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REVIEW

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Impacts of groundwater and climate variability on terrestrial groundwater dependent ecosystems: a review of geospatial assessment approaches and challenges and possible future research directions

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ABSTRACT

Terrestrial groundwater dependent vegetation (TGDV) are crucial ecosystems which provide important goods and services such as carbon sequestration, habitat, water purification and aesthetic benefits in semi-arid environments. Global climate change and anthropogenic impacts on surface water resources have led to increased competing claims on groundwater resources to meet an exponential water demand for environmental needs, agricultural and developmental needs. This has led to the unsustainable exploitation of groundwater resources, resulting in groundwater table declines, threatening the sustainability of TGDV. It is on this premise that the review aims to provide a detailed overview on the progress in remote sensing of TGDV. More specifically, the paper provides a background on TGDV and threats, and then further explores recent knowledge on vegetation response to groundwater variability and climate change impacts on TGDV. This review also focuses on recent progress in remote sensing and geographic information systems (GIS) based techniques for mapping and monitoring of TGDV and explores the available satellite products and delineation techniques. Finally, the challenges of remote sensing and future research direction are explored. To date, research on TGDV has gained considerable interest with the year 2020 resulting in the most scientific journal publications. Of significant importance is an increase in studies integrating field measurements, model-based techniques with remotely sensed estimates. Despite this progress, only 0.06% of groundwater dependent ecosystems (GDE) research has utilized remote sensing techniques in the past 20 years, with the top three publishing countries namely, Australia, USA, and China. The literature reveals that TDGV are highly heterogenous, complex ecosystems with unique responses to varying groundwater levels. The vegetation responses differ with the landscape, vegetation type, and seasonality at specific groundwater table thresholds. Despite significant progress in TGDV scientific research, further remote sensing studies are required to understand the annual and inter-annual vegetation response to groundwater variability at local scales. Further, climate impacts are difficult to discriminate from other influences

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such as disturbances, management, and anthropogenic activities. Moreover, new generation remote sensing products integrated with machine learning techniques have the potential to improve TGDV delineation. Despite these challenges, the development of cloud computing technologies such as google earth engine (GEE) and artificial intelligence (AI) provide advanced computer-processing capabilities for long-term monitoring and integration of multi-source datasets required to capture the effects of climate and groundwater variability on TGDV.

1. Introduction

Vegetation is a major component of terrestrial ecosystems and plays a vital role in energy flow, global carbon circulation, and the hydrological cycle (Zhao et al. 2012). It is estimated that 29% of global carbon emissions are decreased by terrestrial vegetation, thus reducing the accumulation of atmospheric carbon dioxide (Cernusak et al. 2019). Further, desertification processes are buffered by vegetation cover which maintain healthy natural environmental conditions (Lv et al. 2013). About 25–40 tonnes of the topsoil are eroded annually, due to vegetation clearing and cultivation as well as poor land management practices (Lv et al. 2013; FAO and ITPS 2015). During this process, 23–42 tonnes of phosphorous and nitrogen are transported from land, decreasing the soils ability to regulate nutrients, carbon, and water (FAO and ITPS 2015). In addition, terrestrial ecosystems provide other valuable ecosystem services such as flood control, water purification, pollinator habitats and recreational opportunities (Northcote and Atagi 1997; DeFries and Bounoua 2004; Gerten et al. 2004). A study by Blevins and Aldous (2011) revealed that 17% of terrestrial vegetation in the United States were groundwater dependent and provided habitat for 39% invertebrates. In arid regions, vegetation is a major contributor of soil organic material which fosters soil aggregation, water attenuation and nutrient accumulation (Lv et al. 2013). Furthermore, terrestrial ecosystems contribute to the economy through ecotourism, as a genetic hub for bioprospecting and in the preservation of biodiversity (Williams 2018). In 2011, the global economic value of ecosystem services was estimated at 124.8 trillion USD and the benefits of ecosystem conservation far exceed the costs of conservation (Costanza et al. 2014). Therefore, it is imperative that these ecosystems are protected and safeguarded from both natural and anthropogenic threats.

Climate variability affects water availability and temperature which in turn affect vegetation distribution, health and productivity (Barron et al. 2014; Kløve et al. 2014). Moreover, a third of the sub-Saharan African landscape consist of arid and semi-arid land, which experiences low rainfall with annual averages below 500 mm/yr. Only 2% of the average rainfall replenishes groundwater resources (Xu and Beekman 2003; Wada et al. 2010). Available surface water for terrestrial vegetation in these regions is highly limited. Therefore, groundwater is an important resource for growth, species composition and structure as well as the distribution of terrestrial vegetation (Liu 2011). In addition, some terrestrial vegetation in arid and semi-arid regions are maintained by direct and indirect access to groundwater and are collectively called groundwater dependent ecosystems (GDEs), terrestrial groundwater dependent vegetation (TGDV) and sometimes referred to as phreatophytes (Richardson and Kruger 1990).

Global environmental change, infrastructural developments and most importantly, over-exploitation of surface and groundwater resources has largely compromised the ecological integrity of ecosystems (McDowell and Moll 1992; Rouget et al. 2003). Global change has widespread impacts on the Earth's terrestrial ecosystems such as habitat loss and fragmentation, biological invasions, pollution, frequent droughts, and climate change which rapidly erode biodiversity and threaten ecosystem functioning (Lv et al. 2013). For instance, available water for terrestrial vegetation has been compromised due to escalating air temperature, prolonged droughts as well as over-exploitation of groundwater resources for anthropogenic activities (Krogulec 2018; Williams 2018). Subsequently, compromising the ability for TGDV to provide essential ecosystem goods and services (Rouget et al. 2003; Shadwel and Febraury 2017). Monitoring vegetation conditions and its response to environmental and global changes overtime improves our understanding of change processes, and help identify affected and vulnerable areas (Franklin et al. 2016). Information on the nature and types of vegetation-groundwater interactions will guide in policy-making, setting restrictions and developing strategic mechanisms for groundwater use within the region. In this regard, such information is also critical for supporting agendas on sustainable future development, for example the United Nations' (UN) Sustainable Development Goal 15 on 'Life on Land' (United Nations 2017). Vegetation condition and its response to global change, is specified in the lists of Essential Climate Variables (Bojinski et al. 2014) and Essential Biodiversity Variables (Pereira et al. 2013).

So far, groundwater-vegetation interaction monitoring has been limited by the trade-off that exists between the costs, efficiency, and level of detail offered by the techniques employed (Pérez Hoyos et al. 2016). Water chemistry indicators can give direct evidence to groundwater and vegetation interactions, which helps determine groundwater dependence (Colvin et al. 2007; Orellana et al. 2012). Other indicators are inferential and include; Eddy correlation, Bowen ratio, climatic indices, sap flow measurements, plant phenology, and leaf area index using ground-based equipment (specialized leaf area meter), to assess the influence of groundwater variability on vegetation (Colvin et al. 2003; Eamus et al. 2015a; Pérez Hoyos et al. 2016). While these methods provide highly detailed information, they are limited in that they are costly, resource intensive, and are unsuitable for catchment scale assessment of TGDV as they provide site specific information.

Remote sensing has emerged as an efficient monitoring tool that can provide crucial vegetation information on the status and response to environmental change at community or landscape scale (Wessels et al. 2008; Zhu 2017; Griffiths et al. 2019). The success of remote sensing in assessing vegetation response to water availability is well documented in literature (Colvin et al. 2003; Boulton and Hancock 2006; Münch and Conrad 2007; Rohde et al. 2017; Parker et al. 2018). However, there is a dearth in knowledge on the applicability of satellite and spectral data for determining groundwater-vegetation interactions, especially at species level. Current research primarily focuses on global groundwater availability and its impact on society with limited research focusing on ecosystem impacts. The state of knowledge on vegetation and groundwater interactions (Le Maitre et al. 1999; Colvin et al. 2003; Eamus and Froend 2006; Bertrand et al. 2012) and recent techniques for mapping and assessing TGDV (Eamus et al. 2015a; Pérez Hoyos et al. 2016; Klausmeyer et al. 2018) is well documented. Therefore, this review paper aims to develop a detailed synthesis on the progress and development of remote sensing integrated with geographic and information systems in assessing TGDVs over fine spatial and temporal scales. More specifically, the review objectives are to (a) provide a detailed background on GDEs, (b) give an overview of groundwater vegetation interactions, assess the effects of climate induced groundwater variability on terrestrial groundwater dependent ecosystems, (c) exemplify the application of remote sensing (RS) and geographic information systems (GIS) in identifying TGDV, (d) discuss the application potential role of RS and GIS in

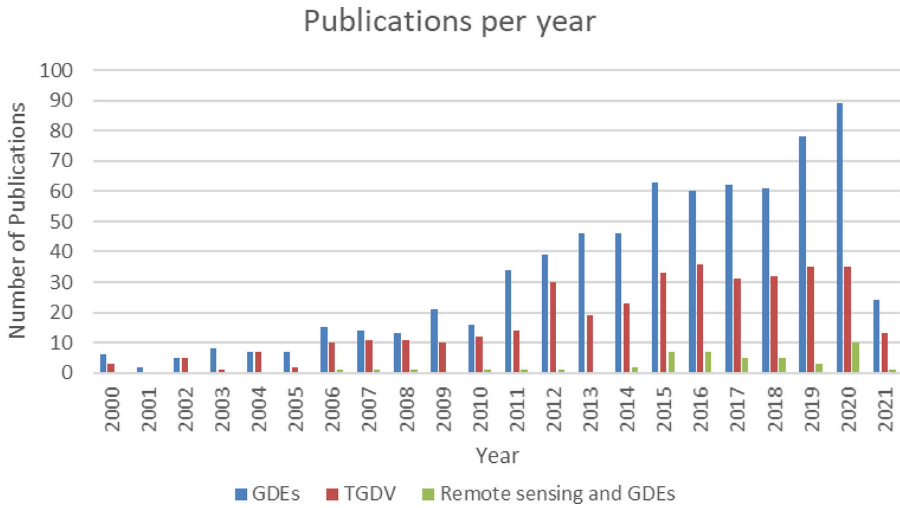

Figure 1. Number of publications on GDEs, TGDV and remote sensing of GDEs from 2000–2021.

future applications. The review will be a synthesis of the state of knowledge on the physical response patterns and threshold to acquire a comprehensive understanding on the degree of dependency of TGDV in arid environments. The assessment on recent techniques in identifying TGDV should prompt research on their potential to acquire information useful for TGDV management.

2. Literature search on groundwater dependent ecosystems

Relevant literature was acquired from several search engines such as google scholar, SCOPUS, and the Web of Science Core Collection (WoSCC). The expressions or topic search key words 'groundwater', 'groundwater dependent ecosystems', 'remote sensing', 'climate and groundwater', 'semi-arid and arid', 'phreatophytes' and 'terrestrial vegetation' were used to source literature from international peer-reviewed journals. The literature search range was from 2000–2021. An increase in the number of publications on groundwater dependent ecosystems and TGDV was noted (Figure 1). An additional source for literature was obtained through a rigorous assessment of references cited by the read papers. The literature search revealed that most publications largely focused on GDEs in general, 52% of those were on groundwater dependent vegetation with only 0.06% GDE incorporating remote sensing approaches.

3. Background on terrestrial groundwater dependent ecosystems

GDEs are communities of plants, animals and microorganisms that continuously or to some extent rely on the available groundwater to maintain their structure and functioning (Colvin et al. 2003; Kløve et al. 2011). GDEs may be maintained by direct or indirect access to groundwater and rely on the flow regime and chemical characteristics of groundwater (Hatton and Evans 1998). In this regard, when groundwater is limited, the functioning and structure of these ecosystems will be significantly altered. Various classification systems have been introduced based on the geographic setting in which they exist and the type of aquifer-ecosystem interface (Hatton and Evans 1998; Sinclair 2001; Colvin et al. 2007). A classification system with three basic classes based on the type of

Table 1. Summary of GDE classification according to Eamus et al. (2006).

Class	Ecosystem type	Members
i	Aquifer and cave systems	Stygofauna
ii	Ecosystems dependent on the surface expression of Groundwater	wetlands, river base flow, floodplains, riparian vegetation, low lying springs, mound springs
iii	Ecosystems dependent on the subsurface expression of Groundwater	Terrestrial Vegetation (Phreatophytes) and associated dependent flora and fauna

groundwater reliance was introduced by Eamus et al. (2006). The ecosystem classification method makes distinguishing and identifying groundwater dependence much easier and help to improve assessments for ecological risks. This review focuses on the terrestrial vegetation class and moreover the third class according to Eamus et al. (2006) which is classification system (Table 1).

TGDV is vital for biodiversity conservation and provides ecological resources in terrestrial ecosystems. Surface water and groundwater resource quality is maintained by groundwater dependent ecosystems (Pérez Hoyos et al. 2016). For example, vegetation aid in the attenuation and infiltration of surface water recharge into the aquifer. Terrestrial vegetation also play an important role in preventing soil erosion, provide vital habitats and act as corridors for migratory species (Kreamer et al. 2015). Terrestrial vegetation dependent on groundwater also acts as nutrient pumps and provide water to shallow rooted plants through hydraulic lift. In recreational areas such as national parks and fisheries, TGDV have economic and aesthetic value and provide ecosystem services such as runoff interception and carbon capture (de Klerk et al. 2012; Rohde et al. 2017). Therefore, research on GDEs has continued to develop, and has renewed interest due to increased natural and anthropogenic threats (Mawdsley et al. 2009; Chambers et al. 2013).

4. Threats to GDEs

Groundwater and associated ecosystems are increasingly threatened by global environmental change. These are planetary-scale changes in the Earths' systems (land, oceans, atmosphere, the planet's natural cycles and deep earth processes), which encompass changes in population, climate, resource use, land use and land cover (Noone et al. 2011). An ever-growing population, agricultural and economic development coupled with a changing climate have heightened the pressure on water resources. Climate change has decreased the reliability of surface water resources. As a result greater consideration has been given to groundwater as a resilient freshwater resource that can augment surface water resources (MacKay 2006; Kundzewicz and Döll 2009). Subsequently, groundwater exploitation has drastically increased with 33% of the global available freshwater supply obtained from groundwater (Vaux 2011; Richey et al. 2015). Moreover, global groundwater levels and volume have been reported to be on the decline (Richey et al. 2015). Modification of groundwater levels and the deviation of flow patterns from the natural groundwater regime due to anthropogenic influence and climate change have detrimental impacts on the structure and functioning of groundwater dependent ecosystems (Loomes et al. 2013; Kløve et al. 2014). Therefore, there is a need to develop management plans and policies, which promote the sustainable use of groundwater resources. Thereby mitigating negative environmental impacts such as storage depletion, saltwater intrusion, wetland and riparian habitat loss, land subsidence and reductions in stream flow. The influence of elevated groundwater demand is exacerbated by a rapidly changing climate (IPCC 2014). Long term variability in precipitation, temperature and wind threatens the health and abundance of GDEs which are influenced by the spatial and temporal availability of groundwater (Chambers et al. 2013). Global average surface temperatures have been estimated to increase by 0.84 degrees Celsius from 1880–2012. This rise has been associated with negative impacts on groundwater quantity and quality. Under all climate scenarios, global surface temperatures are expected to rise. Further, drought and flood events are predicted to increase in the 21st century (IPCC 2014). Reduced precipitation and elevated temperatures are detrimental on groundwater levels because of limited groundwater recharge and increased plant water demand (Noone et al. 2011; Kløve et al. 2014). There is a large body of literature on the anthropogenic impacts on GDEs (Muñoz-Reinoso 2001; Krause et al. 2007; Huang et al. 2020, 2019). However, little scientific research focus on the impacts of climate variability especially on terrestrial vegetation (Kløve et al. 2011; Taylor and Tindimugaya 2011; Barron et al. 2012). Groundwater and associated ecosystems are particularly vulnerable to climate impacts as the resource is unseen and there exists a time lag before the response is noticed (Morsy et al. 2017). In some instances, inappropriate management policies and strategies have also been linked to the degradation of TGDV (Morsy et al. 2017). Therefore, a comprehensive synthesis of knowledge on the interactions and response mechanisms for groundwater and dependent vegetation will ensure the formation of adaptive and holistic management plans.

5. TGDV response to groundwater variability

Groundwater availability affects the spatial distribution and abundance of terrestrial vegetation (Orellana et al. 2012). Numerous studies have been conducted to establish the relationship between groundwater and vegetation (Le Maitre et al. 1999; Rodriguez-Iturbe and Porporato 2005; Eamus et al. 2006). Vegetation response to fluctuating groundwater levels vary from non-observable change to alterations of the entire community structure based on their physical and biological properties (Naumburg et al. 2005). Several studies were conducted to characterize phreatophytes according to their relations to groundwater depth (Robinson 1958; Loheide et al. 2005). They reported that a decreasing water table could result in severe plant water stress, when plant roots cannot develop at sufficient rates or when the soil has low water holding capacity. Therefore, a declining water table limits the amount of water available for vegetation resulting in plant water stress and decreased plant productivity (Loheide et al. 2005; Naumburg et al. 2005). Further, Han and He (2020) reported a decrease in leaf intensity with a receding water table. Alternatively, a rising water table can flood plant roots resulting in anoxic stress (Naumburg et al. 2005). In another study, Meinzer (1929) reviewed TGDV species and characterized them according to their rooting depth. Results revealed that rooting density decreased with an increase in depth to groundwater, the physiological characteristics of TGDV included dimorphic roots, which allow them to exploit deep groundwater sources. It was also determined by Laio et al. (2009) that a decline in groundwater level may cause an increase in the plants rooting zone and an increased aerated soil profile suitable for new root development. Additionally, Zhang et al. (2020) modelled the spectral vegetation response to depth to groundwater table using the Tsallis Entropy Theory. It was reported that vegetation response was not uniform, different thresholds exist for grassland, shrubland, and forest vegetation. They found that at depths (>1 m) NDVI decreased with increasing depth, the alternative was also true, whereby NDVI declined with the rising water table at depths (<1 m) (Figure 2). Therefore, deeper water tables increase soil volume available for the storage of precipitation and hydraulically lifted water that can drastically increase the water available for plant use and growth. Also, in arid environments evapotranspiration can result in salt accumulation in soils, elevated groundwater levels

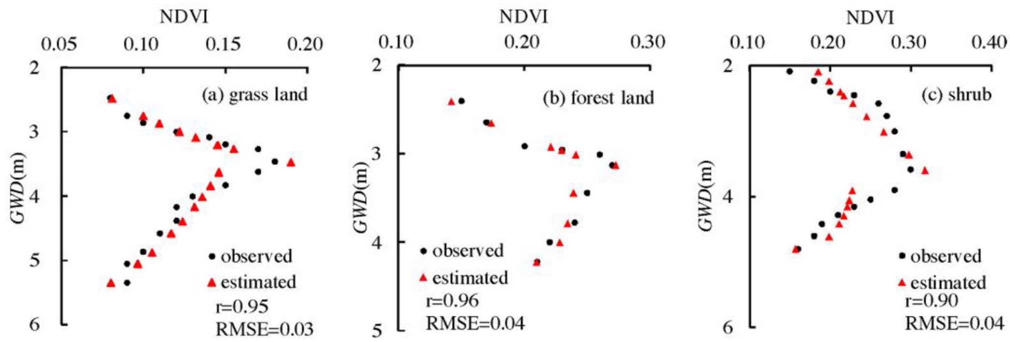

Figure 2. The relationship between NDVI of (a) grass land, (b) forest land, (c) shrub forest and groundwater depth based on Tsellis Theory in Ejina oasis in Hei (Source: Zhang et al. 2020).

limit the rooting zone to saline soils resulting in plant stress from the access saline water (Zhang et al. 2020).

A declining groundwater table has negative effects on plant physiology (Kath et al. 2014). During transpiration, water from the soil is pulled into the plant roots, then transported through the xylem to exit through the leaf surface. A deficit in soil moisture increases the potential pressure in the xylem to the extent where xylem cavitation occurs. When this threshold is reached, the amount of water transported to plant leaves is decreased which causes stomatal closure, a reduction in photosynthetic activity and then branch and crown mortality (Le Maitre et al. 1999; Kath et al. 2014). For instance, Huang et al. (2016) reported the decrease in the ratio of actual and potential evapotranspiration and the groundwater contribution associated with a declining groundwater table. Different plant species have different xylem cavitation resistances. It is reported that riparian vegetation cannot tolerate limited water supply and therefore are vulnerable to xylem cavitation as well as crown and branch mortality (Hancock et al. 2009; Kath et al. 2014; Johansen et al. 2018). On the other hand, xeric phreatophytes are drought tolerant vegetation species and can survive significant water table declines, despite losing some branches and leaf area. In a different study, Muñoz-Reinoso (2001) examined vegetation changes in Spain and the processes causing those changes. Results revealed species composition change into xerophytic communities due to decrease in water availability.

Ecosystems dependent on groundwater show low seasonal variability in vegetation health and transpiration rates when compared to non-GDEs. The effects of groundwater extraction on coastal GDEs in New South Wales were assessed by Adams et al. (2015). Their findings indicated that long-term changes in evapotranspiration from groundwater dependent vegetation occur seasonally. Evapotranspiration rates had low variability than that of vegetation dependent on surface water. Further, tree ring analysis have demonstrated that groundwater availability is an important factor on plant growth rates (Xia et al. 2012; Gholami et al. 2015). Hydraulic lift of moisture from deeper soil horizons provides water for shallow rooted herbaceous vegetation in times of water stress. Increasing groundwater depth has been associated with reduced plant growth rate. In addition, increased growth rates are associated with deeper water tables (Osmond et al. 1987; Sarris et al. 2007). Vegetation response to groundwater variability differ with the plants anoxic and water stress tolerance, water uptake capacity and the change in the distribution and size of the active rooting zone (Naumburg et al. 2005). The variable plant responses to groundwater variability mean that studies on TGDV should not take a generalized approach. However, valuable insights maybe attained from long-term understanding of the relationship between groundwater, TGDV and climate. Understanding the relationship on how groundwater availability affects vegetation and how that translates in terms of spectral signatures, has opened a more cost-effective, efficient methodology for the long term monitoring of TGDV (Barron et al. 2014). A detailed summary of recent studies that have exploited the spectral response of TDGV to assess their interaction with groundwater is provided in Table 2.

6. Climate impact on groundwater and dependent ecosystems

Changes in climate on annual or multi-decadal time scales have been seen to impact groundwater recharge and levels, depending on the aquifer size (Huss et al. 2010; Taylor and Tindimugaya 2011 201). Groundwater resources and associated vegetation depend on the distribution, amount, timing of precipitation, evaporation loss, and land use/landcover characteristics. An aquifer recharge potential depends on the groundwater level. Higher depths to the water table increase recharge potential and capture zones. Properties of the aquifer are also vital; smaller shallow unconfined aquifers are more sensitive to climate change, whereas larger confined aquifers are likely to have a more delayed response (Poiani et al. 1996; Scibek and Allen 2006). Confined non-renewable groundwater will be less sensitive to direct effects of climate change and variability but vulnerable to indirect effects of increased abstractions (Poiani et al. 1996; Scibek and Allen 2006). Subsequently, the degree at which TGDV are affected by climate variability depends on the aquifer characteristics, therefore, vegetation dependent on groundwater from small and shallow unconfined aquifers are more vulnerable to the effects of climate change (Poiani et al. 1996).

Climate warming can influence the availability and demand for groundwater resources thus affecting water available for sustaining ecological functions (Wattendorf et al. 2010; Barron et al. 2012). Further studies on the effects of climate on groundwater and associated vegetation are outlined in Table 3. Climate change impacts on general water resources have been widely investigated. Although impacts on groundwater resources have gained increasing attention over the years, however there is limited information on how TGDV are impacted. The seasonal distribution of precipitation and the temperature determine global climate zones and consequently the distribution of ecosystems, including TGDV (Walter et al. 1973). As they are adapted to specific water regimes, many ecosystems are vulnerable to climate change. For example, the study by Barron et al. (2012) noted that reduced surface water flows and longer dry periods, place TGDV at high risk with an estimated 19% decrease in current habitats in Australia. In addition, GDEs are increasingly likely to be threatened by groundwater abstraction. Extreme climate conditions change the hydrological regime, whereas the extent and seasonality of aquatic environments change the environmental conditions of TGDV (Kløve et al. 2014).

Climate induced changes in groundwater-surface water interactions will directly and indirectly affect wetlands and TGDV. Impacts on TGDV will likely result from changes in groundwater and surface water levels and will vary in intensity depending on the location of the landscape, scale of the system and land use changes. Local and intermediate systems are overly sensitive to groundwater level dynamics and increased temperatures lead to significant changes on these systems. Regional scales systems are less impacted by extreme events, seasonal fluctuations in groundwater level, recharge and increases evapotranspiration rates. For TGDV, a shift in local species composition will occur and decreased leaf density and primary productivity (Shafroth et al. 2000; Naumburg et al. 2005; Mawdsley et al. 2009). Further, Albano et al. (2020), demonstrated that vegetation

Table 2. Summary of recent studies on vegetation response to groundwater variability.

Application	Results	Reference
Hydrological controls on vegetation dynamics	The annual correlation between terrestrial water storage and NDVI is greater than that of rainfall and NDVI. monthly/seasonal correlation between rainfall and NDVI is greater than that of Terrestrial water storage and NDVI.	(Ndehedehe et al. 2019) West and Central Africa
Ecohydrological response	Response to water convergence: 80-day time lag for groundwater 4–7 years for vegetation	(Liao et al. 2020) China
Groundwater and GDE response to ecological water conveyance	Decrease in Depth to water (DT)T ($p < 0.05$) increase in NDVI ($p < 0.05$)	(Huang et al. 2020) China
GDE veg Index using Entropy theory	At DT >1 m) NDVI declines with increasing DT At DT <1 m) veg growth is restricted. NDVI correlation coefficient ($p < 0.01$)	(Zhang et al. 2020) Northern China
Estimate crop groundwater use	50% of irrigation water from groundwater. Seasonal crops more reliant on groundwater than perennial crops. Groundwater dependence increases with drying conditions.	(Hunink et al. 2015) Spain
Effects if Groundwater extraction on Et rates,	Long term change in Et close to extraction zones Sig change Et for Facultative communities ($p < 0.01$)	(Adams et al. 2015) New South Wales
Role of climate, GW availability and land management on veg vigor	Strong correlation between changes in plant vigor, precipitation, groundwater depth and evaporative demand.	(Huntington et al. 2016) United States
Veg response to groundwater drawdown	Vegetation ecophysiology negatively affected by groundwater drawdown.	(Antunes et al. 2018) Spain
Quantify groundwater contribution to *Salix psammophila* water use.	Groundwater contribution to evapotranspiration ration decreases with increasing depth to groundwater table.	(Huang et al. 2016) China
Demonstrate the role of hydraulic path in determining plant intensity.	Leafing intensity decreases with increasing groundwater table depth and plant height	(Han and He 2020) China
Effects of groundwater table decline on vegetation transpiration.	Transpiration rates decrease with declining groundwater table, critical depth is at 3.6 and 2.0 m depths. Groundwater depth correlation with evapotranspiration is 0.98	(Wang et al. 2020) China
Relationship between riparian vegetation and groundwater depth	Peak evapotranspiration rates at groundwater depths <3 m, and evapotranspiration values significantly lower at depths greater than 3 m.	(Lurtz et al. 2020) United States
Assess spatio-temporal evapotranspiration patterns of TGDV	Vegetation in shallow groundwater had high actual evapotranspiration rates as compared to those on deeper groundwater table, during the growth season.	(Sommer et al. 2016)
Influence of water table depth on evapotranspiration rates of in the amazon arc of deforestation	There were no differences in Evapotranspiration (ET), Land surface Temperature (LST) and Enhanced Vegetation Index (EVI) between vegetation and deep and shallow groundwater tables. Higher ET in shallow water table cops than those from deeper water tables during the dry season transition.	(O'Connor et al. 2019) Brazil
Show the extent of groundwater-vegetation interaction distribution	Positive relationships (shallow DT with high Plant productivity) for shrubs in mesic regions. Negative relationship (deep DT with high plant productivity) for forests in humid regions. Vegetation primary productivity and groundwater depth are correlated in more than two thirds of the global vegetated area.	(Koirala et al. 2017) Global

Table 3. Impacts of climate change on groundwater and associated ecosystems.

Application	Key Findings	Reference
Identify key hazards of climate change to develop a DGE risk assessment and decision-making framework	Ecosystem change affected by threshold tolerance of biota. TGDV threatened by groundwater decline due to low rainfall, increased water extraction and land use change to pine plantations. The temporal regime of temperature, groundwater depth were significant floristic change drivers.	(Chambers et al. 2013) Australia
Revealing Impacts of Climate Change on GDEs	Temperature and rainfall variability may be the primary threats to groundwater and GDEs. they reduce recharge and possibly increase groundwater withdrawal rates. Climate change further accentuated the degradation of spring biota by causing changes in the precipitation and evapotranspiration regimes.	(Morsy et al. 2017) Kuwait
Impacts of predicted climate change on groundwater flow systems: Can wetlands disappear due to recharge reduction?	Flow systems their hierarchy can change from nested flow systems to a set of single flow cells. Preservation of TDGV becomes a challenge under these conditions since long-term climate change could potentially have serious consequences, including wetland disappearance.	(Havril et al. 2018) Hungary
Assessing the role of climate and resource management on groundwater dependent ecosystem changes in arid environments.	Time series analysis clearly illustrates that there are strong correlations between changes in vegetation vigor, precipitation, evaporative demand, depth to groundwater, and riparian restoration. Trends in summer NDVI and groundwater level changes were found to be statistically significant, and interannual summer NDVI was found to be moderately correlated to interannual water-year precipitation.	(Huntington et al. 2016) United States
Impacts and uncertainties of climate/CO2 change on net primary productivity (NPP) in dryland vegetation.	Simulations showed consistent temporal pattern of the regional NPP during 2000–2014 that increased during 2008–2011 and decreased during 2005–2006 and 2013–2014. All simulations indicated that ecosystems at high altitudes ($> 47^\circ$) and were dominated by precipitation change.	(Fang et al. 2019) China

responds at long-time scales due to climate variability for riparian vegetation is driven by changes in groundwater and surface water dependence as compared to upland vegetation which are controlled by the gradient of aridity. Other studies also indicated that riparian vegetation had greater potential for groundwater dependence and were therefore sensitive to climate induced groundwater variability (Barron et al. 2012; O. Barron et al. 2014; Froend and Sommer 2010). Further, Kath et al. (2014) demonstrated that climate induced groundwater decline resulted in the deteriorated tree canopy and a shift in species composition from non-vascular to vascular plants.

Highly variable rainfall could result in the reduction of groundwater resources due to a higher frequency of low or high groundwater levels and sea water intrusion on coastal aquifers (Kumar 2013). Climate warming is predicted to alter the magnitude and timing of recharge (Scanlon et al. 2006; Kløve et al. 2014). This will result in a shift in the mean seasonal and annual groundwater levels depending on the rainfall distribution (Scanlon et al. 2006; Liu 2011). Long-term fluctuations in groundwater levels may also be a result of climate variability, in addition to land-use/landcover and anthropogenic induced alterations (Gurdak et al. 2007; Anderson and Emanuel 2008). Further, in areas with highly variable vegetation productivity, it is unclear or difficult to determine if climate variability is the main contributor to changes in vegetation productivity since these systems may gain access to precipitation, shallow groundwater, and surface water, varying across temporal and spatial scales. Therefore, discriminating the influence of climate variability from management practices, disturbance and other long-term human activities require long term monitoring (Hausner et al. 2018). A review of literature revealed that there are limited studies that focused on the impact of climate change (Shafroth et al. 2000; Hancock et al. 2009; Huang et al. 2020). Most studies mainly investigated impacts on surface water and little work has been done on groundwater, this may be because TGDV are highly complex and heterogenous systems that are influenced by multiple factors, which makes it hard to account for their status based on one factor. further, scientifically sound methodologies that include the integration of long-term data and cloud-computing techniques with which are characterized by high processing efficiency have the potential to mitigate these challenges (Huntington et al. 2016; Hausner et al. 2018).

7. Geospatial approaches for identifying and assessing TGDVs

The first step for effective management of TGDV begins with the knowledge on their location, distribution and areal extent (Rohde et al. 2017). Groundwater dependent ecosystems at catchment scale can be identified mainly through field or floristic assessment, numerical modelling and (geospatial) RS and GIS approaches (Eamus et al. 2015b; Glanville et al. 2016). The choice of the selected approach is dependent on the temporal and spatial extent of the study as well as available resources.

7.1. Field based methods for identifying GDEs

Groundwater use by phreatophytes has been assessed using field techniques: isotope analysis (Chapman et al. 2003; Eamus 2009; Cartwright et al. 2010), water balance methods (Colvin et al. 2003), and assessment of ground-based leaf area index (Hatton and Evans 1998; Eamus et al. 2006), vegetation rooting depth (Shafroth et al. 2000; Eamus et al. 2006) as well as depth to groundwater models (Eamus 2009; Hoogland et al. 2010). For instance, water flux measurements were used in determining groundwater use for deciduous black oak trees in California (Miller et al. 2010). The study indicated that black oak trees were obligate phreatophytes, with a groundwater uptake ranging from 4 mm/month to 25 mm/month. Dependence was most in the dry season with 80% of evapotranspiration from groundwater (Miller et al. 2010). In Australia, Jones et al. (2020) emphasized the importance of validating ecohydrological conceptual models of GDEs. While field techniques offer the most detailed insight on the nature, extent, and degree of groundwater ecosystem dependence, they are resource intensive, expensive and represent one-point in time (Eamus et al. 2015b). Therefore, they are ideal for testing and developing a conceptual understanding of TGDV and validating TGDV mapping (Gow et al. 2010; Glanville et al. 2016). However, although these studies demonstrate the importance of field based methods in GDEs characterization, most of these techniques lack spatial representation, which makes it difficult to upscale to larger areas or even complex in areas characterized with heterogeneous plant species.

7.2. Modelling approach for identifying GDEs

Numerical modeling provides simulations on groundwater-vegetation interactions that can be used to infer on ecosystem dependence on groundwater. Model-based methods have been used in conjunction with geospatial techniques (Münch and Conrad 2007) and field studies (Móricz 2010; Wu et al. 2015). These methods demonstrate a unique opportunity in understanding TGDVs as they integrate numerous dataset such as soil water data, groundwater depth, underlying hydrogeological conditions. Due to this ability, it was therefore noted that groundwater contribution and consumption could be modelled with low estimation errors of 0.007 (Móricz 2010; Wu et al. 2015). However, like any other method, these techniques have their own inherent challenges. For example, while numerical models provide innumerable insights; they are not entirely suitable for GDE mapping at catchment scale especially in data sparse areas. In addition, the numerical modelling approach can be time consuming and resource intensive.

7.3. Geospatial approach for identifying and assessing GDEs

Remote sensing and GIS techniques are robust methods for mapping TGDV at catchment scale. Their implementation however, requires basic knowledge on groundwater-ecosystem interactions and their spectral signature response (Barron et al. 2014). These approaches relate the presence of vegetation in unexpected areas and dark soils to high soil moisture content and groundwater availability (Brodie et al. 2002). Remote sensing technologies such as airborne sensors, Light detection and Ranging (LIDAR), Synthetic Aperture Radar (SAR) and space borne satellite sensors provide land surface information used in TGDV identification. For example, LIDAR produces high quality digital elevation models (DEM) used to obtain topographic indicators for locating GDEs such as aspect, slope and topographic wetness index (Pérez Hoyos et al. 2016). Based on the assumption that surface water is the surface expression of groundwater, the SAR provides information on seasonal fluctuations of the water table, surface water inundation, vegetation patterns etc. SAR data can help infer on TGDV water balance and hydrological boundaries. Satellite sensors are also widely used to obtain TGDV indicators such as vegetation pattern, evapotranspiration, and soil moisture saturation (Table 4). Remote sensing equates GDEs to a distinct ecosystem type (green islands), however groundwater dependence is one factor effecting ecosystem productivity.

Literature search has revealed an increase in the use of remote sensing and GIS approaches in eco-hydrogeology and related environmental studies (Tables 2 and 4). Remote sensing can offer new applications that can quickly and synoptically monitor and manage areas at different temporal and spatial resolutions. For example, remote sensing has support timely and spatially explicit assessment of groundwater dependent ecosystems, wetland, water quality monitoring and aquatic weeds etc. (Lv et al. 2013; Klausmeyer et al. 2018; Thamaga and Dube 2018; Zhang et al. 2020). Moreover, continual coverage of sensors provides both near real time and long-term data required for monitoring GDE response to changing groundwater regimes resulting from climate variability. As such, the use of satellite imagery has provided a reliable source of data that is intensively used in hydrology and ecology (Ali and Alandjani 2019). Several satellite sensors are suitable for extracting variables utilized in determining the location of GDEs and their probable response to groundwater fluctuations. Sensor suitability has influenced research needs in terms of spatial, temporal, radiometric and spectral resolution. While sensor resolution is an important consideration, the cost of the satellite imagery is usually the major limiting factor. In general, there exists a tradeoff between spatial resolution and acquisition; this is also true for spatial and temporal resolution. Very high-resolution sensors such as QuickBird, SPOT, IKONOS and Aerial photography with spatial resolutions <0.5 m are high cost. GDE potential have been estimated in Portugal, using SPOT 4 and 5 products (Marques et al. 2019). The high spectral resolution sensors are ideal for vegetation mapping and change detection at species specific and community level. MODIS is a low-cost sensor with low spatial resolution (250 m–1000 m) and multispectral and multi-date data sets are therefore useful for global scale evapotranspiration estimation, monitoring photosynthetic activity, vegetation mapping (Pérez Hoyos et al. 2016). MODIS products have

Table 4. Summary of key research on identifying potential TGDV.

Sensor Type	classifier	Key Findings	Limitations	
Landsat 5 TM	NDVI Principal Component	Compared Top of Atmosphere Reflectance and the Atmospherically corrected images (AC) for inflow dependent vegetation. TOA and AC are in good agreement, Kappa = 0.83. Both methods show high accuracies for capturing Known IDV, 85–91%.	Accuracy of the delineated IDV extent may vary due to difference in landscape characteristics and variations in vegetation type.	(Emelyanova et al. 2018)
Landsat 5 TM MODIS	MODIS (ET, MSSR, Pid) (NDVI, NDWI)	34% of Australian continent contains GDEs of those 5% have high potential for GDEs. Emphasized the need to integrate expert knowledge to gain a conceptual understanding for setting ruled in identifying potential GDEs.	Broad scale approach cannot identify GDEs <25 × 25 m. the method provides a snapshot and GDEs that may be in decline due to other factors may be missed. The GDE atlas requires regular updating.	(Doody et al. 2017) Australian /continent
WorldView-2 SPOT-7 Landsat 8 OLI	Maximum likelihood Classifier Object Based Image Classifier	SPOT-7 (Overall Accuracy= 69%) WorldView-2 (Overall Accuracy= 72%) GDEs are likely to occur in low land areas, and break of slope where groundwater is discharged to the surface.	High misclassification (Overestimation) error along the hillslopes during the wet period and higher misclassifications on the riparian zone during the dry season.	(Dlikilili 2019) South Africa
Landsat MS, TM, ETM, OLI	NDMI[a], NDVI Parameter-elevation Regressions on Independent Slopes Model (PRISM) precipitation data	(0.02%) of Landsat data not included. The map constitutes of layers of local datasets for identifying possible locations of GDEs, in a heavily modified environment.	Not all areas included updated landcover layers, gaps in groundwater depth datasets. GDEs are dynamic systems, therefore require regular updating.	(Klausmeyer et al. 2019) United States
Landsat 7 ETM MODIS	NDVI LAI K-means Classifier	Not all phreatophytes and wetlands are groundwater dependent, only 9% of phreatophytes had high groundwater use potential. 75% of identified GDEs were at soil depths below 45 cm.	The use of vegetation indicators led to overestimations. Cells with mixed vegetation coverage groundwater dependence was not accurately reflected. Resampling of MODIS images may have led to information loss. Lack of previous GDE studies hinders verification of results.	(Gou et al. 2015) Texas, United States
MODIS Terra 7	Standardized NDV K-means cluster classifier	Pixels were likely to be GDV where the groundwater table was shallow.	Standardized NDVI does allow for observing areas with low seasonal variability or inter annual variability. No quantitative method to validate results. Areas with low tree density, GDV were not captured.	(Páscoa et al. 2020)

aNDMI = Normalised difference moisture index.

been incorporated with other satellite products for TGDV assessments (Gou et al. 2015; Hunink et al. 2015; Doody et al. 2017; Huang et al. 2020; Liao et al. 2020). While MODIS datasets are widely used, they lack the spatial resolution suitable for TGDV delineation at scales below community level. The low spatial resolution has resulted in misclassification errors in heterogenous environments with mixed vegetation.

Medium special resolution (30 m) and multispectral sensors such as the LANDSAT series have been extensively used in landcover change detection, vegetation mapping and photosynthetic activity assessments applications at community level (Roy et al. 2016; Kalbus et al. 2006; Yates et al. 2010; O. Barron et al. 2014; Adams et al. 2015; Doody et al. 2017; Mtengwana et al. 2020; Shoko et al. 2016). Landsat series data are easily accessible and have an archive of historical data great for applications in developing economies (Dube et al. 2016). An extensive review on literature has revealed that the potential for new generation multispectral remote sensing products such as Landsat 8 Operational Land Imager (OLI) and Sentinel 2 have yet to be developed in mapping and monitoring TGDV. Landsat 8 OLI has improved signal to noise characteristics, improved calibration and higher radiometric resolution and spectrally narrower wavebands than the previous Landsat 7 ETM+ (Roy et al. 2016). The location of potential TGDV can be greatly improved through these new features. Sentinel 2 has a high spatial and temporal resolution of 10 m and 5-day revisit time, making it suitable for community level classification of GDEs. In Western Australia, Macintyre et al. (2020) assessed the efficacy of Sentinel 2 imagery for classifying multi-seasonal changes in vegetation for complex areas at fine scales. The classification scheme utilized 24 target classes and 60/40 split used for model building and validation. A comparison of the seasonal variations in vegetation indices, spectral bands, classification trees and principal component transformations were used as input for machine learning to separate classes. The study findings revealed that Sentinel 2 has a high potential to determine compositional vegetation characteristics with high accuracies. However, further investigations must be considered to determine the potential for vegetation indices derived from new generation sensors in delineating TGDV. Landsat 8 OLI and Sentinel 2 datasets are considered to provide spatially and site-specific timely information on GDEs that may be used in setting management decisions. However, their applicability is limited to the local and community levels. Advancements in remote sensing technological developments have resulted in the introduction of space and air borne hyperspectral sensors with fine spatial resolution (<10 m), with strategically positioned spectral bands such as panchromatic and red edge, as well as improved signal to noise ratio. For example, Worldview 2 has been used in assessing arid vegetation health in response to environmental variable such as depth to water, groundwater depletion and management practices at tree level (Chávez and Clevers 2012). Unmanned aerial vehicles (AUVs) is an emerging topic in vegetation studies that has the potential to bridge the gap between expensive satellite remote sensing, fieldwork, and classical manned photographs. AUVs combined with multispectral camera and hyperspectral remote sensors produce high quality datasets with user determined revisit period, suitable for long term monitoring of TGDV. AUVs have been used in determining vegetation distribution at individual species level with overall accuracies of 88.9–94.31% (Kaneko and Nohara 2014; Zhaoming 2020). As the field of AUVs is gradually expanding in vegetation studies, there is great potential for AUV application in TGDV mapping in complex heterogenous environments, due to the high spatial resolution (<1cm), and ability to increase pixel purity by adjusting the flying altitude. However, it is important to note that although Hyperspectral remote sensing data improves TGDV investigations, the datasets are often large and with the rapidly increasing archive of data for long term TGDV monitoring, potential challenges such as data storage, computational efficiency, and changes in band width from multigenerational satellite data arise. Google Earth Engine (GEE) cloud computing environmental platform and Climate Engine have emerged as the solution. GEE, stores Petabyte scale multi sensor and GIS databased vector datasets, parallelized cloud computing within GEE. The strength of Cloud Based computing is that it does not need high computer processing power or the latest software, which opens new research opportunities for resource poor regions to engage in TGDV analysis at the advanced nations (Mutanga and Kumar 2019; Gxokwe et al. 2020). While there are advancements in remote sensing and vegetation analysis, there remains a gap in assessing their effectiveness in TGDV investigations.

Another widely used remote sensing technique for mapping groundwater dependent ecosystems is through satellite-derived indices such as the Normalized Difference Vegetation Index (NDVI), which determines vegetation health and photosynthetic activity, as well as other indicators of vegetation density and moisture condition. Previously employed vegetation indices include the Enhanced Vegetation Index (EVI), Leaf Area Index (LAI), the Tasseled Cap Wetness Index (TCWI) and the Normalized Difference Wetness Index (NDWI). A wide range of studies (Roy et al. 2016; Kalbus et al. 2006; Yates et al. 2010; O. Barron et al. 2014; Adams et al. 2015; Doody et al. 2017; Gu et al. 2007; Hunink et al. 2015) have demonstrated the capabilities of indices in locating TGDV. For example, the study by Gow et al. (2010) collated multiple remotely sensed information from MODIS-EVI, SRT DEM, and water table surface to identify and monitor GDEs within the Hat Head National Park. In Australia, Barron et al. (2014) proposed a method for identifying GDEs from Landsat-TM derived indices. Mapping had high producer accuracy ranging from 59% to 91% increasing from regional to local scales. Results showed TGDV with permanent access to groundwater had no significant change in seasonal TGDV size. However, a substantial reduction of $26-56\%$ in total TGDE size is observed over the 10-year period. Mapping demonstrated good agreement with field data were TGDV were associated with riparian vegetation, terrestrial vegetation with access to shallow groundwater depths ($\sim$6 m) and springs. Expert knowledge, field techniques and remote sensing techniques were used to develop a catchment scale mapping method of GDEs in Queensland, Australia (Glanville et al. 2016). They produced a catchment scale map of GDE, which can be scaled up or down, and the study emphasized the value in integrating local experts' knowledge with available spatial data and information. While remote sensing data indices are a robust methodology, the literature indicated that TGDV identification can be substantially improved by the selection of appropriate classification technique. Given, these indices perform differently in different environments due to pixel mixing, cloud cover, shadows in mountainous and built-up areas. However, their performance can also be significantly improved by the sensor's spectral characteristics such as the availability of red edge, near infrared II and panchromatic bands.

8. Available GDE classification algorithms

Spectral discrimination of GDV types in complex environments is challenging as different vegetation types may have similar spectral characteristics, alternatively they may show different spectral signatures. Image classification can aid group image pixels into meaningful clusters. Automatic image classification can be done in two ways, unsupervised or supervised, parametric or non-parametric classification. Unsupervised classifiers such as IsoData and K-means, use clustering mechanisms to group satellite image pixels into unlabeled classes, which are later assigned meaningful labels to produce a well-classified image (Ismail 2009). Unsupervised Classification techniques have been extensively used in mapping and assessing potential GDEs (O. Barron et al. 2014; Davies et al. 2016; Gou et al. 2015; Münch and Conrad 2007; Páscoa et al. 2020). Supervised classification requires input from the analyst in the form of training datasets. For supervised classifiers, classification accuracy depends on the representativeness of the training sample (Ismail 2009). When training cannot account for the complex spatial variations, statistical based (unsupervised) clustering can produce better results (Rozenstein and Karnieli 2011). Common supervised classifiers are Artificial Neural Networks (ANN), Decision tree (DT), Maximum likelihood classifier, K-nearest neighbor etc. The Maximum Likelihood Classifier (ML) is the most extensively used supervised classification algorithm. The application of pixel classifiers to mixed pixel images often produce unsatisfactory classification results due to poor spectral and spatial resolutions (Gow et al. 2010; Barron et al. 2012; Glanville et al. 2016). Increased availability of higher resolution images coupled with the development of machine learning algorithms is predicted to significantly improve classification accuracies (Pérez Hoyos et al. 2016). These include support vector algorithm (SVM) (Boser et al. 1992), ANN (Paola and Schowengerdt 1995) and Random Forest (RF) classifiers. The random forest or random decision forest is a learning method for classification operated by construction of a multitude of decision trees during training and the output is class made of the predicted mean of the individual tree (Raczko and Zagajewski 2017). The advantage to the RF is the short classification time and the method is resistance to overfitting of training datasets (Sabat-Tomala et al. 2020). A previous study by (Pérez Hoyos et al. 2016) compared the classification and regression tree (CART) and RF for estimating TGDV potential. Results revealed the RF classifier was superior to CART in terms of estimates, accuracy of training data, and sensitivity.

SVM produces significant accuracies with little computation power, they work well on small testing data and noisy datasets (Song et al. 2012). Classes are produced from training data models which transforms the space into an optimal hyperplane in the multidimensional of the feature space which separates features into classes with the greatest margin of separation (Mountrakis et al. 2011). The SVM classifier has an advantage on ANN in that they are simple to use, reliable, stable and has a faster processing speed (Raczko and Zagajewski 2017). Reducing training data sample size per sample compromises classification accuracies, however the SVM seems to be insensitive to this effect (Shafroth et al. 2000; Mountrakis et al. 2011). In South Africa Cooper (2010) investigated the potential for SVM recursive feature eliminator (RFE) approach to detect the presence of *Solamum mauritianum* (Bugweed) alien plant within a forest plantation. The SVM-RFE produced an outstanding classification accuracy of 93% and a skills statistics value of 0.83. ANN are complex models that are inspired by biological neural networks to develop classification rules. Raczko and Zagajewski (2017) studied tree species composition in Poland using the SVM, RF and AAN algorithms for tree species classification. The ANN outperformed the other learning algorithms with 77% overall accuracy while the SVM and RF produced 68% and 62.5% respectively. Literature reveals that unsupervised classification techniques are reliable and widely developed (Pérez Hoyos et al. 2016; Peters et al. 2008) while other studies have indicated the potential for machine learning algorithms in GDE assessment (Peters et al. 2007; Klausmeyer et al. 2019; Páscoa et al. 2020). These methods demonstrate a great potential in retrieving GDEs information with a reasonable accuracy. However, their performance is also dependent on the scale of application, satellite spectral and spatial data characteristics. Further, the supervised machine learning algorithms produced great results, although significant limitations have been reported. For example, ANN and SVM are not easily automated and require adjustments to several parameters; whereas models such as the RF have been reported to overfit for datasets as small as the size of a tree, which can take up memory. Thus, cloud image processing simplifies the issues related to supervised machine learning algorithms, however the literature shows that these techniques are underused especially in TGDV assessments (Gxokwe et al. 2020).

9. Challenges in remote sensing of GDEs

Several studies have noted various limitations in the remote sensing approach for detecting and mapping groundwater dependent ecosystems. Remote sensors can detect land surface features such as temperature, vegetation and landcover, therefore information on groundwater is only from indirect inferences. Groundwater-vegetation can only be inferred from indicator variables such as vegetation, temperature and surface water (Barron et al. 2014). As such, information gathered are only estimates that mainly indicate potential TGDV thus the results should be validated using field data. Although numerous works have been done in regional GDEs mapping, most of the studies have not been validated through ground-truthing. For instance, Jones et al. (2020) Investigated groundwater dependent vegetation communities using stable isotope and found that 75% of reported GDE site were using groundwater. Remote sensing offers a snapshot of GDEs, those outside the range may not be identified. There is often a lag between changes in water availability and vegetation response (Gow et al. 2010). Further, ecosystems dependent on groundwater affected by a drought may not be identified as TGDV if their phenology was in decline at the time. Remote sensing is suitable for places that are minimally modified, in urban or cultivated areas vegetation greenness may be attributed to the return in irrigation, runoff and dam releases. Also, there is minimal integration between field and chemical assessment with remote sensing datasets as a result remote sensing and GIS derived information is being undervalued and underused. Remote sensing identifies TGDV based on the principle that ecosystems that are greener than their surroundings during dry periods are likely to be maintained by groundwater, therefore it is suitable for areas with distinct wet and dry seasons (Barron et al. 2012). This method has been criticized because vegetation greenness may be a result of other factors (Glanville et al. 2016). For example, wild fires may results in green islands, as resistant forest vegetation are surrounded by fire prone vegetation (Bowman 2000; Glanville et al. 2016). Further, remote sensing generates GDE maps with little or no information on how each ecosystem is connected to groundwater within the landscape.

The potential for remote sensing applications in GDE monitoring has not been fully explored. This is attributable to the inaccessibility of remote sensing products of Hyperspectral images such as LIDAR, Ikonos and Quickbird with less than 5 m spatial resolution. This has been primarily attributed to their high acquisition costs, the low temporal resolution and smaller swath width. The freely available medium resolution products such as Landsat are limited in the level of detail that can be achieved for assessing TGDV. For instance, some groundwater dependent communities are at sub-pixel level (<30 m) and may be masked out in mixed feature pixels. Thus, TGDV monitoring, and assessment can benefit from a multidisciplinary approach through the integration of eco-hydrological data, geology, soil information, land use and land management practices, soil characteristics, groundwater flux and recharge rates. So far, however such collaborations are limited. Cloud computing techniques provide access to multi-sensor datasets and computing efficiency that can enhance TGDV detection and monitoring especially in resource poor regions at low costs. However, challenges due to unreliable network or internet connectivity, unskilled personnel, and the lack of high-performance computing power limit their applicability in underdeveloped countries where it is needed the most.

10. Possible future direction in remote sensing and GIS applications for GDEs

Several strides have been made in mapping and monitoring TDGV and its response to groundwater variability using satellite data. There is still however limited information on long term monitoring of vegetation response to changing groundwater regimes especially associated with climate change. Investigating the impacts on climate change is limited by the high complexities of TGDV, where multiple factors influence the plants phenology, distribution, and chemical processes. Most of such studies are dominant mainly in Australia, the United States and China; however, there is a dearth in knowledge in resource poor areas such as the arid regions of Africa. The major limitation is that that these methods for GDV identification or delineation is likely to change with differing landscapes, vegetation types and climates; therefore, geospatial techniques need to be evaluated under diverse environmental conditions. Further, determining whether changes in groundwater regime and associated vegetation are products of climate change requires long-term (>50 years) monitoring (Kløve et al. 2014). In addition, to fully understand these ecosystems, groundwater-vegetation responses should be monitored seasonally at catchment or species-specific scales. There have been huge developments in geospatial technologies such as Hyperspectral and AUVs datasets providing new opportunities for species level vegetation monitoring, however they have been poorly utilized in TGDV assessments. Hyperspectral drones, AUVs and world View data potential should be investigated for TGDV assessments. This will provide detailed information useful for decision makers when drawing up strategic catchment management plans. As groundwater dependence is one characteristic of GDEs mapping, there is therefore a need to find the best ancillary (Variables) data and predictive models that can be integrated with freely available datasets. Further, Landsat series and MODIS datasets are the widely used in TGDV mapping, however the major limitation is their low spatial resolution (>30 m). Despite these limitations, the Landsat series has a large historical archive that has not been fully exploited. The introduction of advanced cloud computing methods such as GEE, peta scale image processing and artificial intelligence (AI) have the potential to overcome limitations of spatial resolution, and temporal range through the integration of hyperspectral and coarse scale multispectral datasets. Cloud computing methods can provide new insight in TGDV monitoring and offer new opportunities to resource poor nations where, TDGV investigations were hindered by the cost of acquiring these datasets. Further, more studies integrating field methods with remote sensing in assessing TGDV should be prioritized as this will increase the reliability of the derived spatial and thematic TGDV maps. When there is a large body of local information on TDGV occurrence, geospatial methods can be adequately evaluated and indicate areas of improvement. Further, machine-learning algorithms such as ANN, SVM, and regression tree-based classifiers need to be explored for TGDV assessments and distribution mapping.

11. Conclusions

Groundwater resources are increasingly deteriorating and constantly under threat due to global change, and improved abstraction impacts by vegetation. Literature has revealed the effects of a reduced groundwater table in areas where GDEs are dominant. There is a large base of literature on TGDV response to groundwater variability. Most of these studies have shown that TGDV have responded variably to groundwater availability based on the plant physiological characteristics, such as the plant rooting depth etc. Literature shows that the major responses to a declining groundwater table are reduced photosynthetic rates, plant productivity, reduced leaf area and the change in species composition and distribution. However, TDGV are also affected by the timing/groundwater regime and this needs to be explored further especially with the advent of climate change. Elevated surface temperature and low rainfall are associated with groundwater depth decline leading to TGDV degradation and floristic change. The research reveals the effects of climate variability on TDV are difficult to isolate. Therefore, further long-term climate-vegetation interaction research is required. Remote sensing has emerged as a popular method for TDGV mapping and assessment, because of the efficiency, unique spatial, spectral, and temporal Characteristics that allow TGDV assessment at different scales. While readily available datasets (MODIS and Landsat) have provided critical insights on the state of GDEs, they are however limited by the poor (low) spatial and spectral characteristics. There is therefore a need to enhance remote sensing potential by integrating multiple indicator variables in TGDV investigations. In addition, new generation sensors (Landsat 8 OLI and Sentinel 2) with improved spatial and temporal resolutions and advances in Machine Learning algorithms can further improve the potential for identifying and monitoring groundwater dependent ecosystem. Moreover, the potential of integrating multisource datasets such as drones, AUVs or Worldview to calibrate TGDV models should assessed. Emerging cloud-based image computing techniques such as Google Earth Engine (GEE) can significantly improve the long-term monitoring of TGDV. Moreover, with the effects of climate change there is a need to adequately delineate vulnerable groundwater dependent vegetation communities to ensure their sustainability when allocating groundwater resources for anthropogenic use.

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Data availability statement

Data sharing is not applicable to this article as no new data were created or analyzed in this study.

References

Adams M, Smith PL, Yang X. 2015. Assessing the effects of groundwater extraction on coastal groundwater-dependent ecosystems using satellite imagery. Mar Freshwater Res. 66(3):226–232.

Albano CM, Mcgwire KC, Hausner MB, Mcevoy DJ, Morton CG, Huntington JL. 2020. Drought sensitivity and trends of riparian vegetation vigor in Nevada, USA (1985–2018). Remote Sens. 12(9):1362.
Ali S, Alandjani G. 2019. Mapping land cover damages in mega floods through integration of remote sensing and GIS techniques. 3C Tecnología. 29(2):258–275.
Anderson WP, Emanuel RE. 2008. Effect of interannual and interdecadal climate oscillations on groundwater in North Carolina. Geophys Res Lett. 35(23):1–4.
Antunes C, Chozas S, West J, Zunzunegui M, Diaz Barradas MC, Vieira S, Máguas C. 2018. Groundwater drawdown drives ecophysiological adjustments of woody vegetation in a semi-arid coastal ecosystem. Glob Chang Biol. 24(10):4894–4908.
Barron OV, Emelyanova I, Van Niel TG, Pollock D, Hodgson G. 2014. Mapping groundwater-dependent ecosystems using remote sensing measures of vegetation and moisture dynamics. Hydrol Process. 28(2):372–385.
Barron O, Froend R, Hodgson G, Ali R, Dawes W, Davies P, Mcfarlane D. 2014. Projected risks to groundwater-dependent terrestrial vegetation caused by changing climate and groundwater abstraction in the Central Perth Basin, Western Australia. Hydrol Process. 28(22):5513–5529.
Barron O, Silberstein R, Ali R, Donohue R, McFarlane DJ, Davies P, Hodgson G, Smart N, Donn M. 2012. Climate change effects on water-dependent ecosystems in south-western Australia. J Hydrol. 434–435:95–109.
Bertrand G, Goldscheider N, Gobat JM, Hunkeler D. 2012. Review: from multi-scale conceptualization to a classification system for inland groundwater-dependent ecosystems. Hydrogeol J. 20(1):5–25.
Blevins E, Aldous A. 2011. The biodiversity value of groundwater-dependent ecosystems: a cataloguing of United States federally listed species that depend on groundwater. Wetland Sci Prac. 28:18–24.
Bojinski S, Verstraete M, Peterson TC, Richter C, Simmons A, Zemp M. 2014. The concept of essential climate variables in support of climate research, applications, and policy. Bull Am Meteorol Soc. 95(9): 1431–1443.
Boser BE, Guyon I, Vapnik V. 1992. A training algorithm for optimal margin classifiers. In Proceedings of the Fifth Annual Workshop on Computational Learning Theory, 144–152. ACM Press.
Boulton AJ, Hancock PJ. 2006. Rivers as groundwater-dependent ecosystems: a review of degrees of dependency, riverine processes and management implications. Aust J Bot. 54(2):133–144.
Bowman DMJS. 2000. Rainforests and flame forests: the great Australian forest dichotomy. Aust Geogr Stud. 38(3): 327–331.
Brodie RS, Green R, Graham M. 2002. Mapping groundwater-dependent ecosystems: a case study in the fractured basalt aquifers of the Alstonville Plateau, New South Wales, Australia. In: Balancing the Groundwater Budget.
Cartwright I, Weaver T, Cendón DI, Swane I. 2010. Environmental isotopes as indicators of inter-aquifer mixing, Wimmera region, Murray Basin, Southeast Australia. Chem Geol. 277 (3): 214–226.
Cernusak LA, Haverd V, Brendel O, Le Thiec D, Guehl JM, Cuntz M. 2019. Robust response of terrestrial plants to rising CO_2. Trends Plant Sci. 24(7):578–586.
Chambers J, Nugent G, Sommer B, Speldewinde P, Neville S, Beatty S, Chilcott S, Eberhard S, Mitchell N, D'Souza F, et al. 2013. Adapting to climate change: a risk assessment and decision making framework for managing groundwater dependent ecosystems with declining water levels: development and case studies. Final Report.
Chapman JB, Lewis B, Litus G. 2003. Chemical and isotopic evaluation of water sources to the fens of South Park, Colorado. Env Geol. 43(5):533–545.
Chávez R, Clevers JGPW. 2012. Object-based analysis of 8-bands WorldView2 imagery for assessing health condition of desert trees. CGI Rep. 2012-001 15.
Colvin C, Le Maitre D, Hughes S. 2003. Assessing terrestrial groundwater dependent ecosystems in South Africa, Water Research Commission.
Colvin C, Maitre DL, Saayman I, Hughes S. 2007. An introduction to aquifer dependent ecosystems in South Africa. Natural Resources and the Environment, Water Research.
Cooper M. 2010. Advanced Bash-Scripting Guide An in-depth exploration of the art of shell scripting Table of Contents. Okt 2005 Abrufbar Uber Httpwww Tldp orgLDPabsabsguide Pdf Zugriff. 1112 2005 2274, 2267–2274.
Costanza R, de Groot R, Sutton P, van der Ploeg S, Anderson SJ, Kubiszewski I, Farber S, Turner RK. 2014. Changes in the global value of ecosystem services. Glob Environ Chang.
Davies T, Everard M, Horswell M. 2016. Community-based groundwater and ecosystem restoration in semi-arid north Rajasthan (3): evidence from remote sensing. Ecosyst Serv. 21:20–30.
de Klerk AR, de Klerk LP, Chamier J, Wepener V. 2012. Seasonal variations of water and sediment quality parameters in endorheic reed pans on the Mpumalanga Highveld. WSA. 38(5):663–672.

DeFries R, Bounoua L. 2004. Consequences of land use change for ecosystem services: a future unlike the past. GeoJournal. 61(4):345–351.
Dlikilili S. 2019. Investigating the groundwater dependence and response to rainfall variability of vegetation in the touws river and catchment using.
Doody TM, Barron OV, Dowsley K, Emelyanova I, Fawcett J, Overton IC, Pritchard JL, Van Dijk AIJM, Warren G. 2017. Continental mapping of groundwater dependent ecosystems: a methodological framework to integrate diverse data and expert opinion. J Hydrol Reg Stud. 10:61–81.
Dube T, Mutanga O, Shoko C, Samuel A, Tsitsi B. 2016. Remote sensing of aboveground forest biomass: a review. Trop Ecol. 57(2):125–132.
Eamus D. 2009. Identifying groundwater dependent ecosystems A guide for land and water managers. Braddon, Australia: Australian Government Land & Water Australia.
Eamus DA, Froend RB. 2006. Groundwater-dependent ecosystems: the where, what and why of GDEs. Aust J Bot. 54(2):91–96.
Eamus D, Froend R, Loomes R, Hose G, Murray B. 2006. A functional methodology for determining the groundwater regime needed to maintain the health of groundwater-dependent vegetation. Aust J Bot. 54(2):97.
Eamus D, Zolfaghar S, Villalobos-Vega R, Cleverly J, Huete A. 2015a. Groundwater-dependent ecosystems: recent insights, new techniques and an ecosystem-scale threshold response. Hydrol Earth Syst Sci Discuss. 12:4677–4754.
Eamus D, Zolfaghar S, Villalobos-Vega R, Cleverly J, Huete A. 2015b. Groundwater-dependent ecosystems: recent insights from satellite and field-based studies. Hydrol Earth Syst Sci. 19(10):4229–4256.
Emelyanova I, Barron O, Alaibakhsh M. 2018. A comparative evaluation of arid inflow-dependent vegetation maps derived from LANDSAT top-of-atmosphere and surface reflectances. Int J Remote Sens. 39(20):6607–6630.
Fang X, Chen Z, Guo X, Zhu S, Liu T, Li C, He B. 2019. Impacts and uncertainties of climate/CO2 change on net primary productivity in Xinjiang, China (2000–2014). A Modelling Approach Ecol Modell. 408:108742.
FAO and ITPS. 2015. The role of soils in ecosystem processes. Status of the World's Soil Resources - Main Report.
Franklin J, Serra-Diaz JM, Syphard AD, Regan HM. 2016. Global change and terrestrial plant community dynamics. Proc Natl Acad Sci USA. 113(14):3725–3734.
Froend R, Sommer B. 2010. Phreatophytic vegetation response to climatic and abstraction-induced groundwater drawdown: examples of long-term spatial and temporal variability in community response. Ecol Eng. 36(9):1191–1200.
Gerten D, Schaphoff S, Haberlandt U, Lucht W, Sitch S. 2004. Terrestrial vegetation and water balance - Hydrological evaluation of a dynamic global vegetation model. J Hydrol. 286(1–4):249–270.
Gholami V, Chau KW, Fadaee F, Torkaman J, Ghaffari A. 2015. Modeling of groundwater level fluctuations using dendrochronology in alluvial aquifers. J Hydrol. 529(3): 1060–1069.
Glanville K, Ryan T, Tomlinson M, Muriuki G, Ronan M, Pollett A. 2016. A method for catchment scale mapping of groundwater-dependent ecosystems to support natural resource management (Queensland, Australia). Environ Manage. 57(2):432–449.
Gou S, Gonzales S, Miller GR. 2015. Mapping potential groundwater-dependent ecosystems for sustainable management. Ground Water. 53(1):99–110.
Gow L, Brodie RS, Green R, Punthakey J, Woolley D, Redpath P, Bradburn A. 2010. Identification and monitoring GDEs using MODIS time series: Hat Head National Park – a case study. Groundw. 2010 Chall. Sustain. Manag.
Griffiths P, Nendel C, Hostert P. 2019. Intra-annual reflectance composites from Sentinel-2 and Landsat for national-scale crop and land cover mapping. Remote Sens Environ. 220: 135–151.
Gu Y, Brown JF, Verdin JP, Wardlow B. 2007. A five-year analysis of MODIS NDVI and NDWI for grassland drought assessment over the central Great Plains of the United States. Geophys Res Lett. 34(6):L06407.
Gurdak JJ, Hanson RT, McMahon PB, Bruce BW, McCray JE, Thyne GD, Reedy RC. 2007. Climate variability controls on unsaturated water and chemical movement, high plains aquifer, USA. Vadose Zo J. 6(3): 533–547.
Gxokwe S, Dube T, Mazvimavi D. 2020. Multispectral remote sensing of wetlands in semi-arid and arid areas: a review on applications, challenges and possible future research directions. Remote Sens. 12(24):4190.
Han L, He D. 2020. Leafing intensity decreases with increasing water table depth and plant height in Populus euphratica, a desert riparian species. Acta Oecologica. 109:103672.

Hancock PJ, Hunt RJ, Boulton AJ. 2009. Preface: hydrogeoecology, the interdisciplinary study of groundwater dependent ecosystems. Hydrogeol J. 17(1):1–3.
Hatton T, Evans R. 1998. Dependence of ecosystems on groundwater and its significance to Australia. L Water Resour. 12(98):77.
Hausner MB, Huntington JL, Nash C, Morton C, McEvoy DJ, Pilliod DS, Hegewisch KC, Daudert B, Abatzoglou JT, Grant G. 2018. Assessing the effectiveness of riparian restoration projects using Landsat and precipitation data from the cloud-computing application ClimateEngine.org. Ecol Eng. 120:432–440.
Havril T, Tóth Á, Molson JW, Galsa A, Mádl-Szőnyi J. 2018. Impacts of predicted climate change on groundwater flow systems: can wetlands disappear due to recharge reduction? J Hydrol. 563:1169–1180.
Hoogland T, Heuvelink GBM, Knotters M. 2010. Mapping water-table depths over time to assess desiccation of groundwater-dependent ecosystems in the Netherlands. Wetlands. 30(1):137–147.
Huang F, Chunyu X, Zhang D, Chen X, Ochoa CG. 2020. A framework to assess the impact of ecological water conveyance on groundwater-dependent terrestrial ecosystems in arid inland river basins. Sci Total Environ. 709:136155.
Huang F, Zhang Y, Zhang D, Chen X. 2019. Environmental groundwater depth for groundwater-dependent terrestrial ecosystems in arid/semiarid regions: a review. IJERPH. 16(5):763.
Huang J, Zhou Y, Wenninger J, Ma H, Zhang J, Zhang D. 2016. How water use of Salix psammophila bush depends on groundwater depth in a semi-desert area. Environ Earth Sci. 75:1–13.
Hunink JE, Contreras S, Soto-García M, Martin-Gorriz B, Martinez-Álvarez V, Baille A. 2015. Estimating groundwater use patterns of perennial and seasonal crops in a Mediterranean irrigation scheme, using remote sensing. Agric Water Manag. 162:47–56.
Huntington J, McGwire K, Morton C, Snyder K, Peterson S, Erickson T, Niswonger R, Carroll R, Smith G, Allen R. 2016. Assessing the role of climate and resource management on groundwater dependent ecosystem changes in arid environments with the Landsat archive. Remote Sens Environ. 185:186–197.
Huss M, Hock R, Bauder A, Funk M. 2010. 100-year mass changes in the Swiss Alps linked to the Atlantic Multidecadal Oscillation. Geophys Res Lett. 37(10):n/a–n/a.
IPCC. 2014. Climate change 2014: impacts, adaptation, and vulnerability. Summary for policymakers, climate change 2014: impacts, adaptation and vulnerability - contributions of the working group II to the fifth assessment report.
Ismail MH. 2009. Evaluating supervised and unsupervised techniques for land cover mapping using remote sensing data. Geogr - Malaysian J Soc Sp. 5: 1–10.
Johansen OM, Andersen DK, Ejrnaes R, Pedersen ML. 2018. Relations between vegetation and water level in groundwater dependent terrestrial ecosystems (GWDTEs). Limnologica. 68:130–141.
Jones C, Stanton D, Hamer N, Denner S, Singh K, Flook S, Dyring M. 2020. Field investigation of potential terrestrial groundwater-dependent ecosystems within Australia's Great Artesian Basin. Hydrogeol J. 28(1):237–261.
Kalbus E, Reinstorf F, Schirmer M. 2006. Measuring methods for groundwater—Surface water interactions: A review. Environ Res. 3:873–887.
Kaneko K, Nohara S. 2014. Review of effective vegetation mapping using the UAV (unmanned aerial vehicle) method. JGIS. 06(06):733–742.
Kath J, Reardon-Smith K, Le Brocque AF, Dyer FJ, Dafny E, Fritz L, Batterham M. 2014. Groundwater decline and tree change in floodplain landscapes: identifying non-linear threshold responses in canopy condition. Glob Ecol Conserv. 2:148–160.
Klausmeyer KR, Biswas T, Rohde MM, Schuetzenmeister F. 2019. GDE pulse: taking the pulse of groundwater dependent ecosystems with satellite data.
Klausmeyer K, Howard J, Keeler-Wolf T, Davis-Fadtke K, Hull R. 2018. Mapping indicators of groundwater dependent ecosystems in California: methods report, p. 1–35.
Kløve B, Ala-Aho P, Bertrand G, Boukalova Z, Ertürk A, Goldscheider N, Ilmonen J, Karakaya N, Kupfersberger H, Kvoerner J, et al. 2011. Groundwater dependent ecosystems. Part I: hydroecological status and trends. Environ Sci Policy. 14(7):770–781.
Kløve B, Ala-Aho P, Bertrand G, Gurdak JJ, Kupfersberger H, Kvaerner J, Muotka T, Mykrä H, Preda E, Rossi P, et al. 2014. Climate change impacts on groundwater and dependent ecosystems. J Hydrol. 518:250–266.
Koirala S, Jung M, Reichstein M, de Graaf IEM, Camps-Valls G, Ichii K, Papale D, Ráduly B, Schwalm CR, Tramontana G, et al. 2017. Global distribution of groundwater-vegetation spatial covariation. Geophys Res Lett. 44(9):4134–4142.
Krause S, Heathwaite AL, Miller F, Hulme P, Crowe A. 2007. Groundwater-dependent wetlands in the UK and Ireland: controls, functioning and assessing the likelihood of damage from human activities. Water Resour Manage. 21(12):2015–2025.

Kreamer DK, Stevens LE, Ledbetter JD. 2015. Groundwater-dependent ecosystems – science, challenges, and policy. In: Adelana SM, editors.Groundwater. Hauppauge: Nova Science Publishers, Inc; p. 205–230.
Krogulec E. 2018. Evaluating the risk of groundwater drought in groundwater-dependent ecosystems in the central part of the Vistula River Valley. Poland Ecohydrol Hydrobiol. 18(1):82–91.
Kumar CP. 2013. Recent studies on impact of climate change on groundwater resources. Int J Phys Soc Sci. 3:189–221.
Kundzewicz ZW, Döll P. 2009. Will groundwater ease freshwater stress under climate change? Hydrol Sci J. 54(4):665–675.
Laio F, Tamea S, Ridolfi L, D'Odorico P, Rodriguez-Iturbe I. 2009. Ecohydrology of groundwater-dependent ecosystems: 1. Stochastic water table dynamics. Water Resour Res. 45(5):1–13.
Le Maitre DC, Scott DF, Colvin C. 1999. A review of information on interactions between vegetation and groundwater. Water SA. 25:137–152.
Liao S, Xue L, Dong Z, Zhu B, Zhang K, Wei Q, Fu F, Wei G. 2020. Cumulative ecohydrological response to hydrological processes in arid basins. Ecol Indic. 111:106005.
Liu HH. 2011. Impact of climate change on groundwater recharge in dry areas: an ecohydrology approach. J Hydrol. 407(1–4):175–183.
Loheide SP, Butler JJ, Gorelick SM. 2005. Estimation of groundwater consumption by phreatophytes using diurnal water table fluctuations: a saturated-unsaturated flow assessment. Water Resour Res. 41(7): W07030.
Loomes R, Froend R, Sommer B. 2013. Response of wetland vegetation to climate change and groundwater decline on the swan coastal plain, Western Australia: implications for management. In: Ribeiro L, Stigter TY, Chambel A, Condesso de Melo MT, Monteiro JP, Medeiros A, editors. Groundwater and ecosystems. Leiden, Netherlands: CRC Press; p. 207–219.
Lurtz MR, Morrison RR, Gates TK, Senay GB, Bhaskar AS, Ketchum DG. 2020. Relationships between riparian evapotranspiration and groundwater depth along a semiarid irrigated river valley. Hydrol Process. 34(8):1714–1727.
Lv J, Wang XS, Zhou Y, Qian K, Wan L, Eamus D, Tao Z. 2013. Groundwater-dependent distribution of vegetation in Hailiutu River catchment, a semi-arid region in China. Ecohydrol. 6(1):142–149.
Macintyre P, van Niekerk A, Mucina L. 2020. Efficacy of multi-season Sentinel-2 imagery for compositional vegetation classification. Int J Appl Earth Obs Geoinf. 85:101980.
MacKay H. 2006. Protection and management of groundwater-dependent ecosystems: emerging challenges and potential approaches for policy and management. Aust J Bot. 54(2):231–237.
Marques IG, Nascimento J, Cardoso RM, Miguéns F, Teresa Condesso De Melo M, Soares PMM, Gouveia CM, Kurz Besson C. 2019. Mapping the suitability of groundwater-dependent vegetation in a semi-arid Mediterranean area. Hydrol Earth Syst Sci. 23(9):3525–3552.
Mawdsley JR, O'Malley R, Ojima DS. 2009. A review of climate-change adaptation strategies for wildlife management and biodiversity conservation. Conserv Biol. 23(5):1080–1089.
McDowell C, Moll E. 1992. The influence of agriculture on the decline of west coast renosterveld, south-western Cape, South Africa. J Environ Manage. 35(3): 173–192.
Miller GR, Chen X, Rubin Y, Ma S, Baldocchi DD. 2010. Groundwater uptake by woody vegetation in a semiarid oak savanna. Water Resour Res. 46(10):1–14.
Móricz N. 2010. Water balance study of a groundwater-dependent oak forest. Acta Silv. Lignaria Hungarica. 6:49–66.
Morsy KM, Alenezi A, Alrukaibi DS. 2017. Groundwater and dependent ecosystems: revealing the impacts of climate change. Int J Appl Eng Res. 12:3919–3926.
Mountrakis G, Im J, Ogole C. 2011. Support vector machines in remote sensing: a review. ISPRS J Photogramm Remote Sens. 66(3):247–259.
Mtengwana B, Dube T, Mkunyana YP, Mazvimavi D. 2020. Use of multispectral satellite datasets to improve ecological understanding of the distribution of Invasive Alien Plants in a water-limited catchment. South Africa Afr J Ecol. 58:709–718.
Münch Z, Conrad J. 2007. Remote sensing and GIS based determination of groundwater dependent ecosystems in the Western Cape. Hydrogeol J. 15(1):19–28.
Muñoz-Reinoso JC. 2001. Vegetation changes and groundwater abstraction in SW Doñana. Spain J Hydrol. 242(3–4):197–209.
Mutanga O, Kumar L. 2019. Google earth engine applications. Remote Sens. 11(5):591.
Naumburg E, Mata-Gonzalez R, Hunter RG, McLendon T, Martin DW. 2005. Phreatophytic vegetation and groundwater fluctuations: a review of current research and application of ecosystem response modeling with an emphasis on great basin vegetation. Environ Manage. 35(6):726–740.

Ndehedehe CE, Ferreira VG, Agutu NO. 2019. Hydrological controls on surface vegetation dynamics over West and Central Africa. Ecol Indic. 103:494–508.
Noone KJ, Nobre C, Seitzinger S. 2011. The International Geosphere-Biosphere Programme's (IGBP) scientific research agenda for coping with global environmental change.
Northcote TG, Atagi DY. 1997. Ecological interactions in the flooded littoral zone of reservoirs: the importance and role of submerged terrestrial vegetation with special reference to fish, fish habitat and fisheries in the Nechako Reservoir of British Columbia. Canada. 64: 1–64.
O'Connor J, Santos MJ, Rebel KT, Dekker SC. 2019. The influence of water table depth on evapotranspiration in the Amazon arc of deforestation. Hydrol Earth Syst Sci. 23(9):3917–3931.
Orellana F, Verma P, Loheide SP, Daly E. 2012. Monitoring and modelling water-vegetation interactions in groundwater dependent ecosystems 50(3):1–24.
Osmond CB, Austin MP, Berry JA, Billings WD, Boyer JS, Dacey JWH, Nobel PS, Smith SD, Winner WE. 1987. Stress physiology and the distribution of plants. Bioscience. 37(1):38–48.
Paola JD, Schowengerdt RA. 1995. A review and analysis of backpropagation neural networks for classification of remotely-sensed multi-spectral imagery. Int J Remote Sens. 16(16): 3033–3058.
Parker BM, Sheldon F, Phinn S, Ward D. 2018. Changes in foliage projective cover and its implications for mapping groundwater dependent vegetation across a precipitation gradient. Ecohydrology. 11(4): e1937–9.
Páscoa P, Gouveia CM, Kurz-Besson C. 2020. A simple method to identify potential groundwater-dependent vegetation using NDVI MODIS. Forests. 11(2):147.
Pereira HM, Ferrier S, Walters M, Geller GN, Jongman RHG, Scholes RJ, Bruford MW, Brummitt N, Butchart SHM, Cardoso AC, et al. 2013. Essential biodiversity variables. Science339:277–278. doi: 10.1126/science.1229931pmid:23329036
Pérez Hoyos I, Krakauer N, Khanbilvardi R. 2016. Estimating the probability of vegetation to be groundwater dependent based on the evaluation of tree models. Environments. 3(4):9.
Pérez Hoyos IC, Krakauer NY, Khanbilvardi R, Armstrong RA. 2016. A review of advances in the identification and characterization of groundwater dependent ecosystems using geospatial technologies. Geosci. 6(2):17.
Peters J, De Baets B, Samson RC, Verhoest NE. 2008. Modelling groundwater-dependent vegetation patterns using ensemble learning. Hydrol Earth Syst Sci. 12(2):603–613.
Peters J, De Baets B, Verhoest NEC, Samson R, Degroeve S, Becker P, De Huybrechts W. 2007. Random forests as a tool for ecohydrological distribution modelling. Ecol Modell. 207(2–4):304–318.
Plants as Indicators of Ground. 1929. Water. O. E. Meinzer, J. Geol.
Poiani KA, Johnson WC, Swanson GA, Winter TC. 1996. Climate change and northern prairie wetlands: simulations of long-term dynamics. Limnol Oceanogr. 41(5):871–881.
Raczko E, Zagajewski B. 2017. Comparison of support vector machine, random forest and neural network classifiers for tree species classification on airborne hyperspectral APEX images. Eur J Remote Sens. 50(1):144–154.
Richardson DM, Kruger FJ. 1990. Water relations and photosynthetic characteristics of selected trees and shrubs of riparian and hillslope habitats in the south-western Cape Province. South Africa South African J Bot. 56(2):214–225.
Richey AS, Thomas BF, Lo MH, Reager JT, Famiglietti JS, Voss K, Swenson S, Rodell M. 2015. Quantifying renewable groundwater stress with GRACE. Water Resour Res. 51(7):5217–5238.
Robinson TW. 1958. Phreatophytes. By T. W. Robinson. United States Geological Survey Water-Supply Paper 1423. p. 84, 32 figs. Washington, 1958. Price 40 cents. Geol. Mag.
Rodriguez-Iturbe I, Porporato A. 2005. Ecohydrology of water-controlled ecosystems: soil moisture and plant dynamics. In Ecohydrology of water-controlled ecosystems: Soil Moisture and Plant Dynamics. 1:86–101.
Rohde MM, Froend R, Howard J. 2017. A global synthesis of managing groundwater dependent ecosystems under sustainable groundwater policy. Ground Water. 55(3):293–301.
Rouget M, Richardson DM, Cowling RM, Lloyd JW, Lombard AT. 2003. Current patterns of habitat transformation and future threats to biodiversity in terrestrial ecosystems of the Cape Floristic Region. South Africa Biol Conserv. 112(1–2):63–85.
Roy DP, Kovalskyy V, Zhang HK, Vermote EF, Yan L, Kumar SS, Egorov A. 2016. Characterization of Landsat-7 to Landsat-8 reflective wavelength and normalized difference vegetation index continuity. Remote Sens Environ. 185:57–70.
Rozenstein O, Karnieli A. 2011. Comparison of methods for land-use classification incorporating remote sensing and GIS inputs. Appl Geogr. 31(2):533–544.

Sabat-Tomala A, Raczko E, Zagajewski B. 2020. Comparison of support vector machine and random forest algorithms for invasive and expansive species classification using airborne hyperspectral data. Remote Sens. 12(3):516.
Sarris D, Christodoulakis D, Korner C. 2007. Recent decline in precipitation and tree growth in the eastern Mediterranean. Global Change Biol. 13:1187–1200. doi: 10.1111/j.1365-2486.2007.01348.x
Scanlon BR, Keese KE, Flint AL, Flint LE, Gaye CB, Edmunds MW, Ian S. 2006. Global synthesis of groundwater recharge in semiarid and arid regions. Hydrol Process. 2274:2267–2274.
Scibek J, Allen DM. 2006. Modeled impacts of predicted climate change on recharge and groundwater levels. Water Resour Res. 42(11):W11405.
Shadwell E, February E. 2017. Effects of groundwater abstraction on two keystone treespecies in an arid savanna national park. PeerJ. 5. doi: 10.7717/peerj.2923
Shafroth PB, Stromberg JC, Patten DT. 2000. Woody riparian vegetation response to different alluvial water table regimes. Monte L Bean Life S. 60:66–76.
Shoko C, Mutanga O, Dube T. 2016. Progress in the remote sensing of C3 and C4 grass species aboveground biomass over time and space. ISPRS J Photogramm Remote Sens. 120:13–24.
Sommer B, Boggs DA, Boggs GS, van Dijk A, Froend R. 2016. Spatio-temporal patterns of evapotranspiration from groundwater-dependent vegetation. Ecohydrol. 9(8):1620–1629.
Song X, Duan Z, Jiang X. 2012. Comparison of artificial neural networks and support vector machine classifiers for land cover classification in Northern China using a SPOT-5 HRG image. Int J Remote Sens. 33(10):3301–3320.
Taylor R, Tindimugaya C. 2011. The impacts of climate change and rapid development on weathered crystalline rock aquifer systems in the humid tropics of sub-Saharan Africa: evidence from south-western Uganda. In: Climate change effects on groundwater resources: a global synthesis of findings and recommendations, edited by H. Treidel, J. L. Martin-Bordes, and J. J. Gurda, pp. 17– 32. Boca Raton, FL: Taylor and Francis.
Thamaga KH, Dube T. 2018. Remote sensing of invasive water hyacinth (Eichhornia crassipes): a review on applications and challenges. Remote Sens Appl Soc Environ. 10:36–46.
United Nations. 2017. The sustainable development goal report 2017 [WWW Document]. https://sustainabledevelopment.un.org/aboutmajorgroups.html. https://unstats.un.org/sdgs/files/report/2017/TheSustainableDevelopmentGoalsReport2017.pdf. (accessed 2020 January 26).
Vaux H. 2011. Groundwater under stress: the importance of management. Environ Earth Sci.62:19–23.
Wada Y, Van Beek LPH, Van Kempen CM, Reckman JWTM, Vasak S, Bierkens MFP. 2010. Global depletion of groundwater resources. Geophys Res Lett. 37(20):n/a–5.
Walter H. 1973. Vegetation of the Earth In Relation to Climate and Eco-physiological Conditions. New York, Heidelberg, Berlin: Springer-Verlag; p. 238.
Wang Q, Dong S, Wang H, Yang J, Zhao C, Dong X, Wang T. 2020. Effects of groundwater table decline on vegetation transpiration in an arid mining area: a case study of the Yushen Mining Area, Shaanxi Province, China. Mine Water Environ. 39(4):839–850.
Wattendorf P, Niederberger J, Ehrmann O, Konold W. 2010. Consequences of climate change on the water balance of fen peatlands in Baden-Wuerttemberg. Hydrol. UND WASSERBEWIRTSCHAFTUNG.
Wessels KJ, Pretorius DJ, Prince SD. 2008. The reality of rangeland degradation mapping with remote sensing: the South African experience. 14th Australas. Remote Sens. Photogramm. Conf.
Williams S. 2018. Perceptions of wetland ecosystem services in a region of climatic variability.
Wu Y, Liu T, Paredes P, Duan L, Pereira LS. 2015. Water use by a groundwater dependent maize in a semi-arid region of Inner Mongolia: evapotranspiration partitioning and capillary rise. Agric Water Manag. 152:222–232.
Xia P, Yin S, Jiang J. 2012. Pinus aiwanensis tree-ring chronology and its response to climate. Procedia Environ Sci. 13:307–315.
Xu Y, Beekman HE. 2003. Groundwater recharge estimation in Southern Africa. UNESCO IHP Series. No 64.
Yates MJ, Anthony Verboom G, Rebelo AG, Cramer MD. 2010. Ecophysiological significance of leaf size variation in Proteaceae from the Cape Floristic Region. Funct Ecol. 24(3):485–492.
Zhang G, Su X, Singh VP. 2020. Modelling groundwater-dependent vegetation index using Entropy theory. Ecol Modell. 416:108916.
Zhao X, Zhou D, Fang J. 2012. Satellite-based studies on large-scale vegetation changes in China. J Integr Plant Biol. 54(10):713–728.
Zhaoming W. 2020. A theoretical review of vegetation extraction methods based on UAV. IOP Conf Ser: Earth Environ Sci. 546:032019.
Zhu Z. 2017. Change detection using landsat time series: a review of frequencies, preprocessing, algorithms, and applications. ISPRS J. Photogramm Remote Sens. 130: 370–384.