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**Spatial Characterization of Vegetation Diversity with Satellite Remote
Sensing in the Khakea-Bray Transboundary Aquifer**

by

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A thesis submitted to the Department of Earth Sciences, Faculty of Natural Sciences at the
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ABSTRACT

There have been increasing calls to monitor Groundwater-Dependent Ecosystems (GDEs) more effectively, since they are biodiversity hotspots that provide several ecosystem services. The accurate monitoring of GDEs is an indispensable under Sustainable Development Goal (SDG) 15, because it promotes the existence of phreatophytes. It is imperative to monitoring GDEs, since their ecological significance (e.g., as biodiversity hotspots) is not well understood in most environments they exist. For example, vegetation diversity in GDEs requires routine monitoring, to conserve their biodiversity status and to preserve the ecosystem services in these environments. Such monitoring requires robust measures and techniques, particularly in arid environments threatened by groundwater over-abstraction, landcover and climate change. Although in-situ methods are reliable, they are challenging to use in extensive transboundary groundwater resources such as the Khakea-Bray Transboundary Aquifer. To avoid these setbacks, remote sensing technologies have spatially explicit landscape-scale capabilities for characterising vegetation diversity in GDEs. Remotely-sensed data and the Spectral Variation Hypothesis (SVH) have the inherent capability to provide a unique opportunity to monitor the vegetation diversity of GDEs, and their response to seasonal or intra-annual environmental stressors. Therefore, this research seeks to review the trends and milestones in using remote sensing for characterising vegetation diversity in GDEs, and use satellite remote sensing data (i.e., Sentinel-2 MSI and Landsat 8 OLI) to characterise the vegetation diversity in the Khakea-Bray Transboundary Aquifer. In addition, this thesis aims to monitor the spatio-temporal variations of vegetation diversity in the Khakea-Bray Transboundary Aquifer. Overall, the remote sensing data demonstrated the potential of characterising vegetation diversity in the Khakea-Bray Transboundary Aquifer ($R^2 = 0.61$ and $p = 0.0003$). It was observed that the vegetation diversity in the Khakea-Bray Transboundary Aquifer was concentrated more around natural pans and along roads, fence lines and rivers, and that the changes in vegetation diversity within these areas was driven mainly by land conversion and climate variability. These findings are imperative for natural resource managers seeking to conserve the Khakea-Bray Transboundary Aquifer and to achieve the national or regional biodiversity targets. More importantly, this work provides a spatially explicit framework on how GDEs can be monitored in semi-arid environments, to achieve the SDGs.

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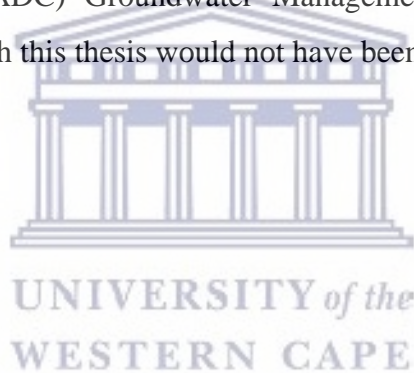
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DECLARATION

I declare that this thesis, entitled “**The spatial characterization of vegetation diversity with satellite remote sensing in the Khakea-Bray Transboundary Aquifer**” is my own work, and has not been submitted before, for any degree or examination at any other university, and that all the sources that I have used, or quoted, have been indicated and acknowledged by means of complete references.

Full name: Kudzai Shaun Mpakairi



Signed:

Date: 24 April 2022



PREFACE

The following manuscripts have been submitted in internationally peer-reviewed journals and presented at local and international conferences. The co-authors played a role in reviewing and improving the manuscripts, with my contribution being the largest:

1. **Mpakairi, K.S.**, Dube, T., Dondofema, F. and Dalu, T. Advances in the remote sensing of vegetation diversity in Groundwater-Dependent Ecosystems (GDEs) within arid environments: A review of the approaches and future trends. *Ecological Engineering (Under review)*
2. **Mpakairi, K.S.**, Dube, T., Dondofema, F. and Dalu, T. Spatial characterisation of vegetation diversity in groundwater-dependent ecosystems, using Sentinel-2 MSI imagery. *Remote Sensing (Accepted)*
3. **Mpakairi, K.S.**, Dube, T., Dondofema, F. and Dalu, T. Spatio-temporal variation of species diversity in groundwater-dependent ecosystems within arid environments. *Ecological Informatics (In press)*

The research was presented at the following conferences:

1. **Mpakairi, K.S.**, Dube, T., Dondofema, F. and Dalu, T. Finding the needle in a haystack: Satellite remote sensing of priority conservation areas in Groundwater Dependent Ecosystems (GDEs). Freshwater Bio-informatics Seminar Series on 18 August 2021, South Africa.
2. **Mpakairi, K.S.**, Dube, T., Dondofema, F. and Dalu, T. Finding the needle in a haystack: Satellite remote sensing of priority conservation areas in Groundwater Dependent Ecosystems (GDEs). The Geo-Information Society of South Africa WC AGM on the 6th of October 2021.
3. **Mpakairi, K.S.**, Dube, T., Dondofema, F. and Dalu, T. Finding the needle in a haystack: Satellite remote sensing of priority conservation areas in Groundwater Dependent Ecosystems (GDEs). Southern African Society for Aquatic Scientists (SASAqS) 2021 Conference, from 2–4 November 2021.
4. **Mpakairi, K.S.**, Dube, T., Dondofema, F. and Dalu, T. Finding the needle in a haystack: Satellite remote sensing of priority conservation areas in Groundwater

Dependent Ecosystems (GDEs). 4th Southern African Development Committee (SADC) Groundwater 2021 Conference, from 10–12 November 2021.



DEDICATION

This thesis is dedicated to science and the conservation of transboundary aquifers.



1.0. CHAPTER 1

GENERAL INTRODUCTION



Environmental heterogeneity in the Khakea-Bray Transboundary Aquifer

(Photo: Courtesy of Kudzai Mpakairi, 2022)

1.1. Monitoring Groundwater-Dependent Ecosystems in Arid Environments

Groundwater is an important water resource (Moosdorf and Oehler, 2017, Liggett and Talwar, 2009) and the existence of most coastal, aquatic and terrestrial ecosystems depends on its availability (Liggett and Talwar, 2009, Murray et al., 2003, Eamus et al., 2015). Terrestrial vegetation (e.g. phreatophytes) accesses soil moisture through capillary action, which is supported by the cohesion theory (Bouwer, 2002, Bian et al., 2009, Kang et al., 2003). Consequently, if groundwater is inaccessible to the plant roots, this might affect groundwater-dependent ecosystems (GDEs) and lead to changes in the ecosystem's structure and function, such as increased vegetation dieback and invasive species (Kang et al., 2003). Most global GDEs are under threat because the rate of groundwater extraction for agriculture, municipal and recreational purposes usually exceeds the rate of groundwater recharge (Murray et al., 2003). These competing claims on groundwater use for ecosystem or livelihood needs requires policies that rationalize groundwater use, especially for those GDEs under threat, such as the Khakea-Bray Transboundary Aquifer (hereafter referred to as Khakea-Bray TBA) (Shah, 2005, Wiek and Larson, 2012). Henceforth, to suppress the possible ramifications of groundwater drawdown and conserve some of the keystone species in GDEs, they require characterization and constant monitoring.

The characterization of GDEs is pivotal for their conservation and management, and characterising GDEs includes understanding the diversity and composition of the vegetation, as well as its response to groundwater drawdown. Understanding these components could assist with rationalizing groundwater use for ecosystem or livelihood needs. However, the current field techniques for characterising GDEs are either time-consuming, laborious or costly (Manfreda et al., 2018). Although field techniques are reliable and accurate, these setbacks limit their applicability (Manfreda et al., 2018, Madonsela et al., 2017). Geographic Information Systems (GIS) and remote sensing methods may be useful and provide reliable information, even in areas where *a priori* information on vegetation diversity is unavailable (Madonsela et al., 2017, Nagendra and Rocchini, 2008). For example, the Rao's Q can provide estimates of the vegetation diversity of any environment (Torresani et al., 2019). Using such metrics and remote sensing data can allow the characterization of GDEs with ease (Torresani et al., 2019). However, using remote sensing for characterising GDEs depends on the spatial and spectral resolution of the remote sensing data used. High spatial and spectral resolution

data are available from Unmanned Aerial Vehicles (UAVs) and commercial satellites (Manfreda et al., 2018), while new generation satellites, such as Sentinel-2 MSI, Landsat 8 OLI and Landsat 9, may be useful since they are free. These satellites have medium-resolution data that might be coupled to improve the characterization of extensive transboundary aquifers, such as the Khakea-Bray TBA.

The successful characterisation of vegetation diversity will provide a framework for monitoring the spatial and temporal variations in vegetation diversity, as well as the drivers of these dynamics. This is important, since the Khakea-Bray TBA is predominantly arid and an increased groundwater draw-down will most likely intensify the proliferation of invasive species, and the imminent effects of climate change may lead to desertification, which will affect the communities around the GDEs. However, there is a dearth of literature on these aspects for the Khakea-Bray TBA, even though the GDEs support livelihoods. Several communities around the Khakea-Bray TBA rely on the groundwater for their survival. These communities are part of Africa's population settled in GDEs, estimated to be ~ 32,8 million in 2015 (Nijsten et al., 2018). Given that the Khakea-Bray TBA is important for the survival of livelihoods and ecosystems, reliable and timely techniques for monitoring its vegetation diversity are imperative. This thesis addresses some of these aspects.

1.2. Aim and Objectives

The aim of the study is to use GIS and remote sensing techniques to characterize the vegetation diversity in the Khakea-Bray Transboundary Aquifer.

1.2.1. Objectives

The objectives of this thesis are:

1. to review the advances that have been made in the remote sensing of vegetation diversity in GDEs within arid environments;
2. to spatially characterize vegetation diversity in the Khakea Khakea-Bray TBA by using remote sensing; and
3. to detect the spatio-temporal trends in vegetation diversity and the drivers of these changes in GDEs.

1.3. Research questions

This thesis addresses the following research questions:

1. Has remote sensing been a reliable technique when monitoring vegetation diversity in GDEs?
2. To what extent can remote sensing be used to characterize the vegetation diversity of GDEs?
3. How does the vegetation diversity vary over space and time, and what drives these changes in GDEs?

1.4. Conceptual framework

This thesis presents a framework of how GIS and remote sensing methods can be used to monitor GDEs in arid and semi-arid environments, the potential of informing decision-makers on the key priority areas in GDEs that need conservation. In addition, it provides the necessary rudimentary information for the conservation of the Khakea-Bray TBA. The conceptual framework of the work undertaken is shown in Figure 1.1 below:

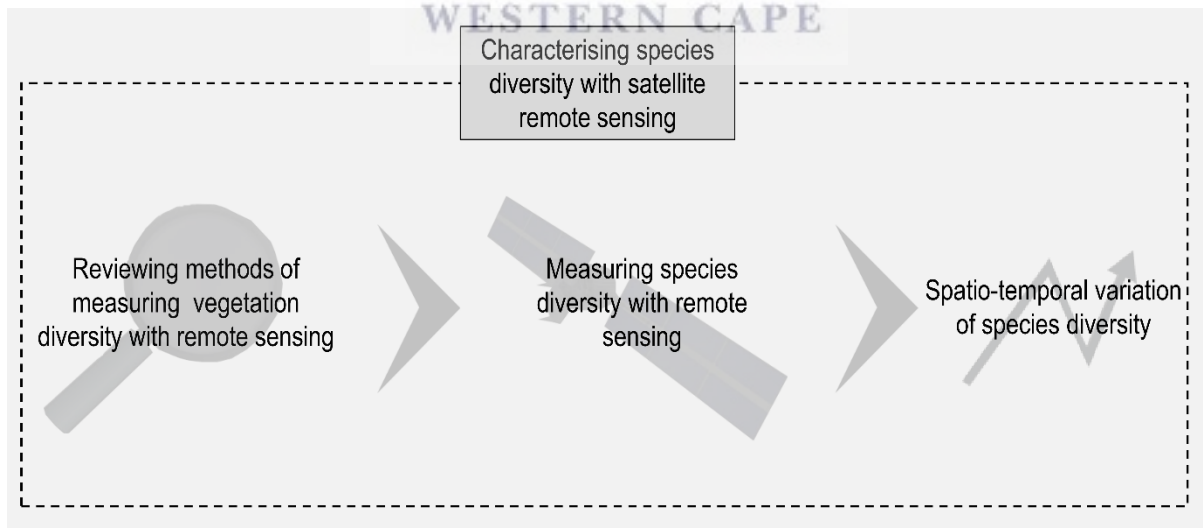


Figure 1.1 Conceptual framework of the key concepts covered in this thesis.

1.5. Description of the study area

The research in this thesis focused on the Khakea–Bray TBA (formerly the Pomfret–Vergelegen Transboundary aquifer), which measures ~30 000 km² and spans across north–western South Africa and south–western Botswana (Figure 1.2). The Khakea–Bray TBA is supported by the low–yielding Khakea–Bray dolomitic aquifer, which measures approximately ~5375.7 km². Rainfall is the main source of recharge to this dolomitic aquifer, with geological lineaments, shallow dolomite outcrops, and alluvial channels along the Molopo River serving as recharge areas (Godfrey and Van Dyk, 2002a). However, the recharge to the Khakea–Bray dolomitic aquifer is limited by the low infiltration rate because of the thick Kalahari sands (>15 m) and the high rate of evaporation (2050–2250 mm per annum) (Altchenko and Villholth, 2013, Turton et al., 2006, Godfrey and Van Dyk, 2002a).

The Khakea–Bray TBA is characteristic of a semi–arid environment, owing to the low annual rainfall (range 107–928 mm) that it receives in the summer months (October–March) (Godfrey and Van Dyk, 2002a). The Khakea–Bray TBA is mainly dominated by the Eastern Kalahari Bushveld Bioregion supporting Molopo Bushveld, Mafikeng Bushveld, and Kuruman Mountain Bushveld (Spickett et al., 2011, Van Dyk, 2005, Mucina and Rutherford, 2006). The bushveld is predominantly *Senegalia nigrescens* and *Vachellia grandicornuta* shrubland intermixed with *Scorzonera humilis*, *Eragrostis* spp, *Ziziphus mucronate*, *Leucas martinicensis* and *Lipia javani*. These vegetation species are facultative phreatophytes (i.e. will use groundwater when it is available). However, information on the significance or distribution of these vegetation types in the Khakea–Bray TBA is unavailable.

Agriculture and wildlife ranching are the main land–uses in the Khakea–Bray TBA, with irrigated agriculture using the bulk of the available groundwater (Turton et al., 2006). In 2002, the groundwater level was reported to have lowered from 20 m to 60 m, due to the unsustainable extraction of groundwater for agricultural purposes (Godfrey and van Dyk, 2002b, Seward and van Dyk, 2018). The total area under irrigation in 1990 had increased by 13.95 ha, from 100 ha (Godfrey and Van Dyk, 2002a). The irrigated farmlands used ~11.1 Mm³ per annum more than the annual recharge in the area and this caused the dewatering of the Khakea–Bray TBA (Altchenko and Villholth, 2013, Turton et al., 2006, Godfrey and Van Dyk, 2002a). After the groundwater in the Khakea–Bray TBA lowered, deeper boreholes were sunk and livelihoods dependent on shallower boreholes were affected (Seward and van Dyk, 2018). The lowering

of the groundwater restricted GDV access to groundwater, risking the ecosystem to invasion by alien plant species (Seward and van Dyk, 2018). The lack of information on the ecological status of the Khakea–Bray TBA, along with the high rate of groundwater abstraction, provide the basis for the need to monitor the spatio–temporal variation of species diversity.

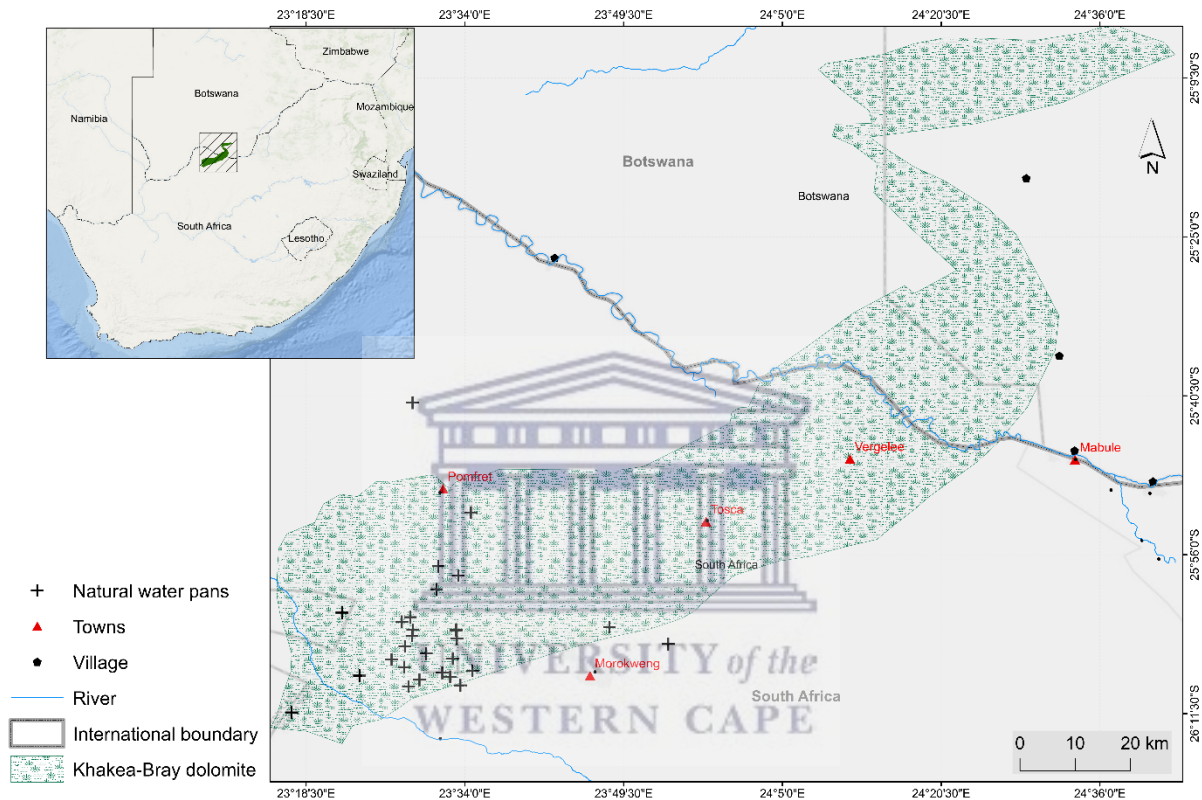


Figure 1.2 Location of the Khakea–Bray Transboundary Aquifer in southern Africa.

1.6. Thesis outline

This thesis is comprised of five chapters, which demonstrate the use of remote sensing in the characterization of vegetation diversity in GDEs. Three of the chapters are presently under review in peer-reviewed journals. Although an effort was made to minimize the repetition and overlaps, instances of overlap and repetition may still be noted, since the chapters are linked and reinforce each other, as they aim to demonstrate how remote sensing can characterize the vegetation diversity in GDEs.

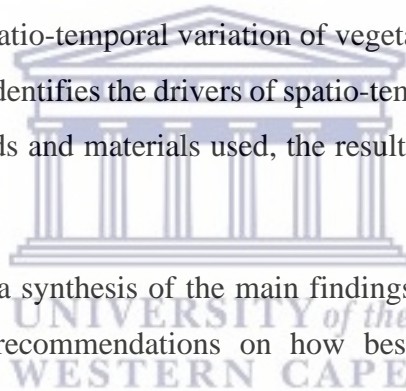
Chapter One introduces the general background of the thesis and presents the significance of the conservation and monitoring of GDEs in arid environments. This is followed by the aim and objectives of the thesis, the research questions, the conceptual framework, and a description of the study area.

Chapter Two reviews the advances that have been made in the use of remote sensing for the monitoring and characterization of GDEs within arid environments.

Chapter Three demonstrates the applicability of the Spectral Variation Hypothesis (SVH) for characterising the vegetation diversity of GDEs in the Khakea-Bray TBA. This chapter also assesses the most suitable measures that can be used for detecting the spectral heterogeneity in GDEs. This chapter presents the materials and methods used, the results of the research and a discussion of the key observations.

Chapter Four identifies the spatio-temporal variation of vegetation diversity in GDEs within the Khakea-Bray TBA. It also identifies the drivers of spatio-temporal change in the vegetation diversity, as well as the methods and materials used, the results and a discussion of the main findings.

Chapter Five finally presents a synthesis of the main findings of the study, the conclusions that can be drawn and the recommendations on how best to conserve GDEs in arid environments.



2.0. CHAPTER 2

ADVANCES IN THE REMOTE SENSING OF VEGETATION DIVERSITY IN GROUNDWATER-DEPENDENT ECOSYSTEMS (GDEs) WITHIN ARID ENVIRONMENTS: A REVIEW OF THE APPROACHES AND FUTURE TRENDS



Dry natural water pan in the Khakea-Bray Transboundary Aquifer during the onset of the wet season (Photo: Courtesy of Kudzai Mpakairi, 2022)

This chapter is based on:

Mpakairi, K.S., Dube, T., Dondofema, F. and Dalu, T. Advances in the remote sensing of vegetation diversity in Groundwater-Dependent Ecosystems (GDEs) within arid environments: A review of the approaches and future trends. *Ecological Engineering* (*Under review*)

2.1. Abstract

There have been increasing calls to monitor Groundwater Dependent Ecosystems (GDEs) more effectively, since they are biodiversity hotspots for keystone plant species. The accurate monitoring of GDEs is an indispensable pursuit for Sustainable Development Goal (SDG) 15. SDG 15 promotes the protection and sustainable use of terrestrial ecosystems, phreatophytes included. The monitoring of GDEs requires robust measures and techniques, particularly in arid environments that face the threat of groundwater draw-down, climate change and species extinction. Geographic Information Systems (GIS) and remote sensing offer the spatially explicit and landscape-scale capability of characterizing the vegetation diversity in GDEs, in addition to monitoring their structure and function. This chapter reviews how remote sensing has been used to characterize vegetation diversity in GDEs within arid environments. It also discusses the trends in using remote sensing and the role of spatial and spectral resolution, and some of the methods that have been used in the mapping of vegetation diversity in GDEs. It was observed that geospatial technologies can undoubtedly contribute towards our current understanding of the global state of GDEs with high accuracy, regardless of the prohibitive costs associated with it. Remote sensing utilizes the spectral response of vegetation to electromagnetic radiation when monitoring vegetation diversity, and GIS can map the diversity. Using remote sensing has increased over the past 20 years, with the Landsat and Moderate Resolution Imaging Spectroradiometer (MODIS) being the most-used sensors. However, considering the spatial resolution of these datasets vis-à-vis the spatial extent and the patchy nature of GDEs, the utility of broadband multispectral sensors cannot detect the subtle phenotypical and structural characteristics of the vegetation. Thus, new-generation sensors with improved sensing characteristics, such as Sentinel-2, and the future launch of hyperspectral sensors such as EnMap and HypSIIRI, will most likely improve the characterization of GDEs. Sensor selection is critical for the characterization of GDEs, since the optical properties of vegetation diversity are complex and driven by several environmental, physiological, and structural factors. The data fusion of active and passive sensors may be useful for characterizing GDEs. Finally, future opportunities are presented that should be explored for the monitoring of vegetation diversity in GDEs, such as Unmanned Aerial Vehicles (UAVs), Phenocam data, advanced machine learning, Cloud computing and Radiative Transfer Models (RTMs).

Keywords: Arid environments; earth observation; spectral resolution; vegetation diversity; UAS; savanna biomes.



2.2. Introduction

Several global ecosystems depend on the availability of groundwater for their existence (Pérez Hoyos et al., 2016). These ecosystems include rivers and lakes (Saylam et al., 2020), subterranean aquifers (Humphreys, 2006), wetlands and springs (Huang et al., 2020b), as well as estuarine and near-shore ecosystems (Pérez Hoyos et al., 2016). Groundwater dependency usually depends on several environmental factors (i.e. hydrogeological settings), namely, the evapotranspiration rate, precipitation, and temperature (Huang et al., 2020b). For instance, most ecosystems in tropical and boreal biomes are independent of the groundwater because of the surplus surface water from preceding precipitation (Eamus et al., 2015). However, given the low precipitation and limited surface water resources in arid environments (e.g. savannah and deserts), groundwater dependency is key for the existence of phreatophytes (Qiu et al., 2019, Meyers et al., 2021, Alaibakhsh et al., 2017). In arid environments, the groundwater balances the water deficit induced by the high evapotranspiration rates and changes in surface water storage (Dawson, 1996, Eagleson, 1978), which facilitates the existence of Groundwater-Dependent Ecosystems (GDEs) (Eamus and Froend, 2006, Pérez Hoyos et al., 2016). Groundwater-Dependent Ecosystems in arid environments are characterized by vegetation communities with a taproot system (i.e. phreatophytes) (Alaibakhsh et al., 2017). These vegetation communities rely strongly on the depth of the groundwater, and the groundwater draw-down can significantly affect the ecosystem structure and its functioning (Kang et al., 2003, Lv et al., 2013).

Groundwater-dependent vegetation communities (e.g. in the Mojave Desert and Succulent Karoo) are biodiverse hotspots and provide a habitat and refuge for several species under threat (i.e. faunal endemism) (Alaibakhsh et al., 2017, Pengra et al., 2007). In arid environments, phreatophytes (e.g. the Shepherd's tree (*Boscia albitrunca*)) are keystone plant species and can assist with plant facilitation because they are capable of redistributing groundwater to the shallower parts of the soil profile to benefit co-existing species (Xu et al., 2015, Lv et al., 2013, Coletti et al., 2017). Groundwater redistribution is important for species that might not adapt fast enough to the changes in groundwater draw-down (i.e. the hydrological regime) (Coletti et al., 2017, Stella and Bendix, 2018). Inherently, the hydrological regime of groundwater and its chemical composition influences the diversity of plant species in GDEs (Münch et al., 2013). For instance, calcium-rich wetlands have a low species diversity, when compared to the less acidic wetlands, because the species richness peaks at an intermediate pH (Cornwell and

Grubb, 2003, Olde Venterink et al., 2003). However, the high acidity or alkalinity in other GDEs has also facilitated the existence of endemic species (e.g. *Prosopis tamarugo*) (Decuyper et al., 2016, Scott and Baer, 2019). Plant facilitation and the interaction of groundwater with the vegetation in GDEs make these environments biodiversity hotspots.

To maintain the biodiversity and ecosystem health in GDEs, it is important to understand their response to environmental stressors (e.g. climate change, groundwater draw-down, droughts, pollution and wildfires) (Lv et al., 2013, Alaibakhsh et al., 2017, Coletti et al., 2017, Stella and Bendix, 2018). The methods used for monitoring ecosystem health in GDEs also include hydrogeological approaches (e.g. using environmental tracers or piezometers), which involves the collection of specific space-and-time data to understand ecosystem health from the interaction of the groundwater with Groundwater-Dependent Vegetation (GDV) (Eamus et al., 2015). However, it may be impossible to monitor the entire GDE by using hydrogeological approaches; therefore, indicators of an ecosystem's health are used instead (Eamus et al., 2015, Caldwell et al., 1998). These indicators include the flow magnitude, the extreme point, and the indicator species. Indicator species are commonly used, since species have varying adaptive capacities to environmental stressors and it is impossible to monitor them simultaneously (Decuyper et al., 2016, Stella and Bendix, 2018). Although widely used, these methods are limited in their spatial coverage and might not provide wall-to-wall coverage of the structure and functioning of the historical ecosystem.

To avoid the use of indicator species in the monitoring of GDEs, robust and spatially-explicit methods are needed to conserve their biodiversity (Rocchini et al., 2015). By using geospatial techniques, mainly Geographic Information Systems (GIS) and remote sensing, the biodiversity in GDEs can be monitored with improved coverage and resolution (e.g. from the extent of the wetland to the extent of the watershed) (Meyers et al., 2021, Alaibakhsh et al., 2017). Countless studies exist on using geospatial techniques for monitoring vegetation diversity in GDEs. However, when measuring their vegetation diversity with geospatial techniques, it is important to understand the aspect of diversity to be measured (i.e. the species, phylogenetic or functional diversity). Coupled with the hydrogeological approaches, remote sensing can provide managers and policymakers with robust information on the condition of the vegetation, and such knowledge can contribute to making informed decisions on the conservation of biodiversity in GDEs (Munch et al., 2013, Coletti et al., 2017). Numerous reviews are available on the types of GDE, their distribution, as well as their response to climate

change and groundwater variability (Eamus and Froend, 2006, Orellana et al., 2012, Boulton and Hancock, 2006, Pérez Hoyos et al., 2016, Eamus et al., 2015), and these reviews provide a detailed overview on using geospatial technologies for mapping GDEs globally. But this chapter seeks to add rudimentary knowledge on how remote sensing technologies can delineate and characterise the vegetation diversity in GDEs within arid environments. This review is one of the first to provide a detailed overview of the progress of remote sensing technologies in the delineation and characterisation of vegetation in GDEs in such environments. The aim of this chapter is to review research articles that focus on earth observation technologies between 2000 and 2020 in the monitoring of vegetation diversity in GDEs. It focuses primarily on literature published in English language on GDEs within arid environments, which was retrieved from SCOPUS, the Web of Science, and other related databases.

Relevant literature was retrieved by using the following search words: "remote sensing", "groundwater dependent vegetation", "vegetation diversity", "arid environment" or "semi-arid environments". The combination of the search words was varied, to improve the output. The ninety articles retrieved were further screened, to exclude those that focused on environments that were not arid or semi-arid. The screening was generalized, and articles that focused on other themes, for example, urban diversity or agriculture, were also excluded. The articles finally reviewed were distributed across all the continents, except Antarctica, and they represented the GDEs within arid environments (see Figure 2.1).

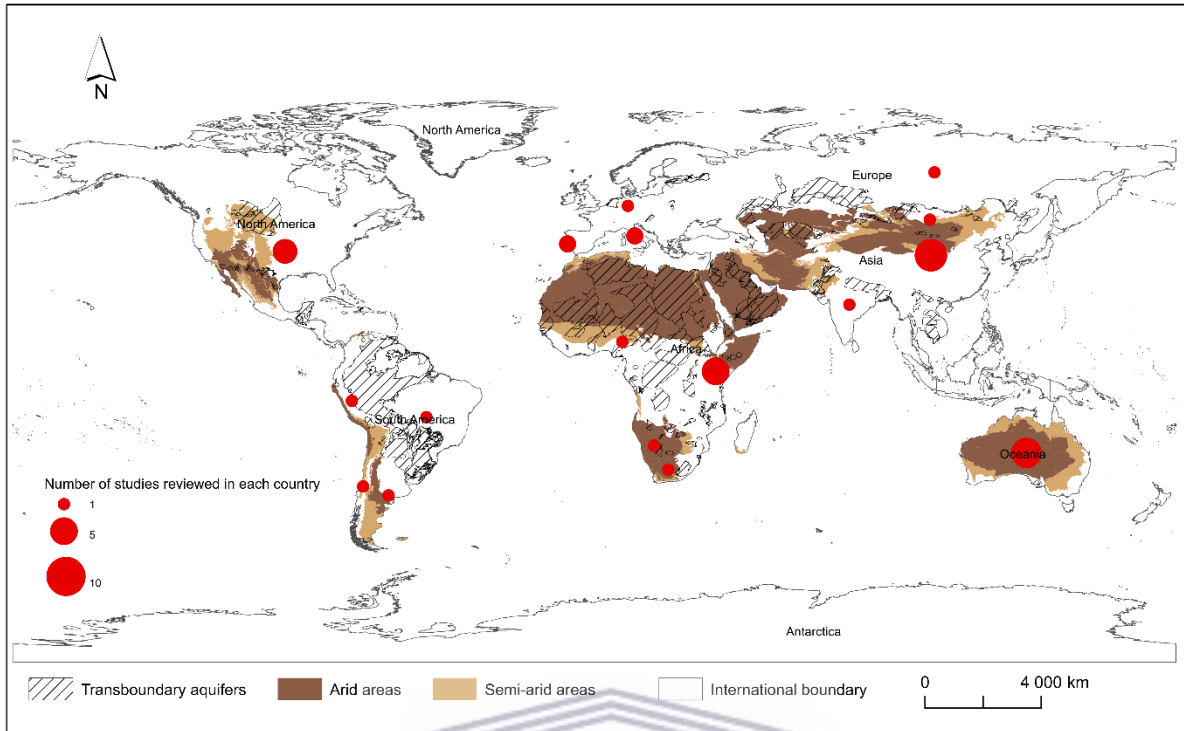


Figure 2.1 Global distribution of the transboundary aquifers and arid regions in the world. The red circles are proportional circles that show the number of studies reviewed in each country. Data on transboundary aquifers are accessible from <https://ggis.un-igrac.org/view/tba>, and the data for arid and semi-arid regions are available from Hoekstra et al. (2010).

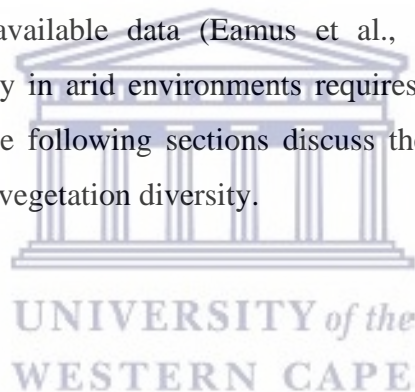
2.3. Progress of remote sensing in the monitoring of vegetation diversity in GDEs

Species extinction has reached an alarming rate since the dawn of the 21st century, and the species in GDEs are no exception (Elewa and Abdelhady, 2020). It is disturbing to note that climate change will probably exacerbate the extinction rate of plant species in arid environments (Elewa and Abdelhady, 2020, Carpenter and Bishop, 2009). The use of remote sensing has increased over the years; it offers many capabilities and can also monitor vegetation diversity in GDEs in arid environments (see Figure 2.1).

Studies on the mapping and monitoring of vegetation (or plant species) diversity, using remote sensing, began with coarse resolution space-borne sensors (e.g. the Advanced Very High-Resolution Radiometer (AVHRR)) and gradually progressed to using high-resolution airborne sensors (e.g. the Portable Remote Imaging Spectrometer (PRISM)) (Table 2.1). Over the past 20 years reviewed, Landsat and the Moderate Resolution Imaging Spectroradiometer (MODIS)

have been the most-used sensors (Figure 2.2); they are available and relatively accurate for monitoring vegetation diversity, hence their continued use. Unlike other sensors (e.g. Worldview 2 and QuickBird), Landsat and MODIS are non-commercial, they have a global coverage and are easily accessible through various platforms (e.g. <https://earthexplorer.usgs.gov/> or <https://earthdata.nasa.gov/>). In addition, they both have a moderate spatial and spectral resolution. Commercial remote sensing data are expensive, given the high cost of these platforms and the payload instruments used (Whitehead and Hugenholtz, 2014, Wang et al., 2019). However, remote sensing data from commercial satellites are more ideal for monitoring the vegetation diversity in GDEs in arid environments, and they provide accurate results.

The capabilities of high-resolution imagery have remained unquestionable over the years. Nonetheless, when using remote sensing data, there is a trade-off between using the most accurate data, or using the available data (Eamus et al., 2015, White et al., 2016b). Understanding species diversity in arid environments requires the use of high spatial- and spectral-resolution sensors. The following sections discuss the role of spatial and spectral resolution in the monitoring of vegetation diversity.



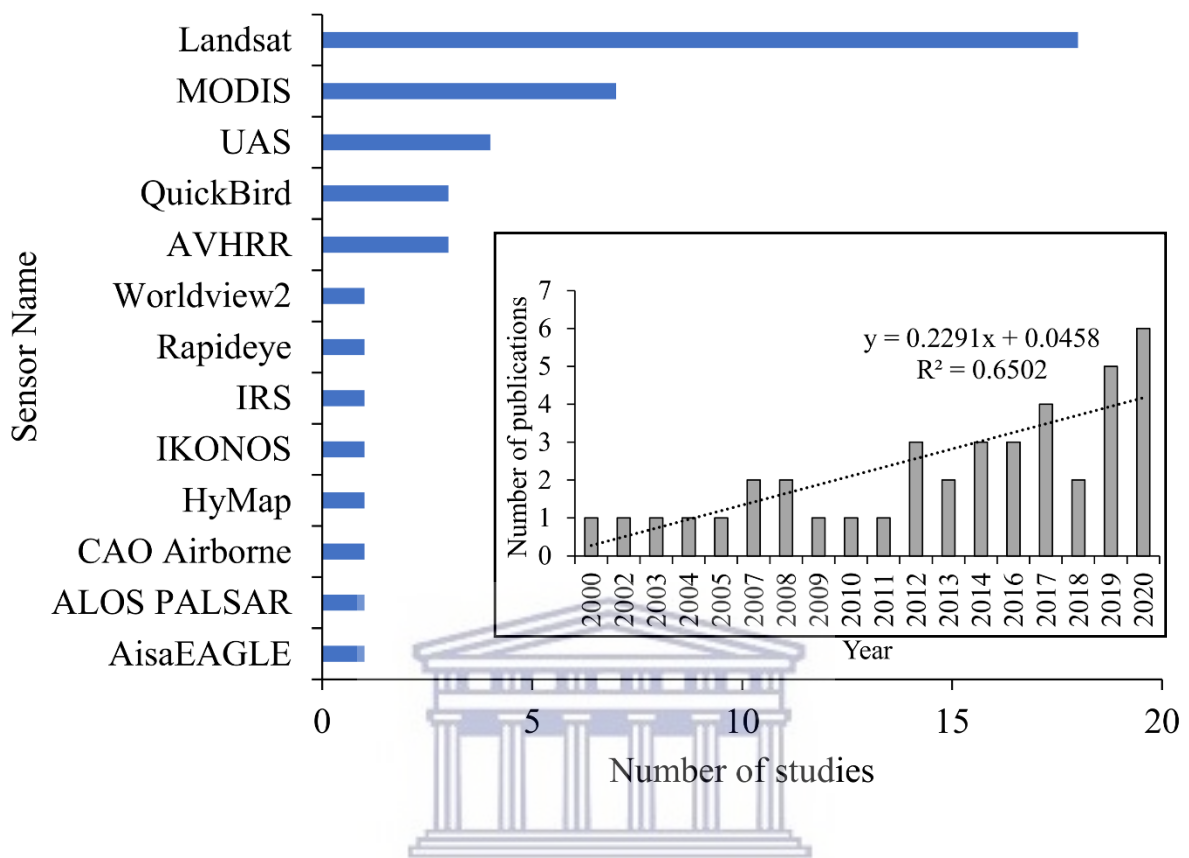


Figure 2.2 Trends in the use of remote sensing sensors for mapping vegetation diversity in Groundwater-Dependent Ecosystems (GDEs) in arid environments. UAS refers to an Unmanned Aircraft System and IRS refers to the Indian Remote Sensing Satellite. The insert shows the increase in the number of studies on the vegetation diversity in GDEs over the past 20 years.

Table 2.1 Remote sensing sensors that are capable of monitoring vegetation diversity in GDEs have different specifications. These sensors can be broadly classified into active and passive sensors, or they can be grouped based on their resolution (i.e., spatial or spectral resolution).

		Active Sensors			Passive Sensors			
Sensor/Instrument Name	Spatial resolution	Number of Spectral bands	Author	Sensor/Instrument Name	Spatial resolution	Number of Spectral bands	Author	
	High Spatial Resolution	DJI Mavic pro quadrotor drone	0.02 cm	3	Qiu et al. (2019)	SPOT 7	1,5 m	3
Zeiss RMK Top aerial photography		0.2 m	3	Tuxen et al. (2011)	QuickBird	3 m	4	Rocchini et al. (2007)
AisaEAGLE		1 m	129	Schäfer et al. (2016)	HyMap	5 m	128	Oldeland et al. (2010)

	Phantom 4 drone	1.5 m	5	Scher et al. (2020)	Rapideye	5 m	5	Li et al. (2017)
	Carnegie Airborne Observatory (CAO) Airborne	2 m	214	Féret and Asner (2014)	IKONOS	4 m	4	Warren et al. (2014)
Medium spatial resolution	ALOS PALSAR	10 m	L-band	Scarth et al. (2019)	Sentinel-2	10-60 m	13	Fauvel et al. (2020)
	GEDI-LiDAR	25 m	NA	Schneider et al. (2020)	Landsat +ETM	30 m	8	Curtis et al. (2019)
	Sentinel-1	5-40 m	C-band	Fauvel et al. (2020)	Indian Remote Sensing Satellite (IRS) 1B LISS 2	36,25 m		Nagendra and Gadgil (1999)
Low spatial				MERIS	300 m	15	Berberoglu et al. (2009)	

RADARSAT	1-100 m	C-band	Gomes and Maillard (2006)	MODIS	500 m	36	Pau et al. (2012)
				AVHRR	8 km	5	von Wehrden and Wesche (2007)



2.4. The Spectral Variation Hypothesis (SVH) and the role of resolution in delineating and characterising GDEs

The optical properties of vegetation are complex and driven by many environmental, physiological and structural factors (Lauver, 1997). Regardless of its complexity, the Spectral Variation Hypothesis (SVH) supports the use of remote sensing for characterising the vegetation in GDEs (Rocchini et al. 2004, Heumann et al. 2015, Schmidtlein and Fassnacht 2017). The hypothesis posits that spectral heterogeneity is a function of ecosystem heterogeneity (Rocchini et al., 2007, Rocchini et al., 2010a), which means that vegetation spectra are related to the structure and composition of an ecosystem (Rocchini, 2007). Essential Biodiversity Variables (EBVs), a measure of spectral variation (e.g. the Leaf Area Index (LAI), the Net Primary Production (NPP), as well as the Chlorophyll content and flux), have been proposed for relating the vegetation spectra and ecosystem composition (Skidmore et al., 2021, Haase et al., 2018). However, most of these EBVs usually represent canopy traits (e.g. aboveground biomass and vegetation canopy height) and work best in temperate and equatorial regions that are characterized by closed canopy cover and minimal understory vegetation (Schneider et al., 2020, Gara et al., 2018). Therefore, the applicability of the SVH in GDEs goes beyond using the measures of spectral variation (EBVs), owing to the sparsely distributed vegetation in GDEs.

When characterising or delineating the vegetation diversity in GDEs, sensor selection is critical. Notwithstanding the merits of using Landsat and MODIS data, the accurate delineation, or characterization, of GDEs requires the use of high spatial- and spectral-resolution sensors (Barron et al., 2014). As suggested by Nagendra and Rocchini (2008), "the devil is in the detail" when using remote sensing for characterising vegetation diversity. High spatial- and spectral-resolution sensors are more capable than medium-resolution sensors (Rocchini et al., 2015). High spatial- and spectral-resolution sensors avoid the possibility of spectral mixing, since the size of the pixel will match the size of the object (i.e. the plant species) (Lausch et al., 2016). With medium-resolution sensors, several plant species may cluster in one pixel, and because of spectral mixing, the spectra of the dominant species are usually reflected (Lausch et al., 2016). This will affect the correct estimation of the species diversity for that pixel (Figure 2.3). The spectral mixing of features with other environmental factors is also possible with medium-resolution sensors. For instance, arid environments are

heterogeneous and the soil brightness may affect the vegetation spectra (Madonsela et al., 2017). In addition, spectral bands from medium-resolution sensors are too coarse for discriminating similar phylogenetic plant species ; thus, there is a need for narrow spectral bands from hyperspectral sensors (e.g. HyMap or the NASA Airborne Visible and Infrared Imaging Spectrometer (AVIRIS)) (Lopatin et al., 2017, Carlson et al., 2007).

Conceptually, spectral bands from hyperspectral sensors can discriminate between different plant species, even after phenotypic plasticity (Cavender-Bares et al., 2020). However, spectral bands from hyperspectral sensors are redundant and highly correlated (Rocchini et al., 2013). The dispersion of vegetation in arid environments might also influence misclassifications, owing to an increase in within-pixel variability (i.e. more noise) when using high-resolution sensors (e.g. QuickBird) (Nagendra, 2001, Rocchini et al., 2010a). Nevertheless, the capabilities of high spatial- and spectral-resolution data in mapping vegetation diversity remain unmatched.

2.5. Active Sensors and the Monitoring of Vegetation Diversity in GDEs

Active sensors (e.g. LiDAR and RADAR) are also capable of seamlessly delineating and characterising GDEs. Unlike passive sensors, LiDAR provides several structural vegetation metrics that can help to assess the vegetation diversity in GDEs. These metrics (e.g. the tree height and height diversity index) can help to complement the high-resolution imagery, when assessing vegetation diversity (Scher et al., 2020, Listopad et al., 2015). Integrating field data and airborne imagery from Unmanned Aerial vehicles (UAVs), or LiDAR, has provided useful insights into vegetation diversity within GDEs. For example, when using low altitude UAVs, Qiu et al. (2019) could detect the vegetation diversity in the Tengger Desert, China. The major setback of using UAVs for monitoring GDEs is that they are costly, that they have limited spatial coverage and work best with localized GDEs. In addition, GDEs in arid environments are characterized by sparsely distributed shrublands, which means that LiDAR metrics may not be useful.

Ultimately, whether airborne or space-borne sensors are used, high spatial- and spectral-resolution sensors are better suited for delineating and mapping species diversity in GDEs within arid environments. The mapping and delineating accuracy decreases when low spatial- and spectral-resolution sensors are used.

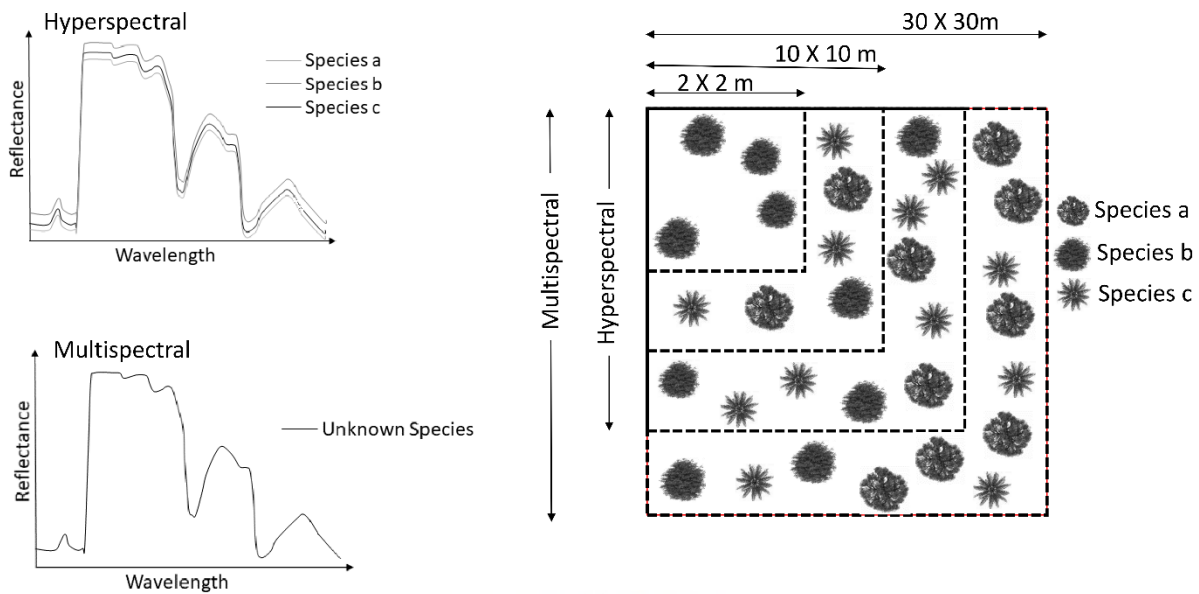


Figure 2.3 Conceptual framework of how the hyperspectral resolution allows the spectral discrimination of species, compared to when multispectral resolution sensors are used. A high spatial resolution increases between pixel variations, while a low spatial resolution increases within pixel variations.

2.6. Approaches to the Mapping of Vegetation Diversity with Remote Sensing in GDEs

2.6.1. Guiding principles for mapping vegetation diversity with remote sensing

Using remote sensing to delineate GDEs has grown over the years, owing to the synoptic view offered by earth observation tools (Gou et al., 2015, White et al., 2016a, Huntington et al., 2016). However, the complexity of remote sensing techniques varies, depending on the GDE type, the spectral response, and the extent. The applicability and transferability of these methods also vary across landscapes, owing to their environmental heterogeneity. Over the years, researchers like (Chen et al., 2014, Eamus et al., 2015, Kreamer et al., 2014, Münch et al., 2013, Parker et al., 2018) have also acknowledged that using remote sensing for delineating and characterising GDEs requires a robust field-dataset for calibrating the remote sensing models.

Several measures of vegetation diversity focus on alpha-diversity (i.e. the local species variation) or beta-diversity (the species turnover) (Rocchini et al., 2010a). Each metric used to estimate vegetation diversity (i.e. whether beta or alpha diversity) has underlying assumptions, which are important and should be understood prior to its use. Species richness, which is a measure of alpha-diversity, is a commonly used measure of vegetation diversity (John et al., 2008, Rocchini et al., 2005). Although its use in estimation vegetation diversity has been criticized (Oldeland et al., 2010, Schmidlein and Fassnacht, 2017), it is easy to measure at different spatial scales. Instead of species richness, measures such as the Rao Q and Bray-Curtis dissimilarity index, a measure of beta-diversity, have been suggested (Féret and Asner, 2014). For example, the Bray-Curtis dissimilarity index focuses mainly on the differences in species composition in two study sites (Ricotta and Podani, 2017, Rocchini et al., 2010b), and the index is convenient when exploring the environmental heterogeneity hypothesis and the SVH hypothesis (Rocchini et al., 2010b). However, equally important to the selection of a diversity metric is the selection of a suitable sampling extent and sampling effort (Rocchini et al., 2010b). A differing plot size or sampling effort might provide different results on the species diversity in the same study area (Rocchini et al., 2010b).

The local field measures of diversity, as well as using the correct method for relating the field-measured species diversity and remote sensing spectra, are important for the delineation and characterization of GDEs in arid environments. The acceptability, accuracy, and precision of these methods in estimating vegetation diversity in GDEs is imperative, and it includes the classification methods, the empirical methods, and the vegetation indices. The methods will be summarized in the following sections:

2.6.2. Image classification and its applicability in the measurement and delineation of vegetation diversity in GDEs

Image classification techniques have been used to assess species diversity at a landscape level in regional and continental studies (Luis Hernandez-Stefanoni and Ponce-Hernandez, 2004). This is supported by the Environmental Heterogeneity Hypothesis (EHH), which theorizes that diverse vegetation types have a spatial or environmental heterogeneity that is highly diverse (Scott and Baer, 2019, Rocchini et al., 2010a).

Image classification can either be supervised (i.e. the use of training data to characterize the image spectra) or unsupervised (i.e. clustering the image spectra into several homogeneous

strata) (Nagendra and Gadgil, 1999). The classified vegetation types can be used as indicators of vegetation diversity at a GDE level (Páscoa et al., 2020, Fasona et al., 2020, Lauver, 1997, Schäfer et al., 2016). Although heterogeneous environments support more species than homogenous environments, classification algorithms have varying accuracies and care must be taken when selecting those that are to be used (Schäfer et al., 2016, Nagendra and Gadgil, 1999, Tuxen et al., 2011, Laliberte et al., 2004, Iglesias et al., 2012).

2.6.3. Empirical methods for measuring vegetation diversity in GDEs by using remote sensing

Species diversity is correlated to the productivity of an ecosystem. This is supported by the productivity hypothesis, which states that vegetation diversity increases with the increasing productivity of an ecosystem (Tilman et al., 1996). This phenomenon has been observed around the equator, where the species diversity is high, and it decreases with the increasing distance away from the equator (Decuyper et al., 2016, Taddeo et al., 2019). In the same way, remote sensing can measure ecosystem productivity from vegetation greenness (e.g. NDVI and EVI) (Scher et al., 2020, Rocchini et al., 2015). Greener areas within a GDE infer the productivity of an ecosystem (i.e. the availability of vegetation), and the vegetation diversity in those areas is expected to be high (Oindo and Skidmore, 2002). Owing to the relationship between ecosystem productivity, species richness and vegetation greenness, empirical methods have been used, when measuring species diversity (Scher et al., 2020, Rocchini et al., 2015).

Statistical methods have been used to explore and establish the empirical relationship between the field measures of vegetation diversity (e.g. the species richness or species evenness) and vegetation spectral images (Taddeo et al., 2019, Oindo and Skidmore, 2002, John et al., 2008). They base their premises on the SVH and productivity hypothesis, in that the field-measured spatial diversity is correlated with the spectral heterogeneity (Oldeland et al., 2010). The regression analysis has been used to explore the relationship between the field measures of diversity and spectral bands in the GDEs. For instance, John et al. (2008) successfully used MODIS-derived productivity indices to estimate the species richness of Inner Mongolia, China, by using statistical models. Years later, Xu et al. (2016) also estimated the species richness of China by using the Spatial Linear Regression Model (SLRM). To improve the coefficient of determination in estimating the vegetation diversity in GDEs, researchers have also explored the use of machine learning algorithms and the inclusion of biotic and abiotic variables (e.g.

the NDVI, the percent tree cover and the maximum average NDVI) (Oindo and Skidmore, 2002). For example, Silveira et al. (2019) used Fisher's alpha, a proxy of tree species diversity, to characterize the diversity and biomass in Brazil. Although the estimated diversity of tree species correlated well with the measured field data ($R^2=0.63$), the results still required the interpretation of the field data, thus limiting their transferability to other areas, including GDEs (Table 2.2).

The empirical relationship between the field and remote sensing measures of vegetation diversity has been well established. However, in most instances, the empirical relationship is not linear and requires the use of ancillary factors to improve the accuracy of the statistical or machine learning models (Silveira et al., 2019, Taddeo et al., 2019). When more variables are used to improve a model's performance, this defies the law of parsimony (Vandekerckhove et al., 2014), which states that the best model is less complicated and has fewer variables (Gauch, 1993, Fauvel et al., 2015). However, there is a trade-off between a model's accuracy and its simplicity. On the one hand, parsimonious models may not be highly predictive and when more variables (i.e. complex models) are used to improve a model's accuracy, this limits the transferability of the model to a new dataset. Therefore, most studies that use hyperspectral data use Partial Least Squares Regression (PLSR) models, which reduces the dimensionality in highly dimensional datasets with collinear variables (Gara et al., 2018, Gara et al., 2019, Fauvel et al., 2015). Therefore, caution must be exercised when using low spatial- and spectral-resolution sensors that require additional variables to improve a model's accuracy.

Table 2.2 The effect of spatial and spectral resolution when using remote sensing for measuring vegetation diversity. The estimation of vegetation diversity increases when sensors with a high spatial and spectral resolution are used.

Sensor Type	Accuracy	Number of spectral bands	Spatial resolution	Region	References
Carnegie Airborne Observatory (CAO)				Amazonian forest, Peru	Féret and Asner (2014)
Airborne	$R^2 = 0.64$	214	2 m		
AisaEAGLE	$R^2 = 0.53$	129	1 m	Taita-Taveta, Kenya	Schäfer et al. (2016)
QuickBird	$R^2 = 0.48$	5	3 m	Tuscany, Italy	Rocchini et al. (2007)
Phantom 4 drone	$R^2 = 0.30$	5	1,5 m	Illinois, United States	Scher et al. (2020)
Landsat TM	$R^2 = 0.45$	7	30 m	Murray Valley National Park, Australia	Curtis et al. (2019)
Landsat OLI	$R^2 = 0.35$	8	30 m	Eastern provinces, South Africa	Madonsela et al. (2017)
MODIS	$R^2 = 0.33$	36	250 m	Hawaii Island, United States	Pau et al. (2012)
AVHRR	$R^2 = 0.19$	5	8 km	Mongolian Gobi, Mongolia	von Wehrden and Wesche (2007)

2.6.4. Vegetation indices as indicators of GDEs and vegetation diversity in GDEs

Vegetation Indices (VI), particularly the Normalized Difference Vegetation Index (NDVI) and the Normalized Difference Water Index (NDWI) have been frequently and successfully used to map GDEs in most environments (Parker et al., 2018, Huang et al., 2020a). The red, red-edge, Near-Infrared (NIR), and Shortwave Infrared (SWIR) spectral regions are the main spectral bands used to calculate vegetation indices (Sharifi, 2020, Xie et al., 2018). Vegetation emissivity is low in other parts of the spectral region; hence, these regions are rarely used. Vegetation emissivity in red, red-edge, NIR and SWIR is driven by xanthophyll, carotene, and chlorophyll pigments (chlorophyll a and b (Xie et al., 2018, Zarco-Tejada et al., 2000). In addition, the morphological and chemical properties of leaves and other vegetation parts are also responsible for the reflectance in the green visible range (500-600 nm) and the NIR region (Sims and Gamon, 2003, Colwell, 1974).

Groundwater-Dependent Vegetation (GDV) is usually distinct from other vegetation types because it is productive during the dry periods. GDVs can be identified by using the measures of soil moisture and vegetation productivity (e.g. NDVI and NDWI), when assessing the vegetation phenology in a dry season or drought period (Emelyanova et al., 2018, Alaibakhsh et al., 2017, Barron et al., 2014, Gou et al., 2015, Huntington et al., 2016, Huang et al., 2020a). For instance, Huang et al. (2020a) used NDVI and NDWI from a MODIS and Landsat ETM to monitor the vegetation dynamics and its response to variations in the groundwater depth. In this way, Huang et al. (2020a) delineated GDVs in the Shiyang River Basin, China. A major setback of using vegetation indices, such as EVI, NDVI and NDWI, is that they have been observed to saturate at a high biomass (Barron et al., 2014). For this reason, the NDVI explained 30% of the woody species richness in the Hawaiian dry forests (Pau et al., 2012). The relationship between the VIs and vegetation is complex and indirect; it could be influenced by other biotic (e.g. vegetation structure) and abiotic (e.g. precipitation) variables with a direct relationship with the VI that is used (Pau et al., 2012, von Wehrden and Wesche, 2007, Madonsela et al., 2017).

Instead of using the NDVI, Parker et al. (2018) proposed the use of the Foliage Projective Cover (FPC), which measures the photosynthetically projected foliage of the vegetation and does not saturate at a high biomass. Unlike the NDVI and EVI, which work well in areas with intermediate biomass (e.g. boreal environments), the FPC can map the spectral heterogeneity

of sparsely-distributed vegetation communities, which are characteristic of arid environments (Scarth et al., 2019, Curtis et al., 2019). When used to delineate GDEs in Queensland, Australia, the FPC, along with other environmental variables (precipitation and vegetation class), adequately delineated the GDEs for that environment (Parker et al., 2018). Vegetation indices, including the FPC, have gained popularity, since they are easy to compute; however, the spatial and spectral resolution of the sensor used to compute the index is equally important (Teillet et al., 1997). Different results are yielded when comparing vegetation diversity with a vegetation index calculated from a low spatial- and spectral-resolution sensor and one calculated from a high spatial- and spectral-resolution sensor (Figure 2.3).

2.6.5. Other geospatial methods for characterising and delineating GDEs

Following the SVH and EHH hypothesis, the spectral distance method assumes spectral variability, infers habitat heterogeneity and can measure vegetation diversity (Rocchini et al., 2009, Rocchini et al., 2015). The method is premised on the notion that the spectral similarity decreases with the increasing spectral distance (Figure 2.4) (Rocchini et al., 2015). The method calculates the spectral distance between the plot centroids on a multidirectional plot of spectral reflectance (Rocchini et al., 2010b). The spectral distance can also be calculated from the centroids of clustered spectra on a multidirectional plot of spectral reflectance (Rocchini et al., 2015), which relate to a homogenous vegetation type. The greater the spectral distance between the centroids, the more heterogeneous the species will be and the more diverse the ecosystem is likely to be (Rocchini et al., 2009, Rocchini et al., 2007). The spectral distance method has been used mainly with the Euclidean distance method for estimating the beta-diversity (Warren et al., 2014, Rocchini et al., 2009). However, this method relies on using hyperspectral data or high-temporal resolution sensors, such as MODIS. Therefore, using the spectral distance method with multispectral sensors may affect the characterization of GDEs

Interpolation techniques have also proved to be worthwhile in mapping species diversity in GDEs (Hernandez-Stefanoni and Ponce-Hernandez, 2006). These techniques assume that ecological processes (e.g. seed dispersal) follow a spatial pattern and these patterns influence the distribution of vegetation communities and species diversity (Moreno et al., 2018, Cheng et al., 2020). Interpolation techniques can generalize the species diversity that is measured from point data, to areas that were not measured (Hernandez-Stefanoni and Ponce-Hernandez, 2006, Moreno et al., 2018). For instance, Cheng et al. (2020) successfully interpolated species

diversity for the Badain Jaran Desert in China. Although the method is not statistically robust, it provides initial assessments that can guide environmentalists and policymakers on the species diversity in GDEs.

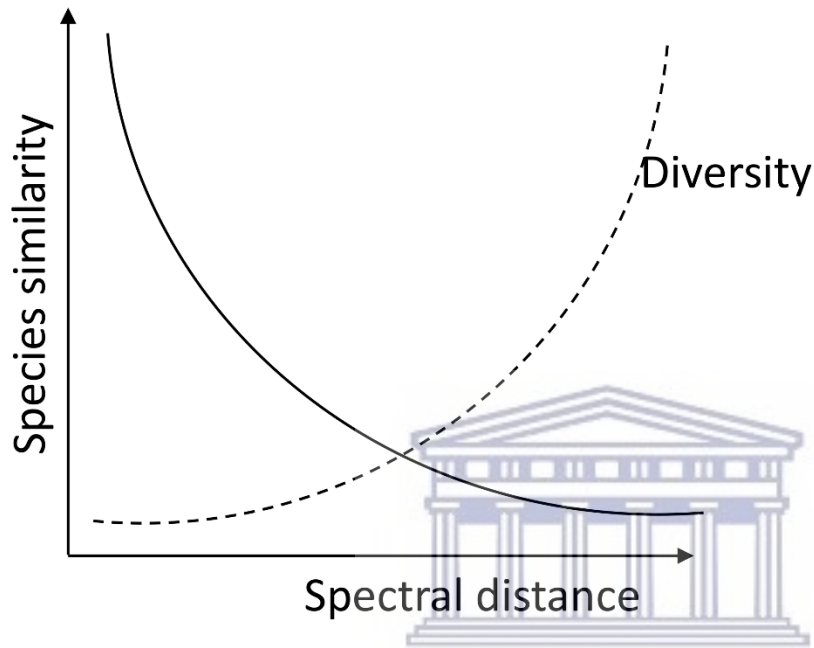


Figure 2.4 Species that are closer together usually have spectra that are clustered and similar, but as the distance between the species increases, they become more dissimilar, owing to the environmental heterogeneity. Thus, species similarity decreases with increasing spectral distance. When species become dissimilar, the species diversity increases.

2.7. The Challenges and Opportunities of Using Remote Sensing to Delineate and Characterize GDEs

Using remote sensing to characterise or delineate GDEs comes with several opportunities and challenges. As shown in the previous sections, monitoring vegetation diversity in GDEs requires the use of high spectral- and spatial-resolution sensors. However, high spectral-resolution sensors (e.g., HySpex) are costly or have a low spectral resolution (e.g., IKONOS and Worldview-4). Spectral bands from new-generation satellites (e.g. Sentinel-2 and WorldView-2) offer reasonable opportunities, given the presence of red-edge and near-infrared spectral bands (Fu et al., 2020). The red-edge spectral region can detect subtle differences in the phenology of the vegetation (Cho et al., 2012, Mutanga et al., 2012) and this may be useful in observing phreatophytes in GDEs.

A trade-off exists as to whether high spatial- or spectral-resolution sensors should be used. Hyperspectral sensors reduce the instance of spectral mixing by spectrally discriminating species, based on their spectral signature, but this is impossible with low spectral resolution sensors. The launch of the Environmental Mapping and Analysis Program (EnMap) hyperspectral space-borne sensor (Fischer et al., 2017, Guanter et al., 2015) will most likely improve the characterisation of vegetation diversity in GDEs. The upcoming EnMap will provide spectral information in the 420 nm–2450 nm spectrum at a spatial resolution of 30 m (Guanter et al., 2015). These specifications could be useful for monitoring GDEs in arid environments, especially when coupled with the LiDAR data. By including structural metrics from the Global Ecosystem Dynamics Investigation (GEDI), LiDAR could enhance the estimation of vegetation diversity in the absence of high spatial-resolution sensors, thus improving the spectral discrimination of species in GDEs (Coyle et al., 2019).

Several ecological processes occur before the revisit period of a satellite sensor and low temporal resolution sensors (e.g., SPOT-5), which may affect our understanding of the vegetation phenology and thus the delineation of GDEs. Using Phenocams may assist in the timely monitoring of changes in the vegetation phenology in response to the groundwater dynamics (Aasen et al., 2020). Phenocams (e.g., LUPUSNET HD–LE971) use imagery from digital cameras to monitor the phenology of vegetation at a high temporal resolution (Richardson et al., 2018, Aasen et al., 2020). Although they may have a limited swath extent, they may improve the identification of GDEs on a local or regional scale.

Depending on the imagery, remote sensing data require a moderate to high computational power (Christophe et al., 2011). On average, a 1500-pixel image can be processed in ~51 minutes with a low-performing computer, whereas this could take 4 minutes 30 seconds with a high-performing computer, (Christophe et al., 2011). Using the Google Earth Engine (GEE) minimizes the need for high computational power, because most of the data available on the GEE platform are ready for analysis (Gorelick et al., 2017, Kumar and Mutanga, 2018). The Google Earth Engine (GEE) is a Cloud computing platform for processing and accessing the multi-petabytes of remote sensing data (Gorelick et al., 2017). Access to data cubes of remote sensing data can enhance the identification and mapping of GDEs by using the algorithms available within the GEE platform. GEE has been used mainly for vegetation and forestry research (Kumar and Mutanga, 2018), and it offers endless possibilities for the characterisation of GDEs.

Limited field-measured data on GDVs can be used for the calibration of empirical models, especially for regional and global assessments (Bongaarts, 2019). Field measurements of vegetation diversity are costly, spatially-limited and can sometimes be destructive, especially when used to calibrate Radiative Transfer Models (RTMs) (Li and Wang, 2013). Although remote sensing may enhance our understanding of vegetation diversity, field-measured data are irreplaceable. In addition, most of the biodiversity in arid environments is present in the subterranean layer and may not be observable when using passive remote sensing sensors. Using Ground Penetrating Radar (GPR) may yield promising results in the observation of stygofauna or the functional traits of roots for biodiversity monitoring in GDEs. However, using GPR requires technical expertise because of the several pre-processing procedures required before the data can become useful.

Algorithms (for empirical models) that have been used to explore the relationship between vegetation diversity and its spectral traits have not produced convincing results. Of the studies reviewed in this paper, the coefficient of determination (R^2) between field-measured vegetation diversity and its spectral traits was below 0.60. Although they are significant, the low R^2 would be acceptable only for regional and global estimates of vegetation diversity and not for localized studies. The localized estimation of vegetation diversity should produce a high R^2 ($R^2 > 0.7$) because there is manageable spectral variance in the local environment, compared to regional or global areas. Instead, when these low values ($R^2 < 0.6$) are used for estimating vegetation diversity in global and regional studies, they may underestimate or overestimate the

vegetation diversity, affecting the allocation of resources (Hu et al., 2019). Using Radiative Transfer Model (RTMs) can prevent problems related to algorithm use and selection. They use physically-based models that estimate biodiversity by using forward-modelling or inverse-modelling (Kattenborn et al., 2017). RTMs have been used to success estimate the spectral traits of vegetation in other environments (Gara et al., 2018, Kattenborn et al., 2017, Gara et al., 2019).

2.8. Conclusions

Groundwater is a key resource for obligatory or non-obligatory groundwater-dependent ecosystems, which may provide habitat for endemic or threatened species. Remote sensing allows the characterisation of the extent and location, vegetation diversity, structure, and composition of GDEs, and their response to stressors. This chapter reviewed the published literature on delineating and characterising vegetation diversity in GDEs by using remote sensing, particularly in arid environments. The focus was on understanding the remote sensing techniques that can delineate and characterise vegetation diversity in GDEs. The chapter also focused on exploring the effects of the resolution on the delineation and characterising GDEs in arid environments.

The chapter showed that studies using remote sensing have increased over the past 20 years and that the Landsat and MODIS data have been used more frequently. However, owing to the issues relating to spatial and spectral resolution, future work on the characterisation of GDEs with remote sensing will require UAS and next-generation sensors. Whilst UAS and Phenocams offer unlimited capabilities for estimating vegetation diversity, only a handful of the studies that were reviewed had used their data. The high cost associated with the image acquisition and processing of UAS and Phenocam data is a major deterrent. Nonetheless, the use of GEE, RTM and GEDI LiDAR data may improve vegetation estimation.

The chapter revealed the following:

1. High spatial and spectral resolution sensors are pivotal in the discrimination of vegetation species in GDEs. High spatial- and spectral-resolution sensors have a high spectral discrimination and low within-pixel variability.
2. Empirical and image classification techniques are more reliable when delineating or characterising GDEs within arid environments.

3. The Google Earth Engine (GEE), Radiative Transfer Models (RTMs), and LiDAR-derived metrics offer several capabilities when monitoring the vegetation diversity in GDEs and should be explored in future studies: and
4. Next-generation hyperspectral sensors (e.g., EnMap and HypsIRI) will significantly improve the global estimation of vegetation diversity. The high spectral resolution of these sensors, along with their robust algorithms or RTMs, will allow the effortless global monitoring of vegetation diversity in GDEs.



3.0. CHAPTER 3

THE SPATIAL CHARACTERISATION OF VEGETATION DIVERSITY IN GROUNDWATER-DEPENDENT ECOSYSTEMS, USING SENTINEL-2 MSI IMAGERY



Vegetation diversity around a wet natural water pan in the Khakea-Bray TBA

(Photo: Courtesy of Kudzai Mpakairi, 2022)

This chapter is based on:

Mpakairi, K.S., Dube, T., Dondofema, F. and Dalu, T. The spatial characterization of vegetation diversity in groundwater-dependent ecosystems, using Sentinel-2 MSI imagery. *Remote Sensing (Accepted)*

3.1. Abstract

Groundwater-Dependent Ecosystems (GDEs) are under threat from the over-abstraction of groundwater, which significantly affects their conservation and effective management. Although the socio-economic significance of GDEs is understood, their ecosystem services or ecological significance (e.g. biodiversity hotspots) in arid environments remain under-studied. Therefore, under Sustainable Development Goal (SDG) 15, the characterization, or identification, of biodiversity hotspots in GDEs improves their management and conservation. In this study, we present the first attempt to spatially characterize the vegetation diversity in the GDEs within the Khakea-Bray Transboundary Aquifer. Vegetation diversity was also used as a proxy for identifying priority conservation areas and biodiversity hotspots. Following the Spectral Variation Hypothesis (SVH), we used remotely sensed data (i.e. Sentinel-2 MSI) to characterize the vegetation diversity. This involved using the Rao's Q to measure vegetation diversity from several measures of spectral variation and validate the measured vegetation diversity using field-measured data. It was observed that the Rao's Q has the potential to spatially characterise the vegetation diversity of GDEs in the Khakea-Bray Transboundary Aquifer. Specifically, we found that the Rao's Q was related to field-measured vegetation diversity ($R^2 = 0.61$ and $p = 0.0003$) and that the Coefficient of Variation (CV) was the best measure for deriving the Rao's Q. The vegetation diversity was more concentrated around the natural pans and along the roads, fence lines and rivers. In addition, vegetation diversity was observed to decrease with increasing distance (>35 m) away from the natural water pans and that it simulated an inverse piosphere. Overall, findings from this study will be vital for natural resource managers when conserving the Khakea-Bray Transboundary Aquifer. The baseline information for identifying priority conservation areas within the Khakea-Bray Transboundary Aquifer is provided. This work provides a pathway for resource managers to achieve SDG 15, as well as the national and regional Aichi biodiversity targets.

Keywords: Khakea-Bray Transboundary Aquifer; Rao's Q; vegetation diversity; GDE

3.2. Introduction

Transboundary groundwater resources are extensive and challenging to monitor or manage for most partner countries (Seward and van Dyk, 2018, Turton et al., 2006). The extent and capacity of the underlying aquifers, and the Groundwater-Dependent Ecosystems (GDEs) in these environments, are usually unknown (Turton et al., 2006, Davies et al., 2013), regardless of the ecosystem services that are offered by the GDEs (e.g. water purification and nutrient cycling) (Eamus et al., 2016, Murray et al., 2006). The over-abstraction of groundwater, climate change and groundwater pollution are the main threats to GDEs (Sousa et al., 2014, Wu et al., 2020). These threats will most likely intensify as the demand for groundwater increases in the future (Clifton et al., 2010, Wu et al., 2020); this, in turn, will affect the water and food security of rural populations whose livelihoods depend upon the GDEs (Programme, 2006, Kreamer et al., 2015, Kløve et al., 2014). Nevertheless, managing or conserving the unknown is impossible, and this is the case with the Khakea-Bray Transboundary Aquifer (hereafter called the Khakea-Bray TBA) (Seward and van Dyk, 2018). Characterising the Khakea-Bray TBA landscape and understanding its ecological and economic significance could advance its conservation and management.

Most GDEs are biodiversity hotspots (e.g. in the Mojave Desert and succulent Karoo) and facilitate the existence of regionally restricted species or species under threat (i.e. faunal endemism) (Alaibakhsh et al., 2017, Pengra et al., 2007). This is caused mainly by the redistribution of groundwater to the shallower parts of the soil profile by keystone species (e.g. the Shepherd's tree (*Boscia albitrunca*)) (Xu et al., 2015, Lv et al., 2013, Coletti et al., 2017). These keystone species make GDEs important conservation areas, since accessing the groundwater assists plant growth and maintains the species diversity in arid environments (Kløve et al., 2011, Howard and Merrifield, 2010, Barron et al., 2014). However, it can be challenging to identify GDEs in the absence of hydrogeological surveys. In arid areas, GDEs can be observed around natural water pans that are supported by groundwater (De Klerk et al., 2016, Fu et al., 2010). Around these natural water pans, the groundwater level is often high and can be easily accessed by Groundwater-Dependent Vegetation (GDV) (Eamus et al., 2006, Orellana et al., 2012, Barron et al., 2014). Ideally, areas around natural water pans are expected to be highly diverse, when compared to environments further away from them, where the groundwater level is low (Figure 3.1). Most studies have used field techniques to assess the species diversity around natural water pans, owing to their reliability and accuracy (Eamus and

Froend, 2006, Eamus et al., 2006, Kreamer et al., 2014, Meyers et al., 2021). However, these techniques are laborious when working in extensive regions, such as transboundary aquifers, and they may be costly in some resource-constrained environments, such as developing nations (Brown et al., 2007, Chao et al., 2014a, Chao et al., 2014b, Charlotte et al., 2019, Chen et al., 2008, Hou et al., 2019, John et al., 2008, Chiloane et al., 2021).

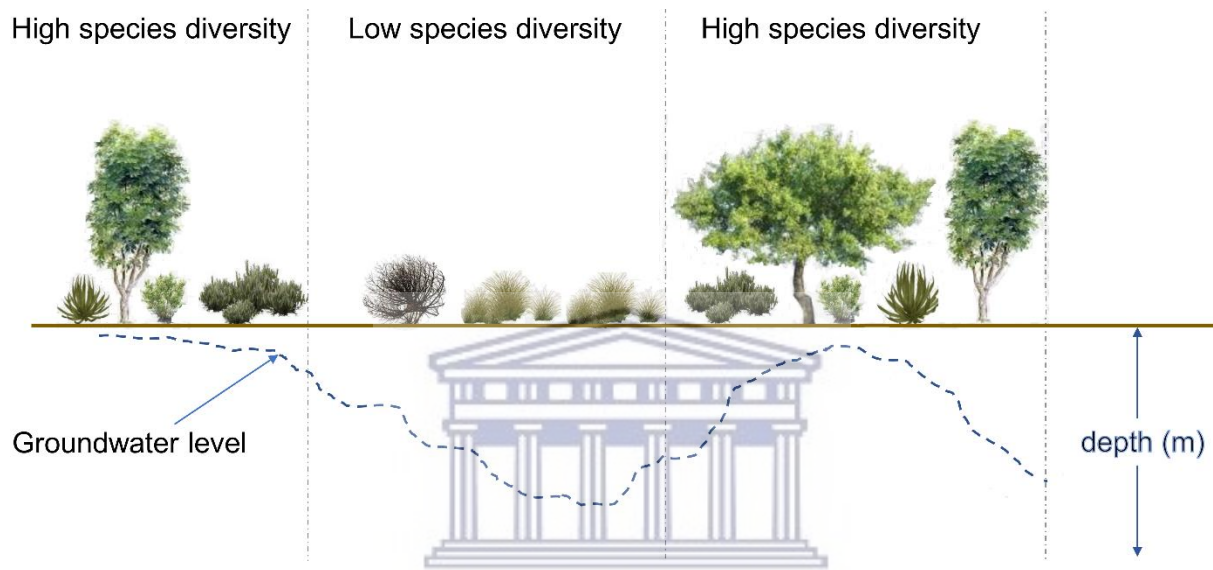


Figure 3.1 The conceptual interaction of groundwater and species diversity in arid environments.

Remotely-sensed species diversity estimates, such as those provided by the Spectral Variation Hypothesis (SVH), are promising, in that they to provide an effective, rapid and direct assessment of the species diversity over complex and large landscapes (John et al., 2008, Li et al., 2017, Nakhoul et al., 2020, Woods and Sekhwela, 2003). Unlike the traditional measures of species diversity (e.g. Shannon-Weiner and Simpson's D), the SVH uses spectral reflectance to characterise the species diversity of an ecosystem (Rocchini et al., 2007, Nagendra and Gadgil, 1999). The SVH posits that spectral heterogeneity is a function of environmental heterogeneity, and that heterogeneous landscapes are more diverse, with several ecological niches (Rocchini, 2007, Rocchini et al., 2005, Rocchini et al., 2004, Rocchini et al., 2017). From the spectral response of heterogeneous landscapes, one can identify unique spectra (i.e. spectral species) and thus quantify the species diversity of an ecosystem (Wang et al., 2016).

Spectral heterogeneity can be detected from measures of spectral variation (e.g. the Coefficient of Variation or NDVI) (Wang et al., 2016, Wang and Gamon, 2019). However, these measures should be able to detect the subtle differences in the spectral variance (Torresani et al., 2021a). Accurate measurements of spectral variation have been mostly derived from high spatial- and spectral-resolution sensors (Nagendra et al., 2010). Where broadband sensors (e.g. AVHRR) are used, the measurement of spectral variation may not distinguish the spectral reflectance of two species under phenotypic plasticity (Chen et al., 2020, Cavender-Bares et al., 2020), and when low spatial resolution sensors are used (e.g. MODIS), the spectral reflectance may be marred by spectral mixing (Rocchini et al., 2010a, Wang and Gamon, 2019). In such situations, the applicability of SVH is limited (Schmidtlein and Fassnacht, 2017). Using the Sentinel-2 Multispectral Instrument (MSI) could bridge the gap between high spatial- and spectral-resolution sensors, since the Sentinel-2 MSI has a medium spatial resolution (10-20 m) with key spectral bands (e.g. red-edge bands), which are important for vegetation mapping (Mandanici and Bitelli, 2016). Nonetheless, when characterising extensive or regional environments, using high spatial- and spectral-resolution sensors may not be feasible, owing to the computational and financial costs related to the scale of their application (Wang and Gamon, 2019).

The common techniques for measuring species diversity by using the SVH include: (i) the distance from the spectral centroid in spectral space (Rocchini, 2007), (ii) the variations in the NDVI (Gould, 2000), (iii) the convex hull volume in the principal component space (Dahlin, 2016), and (iv) the Rao's Q (Torresani et al., 2021a). However, two decades after introducing the SVH, there is still no consensus about which method to use when measuring species diversity. A review of some methods is provided by Wang and Gamon (2019). Nevertheless, over the past decade, the Rao's Q has gained popularity in the measurement of species diversity (Rocchini et al., 2017, Torresani et al., 2021b, Torresani et al., 2019). In several studies, it has outperformed some of the techniques that have been used for calculating species diversity, based on the SVH (Rocchini et al., 2017, Torresani et al., 2021a, Torresani et al., 2019). The Rao's Q estimates spectral diversity by using the abundance and proportion of pixels, as well as the spectral distance between these pixels (Rocchini et al., 2017). Using the Rao's Q for characterising species diversity can provide an *a priori* knowledge of the priority areas that need to be conserved in transboundary ecosystems. This is based on the use of vegetation diversity as a proxy for the stability of an ecosystem. Ideally, stable ecosystems are more

diverse, compared to degraded ecosystems (Barbosa et al., 2001, Fisher et al., 2012). Furthermore, the identification of priority conservation areas with a high biodiversity in extensive transboundary ecosystems is less costly, when compared to the managing the entire ecosystem (Ayyad, 2003, Bongaarts, 2019, Brown et al., 2007, Cavender-Bares et al., 2020).

The Khakea-Bray TBA is one such transboundary ecosystem in which the priority areas with high biodiversity need to be identified. The Khakea-Bray TBA is a transboundary reservoir shared between Botswana and South Africa, and which is under threat from unsustainable groundwater abstraction and looming climate change (Eales, 2010, Bauer and Scholz, 2010, Davies et al., 2013). Despite the threats, no compelling policy exists between the two nations that share the aquifer on the utilisation of groundwater resources in the Khakea-Bray TBA (Ngobe, 2021, Seward and van Dyk, 2018). In 2002, Godfrey and van Dyk (2002b) estimated that the groundwater level had lowered by at least 40 m. When the groundwater level lowers, the GDEs that rely on the groundwater are affected, which leads to their degradation (Ngobe, 2021, Seward and van Dyk, 2018). The GDEs under stress are susceptible to invasion by alien species, which may affect the regionally-restricted species within the GDE (Fisher et al., 2012, Pyšek and Richardson, 2010). Using the Rao's Q and remote sensing data, species diversity can be a proxy for monitoring the health, structure and functioning of the Khakea-Bray TBA ecosystem. Therefore, we present the first attempt at characterising the vegetation diversity in the Khakea-Bray TBA. Our aim was to test how the vegetation communities in this TBA varied and to identify the most dominant vegetation types within this environment. We also tested the applicability of the Rao's Q by spatially characterising the vegetation diversity in this ecosystem, and how vegetation diversity varied, depending on the distance (0 – 100 m) from the natural water pans (dry or wet). Understanding the vegetation diversity can help to identify the priority areas that need to be conserved or monitored for invasive species.

3.3. Materials and Methods

3.3.1. Field campaign and measuring species diversity

Sixteen north-oriented plots were purposefully sampled around the natural pans (dry and wet) within the Khakea-Bray TBA. Natural water pans are surface depressions filled with rainwater or groundwater seepage (Arendt et al., 2021). These pans were selected because they were linked to the Khakea-Bray dolomite aquifer, which supports all the GDEs within this ecosystem

(Godfrey and van Dyk, 2002b, Van Dyk, 2005). The natural water pans were considered to be wet when water was available, and dry when there was no water in them. Since GDEs are more common in these areas, owing to the high groundwater level that supports these natural pans, the sampling was conducted around them (Brown et al., 2007). The sampling plots measured 400 m² (i.e. 20 m × 20 m) and were within 1 km of a natural water pan. The random placement of the plots ensured that they were at least 100 m away from each other, in all directions, to avoid biased sampling from autocorrelation. This was also done to avoid overlapping pixels when relating field measured data and remote sensing imagery. In each sampled plot, the focus was on the composition of woody and herbaceous plant species, as well as their corresponding abundance. Notwithstanding the other forms of vegetation physiognomy, the grasses and forbes were grouped into one class (i.e. *Eragrostis* spp). The species were identified by using field guides (e.g. (Van Wyk, 2013)) or mobile applications (e.g. iNaturalist and PlantSnap). Where the species could not be identified, a specimen was taken to the local botanist for identification. The plots were sampled during the dry season of 2021 (June–July). This period was selected as it is characterized by low rainfall and because the GDVs are usually productive during the dry period, owing to their access to groundwater. This period also excludes non-GDVs, since vegetation that is dependent on the surface water usually dries up soon after the wet season (Chiloane et al., 2021, Eamus et al., 2016).

The Shannon-Weiner Index (H) was used to calculate the species diversity in each plot. H is a commonly-used measure and characterizes the diversity of an area, based on its richness and evenness (Jost, 2010). H can be calculated as:

$$H' = -\sum_{i=1}^S p_i \ln p_i \quad \text{Equation 3.1}$$

Where S is the total individuals in the plot and p_i is the proportion of species i to S.

However, H is an index of diversity and is not diversity itself (Jost, 2006, Chao et al., 2014b), hence the H values were converted to the effective number of species (i.e. true diversity) using an exponential function of H. The effective number of species helps to understand the true diversity of a community (Chao et al., 2014a), it is linear and does not saturate at high values;

instead, it accurately provides the number of species related to a specific diversity value (Chao et al., 2014b, Chao et al., 2014a, Jost, 2006).

3.3.2. Community composition and dominance

Bootstrapping was used to extrapolate the species richness and estimate the number of unobserved species during data collection (Smith and van Belle, 1984, Phan et al., 2021). The technique is non-parametric and estimates the species richness from repeated resampling, under the assumption of randomness (Smith and van Belle, 1984). Bootstrapping was calculated in R, using the vegan package (Oksanen et al., 2007), with the following equation:

$$S_e = S_o + \sum_{i=1}^{S_o} (1 - p_i)^N \quad \text{Equation 3.2}$$

Where S_e is the extrapolated species richness and S_o is the observed species richness. N is the number of plots and p_i is the frequency of species i .

To test whether there were differences in the community composition of the measured field data, this chapter used a Permutational Multivariate Analysis of Variance (PERMANOVA). PERMANOVA tests whether the centroids of dispersion are different between the groups (Razali and Wah, 2011, Anderson, 2001). For this study, PERMANOVA tested whether the observed species in each plot differed from the other sampled plots, by using distance matrices. The significance of the group differences was evaluated by using the p-value (Anderson, 2001). PERMANOVA was used because it is a robust measure capable of handling data that are not normally distributed, which was the case with our data (Shapiro-Wilk test, $p < 0.05$). PERMANOVA was run in R by using the vegan package.

The dominance index (Y) was used to identify the most dominant species in the sampled plots (Lin et al., 2011, Guo et al., 2019). Species with $Y > 0.02$ were considered dominant, compared to all the other species (Lin et al., 2011, Guo et al., 2019, Xu and Chen, 1989). The Y is calculated by using the following formula:

$$Y_i = \frac{N_i}{N} f_i \quad \text{Equation} \quad 3.3$$

Where Y_i is the dominance of species i and N_i is the abundance of species i . N represents the abundance of all the sampled species and f_i is the frequency of species i .

3.3.3. Image acquisition and processing

Cloud-free Sentinel-2 Multispectral Instrument (MSI) imagery, which was corrected for its surface reflectance, was accessed through the Google Earth Engine (GEE) platform (<https://code.earthengine.google.com>). The surface reflectance data at 20 m provide for corrected geometric and atmospheric errors. The date the image was acquired coincides with the date when the fieldwork was conducted (25 June 2021). Cloud remnants were removed by using the mask function in GEE. The Normalized Difference Built-up Index (NDBI) and the Modified Normalized Difference Water Index (MNDWI) were also used to mask the built-up areas and water, respectively (Xu, 2008, Bhatti and Tripathi, 2014, Jiang et al., 2012). These indices were used, owing to their robustness in the mapping of water and built-up areas (Xu, 2008, Bhatti and Tripathi, 2014, Jiang et al., 2012, Zha et al., 2003, Xu, 2006). This was done to avoid the reflectance from built-up areas and water from influencing the analysis. The bare surfaces were not removed since these show the absence of vegetation. A threshold of ≥ 0 for NDBI and ≥ 0 for MNDWI was used to identify the built-up areas and water, respectively. These values were selected, based on the literature (Xu, 2008, Bhatti and Tripathi, 2014, Jiang et al., 2012, Zha et al., 2003, Xu, 2006).

MNDWI can be calculated as:

$$MNDWI = \frac{Green - SWIR 1}{Green + SWIR 1} \quad \text{Equation} \quad 3.4$$

and NDBI as:

$$NDBI = \frac{SWIR 1 - NIR}{SWIR 1 + NIR} \quad \text{Equation} \quad 3.5$$

Where Green, NIR and SWIR 1 are reflectance regions in the green (B2), near-infrared (B8) and shortwave infrared (B11) from Sentinel-2 MSI, respectively.

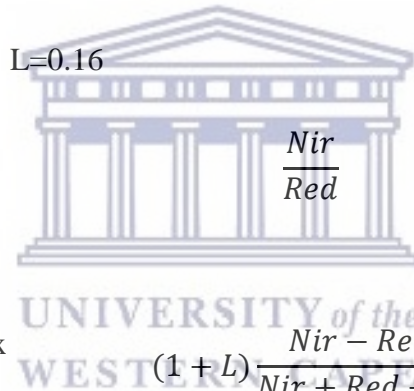
3.3.4. Calculating measures of spectral variation

To characterize the vegetation diversity in the Khakea-Bray TBA, based on the SVH, the spectral variation measurements are usually used. Thirteen measures of spectral variation were used (Table 3.1). These measures were selected, based on their use in SVH studies and how they have been used to characterize landscapes in different environments (Laliberté et al., 2020, Madonsela et al., 2017, Oindo and Skidmore, 2002, Oldeland et al., 2010, Rocchini et al., 2004, Torresani et al., 2021a). Amongst the selected measures of spectral variation, all the spectral bands from Sentinel-2 MSI were also used, along with the first principal component of the spectral bands after the Principal Component Analysis (PCA). The first principal component accounts for the maximum variance and can be a measure of spectral variation (Madonsela et al., 2021, Torresani et al., 2019, Laliberté et al., 2020). All the other measures included were spectral vegetation indices commonly used to characterize the spectral heterogeneity in vegetated landscapes (Torresani et al., 2021b).

Table 3.1 Remote sensing indices for measuring spectral variation, where Green is the reflectance in the green band, blue is the reflectance in the blue band, red is the reflectance in the red-edge band, Nir is the reflectance in the near-infrared band and Swir is the reflectance in the shortwave infrared band.

Name	Band Combination	Reference
Coefficient of variation (CV)	$\frac{\text{Standard deviation of all the bands}}{\text{mean of all the bands}}$	Madonsela et al. (2021)
Enhanced Vegetation Index (EVI)	$2.5 \frac{Nir - Red}{(Nir + 6Red - 7.5Blue + 1)}$	Bohn et al. (2007)

Enhanced Vegetation Index (EVI) 2	$2.5 \frac{Nir - Red}{Nir + 2.4Red + 1}$	Mondal (2011)
Modified Soil Adjusted Vegetation Index (MSAVI) 2	$\frac{2Nir + 1 - \sqrt{(2Nir + 1)^2 - 8(Nir - Red)}}{2}$	Jiang et al. (2007)
Normalized Difference Vegetation Index (NDVI)	$\frac{(Nir - Red)}{(Nir + Red)}$	Jiang et al. (2006)
Normalized Difference Phenology Index (NDPI)	$\frac{Nir - (0.74Red + 0.26Swir)}{Nir + (0.74Red + 0.26Swir)}$	Xu et al. (2021)
Optimized Soil Adjusted Vegetation Index (OSAVI)	$(1 + L) \frac{Nir - Red}{Nir + Red + L}$	Rondeaux et al. (1996)
Simple Ratio Index	$\frac{Nir}{Red}$	Hayashi and Van der Kamp (2000)
Soil Adjusted Vegetation Index (SAVI)	$(1 + L) \frac{Nir - Red}{Nir + Red + L}$	Huete (1988)
	L=0.5	
Renormalized Difference Vegetation Index (RDVI)	$\frac{Nir - Red}{\sqrt{Nir + Red}}$	Haboudane et al. (2004)
Tasseled-cap Greenness Index (TCI)	$-0.28482 Blue + 0.24353 Green + 0.54364 Red + 0.72438 Nir - 0.084011 * Nir - 0.180012 Swir$	Crist and Kauth (1986)

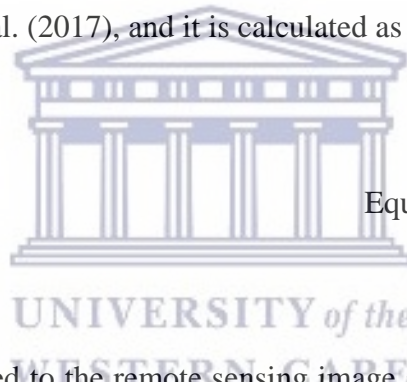


3.3.5. Calculating vegetation diversity with the Rao's Q, using remote sensing data

Rao's Q was used to measure the spectral diversity based on the measures of spectral variation. Originally, it was used in studies that focused on the functional diversity of taxa (Torresani et al., 2019, Torresani et al., 2021b); however, over the past decade, its use in the remote sensing community has increased (Torresani et al., 2021b). Unlike other indices (e.g. Simpson D, Pielou's evenness, or H), which focus only on the abundance and proportion of the species, the Rao's Q also accounts for the distance between the species (Torresani et al., 2021b). By means of remote sensing, the Rao's Q calculates the diversity by using the pair-wise spectral distance between the digital values (DN) of pixels *i* and *j* (Torresani et al., 2021b, Khare et al., 2021). The Rao's Q also incorporates the abundance and proportion of pixels *i* and *j*. The process is iterative and incorporates all the grids covering the study area. More information on the Rao's Q can be found in Rocchini et al. (2017), and it is calculated as follows:

$$Q_{rs} = \sum_{i=1}^{F-1} \sum_{j=i+1}^F d_{ij} p_i p_j$$

Equation 3.6



Q_{rs} represents the Rao Q applied to the remote sensing image and d_{ij} is the distance between the *i* th and *j* th pixel ($d_{ij} = d_{ji}$ and $d_{ii}=0$). *F* is the selected image extent or plot area, with p_i and p_j being the proportion of pixel *i* and *j* to *F*, respectively.

Rao's Q was calculated in R (Team, 2020) for all the measures of spectral variation by using a 3 × 3-pixel moving window with the `spectralrao` function, which is available in Rocchini et al. (2017) and Rocchini et al. (2019).

The Rao's Q calculated from the Enhanced Vegetation Index (EVI), the Enhanced Vegetation Index (EVI) 2, the Modified Soil Adjusted Vegetation Index (MSAVI) 2, the Normalized Difference Vegetation Index (NDVI), the Optimized Soil Adjusted Vegetation Index (OSAVI), the Simple Ratio Index (SR), the Soil Adjusted Vegetation Index (SAVI), the Renormalized Difference Vegetation Index (RDVI) and the Tasseled-cap Greenness Index (TCI) returned zero for over 50% of the study area; hence, the results were not considered. The Rao's Q computes the pairwise differences and returns zero when the pairwise difference of the Digital

Numbers (DNs) from the measures of spectral variation is zero (Rocchini et al., 2017, Torresani et al., 2019).

3.3.6. Evaluating remote sensing-derived diversity

The coefficient of determination (R^2) at a 95% confidence interval was used to examine the linear relationship between the remote sensing-derived diversity (i.e. Rao's Q) and the field measured diversity (i.e. the effective number of species). R^2 was used to examine the proportion of the variance between the Rao's Q and the field measured diversity. The R^2 was calculated for all the Rao's Q metrics derived from the four measures of spectral variation, and the R^2 was



executed in R, using the stats package. The entire methods section for this chapter is summarized in Figure 3.2.

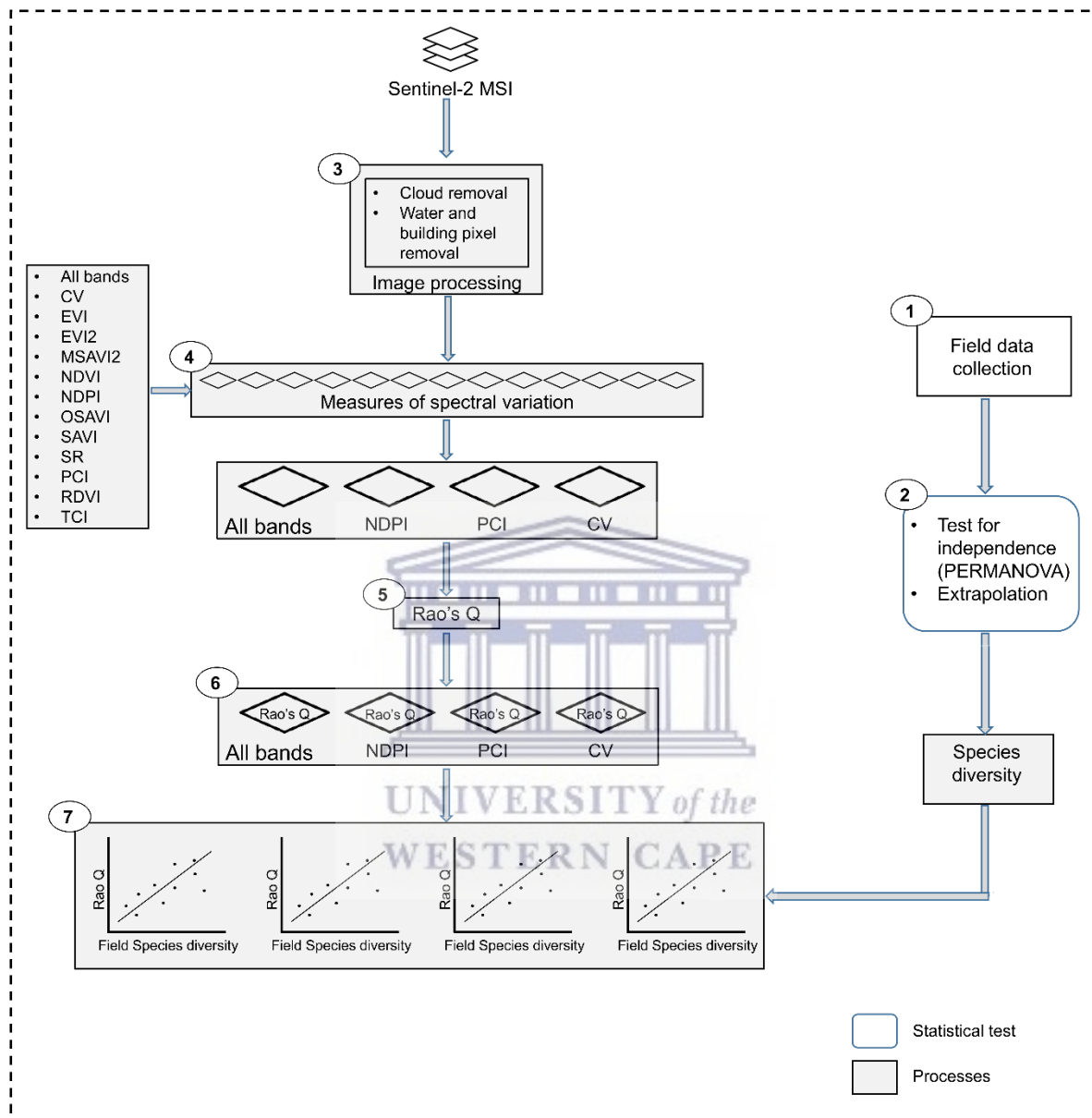


Figure 3.2 Summarised flowchart of the steps and processes followed to characterise the vegetation diversity in the Khakea-Bray TBA. The numbers show the main steps that were followed.

3.3.7. The effect of distance from the natural water pan on vegetation diversity

The best-performing measure of spectral variation was then selected to test the variation of Rao's Q with the increasing distance from the natural pans. This was tested for the dry and wet

natural pans in the Khakea-Bray TBA. To test the response of species diversity to distance, non-overlapping buffers were created around the natural pans, and the corresponding Rao Q was derived by using zonal statistics in ArcMap 10.8 (ESRI, 2020). Curve estimation techniques were used to evaluate the relationship between the distance from the natural pan and the corresponding Rao's Q. To achieve this, six regression models (i.e. linear, cubic, quadratic, inverse, logarithmic and polynomial) were run and evaluated by using the corrected Akaike Information Criterion (AICc) for the wet and dry natural pans. The AIC is an estimator of the model error and a model with a lower AIC is better, compared to a model with a higher AIC (Kletting and Glatting, 2009, Chamaillé-Jammes et al., 2009). In addition, the AIC penalizes models for using more variables, hence balancing the model's fitness and model simplicity (Kletting and Glatting, 2009). The AICc was used instead of the AIC, since it has been corrected for small sample sizes. Lastly, the student *t*-test (Ruxton, 2006) was used to test whether the derived Rao's Q differed between the dry or wet natural pans.

3.4. Results

3.4.1. Species composition, diversity, and dominance

Eighteen plant species were observed in the field (Appendix 1) and bootstrap extrapolation showed that at least 3.56 species were unseen. In addition, the species composition in the sampled plots did not differ significantly ($p = 0.538$), and the species diversity (the effective number of species) was observed to vary within the sampled plots. Most plots had a low species diversity (<2.5), with only a few plots having a high species diversity (>3).

Of the observed plant species, the *Eragrostis* spp. was the most dominant (Dominance Index = 7.3), followed by *Senegalia nigrescens* (Dominance Index = 1.91), *Scorzonera humilis* (Dominance Index = 1.09), and *Leonotis ocymifolia* (Dominance Index = 0.20) (Figure 3.3). Rare species, which were less dominant, were also observed within the sampled plots and included *Ziziphus mucronate*, *Leucas martinicensis* and *Lipia javani*.

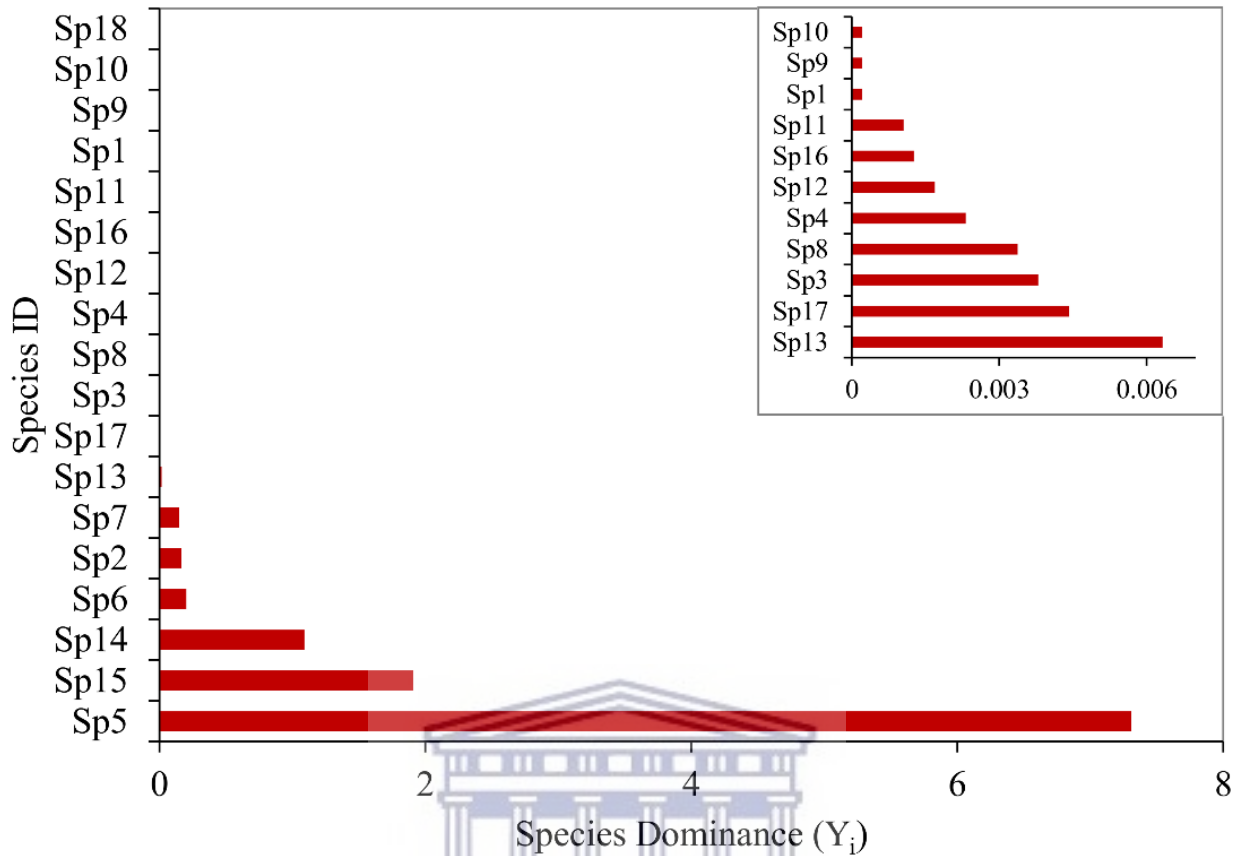


Figure 3.3 Species dominance of the species observed in the sampled plots. The species dominance was measured by using the dominance index. Where Sp1 = *Aloe maculate*, Sp2 = *Asparagus spp*, Sp3 = *Dracaena trifasciata*, Sp4 = *Ehretia rigida*, Sp5 = *Eragrostis spp*, Sp6 = *Leonotis ocymifolia*, Sp7 = *Trifolium repens*, Sp8 = *Grewia flava*, Sp9 = *Leucas martinicensis*, Sp10 = *Lipia javani*, Sp11 = *Meitinas Polyacantha*, Sp12 = *Olea spp.*, Sp13 = *Opuntia ficus indica*, Sp14 = *Scorzonera humilis*, Sp15 = *Senegalia nigrescens*, Sp16 = *Ledebouria marginata*, Sp17 = *Kalanchoe spp* and Sp18 = *Ziziphus mucronate*.

3.4.2. Distribution and performance of spectral diversity from remote sensing data

The remotely sensed diversity (Rao Q), which was derived from the measures of spectral variation, was observed to be higher in the south-western part of the study area. More specifically, the vegetation diversity was highest around the natural water pans and along the fence-lines, roads, and rivers (Figure 3.4). In other parts of the study area, the Rao Q was low or intermediate, typically in the grassland or cultivated areas. High spatial fidelity was observed

when all the spectral bands and the coefficient of variation were used. On the other hand, the NDPI and principal component had a low spatial fidelity.

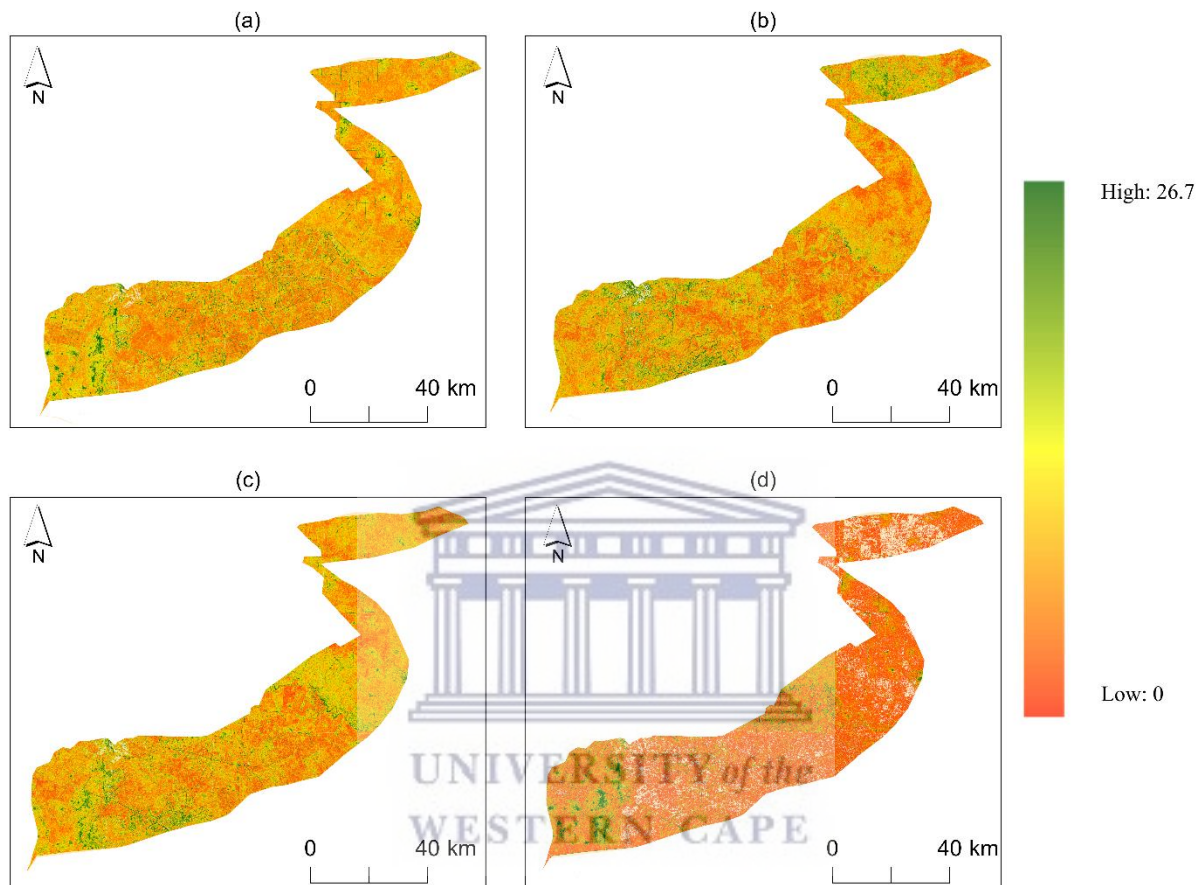


Figure 3.4 Species diversity (Rao Q) derived from the measures of spectral variation: (a) all the spectral bands, (b) coefficient of variation, (c) Normalised Difference Phenology Index (NDPI), and (d) principal component (The white returned NA values).

The coefficient of determination showed that the vegetation diversity measured from the remote sensing data was related to the field data ($R^2 > 0.01$). The association between the field-measured vegetation diversity and the Rao's Q was significantly high for the coefficient of variation and the reflectance of all the spectral bands ($R^2 > 0.3$ and $p < 0.05$) (Figure 3.5).

However, the Normalised Difference Phenology Index and the first principal component did not exhibit a high association.

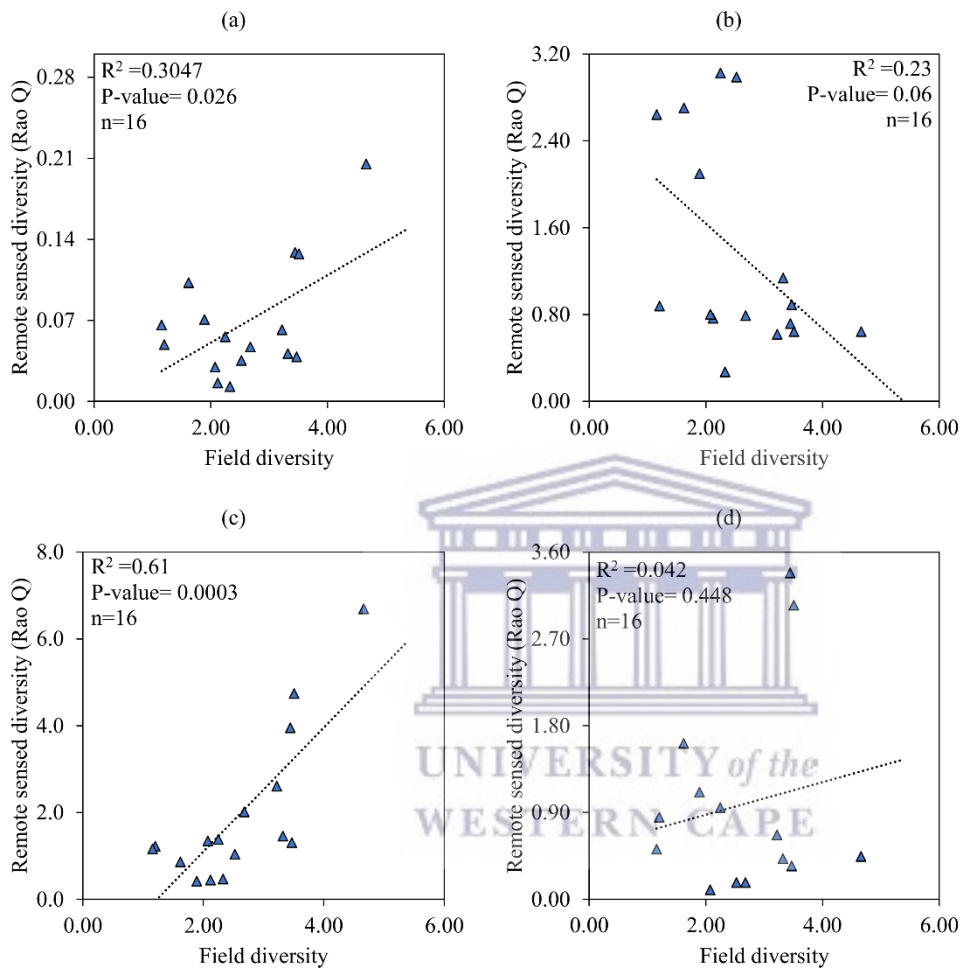


Figure 3.5 Linear regression of field-measured species diversity and remotely sensed diversity (Rao Q) in the Khakea-Bray TBA. Remotely sensed diversity (Rao Q) was derived from 20 m spatial resolution of (a) all the spectral bands, (b) the Normalised Difference Phenology Index (NDPI), (c) the coefficient of variation, and (d) the principal component.

3.4.3. Species diversity and distance from the natural pan

The Rao's Q between the wet and dry natural pans did not differ significantly (Figure 3.6). However, using curve estimation techniques, it was observed that the vegetation diversity around dry and wet natural pans was related to their distance from the natural pans. The

logarithmic equation explained the relationship between vegetation diversity and distance from the wet and dry natural water pans (Table 3.2).

Table 3.2 Curve estimation models for estimating the relationship between remotely sensed diversity (Rao Q) and distance from the wet natural pans. Y represents the vegetation diversity, b denotes the constant, C represents the intercept and X is the distance from the wet natural pans. The bold values show the significant model with the lowest AICc.

Formula	Type	Wet pan	Dry pan
		<i>AICc</i>	<i>AICc</i>
$Y = b_1X + C$	Linear	-69.47	-66.61
$Y = C + b_1\log(X)$	Logarithmic	-353.54	-348.76
$Y = C + b_1/X$	Inverse	-280.18	-123.34
$Y = C + b_1X + b_2X^2$	Quadratic	-78.07	-64.51
$Y = C + b_1X + b_2X^2 + b_3X^3$	Cubic	-78.02	-77.09
$Y = C + b_1X + b_2X^2 + b_3X^3 + b_4X^4$	Polynomial	-74.40	-93.76

Our results showed that species diversity decreased with the increasing distance from the natural pans (Figure 3.7). The decrease in species diversity around the wet natural pans was gradual and only peaked at ~40 m. However, the species diversity around the dry natural pans peaked at ~25 m and dropped sharply afterwards, with the increasing distance.

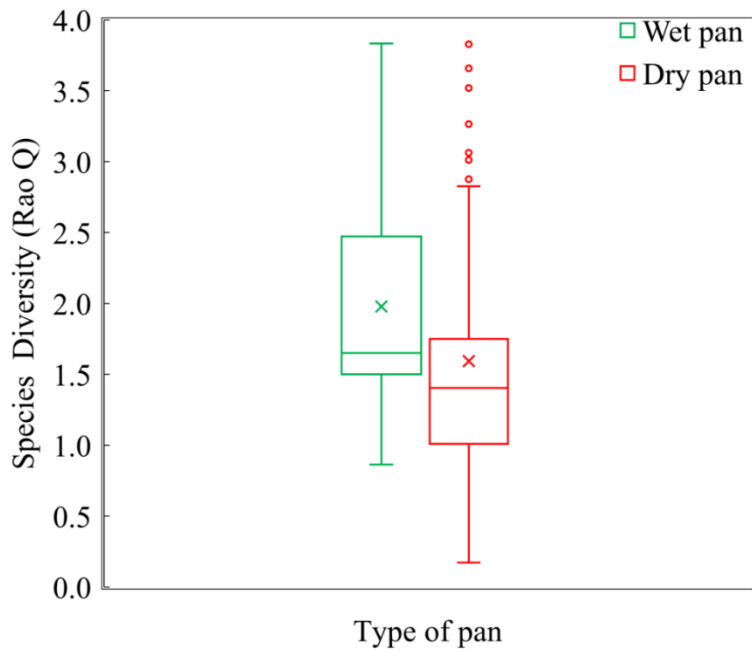


Figure 3.6 Mean variation in remotely sensed diversity (Rao's Q) between wet and dry natural pans, using the coefficient of variation at 20 m spatial resolution.

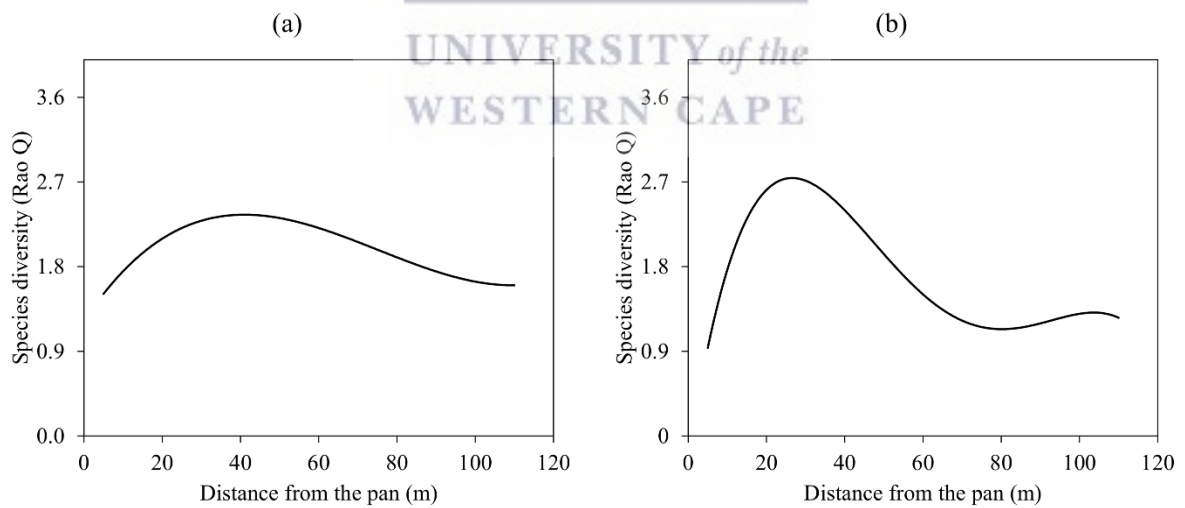


Figure 3.7 The response of remotely sensed species diversity (Rao's Q) to the distance from the natural pan between (a) wet and (b) dry natural pans.

3.5. Discussion

In this chapter, Sentinel-2 MSI was used to test whether the Spectral Variation Hypothesis (SVH) could characterize plant species diversity in Groundwater-Dependent Ecosystems (GDEs) within the Khakea-Bray TBA.

3.5.1. Measures of spectral variation and their performance in estimating vegetation diversity

The Rao's Q estimated from the Coefficient of Variation (CV) performed better than the Rao's Q estimated from all the other measures of spectral variation. In this study, the CV was used to measure the variability in spectral reflectance amongst pixels from all the spectral bands (Wang et al., 2018, Wang et al., 2016). CV is highly sensitive to the reflectance of rare and abundant species and is a measure of spectral variation (Madonsela et al., 2021, Wang et al., 2018). The CV has been used in different studies (Madonsela et al., 2021, Torresani et al., 2019, Wang et al., 2016), and it focuses on monitoring different aspects of the environment (Mapfumo et al., 2016, Arnall et al., 2006). Owing to its ability to detect spectral heterogeneity, the performance of the CV is expected to be better than other measures of spectral variation (Mapfumo et al., 2016, Madonsela et al., 2021).

The structural and chemical properties of leaves usually drive the spectral heterogeneity observed in the spectral reflectance of vegetation (Laliberté et al., 2020). The low performance of the Normalized Difference Phenology Index and the first principal component in estimating the Rao's Q can be explained by how these metrics capture more spectral heterogeneity in vegetated landscapes than in arid environments with intense soil reflectance (Xu et al., 2021, Oldeland et al., 2010). In addition, these measures may be more sensitive to a specific component of diversity (i.e. evenness, abundance, or dominance) (Madonsela et al., 2021, Madonsela et al., 2017). Therefore, these metrics may perform better in areas with a high environmental heterogeneity (e.g. temperate forests) or with a different measure of diversity (Wang et al., 2018, Laliberté et al., 2020).

The SVH does not hold in all environments (Schmidtlein and Fassnacht, 2017), but its applicability has been successfully tested in several environments including alpine conifers (Torresani et al., 2019) and grasslands (Lopes et al., 2017). This study presents the first attempt to utilize the Rao's Q for characterising species diversity in GDEs within an arid environment.

The findings of this study are supported by the empirical data from field-measured diversity, which explain at least 61% of the remote sensing-derived vegetation diversity (Rao's Q). When compared to other studies, for example Madonsela et al. (2017), Madonsela et al. (2021), Rocchini et al. (2004) and Lopes et al. (2017), the results are more robust. For example, Madonsela et al. (2017) and Rocchini et al. (2004) reported a low R^2 (0 - 0.48) when explaining vegetation diversity in South Africa and Italy. The findings of this study are also credible since the Rao's Q from several measures of spectral variation were calculated, unlike other studies, which only used single measures, such as the principal components (Laliberté et al., 2020), NDVI (Madonsela et al., 2017) or CV (Madonsela et al., 2021). The applicability of the SVH relies strongly on the measures of spectral variation used, and the measure should be able to detect the subtle differences in vegetation spectral reflectance with either medium- or low-resolution sensors (Torresani et al., 2021a, Rocchini et al., 2010a). Although this chapter utilized a moderate-resolution sensor, Sentinel-2 MSI, using high-resolution sensors, could have improved the robustness of these results.

The temporal variations in vegetation phenology may also have influenced the detection of spectral heterogeneity, since a single image, and not multi-temporal images, were used in this research study. Caution should also be taken when interpreting these results, since some areas within the Khakea-Bray TBA are not groundwater-dependent, whether they have a high or low vegetation diversity. These limitations do not take away from the merit of these results since they are rigorous and are clear and scientifically relevant. Future studies using the Rao's Q could test it with data from multi-temporal, high-resolution imagery and compare it to other methods for measuring vegetation diversity from spectral reflectance.

3.5.2. Distribution of vegetation diversity in the Khakea-Bray TBA

Vegetation diversity, measured with the Rao's Q, was the highest around the natural water pans and along rivers and roads. Groundwater from the Khakea-Bray dolomitic aquifer discharges into natural water pans and rivers, and this facilitates high vegetation diversity along, and around, these areas (Seward and van Dyk, 2018, Van Dyk, 2005, Ngobe, 2021). In addition, groundwater is usually enriched as it flows through different soils and some of these nutrients improve plant growth (Jansson et al., 2007, Smolders et al., 2010). Consequently, around natural water pans and along rivers (i.e. the riparian zone) species compete for the nutrients and water that are available from the groundwater. This is true since soil moisture and fertility

are limiting factors for plant growth in other parts of our study area, where the vegetation diversity was low. Just as competitive exclusion explains the low diversity in other parts of our study areas, niche partitioning might be responsible for the high vegetation diversity around natural water pans and along rivers (Egeru et al., 2015).

As the groundwater level deepens, the competition between species will likely change and the vegetation diversity will be reduced (Ma et al., 2011). This phenomenon is supported by observations in this study that show how vegetation diversity decreases with the increasing distance from the natural water pans, thus resembling an inverse piosphere. The inverse piospheric response of vegetation diversity around natural water pans means that there is minimal utilization, or grazing of vegetation around natural water pans by livestock (Washington-Allen et al., 2004, Mpakairi, 2019), which gives them a selective advantage over other vegetation species, thus allowing the vegetation diversity to be high around natural water pans (Washington-Allen et al., 2004, Egeru et al., 2015). The observation of a high vegetation diversity around natural water pans and along rivers agree with previous research on how the vegetation diversity is reduced, as the groundwater depth decreases (Zhu et al., 2013, Ma et al., 2011, Egeru et al., 2015).

The results also showed that non-groundwater-dependent areas had a high vegetation diversity. This was observed along roads and fence lines. Roads are dispersal corridors (Spellerberg, 1998), with high propagule pressure caused by the constant disturbance during maintenance and construction (Fowler et al., 2008). The constant disturbance changes the soil properties and improves its fertility (i.e. from the increased decomposition of nutrients) (Fallahchai et al., 2018, Li et al., 2014b). The improved soil fertility facilitates the colonization of roads by synanthropic plant species, specifically ruderal apophytes, which can quickly establish themselves and therefore increase the vegetation diversity along roads (Zielińska, 2007, Li et al., 2014b). This explains the observations made on the dominance of *Eragrostis spp*, since the species can easily invade and establish itself along roadsides (Roberts et al., 2021b, Roberts et al., 2021a). Our findings are similar to those of Li et al. (2014b), Marcantonio et al. (2013) and Zamani et al. (2019), whose observations showed that vegetation diversity along roadsides was mainly driven by fast-growing plant species. On the other hand, observations of a high species diversity along fence lines could plausibly be related to a community preference for using mixed-element fences that consist of living and non-living posts. Mixed-element fences consist of plant species that can easily resprout and that require minimal attention (Harvey et al., 2005).

In addition, the posts for mixed-element fences are made from several tree species for extra strength, thus influencing the vegetation diversity along the fence-line (Pulido-Santacruz and Renjifo, 2011).

3.5.3. The implications of using vegetation diversity for monitoring and conserving GDEs

There is a limited knowledge on biodiversity globally (i.e. the Linnean shortfall), and environments without ecological or economic significance are rarely prioritized in conservation programs, regardless of the associated Sustainable Development Goals (SDG) (Sætersdal and Gjerde, 2011). This approach has led to the degradation of many GDEs, since their significance was not realized in time (Murray et al., 2006, Regos et al., 2021). Although conservation is costly, identifying the priority conservation areas could help to manage ecosystems at risk of degradation (Knight et al., 2008). Although this approach is economically sound, it may put other ecosystems at risk (Knight et al., 2008, Sætersdal and Gjerde, 2011, Regos et al., 2021). The methodology in this study provides resource managers and ecologists with a framework for characterising and identifying priority conservation areas, where *a priori* information does not exist. Using the SVH and remotely sensed data can provide resource managers with insights into the vegetation diversity in the Khakea-Bray TBA, which can be a proxy for identifying the priority areas that need to be conserved or monitored for invasive species.

3.6. Conclusions

Understanding species diversity in GDEs is pivotal for the management and conservation of the Khakea-Bray TBA. Currently, field techniques are costly, and more innovative and accurate ways are being sought to provide us with some knowledge on species diversity in GDEs. Our study presents the first attempt to characterize vegetation diversity in a transboundary aquifer under threat from climate change and anthropogenic activities. This chapter provides evidence on how the SVH can be used with Sentinel-2 MSI to characterize the species diversity of GDEs within the Khakea-Bray TBA. This work also identifies the priority conservation areas in the Khakea-Bray TBA. Our work provides resources managers with a way of achieving the national and regional Aichi biodiversity targets, as well as for meeting SDG 15. Therefore,

future studies can use our methodology to provide *a priori* knowledge on all global ecosystems, including GDEs.



4.0. CHAPTER 4

SPATIO–TEMPORAL VARIATION OF VEGETATION DIVERSITY IN GROUNDWATER-DEPENDENT ECOSYSTEMS WITHIN ARID ENVIRONMENTS



Vegetation heterogeneity around a wet natural pan during the dry season

(Photo: Courtesy of Kudzai Mpakairi, 2021)

Mpakairi, K.S., Dube, T., Dondofema, F. and Dalu, T. Spatio–temporal variation of species diversity in groundwater-dependent ecosystems within arid environments. *Ecological Informatics* (*In press*)

4.1. Abstract

Climate change, land cover change and the over-abstraction of groundwater threaten the existence of Groundwater-Dependent Ecosystems (GDE), despite these environments being regarded as biodiversity hotspots. The vegetation diversity in GDEs requires routine monitoring to conserve and preserve the ecosystem services in these environments. However, the in-situ monitoring of vegetation diversity in extensive, or transboundary, groundwater resources remain a challenge. Inherently, the Spectral Variation Hypothesis (SVH) and remotely-sensed data provide a unique way to monitor the response of GDEs to seasonal or intra-annual environmental stressors, which is the key for achieving the national and regional biodiversity targets. This chapter presents the first attempt at monitoring the intra-annual, spatio-temporal variations in vegetation diversity in the Khakea-Bray Transboundary Aquifer, which is between Botswana and South Africa, by using the coefficient of variation derived from the Landsat 8 OLI Operational Land Imager (OLI). The coefficient of variation was used to measure spectral heterogeneity, which is a function of environmental heterogeneity. Heterogeneous environments are more diverse, compared to homogeneous environments, and the vegetation diversity can be inferred from the heterogeneity of a landscape. The coefficient of variation was used to calculate the α - and β measures of vegetation diversity (the Shannon-Weiner Index and the Rao's Q, respectively), whilst the monotonic trends in the spatio-temporal variation (January-December) of vegetation diversity were derived by using the Mann-Kendall non-parametric test. Lastly, to explain the spatio-temporal variations of vegetation diversity, a set of environmental variables were used, along with a machine-learning algorithm (Random Forest). The vegetation diversity was observed to be relatively high during the wet season and low during the dry season, and these changes were mainly driven by landcover- and climate-related variables. Significant changes in vegetation diversity were observed around natural water pans, along roads and rivers, and in cropping areas. These changes were better predicted by the Rao's Q (MAE = 5.81, RMSE = 6.63 and %RMSE = 42.41), than by the Shannon-Weiner Index (MAE = 30.37, RMSE = 33.25 and %RMSE = 63.94). These observations on the drivers and changes in species diversity provide new insights into the possible effects of future landcover changes and climate variability on GDEs. This information is imperative, considering these environments are biodiversity hotspots that can support many livelihoods. More importantly, this work provides a spatially explicit framework on how GDEs can be monitored to achieve Sustainable Development Goal (SDG) Number 15.

Keywords: Khakea–Bray; Rao’s Q; Random Forest; vegetation diversity; Spectral Variation Hypothesis (SVH); Shannon–Weiner



4.2. Introduction

In response to the stimuli caused by various biotic and abiotic factors, vegetation diversity is constantly changing (Yan et al., 2015, Miranda et al., 2009, Collins et al., 2010, Xia et al., 2010). Understanding the drivers of vegetation diversity is imperative for the conservation of ecologically sensitive environments (e.g. Groundwater-Dependent Ecosystems (GDEs)) (van Engelenburg et al., 2018, Kløve et al., 2011, Kløve et al., 2014). Ideally, stable GDEs are expected to be more diverse, compared to degraded GDEs. In the context of vegetation diversity, stable GDEs are characterised by several ecological niches that allow the existence of various species (Barbosa et al., 2001, Fisher et al., 2012). Landscape degradation affects the species pool and might affect vegetation communities, even after the restoration of the environment (i.e. the species pool hypothesis) (Eriksson, 1993, Lepš, 2001). The species pool hypothesis stipulates that environmental factors drive the species pool in most landscapes and that degraded landscapes have a lower species pool (Eriksson, 1993). Changes in the vegetation diversity within GDEs are driven by various threats. For example, in sub-Saharan Africa, these changes are predominantly driven by groundwater over-abstraction, land-use conversion, climate change and variability (Kløve et al., 2014, Chiloane et al., 2021, Orellana et al., 2012). Furthermore, the vegetation diversity in GDEs is also threatened by invasive species (Chiloane et al., 2021) and groundwater pollution (Rohde et al., 2017). To better conserve the biodiversity in GDEs, the spatio-temporal changes in vegetation diversity need to be understood, since vegetation communities respond differently, and at a different temporal scale, to environmental threats. These threats, along with inadequate policies and legislative frameworks, might drive the endemic species within GDEs to extinction (Kløve et al., 2011, Kløve et al., 2014, Kremer et al., 2014). Therefore, it is important to understand the spatio-temporal variations of vegetation diversity, as well as the drivers of change, to inform policy and management programs.

Climate is an important factor that explains the local (i.e. plot-level) and regional (i.e. longitudinal variations) changes in vegetation diversity (Collins et al., 2010, Yan et al., 2015). For example, water availability drives ~ 40% of the biological processes in most vegetated communities (Martiny et al., 2005) and the increased availability of water may improve the vegetation diversity of GDEs within arid environments (Dalu and Wasserman, 2022). However, during the dry season, competitive exclusion might lower the vegetation diversity in GDEs, which favors Groundwater-Dependent Vegetation (GDV) more than non-GDV (Dwire

and Mellmann-Brown, 2017). These changes in vegetation diversity may be intense in GDEs without keystone species capable of redistributing groundwater to the shallow parts of the soil profile (e.g. the Shepherd's tree *Boscia albitrunca*) (Humphreys, 2006, Eamus and Froend, 2006). The existence of these keystone species makes up most of the GDE biodiversity hotspots, since they facilitate the faunal endemism of regionally-restricted species (Bird et al., 2019, Dalu and Wasserman, 2022). However, when coupled with landcover changes, the biodiversity hotspots in GDEs are susceptible to degradation (e.g. the degraded GDE clusters in California, USA, and Central Asia) (Alaibakhsh et al., 2017, Pengra et al., 2007).

Besides climate, land cover changes also drive the vegetation diversity in most ecosystems, including the GDEs (Boulangat et al., 2014). Urbanization and the need for agricultural land are the predominant drivers of land conversion (Seto et al., 2011, Von Lampe et al., 2014). Like climate, the effects of land cover change on vegetation diversity are varied and depend on the land use. For example, land conversion to agriculture has been observed to decrease the vegetation diversity in tropical areas (Newbold et al., 2014), yet the same conversion in arid areas increases the vegetation diversity (Norfolk et al., 2015). It has been perceived that an increased vegetation diversity is expected in arid areas, since land conversion leads to a high species turnover, and the new species reduces the instance of species extermination (Graham et al., 2019). It is imperative to understand the influence of landcover on the spatio-temporal patterns of vegetation diversity in GDEs, since these environments are threatened by the expansion of agricultural land, to support the growing human population. Hence, to avert the likely effects of land-use and climate change on the stability of the vegetation diversity of GDEs, a proxy of ecosystem stability can be used to constantly monitor GDEs.

Field techniques remain the most reliable and accurate techniques for measuring vegetation diversity, regardless of the environment (Beck and Schwanghart, 2010). However, monitoring the spatio-temporal variations of vegetation diversity with field techniques can be laborious and costly in extensive transboundary aquifers (Brown et al., 2007, Chen et al., 2008, John et al., 2008, Chiloane et al., 2021). Fortunately, the Spectral Variation Hypothesis (SVH) and remotely sensed data can provide a rapid and direct assessment of the vegetation diversity over large and complex landscapes (John et al., 2008, Li et al., 2017, Nakhoul et al., 2020, Woods and Sekhwela, 2003). The working assumption of the SVH is that vegetation diversity can be inferred from the spectral heterogeneity of any landscape, since it is a function of environmental heterogeneity (Rocchini et al., 2010b). Heterogenous environments are

expected to be more diverse, with several ecological niches (i.e. from the different vegetation types), compared to homogenous environments (Rocchini et al., 2004, Rocchini et al., 2017). The SVH has been successfully explored in different environments, including alpine conifers (Torresani et al., 2019) and grasslands (Lopes et al., 2017). Although it does not hold in all environments (Schmidtlein and Fassnacht, 2017), its applicability in arid environments is promising. The SVH can provide estimates of the vegetation diversity in GDEs within arid environments where no prior information exists on the vegetation (e.g., the Khakea–Bray TBA). No *a priori* information exists on the vegetation diversity or ecological status of the Khakea–Bray TBA and the SVH can provide us with a starting point.

The Khakea–Bray TBA is amongst some of the most under-studied and poorly-managed aquifers in southern Africa, yet it supports many livelihoods and GDEs (Seward and van Dyk, 2018). The ecological consequences of groundwater draw-down on GDEs within the Khakea–Bray TBA has not received attention, mainly because its socio–economic needs largely outweigh its ecological integrity (Davies et al., 2013, Nijsten et al., 2018, Ngobe, 2021). In 2002, the aquifer was dewatered after the groundwater abstraction for irrigation increased to 11.1 Mm³ per annum beyond the average capacity of the aquifer (6.9 Mm³ per annum) (Godfrey and Van Dyk, 2002a, Seward and van Dyk, 2018, Van Dyk, 2005). Although the land use has changed, the groundwater remains a key component for supporting key socio–economic needs (Davies et al., 2013, Nijsten et al., 2018). However, the remaining biodiversity in the Khakea–Bray TBA remains threatened from continued groundwater abstraction, land–use conversion and climate change.

Vegetation diversity estimated from environmental heterogeneity using the SVH can be an indicator of ecosystem stability, and the spatio–temporal variations of ecosystem’s stability in the Khakea–Bray TBA can be monitored. The spatio–temporal variation approach allows the monitoring of environmental changes in GDEs and gives a better insight, compared to using the snapshot approach (Solano-Correa et al., 2018). The snapshot approach uses single–date imagery and might not provide the necessary information on the environmental processes before the image was acquired (Solano-Correa et al., 2018). Understanding the intra–annual, or seasonal, variations of vegetation diversity in the Khakea–Bray TBA can also advance its conservation and management, in the face of land-use conversion and climate variability. Therefore, this chapter presents the drivers of the spatio–temporal trends in species diversity

in the Khakea–Bray TBA, by using the SVH and Landsat–8 OLI Operational Line Imager (OLI).

4.3. Materials and methods

4.3.1. Data acquisition and processing

Multi-year Landsat–8 OLI surface reflectance imagery ($n = 535$) was used for this analysis. Landsat–8 OLI was used to maintain the image homogenization and to reduce instances of geometric and spectral inconsistencies from using multi–sensor imagery. Surface reflectance data was preferred since it is corrected for geometric and atmospheric errors. The multi–year images used were acquired between January 2016 and December 2020 from the Google Earth Engine (GEE) platform (<https://code.earthengine.google.com>). The Landsat-8 OLI images were converted to monthly time–series composites derived from the median spectral reflectance of the multi–spectral bands (i.e., blue, green, red, near–infrared (NIR), and two short–wave infrared). Image compositing allows for the enhancement of spectral reflectance by removing the clouds and shade (Gxokwe et al., 2022). The 2016–2020 study period was selected, since the study region has been experiencing severe droughts, including the 2015/2016 El Niño and the ongoing 2018–2021 southern Africa drought (Blamey et al., 2018, Marumbwa et al., 2021). The ongoing drought allows for the enhanced identification of Groundwater-Dependent Vegetation (GDV) since there is minimal surface water available for the non–GDVs.

Since the study focused on monitoring the spatio–temporal variations of vegetation diversity, the built–up water and remnant cloud pixels were masked from the analysis. Cloud pixels were masked by using the QA band (QA60) with in–built functions in GEE, while the Normalized Difference Built–up Index (NDBI) and Modified Normalized Difference Water Index (MNDWI) were used to mask built–up and water pixels respectively. The NDBI and MNDWI indices were selected over other indices, based on their frequent use in water and built–up mapping (Xu, 2008, Bhatti and Tripathi, 2014, Jiang et al., 2012). The NDBI values greater than 0 and MNDWI values greater than 1 were considered built–up and water pixels, respectively. The MNDWI can be calculated as follows:

$$MNDWI = \frac{Green-SWIR}{Green+SWIR} \quad \text{Equation} \quad 4.1$$

and NDBI as:

$$NDBI = \frac{SWIR-NIR}{SWIR+NIR} \quad \text{Equation} \quad 4.2$$

Where Green, NIR and SWIR are reflectance in the green, shortwave infrared, and near-infrared spectral regions, respectively.

From the masked imagery, the Coefficient of Variation (CV) was calculated to measure the spectral variation of all the images. The CV was used because it has been shown to outperform other measures, when estimating species diversity with remote sensing imagery (Madonsela et al., 2017, Madonsela et al., 2021). The CV was calculated using Equation 5.3 below:

$$\text{Coefficient of variation (CV)} = \frac{\text{Standard deviation of all the bands}}{\text{mean of all the bands}} \quad \text{Equation} \quad 4.3$$

4.3.2. Environmental variables

Climate and landcover variables were used to explain the drivers of vegetation diversity in the Khakea–Bray TBA. The climate data included the mean temperature, the minimum temperature, the maximum temperature, the annual precipitation, the potential evapotranspiration, and the wet day frequency. The climate data were provided monthly (January 2016 – December 2020), with a spatial resolution of 0.5° (Harris et al., 2020). The precipitation data were summed to derive annual totals, and for the other climate variables, the annual averages were used. The climate data were then averaged to derive the mean values for the 2016–2020 period. The climate data were accessed from the Climatic Research Unit gridded Time Series (CRU TS) v. 4.05 and downloaded from

<https://crudata.uea.ac.uk/cru/data/hrg/>. In addition to the climate data, land cover data from the European Space Agency (ESA)–Climate Change Initiative (CCI) available from <http://2016africalandcover20m.esrin.esa.int/> was used. The landcover data have several landcover classes, including tree cover, shrub cover, grassland, cropland, aquatic vegetation or regularly flooded, lichens mosses / sparse vegetation, bare land, built-up land, snow and/or ice and open water areas. The Khakea-Bray is characteristic of shrubland savannah (i.e. bushveld) and the landcover data used included this vegetation class (i.e. shrub cover). These data were provided at 20 m and were derived from Sentinel–MSI imagery (Alkhalil et al., 2020). The landcover and climate variables were included, based on their generalized interaction with the groundwater and plant growth (Zhu et al., 2015, Eamus et al., 2006, Brotsma et al., 2010).

4.3.3. Species diversity from remote sensing images

To measure the spatio–temporal variation of vegetation diversity in the Khakea–Bray TBA, the study utilized α - and β -diversity measures, the Shannon–Weiner Index and the Rao’s Q, respectively. The Shannon–Weiner Index calculates vegetation diversity by considering the abundance and richness of spectral values for the entire image (Rocchini et al., 2017) and it can be calculated by using Equation 5.4 below:

$$H' = - \sum_{i=1}^S p_i \ln p_i \quad \text{Equation} \quad 4.4$$

Where S is the image extent or plot area, and p_i is the proportion of pixel i to S.

Although the Shannon–Weiner Index is a commonly-used measure; it has been observed to get saturated over areas with high vegetation diversity and it is affected by subtle changes in the pairwise pixel values (Rocchini et al., 2017), which is the reason the Rao’s Q was also included. In remote sensing, the Rao’s Q calculates vegetation diversity from the pairwise spectral distance between the spectral values of pixel i and j (Torresani et al., 2021b, Khare et al., 2021). The measure also incorporates the abundance and proportion of pixels i and j. Rao’s Q is calculated as follows:

$$Q_{rs} = \sum_{i=1}^{F-1} \sum_{j=i+1}^F d_{ij} p_i p_j$$

Equation

4.5

Where Q_{rs} represents the Rao Q applied to the remote sensing image and d_{ij} is the distance between i th and j th pixel ($d_{ij} = d_{ji}$ and $d_{ii}=0$). The selected image extent or plot area is F , with p_i and p_j being the proportion of pixel i and j to F , respectively.

The coefficient of variation calculated from the pre-processed images was used to calculate the Rao's Q and Shannon-Weiner index in R (Team, 2020), using the spectralrao function provided in Rocchini et al. (2017) and Rocchini et al. (2019). A 3×3 - pixel moving window was used when computing the vegetation diversity.

4.3.4. Spatio-temporal variation analysis

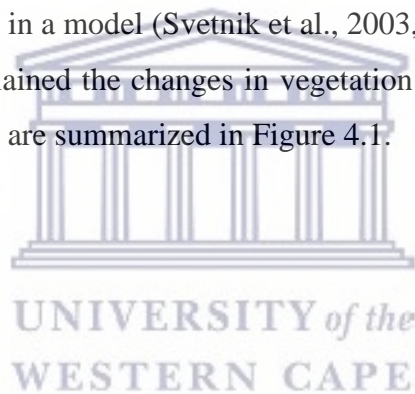
To measure the monthly spatio-temporal variations of the vegetation diversity in the Khakea-Bray, the Mann-Kendall non-parametric test was used. This test measures the monotonic trends in time-series data and has been used in most studies, owing to its robustness (Libiseller and Grimvall, 2002, Shadmani et al., 2012). In this study, the Mann-Kendall test was used to detect trends in the seasonal vegetation diversity from the Rao's Q and the Shannon-Weiner data. The p -value and S -values from the Mann-Kendall test were used to evaluate the significance of the trend and the rate of change in the species vegetation within the Khakea-Bray TBA, respectively. The significance was tested at a $p < 0.05$ confidence interval.

4.3.5. Drivers of species diversity spatio-temporal variation

To determine the drivers in the spatio-temporal variation of vegetation diversity, the variable importance function in the random forest algorithm was used, which uses classification and regression trees to build a highly-predictive ensemble model (Mpakairi and Muvengwi, 2019, Breiman, 2001). The random forest algorithm was used, as it is insensitive to the data structure, it is highly predictive and it does not overfit (Breiman, 2001, Liaw and Wiener, 2002). This model was executed in R, using the caret and randomForest package (Kuhn, 2009, RColorBrewer and Liaw, 2018, Breiman, 2001, Liaw and Wiener, 2002). To build the random forest model, data from the Mann-Kendall test were used, which showed the spatio-temporal variations of vegetation diversity along with climate and land cover variables. The data used to build the model were derived from areas where the spatio-temporal changes in species

diversity were significant (i.e., $p < 0.05$). Seventy-five percent of the data was used for model training and the remaining twenty-five percent was used for model evaluation. To evaluate the accuracy of the model, the Mean Absolute Error (MAE), the Root Mean Square Error (RMSE) and the percentage RMSE (% RMSE) were used. The MAE, RMSE and % RMSE measure the agreement between the actual and predicted values of the model and can compare the predictive errors of different models (Piepho, 2019, Zhang, 2017). A model with a lower RMSE and MAE is considered highly predictive, when compared to a model with a higher RMSE and MAE (Chai and Draxler, 2014). In addition, a model with a low % RMSE means that the model has less residual variance than a model with a high % RMSE (Lin et al., 2016).

To measure the variable contribution, the Increased Impurity Index (IncNodePurity) was utilized, following Mpakairi and Muvengwi (2019), Pal (2005), Svetnik et al. (2003). IncNodePurity measures how a variable decreases the Residual Sum of Squares (RSS) at each node for all the regression trees in a model (Svetnik et al., 2003, Pal, 2005). The variable with the highest IncNodePurity explained the changes in vegetation diversity more than the other variables. All the methods used are summarized in Figure 4.1.



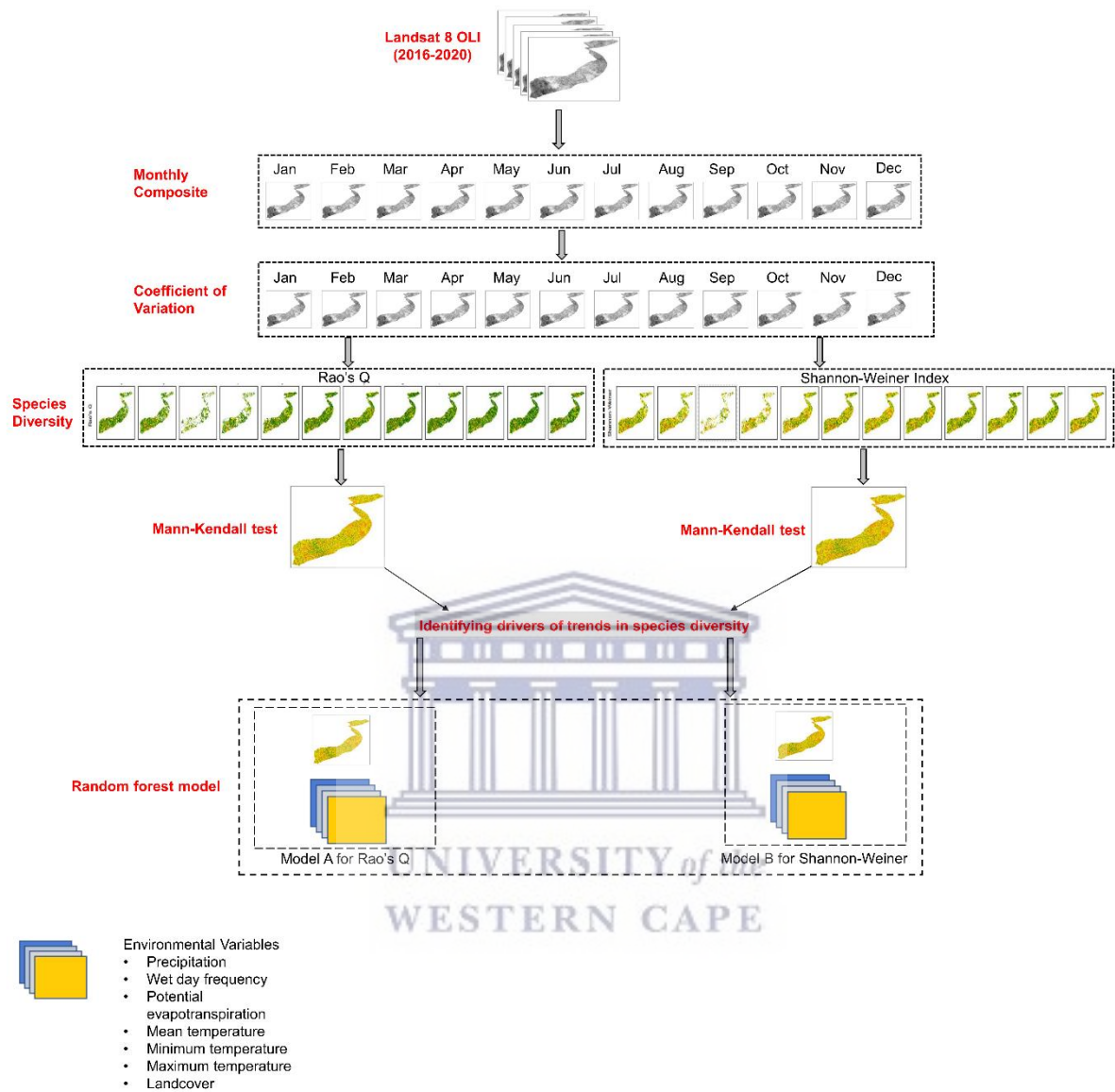


Figure 4.1 Summarised flowchart showing the steps undertaken to detect the trends in vegetation diversity and to identify the drivers of the changes in vegetation diversity.

4.4. Results

4.4.1. Spatio-temporal variation of species diversity

Our results showed that the vegetation diversity was high during the wet season and low during the dry season. Peak species diversity was observed in April and the lowest species diversity was observed in September (Figure 4.2), and it also peaked in winter (July) before summer. These changes were more noticeable when using the Shannon–Weiner Index, rather than the Rao’s Q (Figure 4.3 and Figure 4.4). However, the changes in species diversity from the Shannon–Weiner Index were more generalized, when compared to those from the Rao’s Q, which showed more pronounced changes in the species diversity (Figure 4.5).

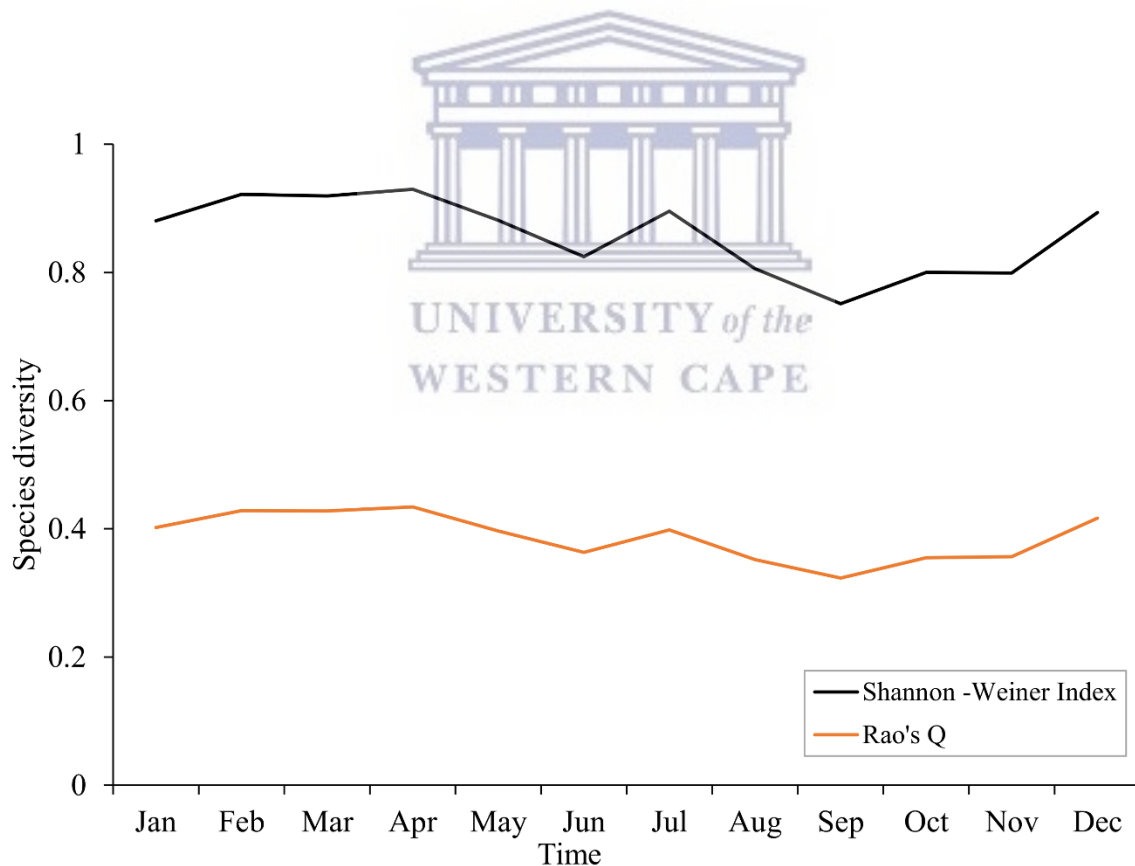


Figure 4.2 Monthly average of species diversity measured by the Shannon–Weiner Index and the Rao’s Q.

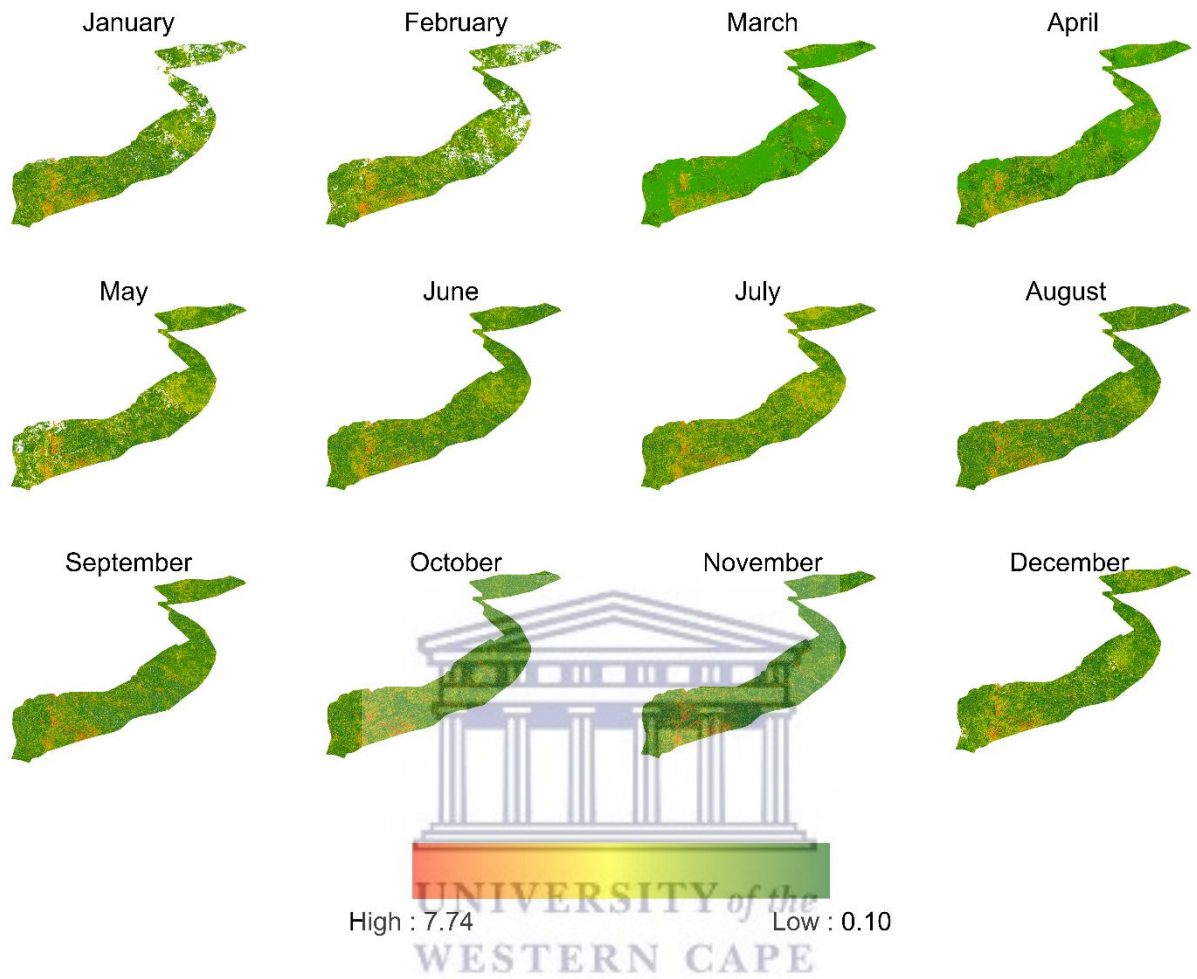


Figure 4.3 Monthly changes in species diversity, as calculated by the Rao's Q.

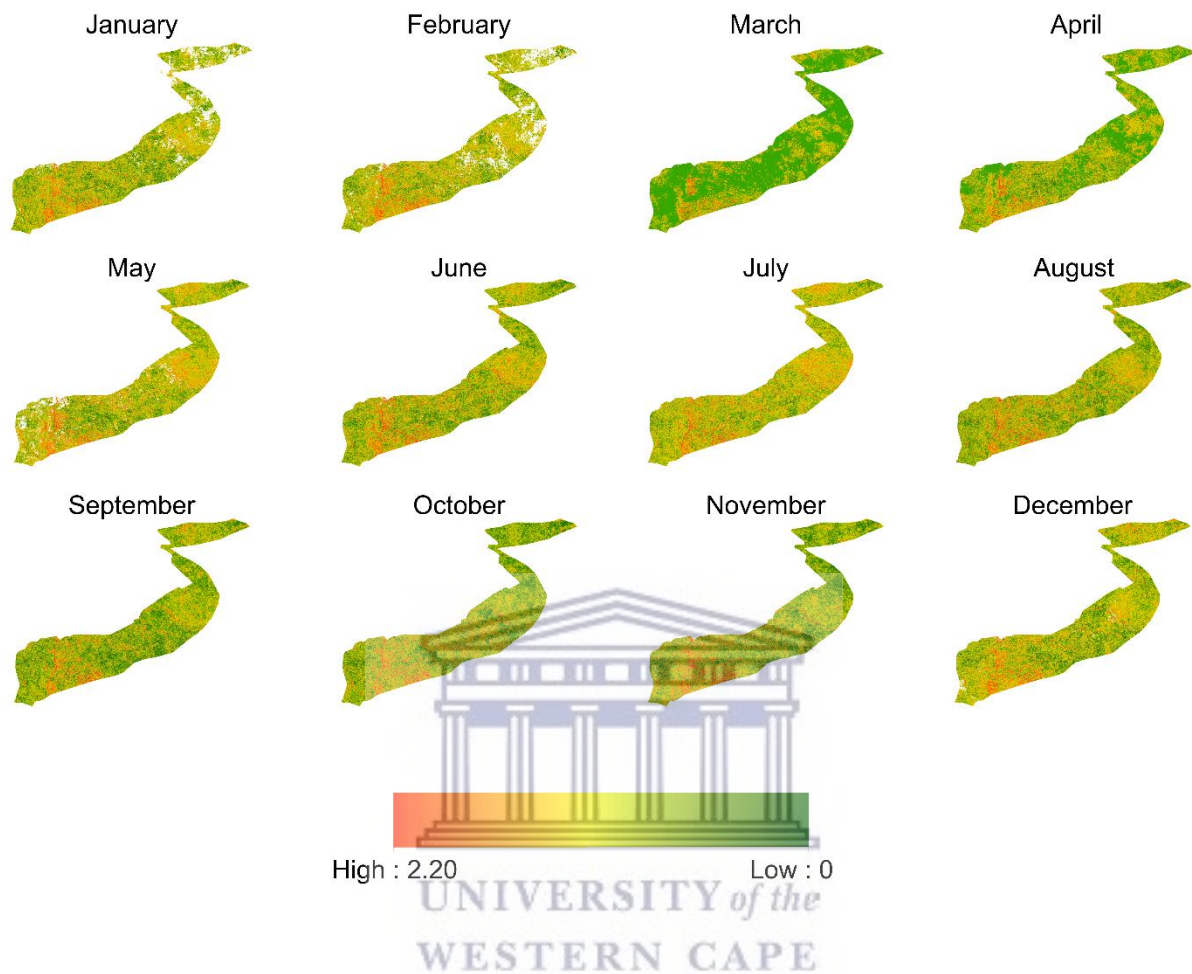


Figure 4.4 Monthly changes in species diversity, as calculated by the Shannon–Weiner Index.

The results of the Mann–Kendall test for the monthly Shannon–Weiner Index and the Rao’s Q showed that the species diversity changed significantly around natural water pans, along roads and rivers, and in most farming areas. A significant decrease in species diversity was observed along the roads and a significant increase was observed in the cropping areas, around natural water pans and along rivers (Figure 4.5).

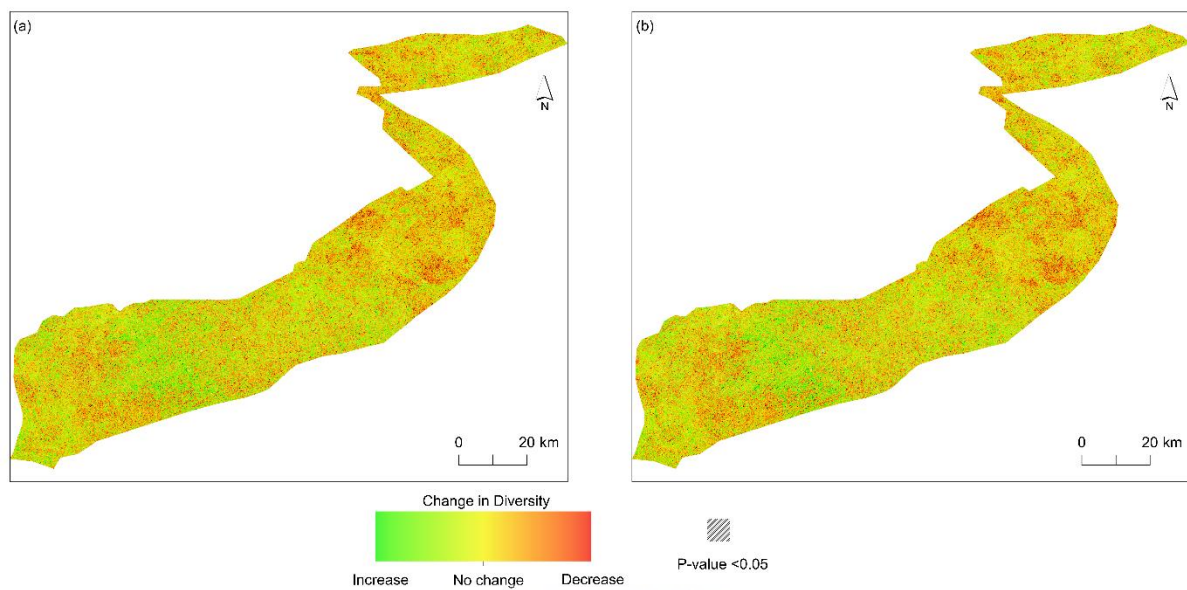


Figure 4.5 Spatio-temporal trends of species diversity as measured by (a) the Shannon–Weiner Index and (b) the Rao’s Q, using the Mann–Kendall test.

4.4.2. Drivers of variation in species diversity

Our random forest models, using the Shannon–Weiner Index (MAE = 30.37, RMSE = 33.25 and %RMSE = 63.94) and the Rao’s Q (MAE = 5.81, RMSE = 6.63 and %RMSE = 42.41), showed the environmental drivers and explain the changes in species diversity. The random forest model, using the Rao’s Q, performed better than when using the Shannon–Weiner Index, since the %RMSE, RMSE and MAE from the Shannon–Weiner Index were higher. Although the models performed differently, the effect of the environmental drivers on the changes in species diversity was relatively similar.

Overall, the changes in species diversity were predominantly driven by land cover, precipitation, the mean temperature, and the wet day frequency (Figure 4.6). On the other hand, the maximum temperature, the minimum temperature, and the potential evapotranspiration contributed least to the changes in the species diversity. For land cover, the changes in species diversity were more noticeable in areas with water, cropland, shrubland and bare land cover (Figure 4.7). In addition, a low wet day frequency (< 4 days/year) facilitated the changes in species diversity more than a high wet day frequency (Figure 4.8). However, changes in the species diversity varied according to the precipitation. Changes in the species diversity were

observed in areas with high rainfall (> 380 mm/year), low rainfall (< 300 mm/year), or with relatively high mean temperatures (20.9 – 21.2°C).

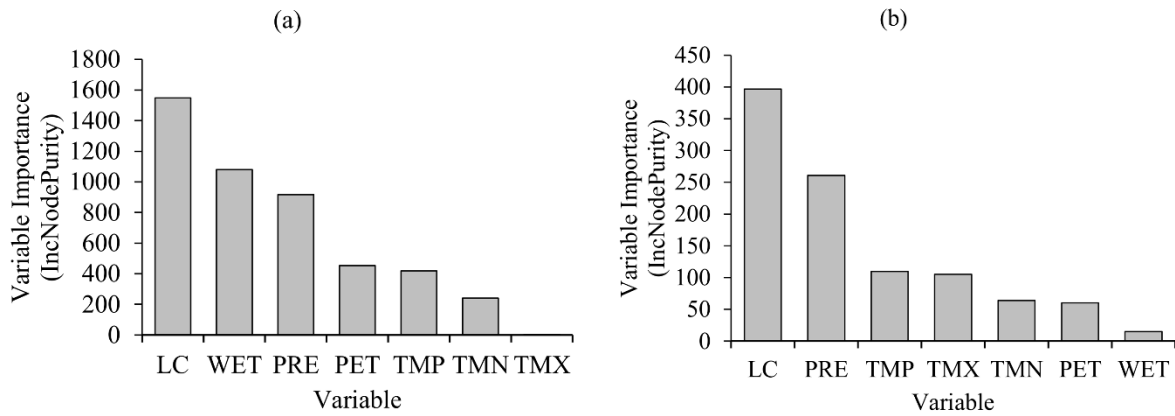
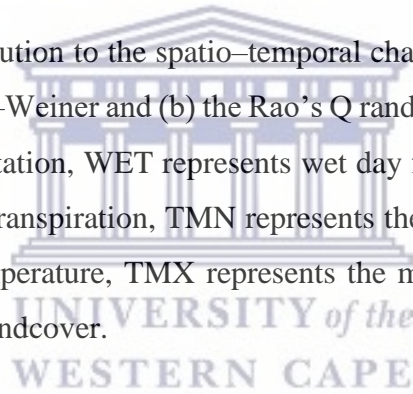


Figure 4.6 Variable contribution to the spatio-temporal changes in species diversity from (a) the Shannon-Weiner and (b) the Rao's Q random forest models. Where PRE refers to precipitation, WET represents wet day frequency, PET represents the potential evapotranspiration, TMN represents the minimum temperature, TMP is the mean temperature, TMX represents the maximum temperature and LC represents the landcover.



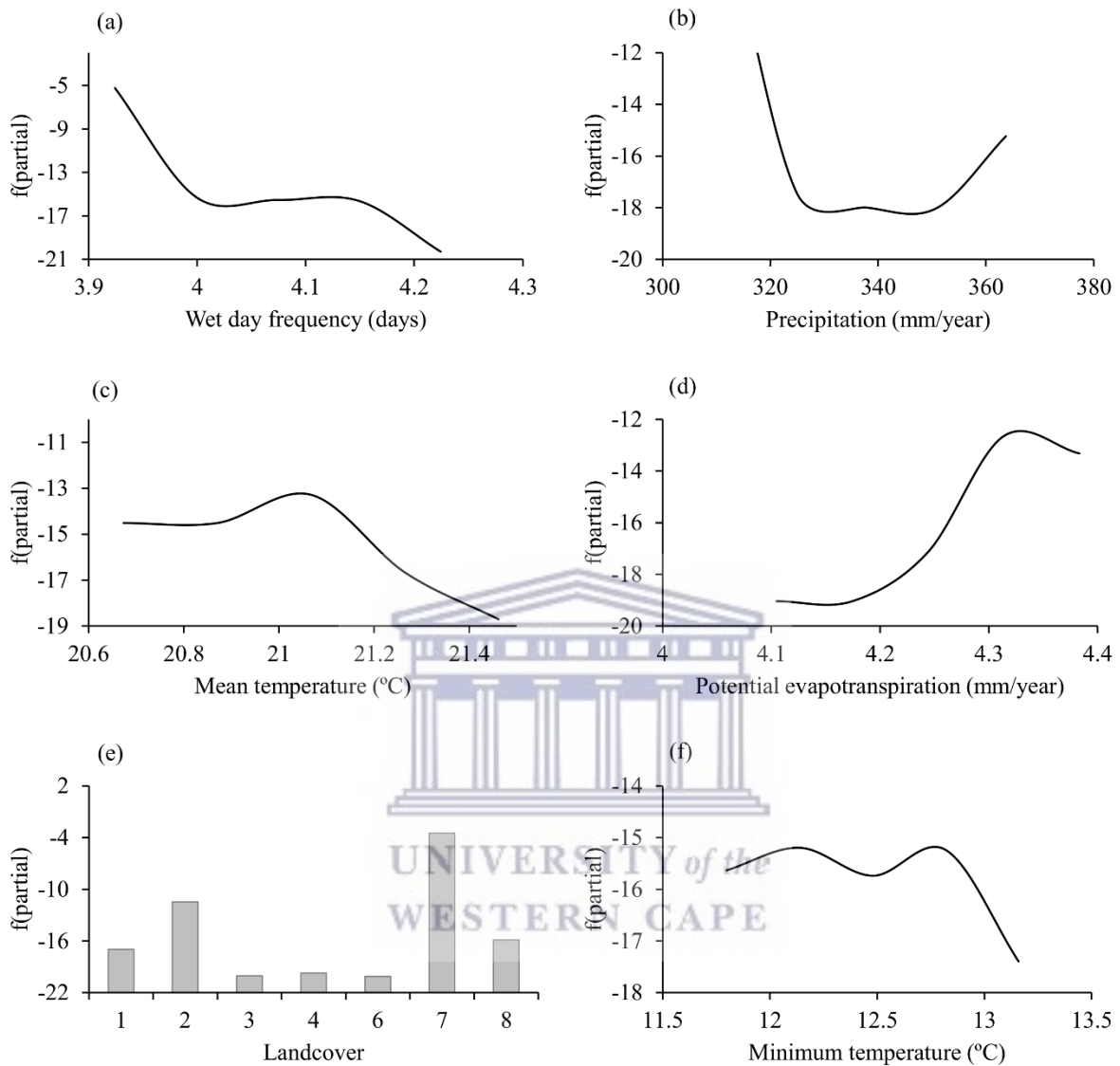


Figure 4.7 Partial dependence plots from the Shannon–Weiner random forest model showing the response in the spatio–temporal variation of species diversity to (a) wet day frequency, (b) precipitation, (c) mean temperature, (d) potential evapotranspiration, (e) land cover (1 = Tree cover, 2 = Shrubland, 3 = Grassland, 4 = Cropland, 6 = Sparse vegetation, 7 = Bare land, 8 = Built-up areas) and (f) minimum temperature. The maximum temperature had zero contribution to the model, hence there was no partial dependence curve for this variable.

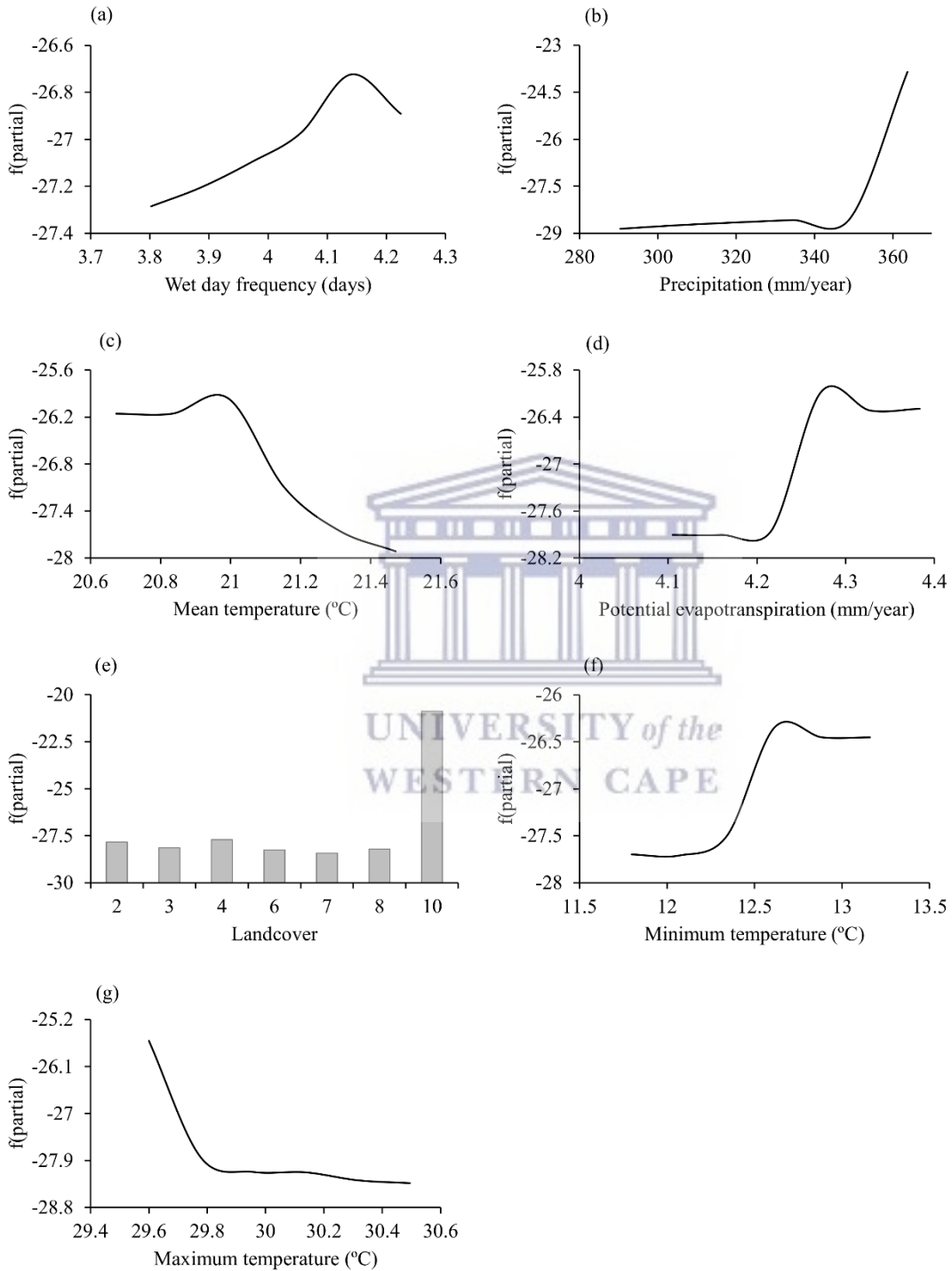


Figure 4.8 Partial dependence plots from the Rao's Q random forest model showing the response in the spatio-temporal variation of species diversity to (a) wet day

frequency, (b) precipitation, (c) mean temperature, (d) potential evapotranspiration, (e) land cover (2 = Shrubland, 3 = Grassland, 4 = Cropland, 6 = Sparse vegetation, 7 = Bare land, 8 = Built-up areas and 10 = Open Water), (f) minimum temperature and (g) maximum temperature.

4.5. Discussion

It is imperative to understand the spatio-temporal variations of vegetative diversity for the conservation of the ecological integrity of GDEs within arid environments. Therefore, this chapter sought to detect the spatio-temporal variations of vegetative diversity in the Khakea-Bray TBA by using remote sensing measures. Overall, the results showed how land cover and climate explain the intra-annual and seasonal changes in species diversity.

Our observation on the response of vegetative diversity to seasonality can be associated with the phenological patterns of the vegetation and the relationship between climate and vegetation (Adole et al., 2016, Wessels et al., 2011). The primary productivity of plants has been observed to peak during the wet season and to decrease during the dry season, owing to limited water and nutrient availability (Byrne et al., 2013, Prev y and Seastedt, 2014). These seasonal changes in productivity affect the vegetative diversity and have been observed in most environments, including arid areas (Kushwaha and Nandy, 2012, Aronson and Shmida, 1992, February et al., 2007). These patterns are important for arid environments in the context of climate change, since the precipitation and temperature seasonality is expected to increase (Scholes, 2020). The projected precipitation and temperature seasonality means that the seasons will most likely be extreme, and this might affect the adaptability of the plants, from one season to the other (Scholes, 2020, Zeppel et al., 2014). The effect of climate seasonality on vegetative diversity is also supported by our observations from the random forest model, which showed that changes in the vegetative diversity responded more to the precipitation and mean temperature. Rainfall drives at least 40% of the biological processes in most vegetated environments by supporting plant growth and development (Martiny et al., 2005). This explains why water availability is one of the driving variables behind the longitudinal variations in vegetative diversity (Collins et al., 2010, Yan et al., 2015).

In arid areas, the effect of precipitation is more crucial than that of temperature, since subtle changes in precipitation have the potential to alter the structure and composition of the species

(Prevéy and Seastedt, 2014, Byrne et al., 2013). However, the negative feedback between wet day frequency and changes in vegetative diversity plausibly means that most species within the arid Khakea–Bray TBA have adapted to water stress, and that more precipitation might cause soil flooding. Soil flooding can suffocate the plant roots, and the reduced soil aeration will cause the death of the aboveground vegetation (Adler and Levine, 2007, Cleland et al., 2013). This is supported by the species pool hypothesis, which states that increased wetness will only support species capable of surviving from the increased availability of water (Grace, 2001).

The counter-intuitive observation on the negative interaction between changes in vegetative diversity and the increasing wet day frequency is corroborated by previous studies (Adler and Levine, 2007, Yan et al., 2015, Swemmer et al., 2007). For instance, Adler and Levine (2007) observed that the increasing precipitation did not affect the species richness in areas with plant annuals within the Colorado prairies. These findings are similar to observations by Cleland et al. (2013), who found that the regional species richness of grasslands was not influenced by annual precipitation; instead, the annual precipitation influenced the richness of the plots. These observations relate to our study since they are extensive and cover several landcover types.

The changes in vegetative diversity around natural water pans, along roads and rivers, and in most farming areas, were supported by the results of the variable importance analysis, which showed that landcover (water, cropland, shrubland and bare land cover) explain most changes in the vegetative diversity. The onset of the farming season and the harvesting period in farming areas may explain the changes in spectral diversity vis-à-vis species diversity (Kindt et al., 2004, Eilu et al., 2003); for example, the land-use change from cattle ranching to crop farming before the growing season, and back to cattle ranching after the rainy season (Dahlberg, 2000, Ramberg et al., 2006). These changes in land use are essential for supporting cattle ranching, which is mostly practiced in the Khakea–Bray TBA, and they therefore explain the trends in the vegetative diversity in farming areas. On the other hand, the seasonality of precipitation and groundwater availability could be driving the increases in species diversity around natural water pans and along rivers (Buchsbaum et al., 2006, Utete et al., 2018). The groundwater level is usually high, with the obligatory and facultative phreatophytes present around natural water pans and along rivers (Hoyos, 2016). Facultative phreatophytes will most likely remain present during the wet season, but in the dry season, the lowering of the groundwater level may affect them and lead to wilting or stunted growth (Ward et al., 2013, Buchsbaum et al., 2006). At a

later stage, the improved groundwater availability from groundwater recharge might improve the plant growth and the development of obligatory and facultative phreatophytes (Thomas, 2014, Torres-García et al., 2021). These dynamics of groundwater availability may explain the changes in vegetation diversity around natural water pans and along rivers. In addition, the changes around natural water pans could be related to the piosphere effect, because water resources benefit livestock more during the dry season and less during the wet season (Andrew, 1988, Carbonell et al., 2021, Shezi et al., 2021). The aggregation of livestock and grazing around natural water pans creates a utilization gradient (Andrew, 1988, Shezi et al., 2021). Our observations on how the vegetation diversity changes around natural water pans, along roads and rivers, and in most farming areas, have been observed before in different environments (Msiteli-Shumba et al., 2017, Junk et al., 2006, Wei and Jiang, 2012, Li et al., 2014a, López-Gómez et al., 2008).

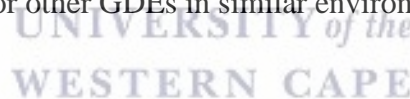
The results showed that the Rao's Q performed better than the Shannon–Weiner Index, since it allows the monitoring of vegetation diversity across landscapes by incorporating the spectral distance (Rocchini et al., 2018, Khare et al., 2019). The Rao's Q can estimate vegetation diversity at a community level, rather than at a plot or pixel-level, as with the Shannon–Weiner Index (Hernández-Stefanoni et al., 2012, Rocchini et al., 2018). These characteristics are ideal, since the Khakea–Bray TBA is an extensive landscape with several vegetation communities, and the Shannon–Weiner Index would be oversaturated from the high vegetation diversity (Khare et al., 2019, Rocchini et al., 2017). However, monthly changes in vegetation diversity were more noticeable with the Shannon–Weiner Index, since it can detect subtle changes in vegetation diversity, compared to the Rao's Q (Féret and de Boissieu, 2020, Rocchini et al., 2018).

Vegetation growth and development are in sync with the precipitation and land cover patterns in most environments (Jamieson et al., 2012, Jolly and Running, 2004, Prasad et al., 2007). Understanding the spatio-temporal variations of vegetation diversity from the interaction of the vegetation, land use and climate patterns can assist to plausibly predict the effects of climate change and land cover on GDEs (van Engelenburg et al., 2018, Dwire et al., 2018, Xu and Su, 2019). The results of this study are robust since they converge and support each other. The principle of converging evidence postulates that when the results converge, then the conclusions of these results are robust (Kuo et al., 2019). However, data on the groundwater level in the Khakea–Bray TBA were not available and future studies should include this

variable, when identifying the drivers of change in vegetation diversity. Regardless of these setbacks, our results have merit, and future studies could focus on the effects of climate change and variability, as well as land use, on the vegetation diversity in GDEs.

4.6. Conclusions

GDEs are sensitive environments and protect keystone species and regionally restricted species. Land-use, climate variability and change are expected to intensify the aridity of southern Africa, which will most likely affect the GDEs in these countries, since they are already at risk from other compounding factors, such as groundwater draw-down and unsustainable groundwater abstraction. There is a dearth of literature on the ecological or economic significance of the Khakea–Bray TBA, although its GDEs are under threat from climate change and unsustainable groundwater extraction and despite their relevance for sustaining livelihoods and biodiversity (Seward and van Dyk, 2018, Van Dyk, 2005). Hence, this study presents the first attempt at monitoring the spatio-temporal variations of vegetation diversity, as well as the drivers of these variations, in the Khakea–Bray TBA. The results will provide resource managers and ecologists with *a priori* information on the role of land cover and climate change in influencing the changes in vegetation diversity. The methods used in this study are robust and can monitor other GDEs in similar environments.



5.0. CHAPTER 5

THE SPATIAL CHARACTERISATION OF VEGETATION DIVERSITY WITH SATELLITE REMOTE SENSING: A GENERAL SYNTHESIS



Vegetation diversity around a wet natural pan during the dry season
(Photo: Courtesy of Kudzai Mpakairi, 2021)

5.1. The mapping of GDEs in the Khakea-Bray Transboundary Aquifer

Most GDEs are neglected and are usually only monitored when they are beyond restoration (Barron et al., 2014). This neglect emanates mainly from non-existent policies or strategies to ration the use of groundwater between the socio-economic and livelihood needs (Boulton and Hancock, 2006). In addition, research on the effects of groundwater draw-down on phreatophytes remains in its infancy for most environments where GDEs exist (Boulton and Hancock, 2006, Brown et al., 2007) and where the socio-economic needs largely outweigh the ecosystem needs, which leads to the over-abstraction of groundwater. Therefore, this thesis provides a framework on how remote sensing techniques can monitor GDEs, in order to avoid the looming effects of climate change, environmental degradation and groundwater over-abstraction (Davies et al., 2013, Eamus and Froend, 2006). This work is imperative for the conservation of the Khakea-Bray TBA since it is being threatened by environmental degradation and the proliferation of invasive species.

Remote sensing remains an invaluable tool for characterising the vegetation diversity of most environments, including GDEs. The Spectral Variation Hypothesis (SVH) supports the use of remote sensing for the estimation of vegetation diversity (Rocchini et al., 2015, Rocchini et al., 2018); it postulates that spectral heterogeneity can measure environmental heterogeneity and that stable environments are more likely to have a greater heterogeneity than degraded environments (Rocchini et al., 2013). However, applying remote sensing for estimating vegetation diversity is still in its infancy and this thesis provides an approach on how remote sensing data can monitor GDEs.

5.2. Summary of findings

This thesis has sought to demonstrate the potential of remote sensing in the characterisation of vegetation diversity by using satellite sensors (Sentinel-2 and Landsat 8). As outlined in the previous chapters, characterising the vegetation diversity of transboundary environments is costly and requires the use of cost-effective, yet accurate and reliable, methods. Sentinel-2 and Landsat 8 satellite sensors were tested to determine their capabilities and efficacy, and the results showed that they are reliable and can monitor the vegetation diversity in GDEs. However, when using remote sensing data to characterise the vegetation diversity in GDEs, it is imperative to consider which metric to use for measuring the spectral variation of the

environment. This study demonstrated that the coefficient of variation is a reliable measure for spectral variability (i.e., environmental heterogeneity) when estimating vegetation diversity with the Rao's Q. The Rao's Q measured from the coefficient of variation was highly associated with field-measured vegetation diversity ($R^2 = 0.61$ and $p \leq 0.0003$). The other measures of spectral variation that were used to calculate the Rao's Q were found to have minimal association with the field-measured vegetation diversity. This emphasises the importance of using the correct measure of spectral variation when estimating vegetation diversity with the Rao's Q. In addition, although other algorithms, besides the Rao's Q, are available for estimating vegetation diversity (e.g., Shannon-Weiner Index), the Rao's Q remains a reliable metric, as shown by the results observed in this study.

Besides characterising the vegetation diversity of GDEs, it is also important to understand the drivers behind the spatio-temporal dynamics of the vegetation diversity. In the Khakea-Bray TBA, the spatio-temporal variations of vegetation diversity follow the seasonal rainfall patterns, with high vegetation diversity during the wet season and low vegetation diversity during the dry season. The spatio-temporal changes of vegetation diversity in the Khakea-Bray are driven mainly by seasonal land conversion. Understanding the factors responsible for the spatio-temporal dynamics of vegetation diversity will improve the management of GDEs in the light of climate change and land cover changes, which are imminent in most African landscapes; as a result, sensitive environments, such as GDEs, need to be constantly monitored and their response to the vegetation diversity needs to be understood.

It is possible to use satellite remote sensing to monitor transboundary GDEs. In most environments where GDEs exist, the funding is channelled mainly towards socio-economic issues and not environmental management, because of the associated costs, which are usually exorbitant. Satellite remote sensing provides resource managers with a cost-effective method for monitoring GDEs by solely understanding their vegetation diversity. The main advantage of using vegetation diversity for monitoring GDEs is that it can be easily derived from remote sensing data, and it can also be a proxy for monitoring the stability, structure and functioning of an ecosystem. Understanding the vegetation diversity of GDEs can help us to identify potential areas that need to be prioritised for conservation, or to identify the main factors responsible for the spatio-temporal dynamics of vegetation diversity. In this way, the ecosystem services provided by GDEs can be maintained for the livelihoods of those who rely on these environments.

The present environmental stressors on GDEs can lead to their degradation if priority conservation areas with keystone species are not identified and if essential environmental drivers of vegetation diversity are not realised. The framework in this thesis allows routine monitoring of GDEs even in areas where *a priori* information on ecosystem stability is not available. Even in the absence of funding, our framework could monitor GDEs for resource constrained managers.

5.3. Conclusions

The over-arching aim of this thesis was to test the use of remote sensing in the characterisation of the vegetation diversity in GDEs in arid environments. The findings of this thesis highlight the capabilities and use of satellite sensors within the Khakea-Bray TBA. Based on the objectives of this thesis originally set out, the following conclusions can be made:

- the SVH, along with remote sensing data, are useful for explaining the vegetation diversity in GDEs;
- when measuring the spectral heterogeneity, the coefficient of variation outperforms other measures, including the recently introduced NDPI;
- vegetation diversity is more common around natural water pans, along rivers, fence-lines, and roads, as well as cropland areas, and spatio-temporal changes in the vegetation diversity are also more common in these areas; and
- land cover, precipitation, the mean temperature, and the wet day frequency are pivotal for driving the changes in vegetation diversity within GDEs.

Overall, these results provide a framework for how GDEs can be characterised, since these areas are considered biodiversity hotspots, with several keystone species that support the existence of regionally restricted species.

5.4. Recommendations

This thesis shows how remote sensing can characterise the vegetation diversity of GDEs. The results of this research study also present a framework for identifying the drivers of spatio-temporal changes in the vegetation diversity, by using satellite sensors. These recommendations are made for the monitoring of species diversity in future studies by using satellite remote sensing:

- vegetation diversity can be used as a valuable tool for monitoring the health and stability of ecosystems in GDEs;
- next-generation multispectral and hyperspectral sensors (e.g., Landsat 9, EnMap and HypsIRI) have the potential to improve the estimation of vegetation diversity in GDEs;
- future studies should test the potential integration of multi-source remote sensing datasets for characterising vegetation diversity in GDEs; and
- future studies should also test the effects of land cover conversion and climate change on the inter-annual dynamics of vegetation diversity in GDEs.



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7.0. Supplementary Material

Supplementary Table 1 Species Inventory of all the species that were observed when sampling the field plots

Species name	Species abundance
<i>Aloe maculata</i>	5
<i>Asparagus spp</i>	87
<i>Dracaena trifasciata</i>	21
<i>Ehretia rigida</i>	8
<i>Eragostis spp</i>	2477
<i>Grewia flava</i>	18
<i>Kalanchoe spp</i>	15
<i>Ledebouria marginata</i>	4
<i>Leonotis ocymifolia</i>	161
<i>Leucas martinicensis</i>	1
<i>Lipia javani</i>	1
<i>Meitinas Polyacantha</i>	6
<i>Olea spp</i>	11
<i>Opuntia ficas indica</i>	16
<i>Scorzonera humilis L</i>	647
<i>Senegalia nigrescens</i>	566
<i>Trifolium repens</i>	700
<i>Ziziphus moconata</i>	1

