecosystems (GDEs). Some of the GDEs such as phreatophytic vegetation draw water from saturated zones especially during the dry season when alternative sources of water become depleted and are also sustained by groundwater when the transpiration rate is high (Eamus and Froend 2006). Phreatophytic vegetation provides critical habitats for many sensitive species, especially in semi-arid environments (Huntington et al., 2016; Dwire et al., 2018). In addition, some wetland ecosystems in semi-arid environments are fed by groundwater to ensure the provision of ecological services and regulations (Thakur et al., 2012). Groundwater-Dependent Ecosystems amongst them including wetlands specifically provide several ecological services such as carbon sequestration, water purification and mitigation of floods and droughts (Yang and Liu, 2020). Thus, GDEs in semi-arid environments need to be studied.

Despite the ecological services provided by GDEs, groundwater is severely under threat from global climate change and anthropogenic impacts such as increasing human population, land-use change and pollution. Hence, groundwater is slowly getting depleted (Doody et al.,

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2017). Excessive abstraction has a negative effect on groundwater levels, potentially impacting water security, ecosystem services, structure, and functioning (van Engelenburg et al., 2018). Consequently, most of the GDEs will not exist in arid and semi-arid regions due to decline or loss of groundwater recharge. For instance, GDEs such as springs are entirely fed by groundwater and hence their existence (Kløve et al., 2011). Thus, this call for more studies to understand the spatial location, distribution, and extent of GDEs for sustainable management and allocation of water resources in arid and semi-arid regions (Kløve et al., 2011). This will assist in balancing human water demands with environmental requirements for sustainable management and conservation of GDEs. Moreover, the assessment and monitoring of GDEs in terms of their spatial extent and health status in the face of climate change as well as water scarcity particularly in data-limited arid environments is important to advance their conservation.

Remotely sensed data with the integration of GIS techniques have proven to successfully provide spatial and temporal data. This is useful in delineating and mapping GDEs in a robust, quick, and efficient manner (Barron et al., 2014; Pérez Hoyos et al., 2016; Nhamo et al., 2017; Wu, 2018). The delineation and mapping of the spatial distribution of GDEs have been investigated through passive, optical sensors including multispectral and hyperspectral remote sensing satellite images such as Landsat, Moderate Resolution Imaging Spectroradiometer (MODIS), Satellite Pour l'Observation de la Terre (SPOT), and Sentinel datasets as well as active sensors such as Light Detection and Ranging (LiDAR) and Radio Detection and Ranging (RADAR) imagery. Other data collection approaches such as field surveys or ground-based measurements have been regarded as time-consuming, labour-intensive, costly, and difficult to implement effectively in mapping the spatial extent of GDEs, especially across larger spatial areas over time.

A significant number of reviews (Gou et al., 2015; White et al., 2015; Nhamo et al., 2017; Chiloane et al., 2020; Liu et al., 2021) on the progress in the use of remote sensing in GDEs has been published. The most used effective active satellite sensors in identifying and mapping GDEs are LiDAR (Wu 2018; Bian et al., 2021) and RADAR imagery with their high spatial, temporal, radiometric and spectral resolutions (Hong et al., 2010; White et al., 2015; Dabboor and Brisco, 2018). However, passive satellite sensors such as Landsat, Sentinel, MODIS, and SPOT with medium to coarse resolution multispectral data have also been used to map GDEs mostly due to their zero to low cost and spatial extent covered by satellite imagery (Pérez Hoyos et al., 2016). Advances in Sentinel datasets with fine spatial resolution (10 m) offers an opportunity for extraction of GDEs characteristics and status (Thamaga et al., 2021).

In addition, there are remotely sensed algorithms that have been widely used to map GDEs including derivation of remote sensing indicators and image classification (Gou et al., 2015; Pérez Hoyos et al., 2016; Orimoloye et al., 2020; Chiloane et al., 2020). The derivation of remote sensing indicators includes Normalized Difference Vegetation Index (NDVI), Normalized Difference Water Index (NDWI), Leaf Area Index (LAI), and Enhanced Vegetation Index (EVI), whereas image classification comprises of supervised and unsupervised classification (Pérez Hoyos et al., 2016).

Even though these reviews documented significant progress on the use of remotely sensed data for GDEs in different climatic zone, less focus on the application of integration of remotely sensed data (i.e., multispectral derived indices), GIS together with algorithms in GDEs in semi-arid and arid areas is not explicitly integrated. The importance of these integration was highlighted by Münch and Conrad (2007), and Tweed et al. (2007). However, several studies (Gou et al., 2015; Chiloane et al., 2020 and Liu et al., 2021) integrated multispectral or hyperspectral derived indices and GIS to map GDEs.

Thus, this paper reviews progress made in the use of remote sensing in delineating the spatial distribution and mapping GDEs in the semi-arid and arid environments. The paper firstly provides a comprehensive overview of remote sensing applications in GDEs. Secondly, it provides the application of remote sensing in GDEs. In the light of this, the applicability of the available remote sensing sensors and the potential of different algorithms in identifying, delineating, and mapping GDEs are presented. Thirdly, seasonal and long-term monitoring of GDEs, with the role climate change are discussed in detail. Lastly, the challenges associated with application of remotely sensed data in GDEs is explored and prospects in identifying, delineating, and mapping GDEs are also provided.

2. Methods

To achieve study objectives, a literature search was conducted in ecology, water, and remote sensing journals. To search for relevant information, articles were selected via relevant search engines including Google Scholar, and SCOPUS for studies that were published between the year 2000 and 2021. The following keywords were used 'remote sensing', 'groundwater-dependent ecosystems', 'arid environments', 'semi-arid environments.' A total of 18 257 articles were retrieved. Out of the total number of retrieved articles, 18 200 were from Google Scholar and 57 from SCOPUS. This review did not include research that did not use geospatial technologies from the selection. Further search was done from the collected articles using keywords 'multispectral sensors' and 'hyperspectral sensors' within the specified time frame. A total of 1340 articles were retrieved from the Google Scholar and 4 from SCOPUS. The third further search was done on the collected articles from second search using the keywords 'groundwater-dependent ecosystem identification' and 'groundwater-dependent ecosystem delineation'. A total of 319 articles within the scope of this review were retrieved.

2.1. *Overview of remote sensing application on groundwater-dependent ecosystems in arid and semi-arid environments*

Remote sensing is regarded as the most useful tool for gathering information on GDEs. Based on the literature of this study, this tool was mainly applied in identifying, mapping and monitoring GDEs' species diversity, vegetation (i.e., productivity and extent), water dynamics (i.e., groundwater depth/level, surface water extent, discharge in the form of evapotranspiration, recharge), Land Use and Land Cover (LULC) impacts (i.e., groundwater decline, salinization), and climate change impacts (Farda 2017; Han et al., 2018; Wang et al., 2020; Bian et al., 2021) (Fig. 1). However, it is demonstrated that GDEs spatial extent delineation remains understudied; species diversity is given less attention, whereas, GDEs water quality has not been given attention using remote sensing. The study of all GDEs aspects can be achieved using technologically advanced sensors and further research is recommended. This therefore, motivates this study to provide a detailed overview of the already available literature on GDEs to be able to identify the gaps in these subject.

Nonetheless, literature gathered in this study demonstrated the remarkable progress in the application of remote sensing in GDEs over the years with $R^2 = 0.71$ (Fig. 2). The progress is attributed to the technological advances that resulted in well-organized data processing. Fig. 2 demonstrate that more GDEs studies using remote sensing datasets were published in 2017/2018 and 2020/2021. The increase in technologically advancements in remotely sensed data (i.e., Sentinel emerged, in 2016 in Fig. 2), shows the potential for growth in the use of remote sensing in GDEs assessment and monitoring in the upcoming years.

Number of studies (e.g., Gou et al., 2015; White et al., 2015; Nhamo et al., 2017; Chiloane et al., 2020; Liu et al., 2021) have been conducted in GDEs using remote sensing techniques in arid and semi-arid regions since 2015. The studies utilised satellite datasets with different spatial, spectral, and temporal resolutions (Fig. 3) with diverse purposes to investigate different aspects of GDEs (Fig. 1). Gou et al. (2015) used derived NDVI from Landsat Enhanced Thematic Mapper (ETM) and MODIS, whereas Liu et al. (2021) used MODIS-derived Enhanced

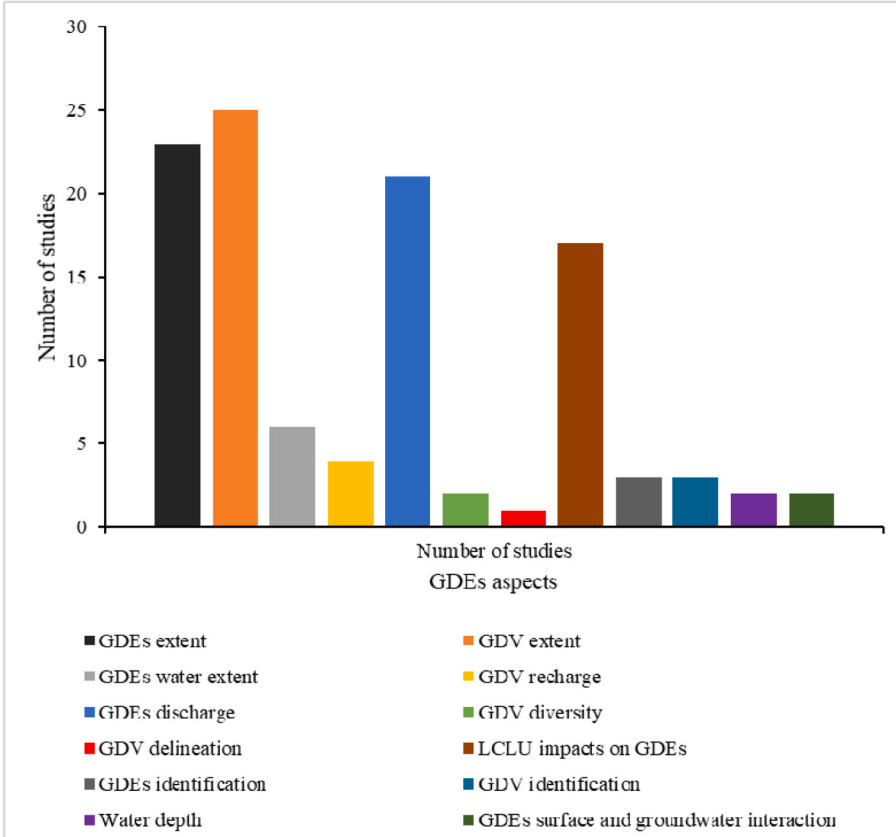

Fig. 1. Assessing, mapping and monitoring GDEs using remotely sensed data.

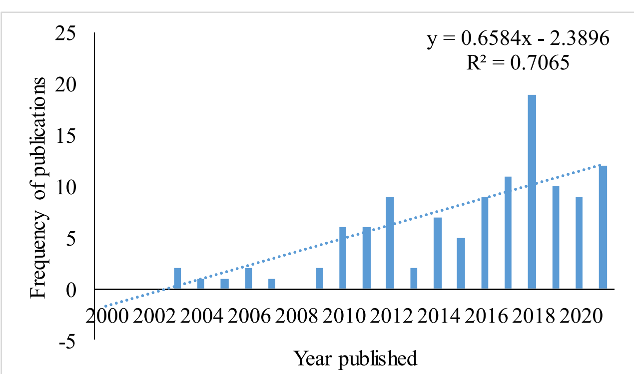

Fig. 2. Remote sensing publication growth in GDEs between 2000 and 2021.

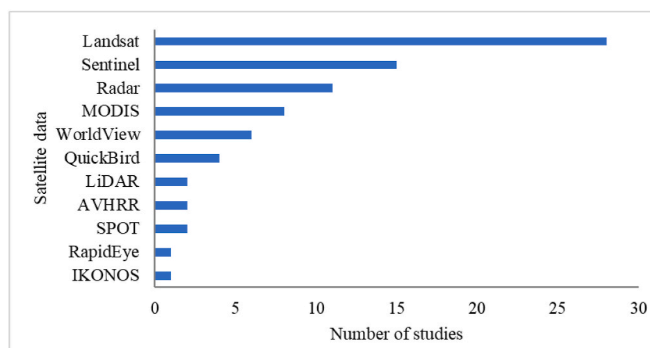

Fig. 3. Number of satellite data application in groundwater-dependent ecosystems studies.

Vegetation Index (EVI) to map groundwater-dependent ecosystems in Texas and Central Asia, respectively. Furthermore, Chiloane et al. (2020) studied the pan inundation in Kgalagadi Transfrontier Park using Sentinel-derived Modified Normalized Difference Water Index (MNDWI). The GDEs aspects were studied successfully due to the capabilities and technological advancement of satellite datasets. For instance, Sentinel with finer spatial (10 m) and higher spectral (13 spectral bands including red edge strategic bands) resolution with varying geographical coverage up to (290 km), which is essential for extraction of GDEs such as wetland ecosystem characteristics and for the evaluation of wetland dynamics (Thamaga et al., 2021).

Most of the GDEs studies utilised medium to coarse multispectral datasets (Landsat and Sentinel) (Fig. 2). Multispectral datasets are freely, timely and readily available datasets (Timothy et al., 2016). Furthermore, they are characterised by spatial, spectral, and temporal resolution that are technologically advanced (Thamaga et al., 2021). For instance, Landsat with wide swath-width (above 185 km), spatial resolution of 30 m and a repeated global coverage has been used in GDEs delineation (Münch and Conrad 2007; Barron et al., 2014; Nhamo et al., 2017), inundation (Huang et al., 2014; Chiloane et al., 2020), land use and land cover (Farda, 2017), climate variability (Huntington et al., 2016) and evapotranspiration (Yang et al., 2011) studies. The advanced and freely accessibility of remotely sensed data indicates the potential in continuous application of the datasets in GDEs assessment and monitoring.

Information gathered for this review demonstrates the capabilities of remote sensing to study GDEs in arid and semi-arid environments. It also shows the growth with improvement of satellite and sensors. Although zero to low-cost satellite data offers medium to course resolution, they

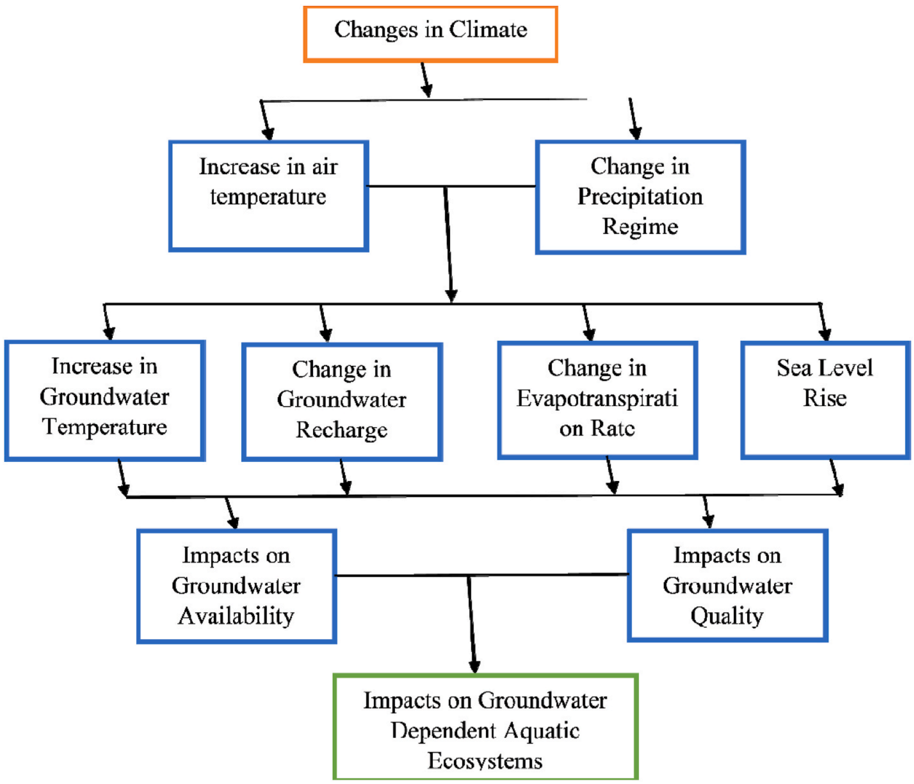

Fig. 4. A conceptual diagram on impacts of climate change on groundwater-dependent ecosystem (Source: Morsy et al., 2017).

can offer reliable results in assessment and monitoring of GDEs. For instance, the use of Landsat in GDEs studies (Tian et al., 2016; Farda 2017; Han et al., 2018; Ghosh and Das 2020) demonstrated over 90% accuracy assessment (Table 1). Furthermore, it requires further investigation to assess variety of GDEs aspects in different environments.

2.2. Remote sensing applications in GDEs identification, delineation, mapping, and monitoring

Earth observation is an important tool to gather information about GDEs dynamics across spatial and temporal scales (Huntington et al., 2016; Pérez Hoyos et al., 2016). Remote sensing provides quick and spatially extensive techniques to assess different aspect of GDEs from vegetation characteristics, water dynamics (i.e., recharge, discharge, quality, and level), and also relationships amongst them and climate variables. Studies have utilised different types of satellite sensors including active sensors such as Radar (Hong et al., 2010; Dabboor and Brisco, 2018) and LiDAR (Wu, 2018), and passive sensors such as Landsat (Doody et al., 2017; Collados-Lara et al., 2021), Sentinel (Kaplan and Avdan, 2017; Slagter et al., 2020), MODIS (Gou et al., 2015; Xu et al., 2021) and SPOT across arid and semi-arid environments with variation of results.

Radar imagery has long been recognized as an important source of data for wetlands identification, monitoring changes in wetland characteristics such as surface water extent (Hong et al., 2010; Brisco, 2015), saturated soils, flooded vegetation, and changes in wetland vegetation cover (White et al., 2015; Dabboor and Brisco, 2018), natural and anthropogenic disturbances (Pérez Hoyos et al., 2016). Synthetic Aperture Radar (SAR) was used in various studies to understand the dynamics of GDEs, amongst the studies including Hong et al. (2010), White et al. (2015), Dabboor and Brisco (2018) and Adeli et al. (2020). For instance, Dabboor and Brisco (2018) used SAR for mapping peatlands and its capability in L-band polarimetric to differentiate between bog and fen peatlands. The results were acceptable due to the penetration of SAR's longer wavelengths and the ability to penetrate beneath the vegetation canopy as well as sensitivity of L-band polarimetric SAR of the water flow characteristics. SAR provides information often unavailable from optical sensors due to presence of clouds and limited orbits and swath coverage. Thus, this makes it ideal for mapping and monitoring changes in vegetation in GDEs in different conditions like the time of the day (i.e., day or night) and through cloud cover.

In a different study, Hong et al. (2010) utilised SAR to detect phase variation in water level changes utilizing Small Temporal Baseline Subset techniques of InSAR with average Root Mean Square Error (RMSE) of 6.6 cm. However, the results were not sufficient since the obtained RMSE provides an uncertainty estimation of the Small Temporal Baseline Subset technique to monitor absolute water levels. Despite the mentioned advantages of SAR, some studies (Grimaldi et al., 2020) indicated that SAR have some difficulties in mapping GDEs' heterogeneous vegetation, they usually result in the radar signal being scattered diffusely since the majority of vegetation canopies are heterogeneous and have high amounts of surface roughness. Moreover, in a different study, White et al. (2015) reported that SAR is not good at distinguishing ice and rough surface water.

Other multispectral and hyperspectral satellite images (Landsat, Sentinel, MODIS, and SPOT) have been used to map GDEs due to their capabilities. Satellite sensors like Landsat images have a repeated global coverage that have resulted in the many publications from local to global on GDEs mapping (Münch and Conrad 2007; Li and Roy 2017; Thamaga et al., 2021). Doody et al. (2017) emphasised the use of Landsat data for GDEs studies since it is capable to identify landscapes which are wetter or greener than surrounding areas, indicating that are accessing additional water, such as groundwater. Multispectral and hyperspectral satellite images are therefore suitable for GDEs assessment and monitoring.

Landsat images offers the best spatial and spectral resolutions, competitive costing structures in comparison to other medium resolution image formats (Münch and Conrad 2007). Landsat images also provide historical information (from the year it was launched) on natural resources that are being investigated (Dube et al., 2016; Huntington

Table 1
Available machine-learning algorithms that have been used in groundwater-dependent ecosystems studies.

Algorithm	Remote Sensing Data	Performance (accuracy assessment)	References
Random Forest (RF)	Sentinel	Wetland classification in Cousen watershed, France (87%)	Rapinel et al. (2019)
	WorldView-2	High density biomass estimation for wetlands in Isimangaliso Wetland Park, South Africa	Mutanga et al. (2012)
	SAR data	Wetland classification, Canada (94%)	Mahdavi et al. (2018)
	Landsat	Wetland classification along Etrix River in North Xinjiang, China (93%)	Tian et al. (2016)
	RapidEye	Wetland mapping in Peninsula, Newfoundland and Labrador, Canada (76.1%)	Mahdianpari et al. (2018)
Classification and Regression Trees (CART)	Landsat	Land cover and land use in Sekara Anakan, Indonesia (97.0%)	Farda (2017)
Support- vector machine (SVM)	Landsat	Analyse spatial and temporal variation of wetlands in Paarl River Delta (94.9%)	Han et al. (2018)
	LiDAR	Classified wetland vegetation (97.7%)	Bian et al. (2021)
	Landsat	Identifying the risk zones of East Kolkata wetlands (91.1%)	Ghosh and Das (2020)
	Landsat	Assessing the extent of waterbodies within wetlands along the Klip River, South Africa (84%)	Zwedzi (2020)
Maximum Likelihood Classification (MLC)	Landsat	Mapping wetlands in Mekong Basin (ranges from 77% to 94%)	MacAlister and Mahaxay (2009)
	IKONOS	Mapping invasive wetland plants in the Hudson River National Estuarine Research Reserve in New York (ranges from 45% to 77.7%)	Laba et al. (2010)
Artificial Neural Network (ANN)	Landsat	Classifying and mapping coastal wetlands of Cukuroval Delta, Turkey (90.2%)	Berberoglu et al. (2004)

et al., 2016; Thamaga et al., 2021), which is good for monitoring these ecosystems for a long period. Thamaga et al. (2021) highlighted that knowledge on previous and recent distribution of ecosystems such as wetlands particularly in Sub-Saharan Africa might ease the understanding of the developments in GDEs such as wetlands (trends and improvements), as well as their contribution to ecosystem goods and services. The above-mentioned characteristics have resulted in many ecosystems mapping and monitoring publications through the application of Landsat data (Fig. 2).

For example, a study by Münch and Conrad (2007) successfully used remote sensing and GIS to identify the presence or absence of GDEs (i.e., wetlands) across three catchments in Western Cape, South Africa. Landscape wetness potential model and the depth to water table model provide slightly better predictors for landscape wetness potential as indicators of groundwater dependency, compared to the field-verified data with 73% and 77.2%, respectively. Similarly, Barron et al. (2014) highlighted the successful use of Landsat data in GIS and remote sensing to delineate and map GDEs in Western Australia with producer accuracy of up to 91% for some areas. These studies utilised image classification methods which is not much reliable when compared to the use of techniques such as remotely sensed derivatives (indices) and machine learning algorithms. However, the technological advances in sensors together with machine learning algorithms further provide more courage to utilise Landsat data to assess and monitor GDEs in arid and semi-arid environments.

The use of high temporal resolution satellites such as MODIS has also been found to be valuable in detecting large-scale land cover features such as wetlands and their dynamics effectively in semi-arid areas (Landmann et al., 2010). MODIS is another type of satellite sensor used in GDEs studies and is characterised by 250 m spatial resolution, and a near to daily observations in 36 spectral resolution bands (Landmann et al., 2010; Chen et al., 2014). For example, Chen et al. (2014) successfully applied a time-series 16-day MODIS NDVI from 2000 to 2012 and developed a method to classify wetland cover types based on timing of inundation with an overall accuracy and kappa coefficient of 80.2% and 0.73, respectively. Hence, MODIS is suitable for GDEs long term dynamic mapping even though their spatial resolution is relatively coarse, and this is due to the high temporal resolution of MODIS.

2.3. *Available remotely sensed algorithms in groundwater-dependent ecosystems*

Techniques such as image classification and remote sensed derivatives (Table 2) coupled with machine-learning algorithm (Table 1) are available for studying GDEs (Bian et al., 2021). Image classification algorithms include supervised classification and unsupervised classification (Pérez Hoyos et al., 2016; Gxokwe et al., 2020), object-based classification, principal component analysis, and hybrid classification. Amongst the algorithms, supervised classification algorithms perform better than the unsupervised classification algorithms (Gxokwe et al., 2020) and were commonly used.

In supervised machine-learning algorithm, the user assigns the preferred classes and then the software uses those training sites and applies them to the entire image, unlike unsupervised classification where user groups pixels with similar spectral values are based on their characteristics (Phillips et al., 2007). There are also different types of machine-learning algorithms, and they are indicated in Table 1. Numerous studies (e.g., Laba et al., 2010; Farda, 2017; Mahdavi et al., 2018; Han et al., 2018; Rapinel et al., 2019; Ghosh and Das, 2020) have used machine learning algorithms depending on the objectives of their studies. Support Vector Machine (SVM) and Random Forest (RF) are the mostly commonly used in the assessment and monitoring of ecosystems such as wetlands (Table 1).

SVM was utilised in Han et al. (2018) study to analyse spatial and temporal variation of wetlands in Paarl River Delta using Landsat and indicated that the SVM model has a high classification accuracy of 95.0% (Table 1). Ghosh and Das (2020) identified the risk zones of East Kolkata Wetlands using Landsat and the results indicated SVM classification results of 91.1%. The SVM classification method yields high accuracies since it is capable of overcoming challenges associated with areas with complex land cover and types. It overcomes such issues by enabling the user to change parameter settings and adding training subsets. For example, the studies have been conducted in different areas (i.e., inland (Han et al., 2018; Zwedzi 2020) and coastal (Farda 2017; Ghosh and Das 2020)) since the GDEs have different spectral characteristics and dynamic properties. Assessment and monitoring of GDEs using image classification method also depends on the integration of the type of satellite image and machine-learning techniques used in the study.

However, the assessment of GDEs' aspects using only supervised classification is considered time-consuming and prone to human mistakes (Bian et al., 2021), because supervised classification requires preparing the training data. This poses challenges for the accurate GDEs aspect studies such as delineation. Hence, algorithms such as SVM and RF are commonly used and produced high accuracies, they are also associated with some limitations. For instance, SVM have been reported

Table 2
Applications of commonly used spectrally derived indices on groundwater-dependent ecosystems.

Index	Remotely sensed data	Aspect	Results	References
Normalized Difference Vegetation Index (NDVI)	Landsat and MODIS	Vegetation	8% of natural vegetation remained green during dry period	Gou et al. (2015)
	QuickBird and WorldView-2	Vegetation	There were significant relationships between NDVI-derived wetland areas and spring flow rate measurements	White et al. (2015)
	MODIS	Vegetation	The results demonstrated declining trends in the extent of vegetated wetland areas between 2002 and 2009, followed by a return of wetland vegetation since 2010	Petus et al. (2013)
Normalized Difference Water Index (NDWI)	Landsat	Water	The results show the significance decrease in wetland extent from 655.416 km^2 in 1987 to 429.489 km^2 in 2017 during the study period	Orimoloye et al. (2020)
	MODIS and Landsat	Water	The wetland area declined by 19% from 2000 to 2015, during the study period	Nhamo et al. (2017)
Modified Normalized Difference Water Index (MNDWI)	Landsat	Water	Lakes experienced an increase in surface water area in 2010 compared to 1986.	Nsubuga et al. (2017)
	Sentinel	Water	The results demonstrated that 2017 had the largest surface water extent covering 23 195.8 m^2, during the wet season and 17 913.3 m^2 in the dry season and 2018 had the smallest surface water extent covering 13 076 m^2 for the wet season and 6032.6 m^2 during the dry season.	Chiloane et al. (2020)

to be too complicated, too difficult to automate and they require an adjustment of many parameters (Shoko et al., 2016). Tian et al. (2016) also indicated difficulty in the classification that was caused by the similar spectral features of the vegetation covers using RF. However, the difficulty was overcome by incorporating phenological difference and the textural information of co-occurrence gray matrix into the classification. Thus, the availability of advanced remote sensing generation (high resolution images) coupled with other parameters such as the developed machine-learning algorithm and *in-situ* remotely sensed data can offer great opportunity for GDEs mapping.

Classification methods like Object-Based Image Analysis (OBIA) approach can achieve greater accuracy for wetland mapping than the traditional pixel-based approach (Kaplan and Avdan, 2017; Wu, 2018; Gxokwe et al., 2020). The OBIA aggregates pixels with similar characteristics into objects, which are then classified using analyst rules, machine-learning algorithms, and statistical approaches (Gxokwe et al., 2020). Kaplan and Avdan (2017) proposed and successfully used object-based classification for extraction of the wetland boundaries with a producer's accuracy of 90.5% in Eskisehir, Turkey. However, the presence of clouds and shadows affected the results, but they were then eliminated by setting the area condition. The study did not yield the highest accuracy also due to the medium resolution satellite image used and this could have been avoided by using technically advanced satellite imagery such as Sentinel and the month in which field data was collected (i.e., especially during the winter season when they few or no clouds).

Since supervised classification are prone to analyst mistakes, the spectrally derivation of remote sensed data remains the widely used approach for identifying, delineating, mapping and monitoring GDEs aspects (Barron et al., 2014; Gou et al., 2015; Pérez Hoyos et al., 2016; Chiloane et al., 2020). Spectrally derivation of remote sensed data includes vegetation indices such as Normalized Difference Vegetation Index (NDVI), Leaf Area Index (LAI) and Enhanced Vegetation Index (EVI) and water indices such as Normalized Difference Water Index (NDWI), Modified Normalized Difference Water Index (MNDWI), Automated Water Extraction Index for Shadow (AWEIsh), Water Ratio Index (WRI), Land Surface Water Index (LSWI) and Topographic Wetness Index (TWI).

Recently the Normalized Difference Phenology Index (NDPI) was developed by Wang et al. (2017) to improve the phenology monitoring capacity. The NDPI was used mostly in aboveground biomass in grassland ecosystems. (Xu et al., 2021). However, NDPI is not yet tested in GDEs, particularly in semi-arid environments. The NDPI would be good in the delineation of GDEs since it overcomes impacts of the heterogeneity of the soil background that usually hinders to delivery of adequate and robust results when other indices are used. It utilizes a red-SWIR (shortwave infrared) combination to replace the red band in the NDVI, in order to adequately deliver robust results without influence on soil background and spatial, temporal and sampling size variability (Dye et al., 2016; Xu et al., 2021).

The NDVI and NDWI are the most used and reliable indices for assessing, identifying, mapping, and monitoring ecosystems such as GDEs aspects like chlorophyll content, vegetation coverage, water extent and density of greenness. The NDVI shows the greenness of an area (Glanville et al., 2016). The NDVI has been used in the identification of GDEs in different studies (Table 2) based on the principle that ecosystems are able to maintain consistent greenness and remain physiologically active even during prolonged dry periods, and also exhibit low inter-annual leaf area changes between dry and wet years are defined as potentially groundwater dependent (Gonzalez et al., 2019; Barron et al., 2014; Gou et al., 2015; Pérez Hoyos et al., 2016).

The NDVI makes use of the red and near-infrared (NIR) bands of the electromagnetic spectrum to determine the vegetation status and photosynthetic activity in a given area (Pérez Hoyos et al., 2016; Bian et al., 2021). White and Lewis (2011) emphasised the successful use of NDVI in arid regions. However, NDVI is considered appropriate for arid region settings because studies found that exceptionally high biomass conditions are not encountered within the arid areas. This limits the NDVI asymptotic 'saturation' effect encountered under high biomass conditions (Petus et al., 2013).

The NDWI determine the wetness of an area and uses NIR and shortwave-infrared (SWIR) bands of the electromagnetic spectrum to determine moisture content, while eliminating the presence of soil and terrestrial vegetation features (Glanville et al., 2016). It has also been successfully used in the delineation of surface water features (Ji et al., 2009; Nhamo et al., 2017; Orimoloye et al., 2020). On the other side, numerous studies (e.g., Balázs et al., 2018; Masocha et al., 2018; Chiloane et al., 2020) have demonstrated the best performance of MNDWI when compared to NDWI on assessing and monitoring waterbodies of different ecosystems. Furthermore, Chiloane et al. (2020) studied pan inundation dynamics over different seasons using MNDWI with an overall accuracy of 84.9% in the Kgalagadi Transfrontier Park, southern Africa compared to other indices used in the study such as AWEIsh (~75%), LSWI (~71.8%), NDWI (~78%) and WRI (~73%). Hence, MNDWI can detect water from other features such as vegetation and soils.

Although different methods have been used for mapping GDEs, using remote sensing data from satellite images with medium to coarse spatial resolution such as Landsat, Sentinel, other satellites images made separating GDEs from the other land cover challenging without integrating additional data such as field measurements and Digital Elevation Model (DEM). Thus, Münch and Conrad (2007), and Tweed et al. (2007) studies highlighted the importance of integrating vegetation indices such as NDVI and/or water indices such as NDWI and other geospatial data like indices such as topographic indices like DEM in improving the results. Digital Elevation Model has been used extensively by researchers for water mapping and has been successfully used to locate GDEs (Tweed et al., 2007; Bian et al., 2021). The majority of these studies (e.g., Tweed et al., 2007; Bijeesh and Narasimhamurthy, 2020) have demonstrated the utility of DEM data in deriving terrain heights and in groundwater recharge and discharge estimation.

Nonetheless, studies (Münch and Conrad 2007; Tweed et al., 2007; Barron et al., 2012; Gou et al., 2015) integrated NDVI with other terrain characteristics, and climatic, topographic, ecological, and hydrogeological factors (to further refine and improve the accuracy of final products. The integration of remotely sensed data (i.e., spectrally derived indices and supervised image classification approach coupling with machine-learning algorithms), technologically advanced satellite image and ancillary data (i.e., topographic data like DEM) as well as integrate with expert knowledge can offer more conceptually comprehensive assessment of GDEs than assessments based solely on one approach. Hence, there are also recently available image-processing techniques such as Google Earth Engine (GEE) and image processing on cloud that simplifies the use of supervised machine-learning algorithms, and they are reported to have been under-utilised in remote sensing of wetlands in arid and semi-arid environment (Farda 2017; Gxokwe et al., 2020). These highlight the value of the different classification methods for mapping GDEs.

2.4. Impacts of climatic variability on groundwater-dependent ecosystems

Groundwater-dependent ecosystems are facing increasing pressure from climate change and anthropogenic activities such as water consumption and irrigation. These pressures modify groundwater levels and their temporal patterns and further threaten important ecosystem services particularly in arid regions (Kløve et al., 2011; Huntington et al., 2016; Morsy et al., 2017). The Intergovernmental Panel on Climate Change (IPCC) estimates that the global mean surface temperature has increased from 0.6 ± 0.2 °C since year 1861 and predicts an increase of 2–4 °C over the next 100 years.

Impacts of climate change amongst others include an increase in temperature that directly increases evaporation rates of water bodies and vegetation transpiration. Consequently, these changes influence precipitation amounts, timings, and intensity rates. Changes in precipitation thus, modifies hydrological regime of groundwater including, water quality and level including their temporal patterns (Kløve et al., 2011), groundwater temperature, storage and flow rates which threaten groundwater-dependent vegetation and other aquatic species (Fig. 4) (Kurylyk et al., 2014; Morsy et al., 2017). Increasing climate change, influences the availability of groundwater resources for socio-economic use and ecosystem services (van Engelenburg et al., 2018).

Study by Yagbasan (2016) found a decline in groundwater recharge by approximately 15% owing to a decrease in precipitation combined with increasing temperatures and evaporation observed between 1964 and 2011 in Küçük Menderes River Basin in western Turkey. Similarly, Meixner et al. (2016) study found 10–20% average decline in total recharge across the western United States when analysing the potential impact of climate change on groundwater recharge. Much of the decline was observed in the southern aquifers, with a wide range of uncertainty. Meixner et al. (2016) study demonstrates the importance of other factors influencing the recharge of groundwater like elevation and uncertainties associated with climate change.

Several studies (e.g., Kløve et al., 2011; Kurylyk et al., 2014; Meixner et al., 2016) further indicated that climate change also affects changes in the magnitude and timing of groundwater recharge. Thus, groundwater recharge is an important hydrological parameter, which may need to be estimated at spatial and temporal scales within a changing climate.

The impacts of climate change extent intensively depend on the landscape location, system scale and land use changes within the GDEs (Barron et al., 2012; Dwire et al., 2018). Dwire et al. (2018) emphasised that smaller scale is more likely to be affected by extreme climate change events like seasonal fluctuations in groundwater level recharge and increases evapotranspiration rates. Dwire et al. (2018) further indicated that areas associated with springs and small streams will probably experience change quickly owing to their small extent. Wetlands water level and groundwater recharge may also be affected by land use changes in the drainage basin and reduce surface runoff into wetlands (Van der Kamp and Hayashi, 1998). For instance, in regions where wetlands are situated near the agricultural areas, there will be reduction in surface runoff into the wetlands.

Evaluating the effect of climate change on GDEs through GIS and remote sensing approach can help in spatial and temporal information that is crucial for decision making in water management particularly in water scare regions. The availability of reliable remotely sensed data offers a unique opportunity for a detailed study of the impacts of climate change by gathering spatial explicit information on the condition, distribution, and spatial configuration of ecosystems (Thamaga et al., 2021). Thus, it is of importance to integrate remote sensing data with climate data to investigate the responses of ecosystems like wetlands to climate variability (Taylor et al., 2013). Furthermore, there has since been a marked rise in published research applying local to global-scale modelling, as well as ground-based and satellite monitoring, which has considerably enhanced our understanding of interactions between groundwater and climate change (Taylor et al., 2013). However, there is sufficient scientific studies on the impacts of climate change on groundwater-dependent ecosystems, however, they are less understood (Morsy et al., 2017).

2.5. Implications and future direction of remote sensing of groundwater-dependent ecosystems assessment

2.5.1. Limitations of satellite sensors in the assessment of groundwater-dependent ecosystems

Despite the availability of advanced robust remote sensing techniques and modelling algorithms, spatial and spectral assessments of GDEs at various scales remain a challenge. This is mainly due to the heterogeneity of GDEs (i.e., ecological water requirements, species diversity) that are difficult to capture especially when using medium to coarse spatial resolution sensors (Kaplan and Avdan, 2017; Gxokwe et al., 2020; Thamaga et al., 2021). For example, Gxokwe et al. (2020) and Landmann et al. (2010) indicated that satisfactory details of GDEs like wetland detection is still a challenge using the medium to low spatial resolution. The spatial resolution of these sensors has limitation on ecosystems that are small or damaged. Zomer et al. (2009), Glanville et al. (2016), and Gxokwe et al. (2020) highlighted that GDEs such as wetlands are missed, confused, or mismatched with other land-cover classes during classification. Furthermore, studies such as Münch and

Conrad (2007) and Gxokwe et al. (2020) further added that the confusion occurs particularly during dry season when targeted ecosystem vegetation is not healthy, resulting in similar spectral reflectance of soils and other land-cover classes. Thamaga et al. (2021) added that high similarity of vegetation spectral characteristics due to wetland fragmentation, also contributes to confusion in species mapping. Tian et al. (2016) further emphasised that the wetland classification from remotely sensed data is usually difficult due to the extensive seasonal vegetation dynamics and hydrological fluctuation.

Also, Münch and Conrad (2007) indicated that classification with Landsat images could not mark differences in riverine and wetland GDEs species due to the resolution of 30 m. The satellite sensor resulted in GDEs indicator species clumps being too fragmented, with spectral characteristics like the adjacent land cover, covering a small area. In a different study, Zomer et al. (2009) indicated that classification of different land cover types of results in most of Landsat pixels mixtures of several land cover types in various proportion due to the use of outdated medium resolution of less than 30 m. Therefore, these results demonstrate the role of finding the correct technologically advanced dataset, with the optimal spectral and spatial resolution, in the remote sensing community.

Furthermore, Landmann et al. (2010) indicated that when using MODIS time series in the landscape or ecosystem which is highly patchy, it results in the problem of mixed classes. Zomer et al. (2009) emphasised that it is usually difficult to obtain accurate map classifications where species are more randomly distributed or patchy at fine scales. Whereas Chen et al. (2014) study found a high overall accuracy and kappa coefficient of 80.2% and 0.73, respectively. However, the water produced significantly high omission error out of dominant land cover types; where about 30% of it was confused with the other land cover types, especially mudflat and emergent vegetation. This indicates the importance of correctly classifying dark objects such as a shadow and water since low to medium images face difficulty to spectrally distinguish them.

Despite the challenges of using low to medium spatial resolution sensors, the advancements in satellite developments have led to the introduction of new generation multispectral sensors in GDEs mapping that has demonstrated by the increased use of Sentinel-2 and Landsat-8 OLI resulting in the better GDEs applications such as wetland delineation since 2015 (Fig. 2). Sentinel dataset has great potential to be applied for the GDEs studies. Sentinel-2 is associated with finer spatial resolution of 10 m and higher spectral resolution with 13 spectral bands including red edge strategic bands that are crucial for extraction of wetland ecosystems (Gxokwe et al., 2020; Thamaga et al., 2021). Mahdavi et al. (2018) further emphasised that the red edge and near-infrared bands are the best optical bands for wetland delineation.

Sentinel data application on GDEs follow that of Landsat and our review assume that the advance with technology will be used more often in future due to the advanced characteristics (Fig. 2). Ludwig et al. (2019) observed the use of Sentinel-2 MSI imagery with an overall accuracy over 92% with different wetland types in Kenya/Uganda (Sio--Siteko Wetland), and Algeria (El-Kala Wetland). Similarly, Kaplan and Avdan (2017) demonstrated the capability of Sentinel-2 in mapping and monitoring wetlands in Sakarbasi spring in Eskisehir, Turkey. The results of the study show the successful mapping and monitoring of wetlands with overall accuracy assessment of 99% and kappa coefficient of 0.95 using the proposed object-based classification for extraction of the wetlands boundaries and the use of NDVI and NDWI for classifying the contents within the wetlands boundaries.

Study by Slagter et al. (2020) demonstrated the successful use of Sentinel-2 in wetland delineation of St. Lucia Wetlands in South Africa with an overall accuracy of 88.5%. The study also resulted in overall accuracy of 90.7% for mapping wetland vegetation types and 87.1% for mapping surface water dynamics. The advanced emerging of Sentinel therefore shows the potential for GDEs studies. Additionally, Rapinel et al. (2019) study used random forest classification of the Sentinel-1 and 2 time series and correctly delineated existing wetlands in with overall accuracy of 87% and kappa coefficient of 0.86 and this highlighted the importance of the advanced freely available Sentinel data series for GDEs assessments and monitoring.

With the machine-learning algorithms, RF as the commonly used algorithm (Table 1), has some limitations like other remote sensed data (Mutanga et al., 2012; Gxokwe et al., 2020). For instance, Mutanga et al. (2012) indicated that RF underestimated the high biomass values that fall beyond the range of the training dataset, and this demonstrated the need for integration with more groundtruthing with large datasets to improve the performance.

Similarly, with indices like commonly used NDVI and NDWI for GDEs identification, delineation, and mapping, research also encounters some challenges when they are being applied. For instance, previous studies reported the limitations of NDVI, which include poor performance in sparsely vegetated areas and its saturation in densely vegetated areas (Tian et al., 2016) or during peak phase particularly in grassland ecosystems (Mutanga et al., 2012). However, this drawback motivated researchers to develop and implement other indices, which outperform the NDVI, such as the NDVI-based indices (e.g., NDVI derived using red edge bands) that is very effective (Mutanga et al., 2012; Shoko et al., 2016).

Since each proposed method to delineate, map, assess and monitor GDEs and its aspects is associated with some pitfalls depending on its location, further research is needed to test and understand the integration of remotely sensed techniques to find solutions to the previously uncounted problems. We, therefore, recommend that an integration of supervised classification coupled with improved algorithms, improved indices and technologically advanced high resolution satellite images, ancillary data, and climate variables for better results in GDEs studies. Furthermore, more studies in delineation of GDEs in arid and semi-arid environments is required since the attention is mostly given to mapping of GDEs.

3. Conclusion

Studies (e.g., Hong et al., 2010; Gou et al., 2015; White et al., 2015; Nhamo et al., 2017; Liao et al., 2020) have been conducted on the GDEs in both arid and semi-arid environments, however, there is little attention on the spatial extent of the GDEs studied. The assessment of GDEs' spatial extent and long-time monitoring as well as climate variability influences are required for sustainable and effective management of GDEs. The remote sensing application in GDEs has gained considerable attention, since the emergence of multispectral and hyperspectral datasets that have enabled substantial research to be conducted over the past decades. Even though, the sensors are used in GDEs studies, there are significant challenges in discriminating different land cover classes during classification due to spectral mixing and poor data quality that might be attributed to poor spatial resolution and classification methods used. Small geographical coverage and acquisition costs of hyperspectral dataset imposes the challenge in their utilisation. Encountered challenges such as difficulty in discrimination of different land covers resulted in a shift towards the use of new advanced satellite imagery such as technologically advanced Sentinel. Sentinel datasets provide valuable opportunities in assessment and monitoring of GDEs. Additionally, the advancement in algorithms including vegetation, water and phenological indices have the potential to further increase the identification of the optimal remote sensing variables for the accurate identification, delineation, mapping, assessing, and monitoring of GDEs. Furthermore, there is a need for future studies to integrate new advanced satellite imagery integrating with additional data such as ancillary data like DEM with robust advanced machine-learning algorithms such as principal component analysis, support vector machine and cloud computing systems such GEE, artificial intelligence and Petascale image-processing techniques (Gxokwe et al., 2020; Bian et al., 2021) for well-informed management of GDEs.

Data availability statement

This work was solely based on metadata analysis (review of literature).

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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