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Multispectral remote sensing of potential groundwater dependent vegetation in the greater Floristic region of the Western Cape, South Africa

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ABSTRACT

Groundwater dependent vegetation (GDV) is increasingly threatened by the transformation of the natural environment. An understanding of the nature of GDV at the appropriate scale helps environmental managers make suitable decisions. This study assesses the potential for mapping the distribution of GDV within the Heuningnes Catchment using multispectral remotely sensed data (i.e., Landsat 8 (L8) and Sentinel 2 (S2)), the derived vegetation indices (Normalised Difference Vegetation Index (NDVI) and the Soil-Adjusted Vegetation Index (SAVI)) and *in-situ* data. The GDV distribution maps were produced by integrating vegetation productivity, landcover, and topographic layers as GDV indicators. The findings of the study revealed that the spectral indices had a significant influence on the sensor's GDV classification performance. Specifically, the S2-derived SAVI mapped the GDV areas with the highest overall accuracy (97%), followed by the S2-derived NDVI, with an accuracy of 95%. Comparatively, the L8(NDVI) GDV map was achieved with an overall accuracy of 92% and the L8(SAVI) map had an overall accuracy of 96%. The estimated coverage of potential GDV within the catchment ranges between 2.34 and 2.60%. This work demonstrated the capabilities of a combined remote sensing and GIS methodological framework, which can improve our knowledge on GDV.

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Arid environments; fynbos; moderate resolution; invasive plants; satellite data; water resources management

3.1 Introduction

Groundwater is important for all life forms and environment. Terrestrial vegetation that is maintained by (in)direct access to groundwater in semi-arid regions is called Groundwater Dependent Vegetation (GDV) (Zhang et al., 2020). Factors such as precipitation, temperature and groundwater level affect the distribution and vigour of GDV (Havril et al., 2018; Johansen et al., 2018; Krause et al., 2007; Loomes et al., 2013). Vegetation is a major component of terrestrial ecosystems and plays a vital role in energy flow, global carbon and the water cycle (Zhao et al., 2012). Terrestrial vegetation may also have a high economic value, for example, the Cape Floristic region contributes 10% of

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South Africa's Gross Geographic Product (provincial contribution to the Gross Domestic Product (GDP)) (Turpie et al., 2003). Additionally, natural terrestrial ecosystems not only contribute to the economy through ecotourism, but they are also the genetic hub for bioprospecting and the preservation of biodiversity (Williams, 2018). Terrestrial ecosystems provide valuable ecosystem services, such as flood control, water purification (Murray et al., 2006), pollinator habitats (Currie et al., 2009) and recreational opportunities (Costanza et al., 1997). In arid regions, vegetation is a major producer of organic material and contributes towards the accumulation of the necessary biological components of soil (Lv et al., 2013). The vegetation cover buffers against desertification and maintains natural environmental conditions (Lv et al., 2013; Wang et al., 2018). Because of the numerous benefits that are gained from terrestrial vegetation, it is imperative that these ecosystems are protected and safeguarded.

The main threats to the sustainability of GDV are plantation forestry, urban development and the conversion of natural land to agriculture (McDowell and Moll, 1992; Rouget et al., 2003). Moreover, reduced groundwater levels, due to over-abstraction for economic activities, endangers GDV. Extreme climatic conditions, such as droughts and climate variability increase the reliance on groundwater. For instance, with the advent of the 2015–2017 drought in the Western Cape of South Africa, groundwater resources were exploited to meet the demand for water (Botai et al., 2017; Seyler et al., 2017). Consequently, groundwater levels were reported to have declined substantially over the previous four years with detrimental effects on terrestrial vegetation (Froend & Sommer, 2010; Seyler et al., 2017). Moreover, the slight increase in groundwater depth (<2.2 m), coupled with the extreme summer temperatures, can result in a 20–80% vegetation mortality rate (Groom et al., 2000). Plantation forestry reduces groundwater recharge and surface water flow while increasing groundwater discharge. For instance, Munoz-Reinoso (2001) reported a greater depth of groundwater in Donana, Spain, due to increased drawdown and abstraction of the urban water supply and the transpiration of large pine plantations. Areas in South Africa that are heavily encroached by alien invasive plants also have reduced stream flow and groundwater levels (Dzikiti et al., 2013; Scott et al., 1999; Prinsloo and Scott, 2008), which has an adverse effect on the native GDV (Vila et al., 2011). Invasive plant species can tap into multiple water sources; thus, outcompeting the endemic vegetation (Dawson and Elleringer, 1991). A growing concern is that the rate of spread of invasive alien plants indicates that there is a higher likelihood of water scarcity (Hoffman & Cowling, 1990; Van Wilgen & Richardson, 2012). Since the role of groundwater for augmenting water resources is increasing, it is important to determine the vegetation that is dependent on this groundwater and its distribution within the landscape. This will help to set up effective groundwater management strategies that focus on ensuring ecological sustainability. Monitoring the condition of the vegetation and its response to environmental and global changes over time creates an understanding of the processes of change and the possible areas that are affected and at risk (Franklin et al., 2016). Information on the distribution of GDV assists with setting up conservation hotspots, determining ecological water allocations, as well as restricting and planning for groundwater use within the region. Such information is critical for supporting an agenda for sustainable future development e.g. the United Nations' (UN) Sustainable Development Goal 15 on 'Life on Land' (United Nations 2018). The condition of vegetation, together with its response to environmental changes is specified in the list of Essential Climate Variables (Bojinski et al., 2014) and Essential Biodiversity Variables (Pereira et al. 2013).

The monitoring of groundwater dependent vegetation has been limited because of the trade-offs that exist between efficiency, level of detail and the cost of measurement techniques (Pérez Hoyos et al., 2016). Only water chemistry indicators can give conclusive evidence of the groundwater and vegetation interactions and may help to identify where plants use groundwater and how much is used. Other indicators for assessing the influence of groundwater variability on the vegetation are indirect. They include Eddy correlation, Bowen ratio, climatic indices, sap flow measurements, plant phenology and the ground-based leaf area index (Colvin et al., 2003; Eamus et al., 2015; Hoyos et al., 2016). Although these methods provide highly detailed information, they are limited by their low spatial and temporal scale, cost, and labour requirements. Remote Sensing (RS) has emerged as an efficient monitoring tool that can provide crucial information regarding the status of vegetation, its response to change, and the current disturbance regimes on a community or landscape scale (Griffiths et al., 2019; Móricz, 2010; Wessels et al., 2008; Zhu, 2017). Remote sensing techniques provide a robust methodology for mapping GDV on a regional and local scale, and they help to identify GDV by looking at the relationship between groundwater, vegetation and the spectral signatures of GDV in contrast to the surrounding vegetation (Barron et al., 2014). Spectral indices determine the plant density, vegetation productivity (greenness) and vegetation distribution, which is useful for discriminating GDV. Remote sensing methodologies have been successfully applied in other studies to map GDV. Dresel et al. (2010) utilized the moderate resolution imaging spectroradiometer (MODIS) enhanced vegetation index standard deviation, the mid-summer Landsat Normalised Difference Vegetation Index (NDVI) and the unsupervised classification of Landsat spectral data to produce a state-wide GDV map. Barron et al. (2014) also used Landsat 8-derived NDVI and Normalized Difference Water Index (NDWI) metrics to identify Groundwater Dependent Ecosystems (GDEs) by evaluating vegetation with active greenness during dry periods. Their methodology had a high-performance level and more than 91% producer accuracy. GDE mapping can be applied on a continental, regional and local scale (Brodie et al., 2002; Doody et al., 2017; Dresel et al., 2010; Glanville et al., 2016). Advances in sensor technologies have led to the acquisition of freely available satellite imagery such as S2 and L8, which is suitable for GDV mapping, especially in resource-limited areas (Chiloane et al., 2021; Gxokwe et al., 2020). They provide the appropriate detection resolutions required to map GDV compared to previous non-commercial sensors like MODIS. Due to the sporadic distribution of GDV in semi-arid environments, identifying GDV remains a challenge because it requires a high spatial and spectral resolution (Hoyos et al., 2016). Consequently, sensors with a high spectral, spatial, temporal, and radiometric resolution are required on a broader scale to understand the distribution of GDV and to enhance management practices. Landsat 8 and Sentinel 2, which are characterized by their finer spatial (10–30 m), spectral resolution (11–13 bands, including red edge) and swath width (185–285 km), are suitable for detecting subtle changes and for the broadscale mapping of GDV which is often obscured by the background (Shoko et al., 2016; Thamaga et al., 2021). For instance, Doody et al. (2017) identified the location of GDEs in Australia by integrating expert knowledge, RS data and GIS analysis. In another study, Münch and Conrad (2007) used a combination of Landsat imagery for extracting bioclimatic indicators, vegetation productivity and RS modelling to identify GDV in the Western Cape of South Africa. GDE identification has been enhanced by incorporating machine learning and vegetation indices. For example, Pérez Hoyos et al. (2016) used the classification of Trees and Random Forest to identify probable GDEs by modelling the relationship between the known location of GDEs and the climatic factors (the aridity index and the water table depth) with a high accuracy (97%). Vegetation indices, such as the NDVI and Soil Adjusted Vegetation Index (SAVI), improve the detection of GDV. Vegetation indices overcome the effects of soil background, zenith angle and atmospheric composition, while they improve the vegetation signal when determining the vegetation characteristics (Thamaga et al., 2021). For instance, Thamaga et al. (2018) observed that spectral vegetation indices derived from Landsat 8 and Sentinel 2 outperformed the raw spectral bands in discriminating vegetation. The performance of vegetation indices may be linked to the greater ability of the NDVI to minimize background effects, such as shadows, soil and atmospheric impurities compared to spectral bands. It is therefore perceived that data from Sentinel 2 and Landsat 8, with a 5 to 16-day revisit period and 10–30 m pixel size are likely to provide information on the distribution of GDV at the appropriate scales, for continued GDV mapping. This study proposes a remote sensing approach to determine and map the distribution of potential GDV within the Heuningnes Catchment by using moderate remotely sensed data.

3.2 Research methodology

3.2.1 Study area description

Currently regarded as the hottest biodiversity hotspot, the Cape Floristic Region (CFR) is one of the six floral kingdoms in the world. It has the most outstanding diversity, with 95,000 species that are endemic to the area. The region is home to 1406 red listed plant species, which is the largest concentration globally (Allsopp et al., 2019). This study will concentrate on part of the CFR, the Heuningnes catchment (Figure 1) which covers an area of 1403 km^2 within the Cape Algulhas region in the Western Cape and is straddled by the Bredasdorp Mountains along the northern watershed (Kinoti, 2018). It is characterized by several ephemeral ponds, rivers, freshwater springs, and wetlands (riparian and non-riparian). There are two main rivers, the Nuwejaars and Kars Rivers, as well as several wetlands including the Soetendalsvlei and the Voelvlei that are interlinked with streams. Riparian zones in this area are infested by invasive plant species such as *Acacia longifolia* (Mkunyana et al., 2019). The geology is distributed into three main groups, namely, the Table Mountain Group (TMG), which consists of quarzitic sandstone, while shale and siltstone dominate the north-western parts of the catchment. A secondary aquifer has formed owing to the deformation of the TMG. The Bokkeveld Group overlies the TMG and occupies the eastern and middle parts of the catchment in the Elim and Soetendalsvlei areas. Shales belonging to the Bokkeveld Group have notable fractures, faults and saline groundwater. Similarly, the Bredasdorp Group, which consists of shallow Cenozoic marine aeolian deposits, extends over the TMG and Bokkeveld Group (Mkunyana et al., 2019; Mokoena, 2019). Southern coastal regions of the catchment have a distinctive lithology which is comprised of calcified dunes and coastal limestone. Groundwater flow in this area follows the topography because it is heavily influenced by the underlying geology and structural properties. The groundwater is

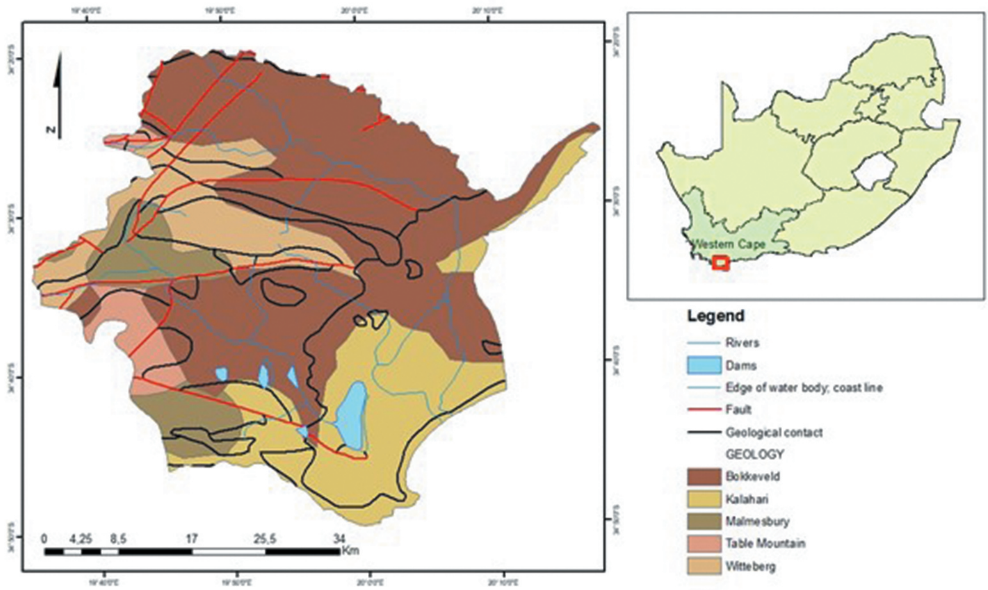

Figure 1. The Heuningnes catchment area and associated geology the quaternary catchments are indicated by G50B, G50C, G50D, G50E, and G50D.

found in both primary and secondary aquifers (Mkunyana et al., 2019) and the region has primarily fractured aquifer types with several springs distributed along the catchment. In the lower part of the catchment there is an intergranular aquifer with low-yielding shale (Mokoena, 2019). The groundwater in the area is used for livestock farming and domestic purposes. Land cover is mainly natural with dominant shrubland fynbos which is in demand for the ornamental and pharmaceutical industries (Turpie et al., 2003). Natural eco-tourism contributes to the local economy through the De Mond Nature Reserve and the Algulhas National Park. The primary land uses in this region are agricultural, mainly for wheat, livestock farming, as well as a few vineyards (Thamaga & Dube, 2018) and pine plantations (Kinoti, 2019). Since the economic activities rely heavily on water, there is a challenge to support economic development and social redress while also maintaining the water-dependent ecosystems. This is exacerbated by the competing demands of agriculture, the ecology and invasive plants for the environmental water reserves (Mazvimavi, 2018; Mkunyana et al., 2019).

3.2.2 Data acquisition

3.2.2.1 Floristic survey. Baseline and field data were collected to map and validate the groundwater dependent vegetation within the Heuningnes Catchment. The vegetation data were acquired from reference data (Colvin et al., 2003; Mkunyana et al., 2019; Mtengwana et al., 2021) and a floristic survey was conducted during the wet and flowering season for easy plant identification. Sampling points were located in accessible areas around pre-existing University of the Western Cape groundwater monitoring sites and roads because the area is largely agricultural land. Information on the dominant vegetation, plant phenology and other land cover types in the area was collected within

10 m × 10 m plots. The Global Positioning System (GPS) coordinates of the plots were recorded using the eTrex 10 Garmin GPS, with an error margin of 2.65 m. Samples and pictures of the dominant vegetation within the plots were collected for further species identification using the SANBI iNaturalist Plant Identification application. The application uses crowd-sourced data and an impressive artificial intelligence identification algorithm that provides the real time identification of the plants posted.

3.2.2.2 Satellite data. The study sought to compare the Sentinel 2- and Landsat 8-derived models to map the potential distribution of the GDV. These models were produced from bio-indicators (vegetation productivity), land cover, as well as the topographic features including the slope and surface curvature (Brodie et al., 2002; Münch & Conrad, 2007). The L8 Level 1C satellite dataset was downloaded from the online USGS Earth Explorer Earth Observation database (https://earthexplorer.usgs.gov/). Dry period satellite images primarily from the year 2017, were specifically selected to exploit the impact of water scarcity on the vegetation. The GDV with access to groundwater would have a higher vegetation productivity than the surrounding vegetation. A single L8 scene, which was acquired on the 15th of January covered the entire expanse of the study area. Two S2 Level 1C products with minimal cloud cover (<2%) were obtained from the 11th and 08th of January 2017. The need for cloud-free images resulted in different acquisition dates. However, it is assumed that there were negligible land cover changes within this period. The Shuttle Radar Topography Mission (SRTM) void-filled image with a 30 m spatial resolution was downloaded from the USGS online resource and the land cover map was obtained from the Department of Forestry, Fisheries and Environment database (https://egis.environment.gov.za/gis_data_downloads). The land cover map was generated from multi-seasonal Sentinel 2 images with an overall accuracy of 90.14% and used to extract the areas with natural vegetation that are suitable for GDV.

3.2.3 Data processing and classification

Level 1C products for L8 and S2 are radiometrically and geometrically corrected, with spatial registration and ortho-rectification (Suhet, 2015). The Top of Atmosphere (TOA) reflectance was used for determining the vegetation indices because Emelyanova et al. (2018) demonstrated that the TOA and Atmospheric Correction (AC) reflectance are equally appropriate for groundwater dependent ecosystems mapping. Landsat 8 OLI and Sentinel 2A images were re-projected to the WGS84 UTM zone 34S geographical co-ordinate system. The NDVI and SAVI were used as a proxy for vegetation productivity. Several studies have demonstrated the suitability of the NDVI for GDV mapping (Doody et al., 2017; Liao et al., 2020; Münch & Conrad, 2007; N. Z. Jovanovic et al., 2011; Thamaga et al., 2018; Zhang et al., 2020). The SAVI minimizes the influence of soil brightness on the vegetation spectral reflectance, which is suitable for areas with a low vegetation cover (Huete, 1988; Rhyma et al., 2020). Near Infrared (NIR) and red (R) bands required for calculating the SAVI and NDVI were processed further by clipping them to fit the extent of the study area. Vegetation indices (VI) were then calculated (Equations 1 and 2) by using the map algebra tool from the spatial analyst tools in ARMAP 10.8.

$$NDVI = \left(\frac{NIR - R}{NIR + R}\right) \tag{1}$$

$$SAVI = \left(\frac{NIR - R}{NIR + R + L}\right) \times (1 + L) \tag{2}$$

Where NIR is Band 5 for L8 and Band 8 for S2, R is Band 4 for L8 and Band 4 for S2. The brightness correction factor (L) is 0.5.

The NDVI and SAVI spatial layers were also classified by using the IsoData Unsupervised Classification technique to discriminate vegetation with access to groundwater and those that do not have access. There were five classes, ranging from 1 to 5. Vegetation Index class 5 represented highly productive vegetation associated with greater water availability, while classes 1–4 characterized unhealthy vegetation with limited access to groundwater. he first four classes were masked out, leaving class 5 which represented the areas with the highest potential for groundwater dependence. This is because vegetation with an above-average productivity indicates that it has access to water during the dry period. The land cover dataset was resampled to fit the study area. From the land cover layer, only the wetland and natural vegetation classes are suitable for GDV; consequently, the other classes were masked out.

The SRTM void-filled dataset was also clipped and then the slope and profile curvature were calculated. Rules for selecting areas with topographic characteristics suitable for GDV were set as areas with a gentle slope of less than 3%, and a positive profile curvature value, that is areas of depression (Münch & Conrad, 2007). Figure 2 summarizes the steps for potential GDV distribution mapping. The land cover, slope, profile curvature and VI layers were all subjected to binary classification where the pixel value of 1 represents the pixels with a high potential for GDV and 0 represents those pixels with no potential. All four layers (landcover, slope, vegetation productivity and surface curvature) were integrated by using the weighted sum overlay tool, with pixel values above three indicating the potential for GDV and those below three being masked out, as they did not satisfy the criteria. Different indices from the two sensors (L8(SAVI), L8(NDVI), S2(SAVI) and S2 (NDVI)) were used to produce four potential GDV maps as final outputs. The area extent of the GDV and non-GDV classes was computed to estimate the percentage coverage of GDV within the Heuningnes Catchment.

A google Earth image with a 5 m resolution was used as a reference to assess the validity of the four binary classified maps. It provided data on the land cover characteristics at the time. One hundred and ninety-six random stratified points (40 for the GDV class and 156 for the non-GDV class) per map were overlaid on a January 2017 Google image to assess the quality of information derived from the classified models. The 196 points were created because the area is relatively small and sample point allocation per class from the binary classification is unbalanced (Foody, 2002; Stehman, 2000, 2009). Classification accuracy was assessed using the binary confusion matrix to compute the producers, users, and overall accuracies, as well as commission and omission errors (Olofsson et al., 2013). The McNemar's test was also used to find any significant differences in the overall performance of the classified images.

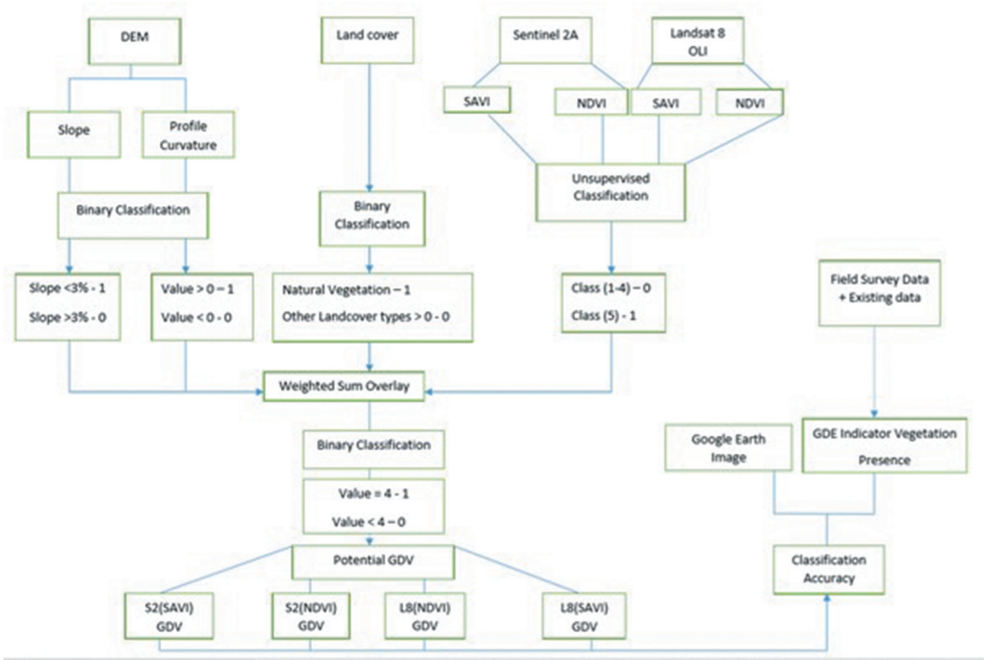

Figure 2. Flow chart summarizing the critical analysis steps for mapping the potential distribution of GDV.

3.1 Results

3.1.1 Indicator variables for potential GDV mapping and the resultant GDV indices

Results from binary classification of the indicator variables were used for producing the four potential GDV indices (Figure 3). Compared to the northern regions, southern regions of the catchment are characterized by gentle slopes while the surface depressions are evenly spread within the catchment. Natural vegetation dominates the catchment and the L8 and S2 vegetation indices indicate similar results for areas with a high vegetation productivity. The catchment areas with class 1 are characterized by gentle slopes of less than 3% depression areas, natural vegetation, and highly productive vegetation. Class 0 areas do not have suitable characteristics for GDV potential.

Figure 4 represents a visual description of the potential GDV, as well as its distribution within the catchment. The four models produced visually similar results on the distribution of GDV. This is in line with the quantitative results, where the L8 models show about 2.6% of the area is suitable for GDV, compared to the S2(SAVI) and S2(NDVI) which determine that 2.4% and 2.34% of the area has GDV potential, respectively. The north-western region of the catchment has a higher potential for GDV when compared to the other lower parts of the catchment where GDV is widely spread and sporadic. The GDV in the north-western region is riparian vegetation where the groundwater level is close to the surface while the GDV in the south of the catchment taps into the shallow primary

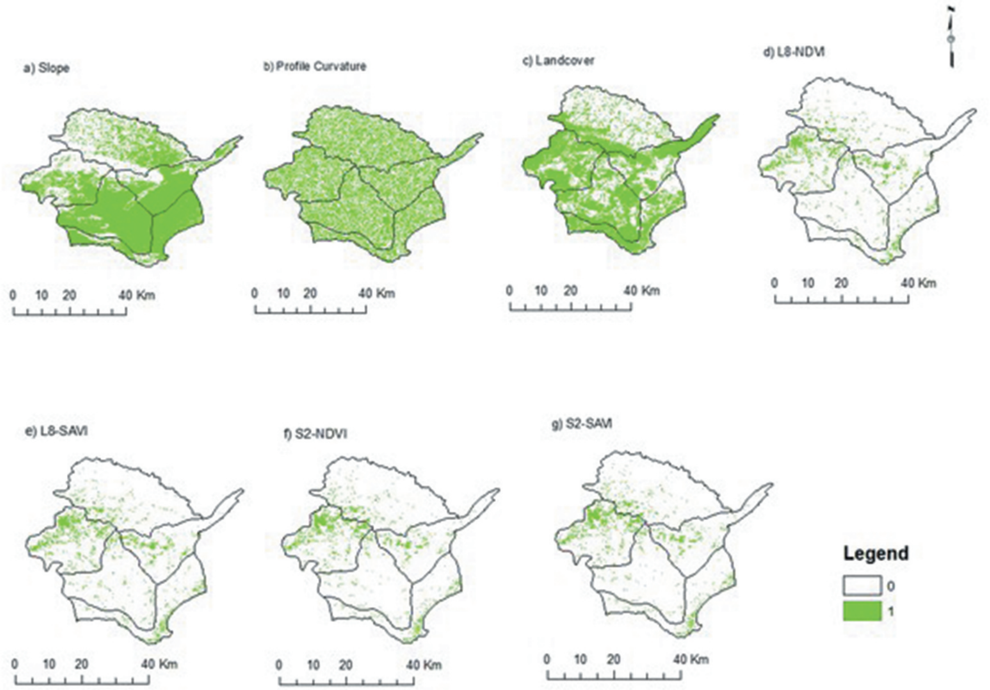

Figure 3. Binary classification of indicator variables used to produce the four potential GDV indices; class 1 indicates the areas with GDV suitability, with class 0 indicating unsuitable areas.

aquifer of the Bredasdorp Group. Communities of GDV are not only distributed along the riparian zone, but they are also found in areas further away from streams.

3.1.2 Potential GDV model classification assessment

Overall, the S2(SAVI) model produced the best results for identifying the potential GDV, with an OA of 97% and the highest level of agreement (93%). Table 1 shows GDV and Non-GDV classification accuracies for the Heuningnes Catchment with overall accuracies ranging from 92% to 97%. The GDV classification has better UA than PA, while the opposite is true for the non-GDV classification (Table 1). When looking at the L8 models, the L8(SAVI) model performed better than the L8(NDVI) model in terms of the PA, the UA and the OA. The accuracy assessment results show that the SAVI is the better-performing index for determining bio-indicators when using L8. This is also true for the S2-derived maps where the SAVI maps had a higher PA (93%) and UA (95%) compared to the NDVI PA (88%) and UA (90%) for the GDV classification. Looking at the sensors, S2(SAVI) outperformed L8(SAVI) by 1%, and by 3% for the NDVI model. Overall, the results reveal that S2 performs better than L8 when evaluating the capability for detecting and mapping the potential distribution of GDV within areas with limited GDV potential.

The level of agreement and disagreement for the four models is shown on Figure 5. Agreement is higher than disagreement (errors of commission and omission) for both classes. However, the error of omission is high for the GDV class, while the non-GDV

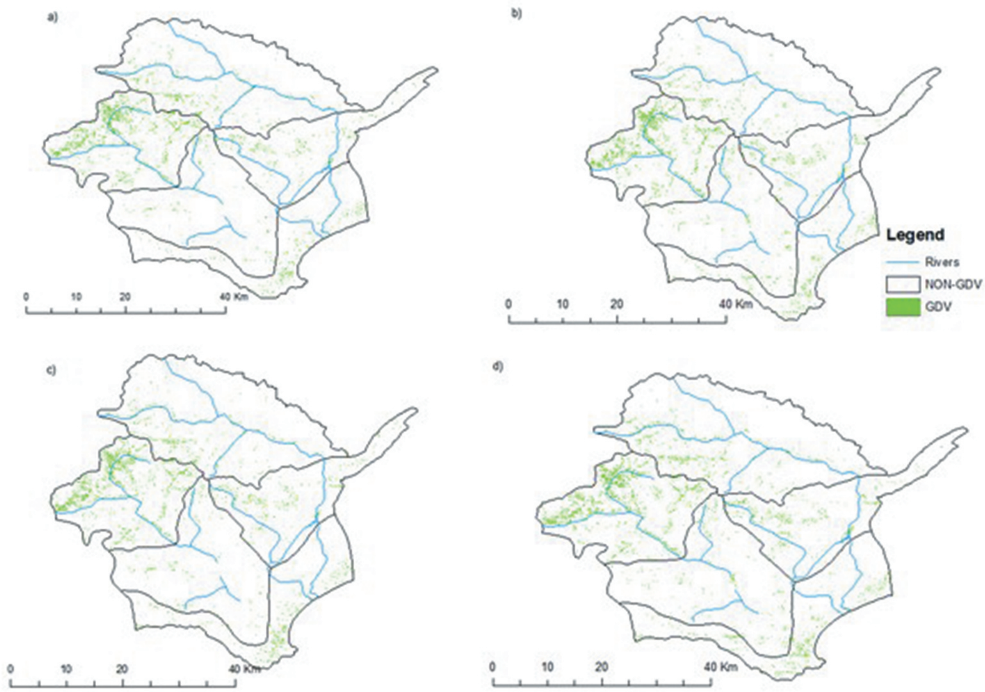

Figure 4. Distribution of potential GDV within the Heuningnes catchment derived from the GDV indices: a) S2(SAVI), b) L8(SAVI), c) S2(NDVI) and d) L8(NDVI).

Table 1. Accuracy assessment results for the binary classification of potential GDV for the Heuningnes catchment.

		PA	UA	OA	Kappa
L8(NDVI)	GDV	79.55	85.37	92.35	0.77
	Non-GDV	96.05	94.19		
L8(SAVI)	GDV	90.24	92.50	96.43	0.89
	Non-GDV	98.06	97.44		
S2(NDVI)	GDV	87.80	90.00	95.41	0.86
	Non-GDV	97.42	96.79		
S2(SAVI)	GDV	92.68	95.00	97.45	0.93
	Non-GDV	98.71	98.08		

class has a higher error of commission. The L8(NDVI) underperformed with a high level of disagreement (35%), largely from the high omission error (20.45%) for the GDV class. Disagreement for the classification from S2(SAVI) was (4%) which was equally contributed by the commission and the omission errors for the GDV class. Difference in performance between the sensors indicated that potential GDV can be more accurately detected when using Sentinel 2 within the Heuningnes Catchment. A McNemar statistical test ($p > 0.05$) revealed that there were no significant differences in the performance of the classifications.

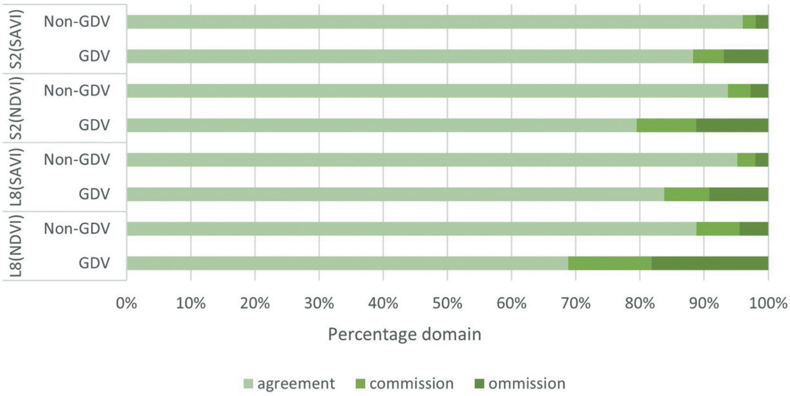

Figure 5. Allocation of agreement, commission, and omission errors for the four potential GDV maps.

3.1.3 Vegetation species as an indicator of GDV occurrence

Vegetation that is known to be dependent on groundwater can be used to assess the GDV classification. If the known GDV is found in the identified areas, the classification is validated (Le Maitre et al., 1999; Páscoa et al., 2020). Dominant vegetation within the catchment is presented in Table 2. The catchment flora consists of both endemic and invasive species that are linked with groundwater dependency (Colvin et al., 2003; Le Maitre et al., 1999).

Table 2. Plant species identified in the Heuningnes catchment.

	Scientific Name	Family Name	Cover (%)
Plot 1	*Plecostachys serpyllifolia*	Fabaceae	75–80
Plot 2	*Ornithogalum thyroides*	Asparagaceae	65–70
Plot 3	*Acacia saligna*	Fabaceae	75–85
Plot 4	*Liliopsida*	Liliaceae	50–65
Plot 5	*Ornithogalum thyroides*	Asparagaceae	65–70
Plot 6	*Ornithogalum thyroides*	Asparagaceae	50–60
Plot 7	*Thamnochortus insignis*	Restionaceae	55–70
Plot 8	*Acacia saligna*	Fabaceae	70–85
Plot 9	*Acacia lonifolia*	Fabaceae	70–85
Plot 10	*Acacia saligna*	Fabaceae	65–80
Plot 11	*Nassella trichotoma*	Poaceae	65–75
Plot 12	*Pinus pinaster*	Pinaceae	60–70
Plot 13	*Acacia lonifolia*	Fabaceae	65–80
Plot 14	*Acacia saligna*	Fabaceae	65–80
Plot 15	*Leucadendron laureolun*	Proteaceae	50–65
Plot 16	*Acacia lonifolia*	Fabaceae	50–60
Plot 17	*Helichrysum splendidum*	Asteraceae	55–60
Plot 18	*Leucadendron salignum*	Proteaceae	50–65
Plot 19	*Diospyros glabra*	Ebenaceae	50–70
Plot 20	*Pinus pinaster*	Pinaceae	50–65
Plot 21	*Plecostachys serpyllifolia*	Asteraceae	65–80
Plot 22	*Oncosiphon pilulifer*	Asteraceae	60–75
Plot 23	*Cyathea capensis*	Cyatheaceae	50–70
Plot 24	*Athanasia Trifurcata*	Asteraceae	50–60

3.2 Discussion

The study found that moderate spatial resolution sensors have a high potential for GDV identification, with an overall accuracy of above 90% in the Heuningnes Catchment. The accurate estimation of GDV distribution is important when determining ecological reserves and for allocating groundwater resources (Colvin et al., 2003, 2007). There were small differences in the sensor performance for GDV classification, with the S2 models outperforming the L8 models. This is in accordance with previous studies that compared the two sensors. It has been established that S2 has superior capabilities for vegetation mapping than L8 (Mtengwana et al., 2020; Thamaga & Dube, 2018). The differences in performance between the sensors indicates that the pixel size is an important factor in the classification of GDV. Groundwater dependent vegetation is widely spread and patchy within the catchment, with some small clusters. Consequently, there is a need to decrease the pixel size. The S2 has a spatial resolution (10 m) that is three times higher than the L8, thereby decreasing the effects of the mixed pixels. Therefore, it can classify the distribution of smaller and isolated GDV communities effectively. Moreover, Moreover, potential areal coverage estimations were higher for the L8 models compared to those of S2. For L8, the GDV communities that were larger than half the pixel size were misclassified as being fully covered by GDV. This resulted in the over-estimation seen in the results. In terms of the vegetation indices, the SAVI has the capabilities to improve sensor performance for potential GDV detection when compared to the NDVI. The SAVI considers the effects of senescent vegetation and background soil effects which lead to the estimation errors caused by soil brightness and the cover of bare soil (Colvin et al., 2003; Dube et al., 2019; Parker et al., 2018; Thamaga et al., 2018). For this reason, the SAVI is more suitable for estimating GDV cover seen at low densities during dry periods. The McNemar test also revealed no significant differences ($\alpha = 0.05$) between the potential GDV indices classifications.

The occurrence of vegetation which is associated with groundwater use has been used as a qualitative verification method for GDV/GDE mapping in previous studies (Dzikiti et al., 2013; Páscoa et al., 2020; Scott & le Maitre, 1998). This study found a high potential for GDV occurrence in the north-western region of the Heuningnes Catchment. The identified vegetation species were the native *Leucadendron salignum, Helichrysum splendidum, Ornithogalum thyroides* and *Diospyros glabra* species, as well as the invasive Acacia and Pinus species. The endemic plants belong to the Renosterveld of the South Coast Centre and Mountain Centre vegetation and have been determined to be xeric (Colvin et al., 2003; Rutherford et al., 2006). Renosterveld shrubs may develop deep roots where possible but have limited interaction because of the hard shales. Groundwater may play a critical role in the quaternary sands on the western, southern and south-eastern coasts, as well as on the limestones on the laterites of the Agulhas-Riversdale coastal plain (Le Maitre et al., 1999). The north-western hillslopes and riparian zones of the catchment are heavily invaded by invasive species (Mkunyana et al., 2019; Mtengwana et al., 2020; Shoko et al., 2020; Münch & Conrad, 2007). Studies have demonstrated that the Acacia species may be tapping into the groundwater, and that their evapotranspiration may exceed rainfall. For example, Morris et al. (2020) assessed the ecophysiological traits of *A. Cyclops* with the native vegetation in the Cape Floristic region. They found that *A. Cyclops* maintained a higher photosynthetic rate during the dry summer months than the endemic species. This is attributed to the plant's deep rooting system that taps into groundwater. Furthermore, the north-western region of the catchment has a secondary fractured aquifer (Mokoena, 2019), and it is also possible that these vegetation communities may be maintained by springs. This study revealed that both endemic and invasive vegetation potentially rely on groundwater within the catchment. Invasive GDV threatens the endemic GDV as it can out-compete the endemic GDV and is more resilient to decreasing groundwater levels (Le Maitre et al., 1996; N. Jovanovic et al., 2013; Rouget et al., 2003; van Wilgen et al., 2008). Invasive vegetation not only exploits groundwater resources, but they also reduce groundwater recharge which limits the available water for endemic GDV.

The findings imply that biodiversity conservation management should consider that ecological groundwater reserves could be used by invasive species (Currie et al., 2009). Therefore, an emphasis must be placed on the need for invasive species control and restoration. Overall, S2- and L8-derived GDV have a high potential for GDV mapping. The level of accuracy can be slightly improved by using a suitable vegetation index for determining bioclimatic indicators and using a sensor with a higher spatial resolution. The distribution of GDV is important for setting up proactive and preventative management strategies. For instance, a GDV map can be used as a layer that is integrated with other spatial datasets to understand the distribution of GDV and how they are connected to the broader hydrological processes within the landscape (Glanville et al., 2016). Furthermore, they may serve as baseline data that are provided for planning, assessment and regulating development activities in specific areas which may affect the GDV within the Heuningnes Catchment.

This research observed two major limitations relating to the method used for GDV mapping. Firstly, as seen from the visual representation, there are areas of probable GDV that may not be included in the four models because of the selected threshold that tried to capture areas with the highest potential for GDV, based on the four indicators. For example, the GDV communities located on higher slopes and close to water bodies could have been masked out because they are located at slopes>3%. Mapping quality can be improved by investigating alternative vegetation indices, and by incorporating machine learning algorithms and investigating their performance across a range of index values. Confidence in models can be improved by using the spatial relationship between groundwater depth and the distribution of GDV. In this study however, groundwater depth datasets could not be included as a spatial layer because there were gaps in the data and it was unevenly distributed. Secondly, field verification of the GDV indicator species was not easily quantifiable because the indicator species groups were highly fragmented within the landscape. They also had similar spectral signatures to the adjacent land cover and could not be discriminated by the remotely-sensed datasets. The indicator vegetation is useful for gauging the reliability of the maps, rather than a quantitative assessment of the GDV maps. Nevertheless, the findings from this study provide useful insights on the state of the environment in the Heuningnes Catchment. This information can be used as baseline data for further work on GDV monitoring and management in this area and beyond.

3.3 Conclusion

This study determined the suitable L8 and S2 models that can be used for mapping the potential GDV within the Heuninges Catchment. The main indicators for the GDV potential were the topographic characteristics of the landscape, the land cover and vegetation productivity. The models showed great potential for GDV mapping within the catchment; however, the S2(SAVI) model showed the greatest potential in terms of its overall assessment. The L8(NDVI) model's performance was lower, which was attributed to the misclassifications that resulted from Landsat's coarser spatial resolution. The GDV is densely distributed in the north-western region, with some found along the riparian zone. Although GDV in the south-eastern region is sporadic and relies on the shallow alluvial aquifer. Groundwater dependent vegetation is both endemic and invasive within the catchment and this has major implications for biodiversity and conservation management. The findings underscore the need for further investigation into the types of GDV distributed across the catchment, how they are linked to groundwater, as well as their level of dependency. Overall, the findings provide valuable data for further GDV assessments within the Heuningnes Catchment

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