Multispectral remote sensing of vegetation responses to groundwater variability in the Greater Floristic Region of the Western Cape, South Africa

UNIVERSITY of the WESTERN CAPE

CHANTEL NTHABISENG CHILOANE (3603088)

A thesis submitted in fulfilment of the requirements for the degree of Environmental and Water Science Magister Scientiae in the Department of Earth Sciences (Natural Sciences), University of the Western Cape.

Supervisors: Prof. T. Dube (University of the Western Cape)

Dr. C. Shoko (University of the Witwatersrand)

February 2022

ABSTRACT

Groundwater dependent vegetation (GDV) communities are increasingly threatened by the transformation of the natural environment to different land use/land cover, over-exploitation of groundwater resources and the proliferation of invasive species within the Cape Floristic Region (CFR). These changes affect the groundwater regime, level, and quality, which supports GDV. Natural resource managers often lack an understanding at appropriate scales of the nature of dependency of GDV to make informed sustainable decisions. This work thus assesses the spatial distribution of GDV and their responses to groundwater variability within the Cape floristic region from June 2017 to July 2018. To achieve this aim, firstly a literature review on the background of GDV, threats and the impact of climate change was assessed. Further, the literature elaborated on progress of geospatial technology for GDV detection and monitoring, associated challenges, and possible future research directions. The review has indicated that scientific research on GDV has gained considerable attention. Of significant importance is an increase in studies integrating field measurements and model-based techniques with remotely sensed estimates. Despite the progress in GDV scientific research, further remote sensing studies are required to understand the annual and inter-annual vegetation response to groundwater variability at local scales. Moreover, new generation remote sensing products integrated with machine learning techniques have the potential to improve GDV assessments. The review has also revealed that vegetation response to groundwater variability is dependent on the type of vegetation at certain thresholds. Secondly, the performance of the two multispectral data from Landsat 8 OLI (L8) and Sentinel 2A (S2) were investigated. Further, the influence of derived spectral indices in mapping the potential distribution of GDV in the catchment was also assessed. The GDV distribution maps were produced by integrating vegetation productivity, landcover, slope and surface curvature layers as GDV potential indicators. Landcover, slope, and surface curvature layers were kept constant while the vegetation productivity layers were derived from the normalised difference vegetation index (NDVI) and the soil-adjusted vegetation index (SAVI). The findings of the study revealed that the GDV classification had no significant difference based on the McNemar's test. Specifically, the S2-derived SAVI mapped GDV areas with the highest overall accuracy (97%), followed by the L8-derived SAVI with 96%. The L8(NDVI) derived GDV map has an accuracy of 92%. Overall, the area has a 2.34-2.60% coverage of potential GDV. It was further observed that the north western parts of the catchment had a high potential for GDV when compared to other areas. This work demonstrated the capabilities of a combined remote sensing and GIS methodology to improve knowledge on GDV and their management. Lastly, groundwater and vegetation interaction during a drought period (June 2017 to July 2018) was investigated for riparian and hillslope environments using moderate resolution remote sensing data. The NDVI derived from Moderate Resolution Imaging Spectroradiometer (MODIS) was used as a vegetation proxy to assess vegetation dynamics. In addition, the relationship between vegetation productivity, rainfall, and temperature was analysed using regression techniques. The time series analysis and linear regression indicated that groundwater depth is strongly associated with 1-month lagged R (0.54 - 0.71) compared to the non-lagged R (0.45 - 0.62). Hillslope vegetation was observed to be more sensitive to groundwater than riparian vegetation. This was evidenced by the larger gain/loss range in NDVI with variations in groundwater levels. However, these responses varied significantly between the sites under study. The study demonstrated that groundwater depth variability is a function of seasonal changes, which induces a response to vegetation productivity. Rainfall and groundwater depth had minimal impacts on vegetation productivity, except for riparian vegetation that demonstrated a strong association with rainfall. The findings of this study underscore the relevance of remote sensing datasets and statistical analysis methods in understanding prevalent groundwater-vegetation interactions in semi-arid environments.

Keywords: Arid environments; fynbos ecosystem; invasive species; satellite data; vegetation health; water scarcity

PREFACE

This research study was conducted in the Department of Earth Sciences, Faculty of Natural Sciences, University of the Western Cape in South Africa from February 2020 to November 2021 under the supervision of Professor Timothy Dube and Professor C Shoko.

Full name: Chantel Nthabiseng Chiloane Signature: ……………… Date: 10 February 2022

As the candidate's supervisor, I certify the above-mentioned statement and have approved this thesis for submission.

Full name: Prof. Timothy Dube Signature: …………………………... Date: 10 February 2022

Full name: Dr C Shoko Signature: ……………………………………. Date: 10 February 2022

DECLARATION

I declare that the thesis entitled "Multispectral remote sensing of vegetation responses to groundwater variability in the Greater Floristic Region of the Western Cape, South Africa" is my own work that it has not been submitted before for any degree or examination in any other university. All the sources I have used or quoted have been indicated and acknowledged by means of complete references.

Full name: Chantel Nthabiseng Chiloane **Signature**: Date: 10 February 2022

Publications and Manuscripts

The following manuscripts have been submitted and are still under review in international peer reviewed journals. The manuscripts have also been presented in two conferences. The co-authors played a major role in reviewing and improving the manuscript. I was the main author.

Chiloane, C., Dube, T. and Shoko, C., 2021. Impacts of groundwater and climate variability on terrestrial groundwater dependent ecosystems: a review of geospatial assessment approaches and challenges and possible future research directions. *Geocarto International*, pp.1-25.

Chiloane, C., Dube, T. and Shoko, C. Multispectral remote sensing of potential groundwater dependent vegetation in the Greater Floristic Region of the Western Cape, South Africa. South African Geographical Journal (Manuscript ID RSAG-2021-0063)-under revision.

Chiloane, C., Dube, T. and Shoko, C. Multispectral remote sensing of vegetation responses to groundwater variability in the Greater Floristic region of the Western Cape, South Africa. Journal of Water SA (Manuscript ID WSA-3962)-under revision

The research was presented at the following online conferences:

1. The Geo-Information Society of South Africa WC AGM on the 6th of October 2021, South Africa
2. The South African National Space Agency 3rd Biannual student workshop on the 22nd of October 2021, South Africa.

Acknowledgements

I would like to thank my supervisor Prof T Dube for the guidance, encouragement, and advice provided during this time as your student. I am grateful for believing in me and your support.

I also extend my gratitude to my co-supervisor, Dr C Shoko from the University of Witwatersrand, thank you for the constructive critique on my work that has sharpened my writing.

To Eugene Maswanganye, thank you for the groundwater data that help in my analysis and, assisting with the data collection trips. I also appreciate the discussions on my work that helped me gain clarity and assisted in interpreting my results, to this I also extend my gratitude to miss Yonela Mkunyana.

To my fellow colleagues at the Department of Earth Sciences, especially Munash Mashabata, Refiloe Maphiri and Siyamthanda Gxokwe, I would like to extend my appreciation. You have all contributed to the progress of my project and for that I am truly grateful.

To my family and friends, Koekie Mashego, Lesego Chiloane, Idah Mphaphuli and Nelly Mtsweni, thank for your unconditional support, vent sessions and love that kept me going throughout the Masters period.

Finally, I extend my gratitude to the South African National Space agency (SANSA), for the full financial and academic growth support. I recognise that this project would not have been conducted without their financial support.

Dedication

To My mother Koekie T Mashego

To my sister Lesego T Chiloane

TABLE OF CONTENTS

ABSTRACT i
PREFACE iii
DECLARATION iv
Publications and Manuscripts v
Acknowledgements vi
Dedication vii
TABLE OF CONTENTS viii
LIST OF TABLES xi
List of figures xii
CHAPTER ONE 1
1.1 Introduction 1
1.2 Problem Statement 3
1.3 Main Aim 4
1.4 Thesis Outline 4
CHAPTER TWO 6
Impacts of Groundwater and Climate Variability on Groundwater Dependent Vegetation: A Review of Geospatial Assessment Approaches, Challenges and Possible Future Research Directions 6
2.1 Introduction 7
2.2 Literature Search on Groundwater Dependent Ecosystems 10
2.3 Background on Groundwater Dependent Ecosystems 11
2.4 Threats to GDV 12
2.5 GDV Response to Groundwater Variability 13
2.6 Climate impact on groundwater and dependent ecosystems 17
2.7 Geospatial Approaches for Identifying and Assessing GDV. 21
2.7.1 Field based methods for identifying GDEs 21
2.7.2 modelling approach for identifying GDV 21
2.7.3 Geospatial approach for identifying and assessing GDV 22
2.8 Available GDE Classification Algorithms 29

2.9 Challenges in Remote Sensing of GDEs 30
2.10 Possible Future Direction in Remote Sensing and GIS Applications for GDEs. 32
2.11 Conclusions 33
CHAPTER THREE 35
Assessing the potential for using multispectral, remotely sensed data to identify groundwater dependent vegetation in the Greater Floristic Region of the Western Cape, South Africa 35
Abstract 35
Keywords: Arid environments; catchment management; fynbos; moderate resolution; invasive plants; groundwater; satellite data; water resources management 36
3.1 Introduction 36
3.2 Research Methodology 40
3.2.1 Study area description 40
3.2.2 Data acquisition 42
3.2.3 Data processing and classification 43
3.1 Results 46
3.1.1 Potential GDV model classification assessment 46
3.1.2 Vegetation species as an indicator of GDV occurrence 47
3.1.3 Indicator variables for potential GDV mapping and the resultant GDV indices 48
3.2 Discussion 51
3.2 Conclusion 53
CHAPTER FOUR 54
Multispectral remote sensing of vegetation responses to groundwater variability in the Greater Floristic Region of the Western Cape, South Africa 54
4.1 Introduction 55
4.2 Research Methodology 57
4.2.1 Study site 57
4.2.2 Data acquisition 59
4.2.3 Data analysis 60
4.3 Results 61
4.3.1 NDVI and groundwater depth trend during the study period 61
4.3.2 Quantitative relation between groundwater and NDVI 66

4.3.3 Mean temperatures and monthly mean rainfall for the study period 67
4.4 Discussion 70
4.4.1 Relational trends between the groundwater depth and the NDVI 70
4.4.2 Relational trends between NDVI, groundwater depth, rainfall, and temperature 71
4.5 Limitations and recommendations 72
4.6 Conclusion 73
CHAPTER FIVE 74
Multispectral remote sensing of vegetation responses to groundwater variability in the Greater Floristic Region of the Western Cape, South Africa: Synthesis 74
5.1 Summary of the Study Findings 74
5.2 Conclusions 76
5.3 Recommendations 77
References 78

LIST OF TABLES

Table 2. 1 Summary of GDE Classification according to Eamus et al., (2006) 12
Table 2. 2 Summary of recent studies on vegetation response to groundwater variability 16
Table 2. 3 Impacts of climate change on groundwater and associated ecosystems 19
Table 2. 4 Summary of key research that utilises geospatial techniques to identify potential GDV 27
Table 3. 1 Accuracy assessment results for the binary classification of potential GDV for the Heuningnes Catchment 45
Table 4. 1 Location of sampling points and borehole depth 59
Table 4. 2 Summary of the Bayesian correlation for the groundwater depth and NDVI 67
Table 4. 3 Multiple Regression model summary 69
Table 4. 4 The correlation and level of significance of the relationship of the NDVI with rainfall, groundwater depth and temperature 69

List of figures

Figure 2. 1 Number of publications on GDEs, GDV and remote sensing of GDEs from 2000-2021……………………………………………………………………….........11
Figure 2. 2 The relationship between NDVI of a) grass land b) forest land c) shrub forest and groundwater depth based on Tsellis Theory in Ejina oasis in Hei (Source: Zhang et al., 2020)……………………………………………………………………………..15
Figure 3. 1 The Heuningnes Catchment study area and its geology in the Western Cape region of South Africa………………………………………………………………….40
Figure 3. 2 Flow chart summarizing the critical analysis steps for mapping the potential distribution of GDV………………………………………………………………44
Figure 3. 3 Allocation of agreement, commission, and omission errors for the four potential GDV maps……………………………………………………………………...46
Figure 3. 4 The binary classification of indicator variables used in producing the four potential GDV indices; Class 1 indicates the areas with GDV suitability, with Class 0 indicating the unsuitable areas 48
Figure 3. 5 Distribution of potential GDV within the Heuningnes Catchment derived from the GDV indices: a) S2(SAVI), b) L8(SAVI), c) S2(NDVI) and d) L8(NDVI) 49
Figure 4. 1 Location of the G50B quaternary catchment and study sites within the Heuningnes Catchment………………………………………………………………………59
Figure 4. 2 a) Monthly time series of groundwater depth and vegetation greenness for the study period for vegetation around Bh7; and b) Groundwater depth and NDVI deviation from their annual average for vegetation around Bh7. The 0-line is the mean NDVI and groundwater depth throughout the study period 61
Figure 4. 3 a) Monthly time series of groundwater depth and vegetation greenness for the study period for vegetation around Bh8; and b) Groundwater depth and NDVI deviation from their annual average for vegetation around Bh8. The 0-line is the mean NDVI and groundwater depth throughout the study period 62
Figure 4. 4 a) Monthly time series of groundwater depth and vegetation greenness for the study period for vegetation around Bh10; and b) Groundwater depth and NDVI deviation from their annual average for vegetation around Bh10. The 0-line is the mean NDVI and groundwater depth throughout the study period 63
Figure 4. 5 a) Monthly time series of groundwater depth and vegetation greenness for the study period for vegetation around Bh12; and b) Groundwater depth and NDVI deviation from their annual average for vegetation around Bh12. The 0-line is the mean NDVI and groundwater depth throughout the study period 64
Figure 4. 6 a) Monthly time series of groundwater depth and vegetation greenness for the study period for vegetation around Bh14; and b) Groundwater depth and NDVI deviation

from their annual average for vegetation around Bh14. The 0-line is the mean NDVI and groundwater depth throughout the study period 65
Figure 4. 7 Mean daily temperature for the study period.. 66
Figure 4. 8 Mean monthly rainfall for the four study sites within the G60B catchment……....67

CHAPTER ONE

1.1 Introduction

Terrestrial vegetation is a major component of terrestrial ecosystems and plays a vital role in energy flow, global carbon, and water cycles (Zhao et al., 2018). Not only do natural terrestrial ecosystems contribute to the economy through ecotourism; they are also the genetic hub for bioprospecting and the preservation of biodiversity (Williams, 2018). Vegetation provides valuable ecosystem services such as flood control, water purification, pollinator habitats and recreational opportunities. In arid regions, vegetation is a major producer of organic material contributing biological components to the soil (Lv et al., 2013). Vegetation buffers desertification process and maintains natural environmental conditions (Lv et. al., 2013; Wang et al., 2011). With the many benefits gained from terrestrial vegetation, it is imperative that these are protected and safeguarded.

Factors such as precipitation, temperature, and groundwater affect vegetation distribution and vigour. In arid and semi-arid environments, potential evaporation exceeds annual precipitation. Two-thirds of the sub-Saharan African landscape comprises arid and semi-arid land that experiences less than 500mm/yr of precipitation and of that amount; only 2% replenishes groundwater resources (Wada et al., 2010; Xu and Beekman, 2003). Terrestrial vegetation has limited access to surface water. Therefore, groundwater is an important resource affecting soil moisture availability, which affects vegetation structure and distribution (Liu et al., 2017). Some terrestrial vegetation in semi-arid regions is maintained by direct and indirect access to groundwater and is collectively called Groundwater Dependent Vegetation (GDV) (Zhang et al., 2019). Global environmental change, infrastructural developments and the overexploitation of water resources threaten the ecological integrity of GDV (McDowell and Moll, 1992; Rouget et al., 2003). For instance, global change has widespread effects on the Earth's terrestrial ecosystems such as habitat loss and fragmentation, biological invasions, pollution, and climate change, which are rapidly eroding biodiversity and threaten ecosystem functioning and services (Foley et al. 2005; Maxwell et al. 2016). This compromises the sustained provision of ecosystem goods and services (Rouget et al., 2003; Shadwel and Febraury, 2017). Monitoring vegetation condition and its response to environmental and global changes overtime creates an understanding of change processes and potential areas affected and at risk (Franklin et al. 2016). Information on vegetation-groundwater interactions will guide in policy making, setting restrictions and strategic planning for groundwater use within the region. Such information is also critical for supporting agendas on sustainable future development, e.g., the United Nations' (UN) Sustainable Development Goal 15 on 'Life on Land' (United Nations, 2018). Vegetation condition and its response to global change, is specified in the lists of Essential Climate Variables (Bojinski et al. 2014) and Essential Biodiversity Variables (Pereira et al. 2013).

The trade-off that exists between the efficiency, level of detail, costs offered by the monitoring techniques limits groundwater-vegetation interaction monitoring (Hoyos et al., 2016). Only water chemistry indicators can give conclusive evidence to groundwater and vegetation interactions and may help identify where plants use groundwater and the amount of water used. Other indicators are indirect and include Eddy correlation, Bowen ratio, climatic indices, sap flow measurements, plant phenology, ground-based leaf area index etc. to assess the influence of groundwater variability on vegetation (Colvin et al, 2003; Eamus et al., 2015; Hoyos et al., 2016). While these methods provide highly detailed information, the low spatial and temporal scale limits their applicability at broad scales. These methods are also costly and labour intensive.

Remote sensing has emerged as an efficient monitoring tool that can provide crucial vegetation information about its status and even response to change or changing disturbance regimes at community or landscape scale (Griffiths et al., 2018; Wessels et al., 2007; Zhu et al. 2019). The potential for remote sensing in monitoring vegetation-groundwater interaction must be determined (Münch and Conrad, 2007; Rohde et al., 2017). There is a lack of knowledge on the applicability of satellite and spectral data in determining groundwater-vegetation interactions, especially at species and community levels. Therefore, Sentinel 2, with a 5-day revisit period and 10m pixel size, is likely to provide new opportunities for vegetation mapping–a previously challenging task with coarse resolution satellite products. Unlike its predecessors, i.e., Landsat series, MODIS, AVHRR data, Sentinel 2 data provides new information in other applications which include vegetation mapping (Grabska et al, 2019; Da Silveira et al., 2018), biomass estimation (Sibanda et al., 2015) and water quality monitoring (Du Y, et al., 2016). It is on this premise that this study utilises sensors with improved sensing characteristics to identify and assess GDV and the response to groundwater dynamics. This study proposes a remote sensing methodological framework to understand vegetation responses to groundwater variability under extreme climate conditions.

1.2 Problem Statement

Climate variability and its associated changes in rainfall distribution and amount pose a threat to groundwater resources and related groundwater dependent vegetation (Eamus et al., 2015a). There is adequate understanding of vegetation responses under normal seasonal variations in groundwater, and the effects of a declining water table because of over abstraction. However, there is a gap in understanding vegetation response under extreme climate conditions, such as droughts. The lack of knowledge is because of the hydrological complexities of groundwater-vegetation interactions intensified by the heterogeneity, anisotropy, difficulty in setting parameters and scale issues (Naumburg et al., 2005; Eamus et al., 2015). There is thus a need to establish robust methodologies that can aid in monitoring groundwater dependent vegetation and its response to variations in groundwater under a drought period. The information gained will facilitate the adaptive management of groundwater and help conserve the endemic fauna. The following research questions need to be addressed.

1. To what degree can remote sensing be used to delineate groundwater dependent vegetation in the Cape floristic region?

2. How does terrestrial vegetation productivity respond to groundwater fluctuations?

3. What is the strength of vegetation dependence on groundwater?

4. Do vegetation responses to groundwater variability vary between riparian and hillslope environments?

1.3 Main Aim

The aim of this study is to assess the distribution of groundwater dependent vegetation and their responses to groundwater variability within the Cape floristic region in the Western Cape, South Africa.

Specific objectives:

i. To determine the spatial distribution of groundwater dependent vegetation within the Heuningnes catchment.
ii. To characterize dominant vegetation species within this catchment.
iii. To assess riparian and hillslope vegetation responses to groundwater variability over time and space.
iv. To assess the influence of climate factors on riparian and hillslope vegetation productivity.

1.4 Thesis Outline

General outline of the thesis

This dissertation comprises five chapters, with three standalone papers that are based on the literature review and two analysis papers from the objectives. Some of these have been presented as published in the international journals, and some have a few minor adjustments suitable to fit the dissertation format. However, repetition or overlaps may be present because of the consistency of each manuscript with the overall aim of this study.

Chapter 1: Introduction

This chapter provides the overview and background of this study. The driving research questions, principal aim and objectives of this study are presented.

Chapter 2: Literature Review

This chapter aims to provide a detailed overview of the progress in remote sensing of terrestrial groundwater dependent vegetation (GDV). The chapter provides a background on GDV and threats, and then further explores recent knowledge on vegetation response to groundwater variability and climate change impacts on GDV. This review also focuses on recent progress in remote sensing (RS) and geographic information systems (GIS) based techniques for mapping and monitoring of GDV and explores the available satellite products and classification techniques. Finally, the challenges of remote sensing and future research direction are explored.

Chapter 3: Objective one and two

This chapter aimed to assess and map the potential distribution of GDV within the Heuningnes Catchment using multispectral remotely sensed (i.e., Landsat 8: L8 and Sentinel 2: S2) and in situ data. The study also compared the performance of the two multispectral data and the influence of derived spectral indices in mapping the distribution of GDV in the catchment.

Chapter 4: Objective three and four

This chapter aimed to assess groundwater and vegetation interaction during a drought period between June 2017 to July 2018 for riparian and hillslope environments using multispectral remote sensing data. In addition, the relationship between the vegetation productivity, rainfall and temperature was analysed. Specifically, the vegetation and groundwater depth correlation were investigated for immediate and lagged interactions.

Chapter 5: Synthesis

This chapter summarises the main findings, conclusions, and recommendations drawn from the study.

CHAPTER TWO

Impacts of Groundwater and Climate Variability on Groundwater Dependent Vegetation: A Review of Geospatial Assessment Approaches, Challenges and Possible Future Research Directions

Abstract

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

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

Keywords: Arid environments; Cloud computing; Groundwater resources; Satellite data; Vegetation responses

2.1 Introduction

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

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

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

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

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

2.2 Literature Search on Groundwater Dependent Ecosystems

Relevant literature was acquired from several search engines such as google scholar, SCOPUS, and the Web of Science Core Collection (WoSCC). Numerous expressions or topic search key words were used, and these included: “groundwater”, “groundwater dependent ecosystems”, “remote sensing”, “climate and groundwater”, “semi-arid and arid”, “phreatophytes” and “terrestrial vegetation” were used to source literature from international peer-reviewed journals. These words were selected to retrieve information that provides the background on the interaction of groundwater and the dependent vegetation and highlight the progress in the use of remote sensing approaches. The literature search range was from 2000-2021 with a total of 200 articles from international peer reviewed journals, thesis and reports. An additional source for literature was obtained through a rigorous assessment of references cited by the read papers. Due to the paucity of studies of remote sensing applications the review was not limited to a specific criterion. Consequently, studies that used remote sensing data for the assessment and monitoring of GDV were considered. The literature search revealed that most publications largely focused on GDEs in general, 52% of those were on groundwater dependent vegetation with only 0.06% GDE incorporating remote sensing approaches. An increase in the number of publications on groundwater dependent ecosystems and GDV was noted (Figure 2.1).

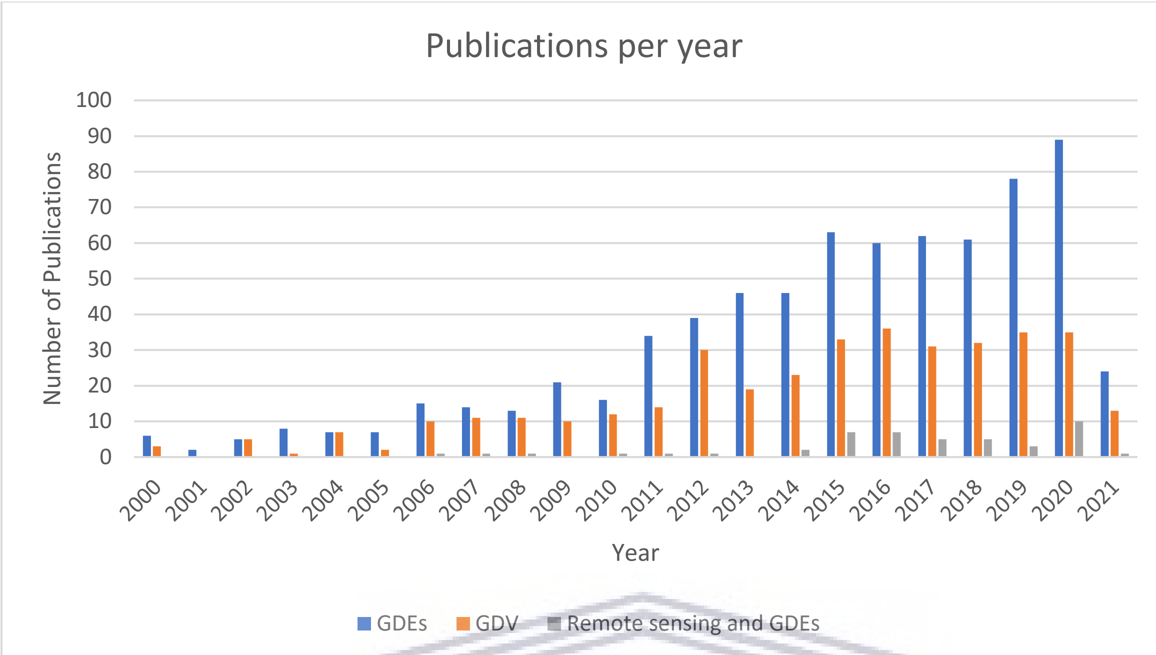


Figure 2. 1 Number of publications on GDEs, GDV and remote sensing of GDEs from 2000-2021

2.3 Background on Groundwater Dependent Ecosystems

GDEs are communities of plants, animals and microorganisms that continuously or to some extent rely on the available groundwater to maintain their structure and functioning (Colvin et al., 2003; Kløve et al., 2011). GDEs may be maintained by direct or indirect access to groundwater and rely on the flow regime and chemical characteristics of groundwater (Hatton and Evans, 1998). In this regard, when groundwater is limited, the functioning and structure of these ecosystems will be significantly altered. Various classification systems have been introduced based on the geographic setting in which they exist and the type of aquifer-ecosystem interface (Hatton and Evans 2003; Sinclair 2001; Colvin et al., 2007). A classification system with three basic classes based on the type of groundwater reliance was introduced by Eamus et al., (2006). The ecosystem classification method makes distinguishing and identifying groundwater dependence much easier and improves ecological risk assessments. This review focuses on the terrestrial vegetation class and moreover the third class according to Eamus et al., (2006) which is a classification system (Table 2.1).

Table 2. 1 Summary of GDE Classification according to Eamus et al., (2006)

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

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

2.4 Threats to GDV

Groundwater and associated ecosystems are increasingly threatened by global environmental change. These are planetary-scale changes in the Earths' systems (land, oceans, atmosphere, the planet's natural cycles and deep earth processes), which encompass changes in population, climate, resource use, land use and land cover (Noone et al., 2011). An ever-growing population, agricultural and economic development coupled with a changing climate have heightened the pressure on water resources. Climate change has decreased the reliability of surface water resources. As a result greater consideration has been given to groundwater as a resilient freshwater resource that can augment surface water resources (MacKay, 2006; Kundzewicz and Döll, 2009). Subsequently, groundwater exploitation has drastically increased with 33% of the global available freshwater supply obtained from groundwater (Vaux, 2011; Richey et al., 2015). Moreover, global groundwater levels and volume have been reported to be on the decline (Richey et al., 2015).

Modification of groundwater levels and the deviation of flow patterns from the natural groundwater regime due to anthropogenic influence and climate change have detrimental impacts on the structure and functioning of groundwater dependent vegetation communities (Kløve et al., 2014; Loomes et al., 2013). Therefore, there is a need to develop management plans and policies, which promote the sustainable use of groundwater resources. Thereby mitigating negative environmental impacts such as storage depletion, saltwater intrusion, wetland and riparian habitat loss, land subsidence and reductions in stream flow. The influence of elevated groundwater demand is exacerbated by a rapidly changing climate (IPCC, 2014). Long term variability in precipitation, temperature and wind threatens the health and abundance of GDV which is influenced by the spatial and temporal availability of groundwater (Chambers et al., 2013). Global average surface temperatures have been estimated to increase by 0.84 degrees Celsius from 1880-2012. This rise has been associated with negative impacts on groundwater quantity and quality. Under all climate scenarios, global surface temperatures are expected to rise. Further, drought and flood events are predicted to increase in the 21st century (IPCC, 2014). Reduced precipitation and elevated temperatures are detrimental on groundwater levels because of limited groundwater recharge and increased plant water demand (Noone et al., 2011; Kløve et al., 2014). There is a large body of literature on anthropogenic impacts on GDV (Muñoz-Reinoso, 2001; Krause et al., 2007; Huang et al., 2020). However, there is little scientific research focus on the impacts of climate variability especially on terrestrial vegetation (Barron et al., 2012; Kløve et al., 2011; Taylor and Tindimugaya, 2011). Groundwater and associated ecosystems are particularly vulnerable to climate impacts as the resource is unseen and there exists a time lag before the response is noticed (Morsy et al., 2017). In some instances, inappropriate management policies and strategies have also been linked to the degradation of GDV (Morsy et al., 2017). Therefore, a comprehensive synthesis of knowledge on the interactions and response mechanisms for groundwater and dependent vegetation will ensure the formation of adaptive and holistic management plans.

2.5 GDV Response to Groundwater Variability

Groundwater availability affects the spatial distribution and abundance of terrestrial vegetation (Orellana et al., 2012). Numerous studies have been conducted to establish the relationship between groundwater and vegetation (Eamus et al., 2006; Rodriguez-Iturbe and Porporato, 2005;

Le Maitre et al., 1999). Vegetation response to fluctuating groundwater levels varies from non-observable changes to alterations of the entire community structure based on their physical and biological properties (Naumburg et al., 2005). Several studies were conducted to characterize phreatophytes according to their relations to groundwater depth (Robinson, 1958; Loheide et al., 2005). They reported that a decreasing water table could result in severe plant water stress when the rate of plant root development is insufficient or when the soil has low water holding capacity. Therefore, a declining water table limits the amount of water available for vegetation resulting in plant water stress and decreased plant productivity (Loheide et al., 2005; Naumburg et al., 2005). Further , Han and He, (2020) reported a decrease in leaf intensity with a receding water table. Alternatively, a rising water table can flood plant roots resulting in anoxic stress (Naumburg et al., 2005). In another study, Meinzer, (1929) reviewed GDV species and characterized them according to their rooting depth. Results revealed that rooting density decreased with an increase in depth to groundwater, the physiological characteristics of GDV included dimorphic roots, which allow them to exploit deep groundwater sources. It was also determined by Laio et al., (2009) that a decline in groundwater level may cause an increase in the plants rooting zone and an increased aerated soil profile suitable for new root development. Additionally, Zhang et al., (2020) modelled the spectral vegetation response to depth to groundwater table using the Tsallis Entropy Theory. It was reported that vegetation response was not uniform, different thresholds exist for grassland, shrubland, and forest vegetation. They found that at depths (>1m) normalised vegetation index (NDVI) decreased with increasing depth, the alternative was also true, whereby NDVI declined with the rising water table at depths (< 1m) (Figure 2.2). Therefore, deeper water tables increase soil volume available for the storage of precipitation and hydraulically lifted water that can drastically increase the water available for plant use and growth. Also, in arid environments evapotranspiration can result in salt accumulation in soils, elevated groundwater levels limit the rooting zone to saline soils resulting in plant stress from the access saline water (Zhang et al., 2020).

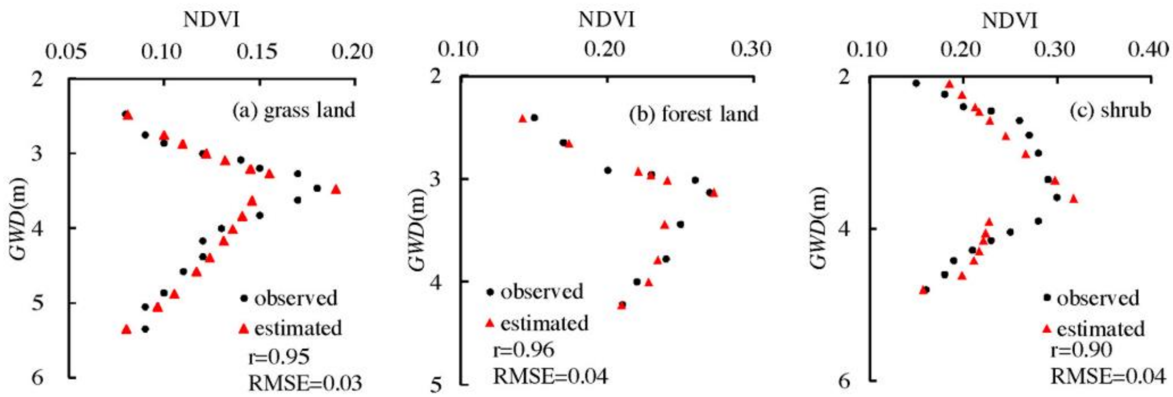


Figure 2. 2 The relationship between NDVI of a) grass land b) forest land c) shrub forest and groundwater depth (GWD) based on Tsellis Theory in Ejina oasis in Hei (Source: Zhang et al., 2020)

A declining groundwater table has negative effects on plant physiology (Kath et al., 2014). During transpiration, water from the soil is pulled into the plant roots, then transported through the xylem to exit through the leaf surface. A deficit in soil moisture increases the potential pressure in the xylem to the extent where xylem cavitation occurs. When this threshold is reached, the amount of water transported to plant leaves is decreased which causes stomatal closure, a reduction in photosynthetic activity and then branch and crown mortality (Le Maitre et al., 1999; Kath et al., 2014). For instance, Huang et al., (2016) reported the decrease in the ratio of actual evapotranspiration, potential evapotranspiration and a declining groundwater table. Different plant species have different xylem cavitation resistances (Kath et al., 2014; Naumburg et al., 2005). It is reported that riparian vegetation cannot tolerate limited water supply and therefore are vulnerable to xylem cavitation as well as crown and branch mortality (Kath et al., 2014; Hancock et al., 2009; Johansen et al., 2018). On the other hand, xeric phreatophytes are drought tolerant vegetation species and can survive significant water table declines, despite losing some branches and leaf area. In a different study, Muñoz-Reinoso, (2001) examined vegetation changes in Spain and the processes causing those changes. Results revealed species composition change into xerophytic communities due to decrease in water availability.

Ecosystems dependent on groundwater show low seasonal variability in vegetation health and transpiration rates when compared to non-GDEs. The effects of groundwater extraction on coastal GDEs in New South Wales were assessed by Adams et al, (2015). Their findings indicated that long-term changes in evapotranspiration from groundwater dependent vegetation occur seasonally. Evapotranspiration rates had low variability than that of vegetation dependent on surface water. Further, tree ring analysis have demonstrated that groundwater availability is an important factor on plant growth rates (Xia et al., 2012; Gholami et al., 2015). Hydraulic lift of moisture from deeper soil horizons provides water for shallow rooted herbaceous vegetation during water stress conditions. Increasing groundwater depth has been associated with reduced plant growth rate. In addition, increased growth rates are associated with deeper water tables (Osmond et al., 1987; Sarris et al., 2007). Vegetation response to groundwater variability differs with the plants anoxic and water stress tolerance, water uptake capacity and the change in the distribution and size of the active rooting zone (Naumburg et al., 2005). The variable plant responses to groundwater variability mean that studies on GDV should not take a generalized approach. However, valuable insights maybe attained from long-term understanding of the relationship between groundwater, GDV and climate. Understanding the relationship on how groundwater availability affects vegetation and how that translates in terms of spectral signatures, has opened a more cost-effective, efficient methodology for the long term monitoring of GDV (Barron et al., 2014). A detailed summary of recent studies that have exploited the spectral response of DGV to assess their interaction with groundwater is provided in Table 2.2.

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

Application	Results	Reference
Hydrological controls on vegetation dynamics	The annual correlation between terrestrial water storge and NDVI is greater than that of rainfall and NDVI. monthly/seasonal correlation between rainfall and NDVI is greater than that of Terrestrial water storage and NDVI.	(Ndehedehe et al., 2019) West and Central Africa
Ecohydrological response	Response to water convergence: 80-day time lag for groundwater 4-7 years for vegetation	(Liao et al., 2020) China
Groundwater and GDE response to ecological water conveyance	Decrease in Depth to water (DT)T ($p<0.05$) increase in NDVI ($p<0.05$)	(Huang et al., 2020) China
GDE veg Index using Entropy theory	At DT >1m) NDVI declines with increasing DT At DT <1m) veg growth is restricted. NDVI correlation coefficient ($p<0.01$)	(G. Zhang et al., 2020) Northern China
Estimate crop groundwater use	50% of irrigation water from groundwater. Seasonal crops more reliant on groundwater than perennial crops. Groundwater dependence increases with drying conditions.	(Hunink et al., 2015a) Spain
Effects if Groundwater extraction on Et rates,	Long term change in Et close to extraction zones Sig change Et for Facultative communities ($p<0.01$)	(Adams et al., 2015) New South Wales

Role of climate, GW availability and land management on veg vigour	Strong correlation between changes in plant vigour, precipitation, groundwater depth and evaporative demand.	(Huntington et al., 2016) United States
Veg response to groundwater drawdown	Vegetation ecophysiology negatively affected by groundwater drawdown.	(Antunes et al., 2018) Spain
Quantify groundwater contribution to *Salix psammophila* water use.	Groundwater contribution to evapotranspiration ration decreases with increasing depth to groundwater table.	(Huang et al., 2016) China
Demonstrate the role of hydraulic path in determining plant intensity.	Leafing intensity decreases with increasing groundwater table depth and plant height	(Han and He, 2020) China
Effects of groundwater table decline on vegetation transpiration.	Transpiration rates decrease with declining groundwater table, critical depth is at 3.6 and 2.0 m depths. Groundwater depth correlation with evapotranspiration is 0.98	(Wang et al., 2020) China
Relationship between riparian vegetation and groundwater depth	Peak evapotranspiration rates at groundwater depths <3m, and evapotranspiration values significantly lower at depths greater than 3m.	(Lurtz et al., 2020) United States
Assess spatio-temporal evapotranspiration patterns of TGDV	Vegetation in shallow groundwater had high actual evapotranspiration rates as compared to those on deeper groundwater table, during the growth season.	(Sommer et al., 2016)
Influence of water table depth on evapotranspiration rates of in the amazon arc of deforestation	There were no differences in Evapotranspiration (ET), Land surface Temperature (LST) and Enhanced Vegetation Index (EVI) between vegetation and deep and shallow groundwater tables. Higher ET in shallow water table cops than those from deeper water tables during the dry season transition.	(O'connor et al., 2019) Brazil
Show the extent of groundwater-vegetation interaction distribution	Positive relationships (shallow DT with high Plant productivity) for shrubs in mesic regions. Negative relationship (deep DT with high plant productivity) for forests in humid regions. Vegetation primary productivity and groundwater depth are correlated in more than two thirds of the global vegetated area.	(Koirala et al., 2017) Global

2.6 Climate impact on groundwater and dependent ecosystems

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

Climate warming can influence the availability and demand for groundwater resources thus affecting water available for sustaining ecological functions (Barron et al., 2012; Wattendorf et al., 2010). Further studies on the effects of climate on groundwater and associated vegetation are outlined in Table 2.3. Climate change impacts on general water resources have been widely investigated. Although impacts on groundwater resources have gained increasing attention over the years, there is limited information on how GDV are impacted. The seasonal distribution of precipitation and the temperature determine global climate zones and consequently the distribution of ecosystems, including GDV (Richards et al., 1975). As they are adapted to specific water regimes, many ecosystems are vulnerable to climate change. For example, the study by Barron et al., (2012) noted that reduced surface water flows and longer dry periods, place GDV at high risk with an estimated 19% decrease in current habitats in Australia. In addition, GDEs are increasingly likely to be threatened by groundwater abstraction. Extreme climate conditions change the hydrological regime, whereas the extent and seasonality of aquatic environments change the environmental conditions of GDV (Kløve et al., 2014).

Table 2. 3 Impacts of climate change on groundwater and associated ecosystems

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

Climate induced changes in groundwater- surface water interactions will directly and indirectly affect wetlands and GDV. Impacts on GDV will likely result from changes in groundwater and surface water levels and will vary in intensity depending on the location of the landscape, scale of the system and land use changes. Local and intermediate systems are overly sensitive to groundwater level dynamics and increased temperatures lead to significant changes on these systems. Regional scales systems are less impacted by extreme events, seasonal fluctuations in groundwater level, recharge and increases evapotranspiration rates. For GDV, a shift in local species composition will occur and decreased leaf density and primary productivity (Mawdsley et al., 2009 ; Naumburg et al., 2005; Shafroth et al., 2000). Additionally, Albano et al., (2020) demonstrated that long-term riparian vegetation response due to climate variability is driven by changes in groundwater and surface water dependence as compared to upland vegetation which is controlled by the aridity gradient. Other studies also indicated that riparian vegetation had greater potential for groundwater dependence and were therefore sensitive to climate induced groundwater variability (Barron et al., 2012; Barron et al., 2014; Froend and Sommer, 2010). Further, Kath et al., (2014) demonstrated that climate induced groundwater decline resulted in the deteriorated tree canopy and a shift in species composition from non- vascular to vascular plants.

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

2.7 Geospatial Approaches for Identifying and Assessing GDV.

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

2.7.1 Field based methods for identifying GDEs

Groundwater use by phreatophytes has been assessed using field techniques: isotope analysis (Eamus, 2009; Chapman et al., 2003; Cartwright et al., 2010), water balance methods (Le Maitre and Hughes, 2003), and assessment of ground-based leaf area index (Eamus, 2006; Hatton & Evans, 1998), vegetation rooting depth (Eamus, 2006; Shafroth et al., 2000) as well as depth to groundwater models (Hoogland et al., 2010; Eamus, 2009). For instance, water flux measurements were used in determining groundwater use for deciduous black oak trees in California (Miller et al., 2010). The study indicated that black oak trees were obligate phreatophytes, with a groundwater uptake ranging from 4mm/month to 25mm/month. Dependence was most in the dry season with 80% of evapotranspiration from groundwater (Miller et al., 2010). In Australia, Jones et al., (2019) emphasized the importance of validating ecohydrological conceptual models of GDV. While field techniques offer the most detailed insight on the nature, extent, and degree of groundwater ecosystem dependence, they are resource intensive, expensive and represent one-point in time (Eamus et al., 2015b). Therefore, they are ideal for testing and developing a conceptual understanding of GDV and validating GDV mapping (Glanville et al., 2016a; Gow et al., 2010). However, although these studies demonstrate the importance of field-based methods in GDV characterisation, most of these techniques lack spatial representation which makes it difficult to upscale to larger areas and is complex in areas characterised by heterogeneous plant species.

2.7.2 modelling approach for identifying GDV

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

2.7.3 Geospatial approach for identifying and assessing GDV

Remote sensing and GIS techniques are robust methods for mapping GDV at catchment scale. Their implementation however, requires basic knowledge on groundwater-ecosystem interactions and their spectral signature response (Barron et al., 2014). These approaches relate the presence of vegetation in unexpected areas and dark soils to high soil moisture content and groundwater availability (Brodie, et al., 2002). Remote sensing technologies such as airborne sensors, Light detection and Ranging (LIDAR), Synthetic Aperture Radar (SAR) and space borne satellite sensors provide land surface information used in GDV identification. For example, LIDAR produces high quality digital elevation models (DEM) used to obtain topographic indicators for locating GDEs such as aspect, slope and topographic wetness index (Hoyos et al., 2016). Based on the assumption that surface water is the surface expression of groundwater, the SAR provides information on seasonal fluctuations of the water table, surface water inundation, vegetation patterns etc. SAR data can help infer on GDV water balance and hydrological boundaries. Satellite sensors are also widely used to obtain GDV indicators such as vegetation pattern, evapotranspiration, and soil moisture saturation (Table 2.4). Remote sensing equates GDEs to a distinct ecosystem type (green islands), however groundwater dependence is one factor effecting ecosystem productivity.

Literature search has revealed an increase in the use of remote sensing and GIS approaches in eco-hydrogeology and related environmental studies (Table 2.2 and 2.4). Remote sensing can offer new applications that can quickly and synoptically monitor and manage areas at different temporal and spatial resolutions. For example, remote sensing has support timely and spatially explicit assessment of groundwater dependent ecosystems, wetland, water quality monitoring and aquatic weeds etc. (Zhang et al., 2020; Klausmeyer et al., 2018; Thamaga and Dube, 2018; Lv et al., 2013). Moreover, continual coverage of sensors provides both near real time and long-term data required for monitoring GDE response to changing groundwater regimes resulting from climate variability. As such, the use of satellite imagery has provided a reliable source of data that is intensively used in hydrology and ecology (Ali and Alandjani, 2019). Several satellite sensors are suitable for extracting variables utilized in determining the location of GDV and their probable response to groundwater fluctuations. Sensor suitability has influenced research needs in terms of spatial, temporal, radiometric and spectral resolution. While sensor resolution is an important consideration, the cost of the satellite imagery is usually the major limiting factor. In general, there exists a trade-off between spatial resolution and acquisition; this is also true for spatial and temporal resolution. Very high-resolution sensors such as QuickBird, SPOT, IKONOS and Aerial photography with spatial resolutions < 0.5m are high cost. GDE potential have been estimated in Portugal, using SPOT 4 and 5 products (Marques et al., 2019). The high spectral resolution sensors are ideal for vegetation mapping and change detection at species specific and community level. MODIS is a low-cost sensor with low spatial resolution (250m-1000m) and multispectral and multi-date data sets are therefore useful for global scale evapotranspiration estimation, monitoring photosynthetic activity, vegetation mapping (Hoyos et al., 2016). MODIS products have been incorporated with other satellite products for GDV assessments (Gou et al., 2015; Hunink et al., 2015; Doody et al., 2017; Huang et al., 2020; Liao et al., 2020). While MODIS datasets are widely used, they lack the spatial resolution suitable for GDV delineation at scales below community level. The low spatial resolution has resulted in misclassification errors in heterogenous environments with mixed vegetation.

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

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

Table 2. 4 Summary of key research that utilises geospatial techniques to identify potential GDV

Sensor Type	classifier	Key Findings	Limitations	
Landsat 5 TM	NDVI Principal Component	Compared Top of Atmosphere Reflectance and the Atmospherically corrected images (AC) for inflow dependent vegetation. TOA and AC are in good agreement, Kappa = 0.83. Both methods show high accuracies for capturing Known IDV, 85-91%.	Accuracy of the delineated IDV extent may vary due to difference in landscape characteristics and variations in vegetation type.	(Emelyanova et al., 2018a)
Landsat 5 TM MODIS	MODIS (ET, MSSR, Pid) (NDVI, NDWI)	34% of Australian continent contains GDEs of those 5% have high potential for GDEs. Emphasized the need to integrate expert knowledge to gain a conceptual understanding for setting ruled in identifying potential GDEs.	Broad scale approach cannot identify GDEs <25X25 m. the method provides a snapshot and GDEs that may be in decline due to other factors may be missed. The GDE atlas requires regular updating.	(Doody et al., 2017) Australian /continent
WorldView-2 SPOT-7 Landsat 8 OLI	Maximum likelihood Classifier Object Based Image Classifier	SPOT-7 (Overall Accuracy= 69%) WorldView-2 (Overall Accuracy= 72%) GDEs are likely to occur in low land areas and break of slope where groundwater is discharged to the surface.	High misclassification (Overestimation) error along the hillslopes during the wet period and higher misclassifications on the riparian zone during the dry season.	(Dlikilili, 2019) South Africa
Landsat MS, TM, ETM, OLI	[1]NDMI, NDVI Parameter-elevation Regressions on Independent Slopes Model (PRISM) precipitation data	(0.02%) of Landsat data not included. The map constitutes of layers of local datasets for identifying possible locations of GDEs, in a heavily modified environment.	Not all areas included updated landcover layers, gaps in groundwater depth datasets. GDEs are dynamic systems, therefore require regular updating.	(Klausmeyer et al., 2019) United States
Landsat 7 ETM MODIS	NDVI LAI K-means Classifier	Not all phreatophytes and wetlands are groundwater dependent, only 9% of phreatophytes had high groundwater use potential. 75% of identified GDEs were at soil depths below 45cm.	The use of vegetation indicators led to overestimations. Cells with mixed vegetation coverage groundwater dependence was not accurately reflected. Resampling of MODIS images may have led to information loss. Lack of previous GDE studies hinders verification of results.	(Gou et al., 2015) Texas, United States
MODIS Terra 7	Standardized NDV K-means cluster classifier	Pixels were likely to be GDV where the groundwater table was shallow.	Standardized NDVI does allow for observing areas with low seasonal variability or inter annual variability. No quantitative method to validate results. Areas with low tree density, GDV were not captured.	(Páscoa et al., 2020)

1 NDMI = Normalised Difference Moisture index

2.8 Available GDE Classification Algorithms

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

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

2.9 Challenges in Remote Sensing of GDEs

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

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

2.10 Possible Future Direction in Remote Sensing and GIS Applications for GDEs.

Several strides have been made in mapping and monitoring GDV and its response to groundwater variability using satellite data. There is still however limited information on long term monitoring of vegetation response to changing groundwater regimes especially associated with climate change. Investigating the impacts on climate change is limited by the high complexities of GDV, where multiple factors influence the plants phenology, distribution, and chemical processes. Most of such studies are dominant mainly in Australia, the United States and China; however, there is a dearth in knowledge in resource poor areas such as the arid regions of Africa. The major limitation is that these methods for GDV identification or delineation are likely to change with differing landscapes, vegetation types and climates; therefore, geospatial techniques need to be evaluated under diverse environmental conditions. Likewise, determining whether changes in groundwater regime and associated vegetation are products of climate change requires long-term (>50 years) monitoring (Kløve et al., 2014). To fully understand these vegetation communities, groundwater-vegetation responses should be monitored seasonally at catchment or species-specific scales. There have been huge developments in geospatial technologies such as hyperspectral and AUVs datasets providing new opportunities for species level vegetation monitoring, however they have been poorly utilized in GDV assessments. Hyperspectral drones, AUVs and Worldview data potential should be investigated for GDV assessments. Sentinel 1 offers high spatial and spectral resolution datasets that provide valuable information for vegetation mapping and validation. For example, the ground penetrating E band offers soil moisture data, a valuable variable for GDV mapping. This will provide detailed information useful for decision makers when drawing up strategic catchment management plans. As groundwater dependence is one characteristic of GDV mapping, there is therefore a need to find the best ancillary (variables) data and predictive models that can be integrated with freely available datasets. Further, Landsat series and MODIS datasets are the widely used in GDV mapping, however the major limitation is their low spatial resolution (>30m). Despite these limitations, the Landsat series has a large historical archive that has not been fully exploited. The introduction of advanced cloud computing methods such as GEE, peta-scale image processing and artificial intelligence (AI) have the potential to overcome limitations of spatial resolution, and temporal range through the integration of hyperspectral and coarse scale multispectral datasets. Cloud computing methods can provide new insight in GDV monitoring and offer new opportunities to resource poor nations where, GDV investigations were hindered by the cost of acquiring these datasets. Further, more studies integrating field methods with remote sensing in assessing GDV should be prioritized as this will increase the reliability of the derived spatial and thematic GDV maps. When there is a large body of local information on GDV occurrence, geospatial methods can be adequately evaluated and indicate areas of improvement. Further, machine-learning algorithms such as ANN, SVM, and regression tree-based classifiers need to be explored for GDV assessments and distribution mapping.

2.11 Conclusions

Groundwater resources are increasingly deteriorating and constantly under threat due to global change, and increased abstraction impacts vegetation. Literature has revealed the effects of a reduced groundwater table in areas where GDV is dominant. There is a large base of literature on GDV response to groundwater variability. Most of these studies have shown that GDV have responded variably to groundwater availability based on the plant physiological characteristics, such as the plant rooting depth etc. Literature shows that the major responses to a declining groundwater table are reduced photosynthetic rates, plant productivity, reduced leaf area and the change in species composition and distribution. However, GDV is also affected by the timing/ groundwater regime and this needs to be explored further especially with the advent of climate change. Elevated surface temperature and low rainfall are associated with groundwater depth decline leading to GDV degradation and floristic change. The research reveals the effects of climate variability on GDV are difficult to isolate. Therefore, further long-term climate-vegetation interaction research is required. Remote sensing has emerged as a popular method for GDV mapping and assessment, because of the efficiency, unique spatial, spectral, and temporal Characteristics that allow GDV assessment at different scales. While readily available datasets (MODIS and Landsat) have provided critical insights on the state of GDV, they are however limited by the poor (low) spatial and spectral characteristics. There is therefore a need to enhance remote sensing potential by integrating multiple indicator variables in GDV investigations. In addition, new generation sensors (Landsat 8 OLI and Sentinel 2) with improved spatial and temporal resolutions and advances in Machine Learning algorithms can further improve the identification and monitoring of groundwater dependent vegetation. Moreover, the potential of integrating multisource datasets such as drones, AUVs, Worldview and Sentinel 1 to calibrate GDV models should be assessed. Emerging cloud-based image computing techniques such as Google Earth Engine (GEE) can significantly improve the long-term monitoring of GDV. The effects of climate change have created a need to adequately delineate vulnerable groundwater dependent vegetation communities to ensure their sustainability when allocating groundwater resources for anthropogenic activities.

CHAPTER THREE

Assessing the potential for using multispectral, remotely sensed data to identify groundwater dependent vegetation in the Greater Floristic Region of the Western Cape, South Africa

Abstract

Groundwater Dependent Vegetation (GDV) is increasingly threatened by the transformation of the natural environment to different land uses/land covers, the over-exploitation of groundwater resources and the proliferation of invasive species within the Cape Floristic Region (CFR). These changes affect the regime, level and quality of the groundwater that supports the GDV. Natural resource managers often lack an understanding of the appropriate scale of the nature of GDV, which prevents them from making sound sustainable decisions. The first step in the effective management of GDV requires a detailed comprehension of its distribution, its possible threats, and its health condition. This chapter aims to assess and map the potential distribution of GDV within the Heuningnes Catchment using multispectral remotely sensed (i.e. Landsat 8 (L8) and Sentinel 2 (S2)) and *in-situ* data. This study also compares the performance of the two types of multispectral data and the influence of derived spectral indices in mapping the spatial distribution of GDV in the catchment. The GDV distribution maps were produced by integrating the vegetation productivity, landcover, slope and surface curvature layers as the potential GDV indicators. The landcover, slope and surface curvature layers were kept constant, while the vegetation productivity layers were derived from the Normalised Difference Vegetation Index (NDVI) and the Soil-Adjusted Vegetation Index (SAVI). This was undertaken to assess the performance of the vegetation indices for GDV classification. The findings of the study revealed that the spectral indices had a significant influence on the sensor's GDV classification performance. Specifically, GDV detected from the S2(SAVI) index had the highest overall accuracy (97%), followed by the S2-derived NDVI, with an accuracy of 95%. Comparatively, the L8(NDVI) GDV map was achieved with an overall accuracy of 92% and the L8(SAVI) map had an overall accuracy of 96%. Overall, the area has a 2.34-2.60% coverage of the potential GDV. All four models also produced similar GDV distribution patterns. It was further observed that the north-western parts of the catchment have a high potential for GDV, compared to other areas. This work demonstrated the

capabilities of a combined remote sensing and GIS methodology, which can improve our knowledge on GDV and its management.

Keywords: Arid environments; catchment management; fynbos; moderate resolution; invasive plants; groundwater; satellite data; water resources management

3.1 Introduction

Some terrestrial vegetation in arid and semi-arid regions may be maintained by the direct and indirect access to groundwater, and this is collectively called Groundwater Dependent Vegetation (GDV) (Zhang et al., 2020). Factors such as precipitation, temperature and groundwater affect the distribution and vigour of GDV. Vegetation is a major component of terrestrial ecosystems and plays a vital role in energy flow, global carbon and the water cycle (Zhao et al., 2012). Furthermore, terrestrial vegetation boosts the economy of arid regions. For example, the Cape Floristic region contributes 10% of South Africa's Gross Geographic Product (GGP), and the same applies to other regions across the globe. Not only do natural terrestrial ecosystems contribute to the economy through ecotourism, but they are also the genetic hub for bioprospecting, as well as for the preservation of biodiversity (Williams, 2018). Vegetation provides valuable ecosystem services, such as flood control, water purification, pollinator habitats and recreational opportunities. In arid regions, vegetation is a major producer of organic material and contributes to the necessary biological components of the soil (Lv et al., 2013). The vegetation cover buffers the desertification process and maintains the natural environmental conditions (Lv et al., 2013; Wang et al., 2018). Because of the numerous benefits that are gained from terrestrial vegetation, it is imperative that these ecosystems are protected and safeguarded.

Plantation forestry, urban development and the conversion of natural land to agriculture (McDowell and Moll, 1992; Rouget et al., 2003), as well as the over-exploitation of water resources (Rouget et al., 2003), are the main threats to the sustainability of GDV. Reduced groundwater levels, due to over-abstraction for supporting agriculture, urban and industrial development, endanger the GDV. The excessive use of groundwater resources is further compounded by extreme climatic conditions, such as droughts and climate variability. For example, with the advent of the 2015-2017 drought in the Western Cape, South Africa, alternative surface water resources had to be rapidly explored and developed, to meet the demand for water.

This included the abstraction of groundwater resources for agricultural, municipal and industrial use. The groundwater levels were reported to have declined substantially over the previous four years, with 65% of the groundwater resources being consumed by the agricultural sector (Seyler, 2017). A decline in groundwater levels has been found to negatively affect terrestrial vegetation (Froend and Sommer, 2010). Furthermore, the long-term effects of groundwater abstraction were assessed in Western Australia. It was determined that the increased depth of the groundwater (2.2 m), coupled with the extreme summer temperatures, resulted in a 20-80% adult mortality rate of the over-story vegetation and up to a 64% mortality rate of the understory vegetation (Groom et al., 2000). Plantation forestry reduces the groundwater recharge and the surface water flow, and it increases the groundwater discharge. For instance, Munoz-Reinoso (2001) reported a greater depth of groundwater in Donana, Spain, due to the increased drawdown and abstraction of the urban water supply and the transpiration of large pine plantations. In South Africa, areas that are heavily encroached by alien invasive plants, have reported reduced stream flow and groundwater levels (Dzikiti et al., 2013; Fourie et al., 2002; Scott et al., 2008; Prinsloo and Scott, 1999), which has an adverse effect on the native GDV (Vila et al., 2011). Invasive plant species can tap into multiple water sources; thus, they outcompete the endemic vegetation (Dawson and Elleringer, 1991). The rate of spread of invasive alien plants indicates that there is a higher likelihood of water scarcity (Hoffman and Cowling, 1990; van Wilgen and Richardson, 2012), which is a growing concern. Since the role of groundwater for augmenting water resources is increasing, it is important to determine the vegetation that is dependent on this groundwater and its distribution within the landscape. This will help to set up effective groundwater management strategies, to ensure ecological sustainability. Monitoring the condition of the vegetation and its response to environmental and global changes over time, creates an understanding of the change processes and the possible areas that are affected and that are at risk (Franklin et al., 2016). Information on the distribution on GDV helps to determine the ecological water allocation, the setting up of conservation hotspots, as well as the restrictions and strategic planning for groundwater use within the region. Such information is also critical for supporting an agenda for sustainable future development e.g., the United Nations' (UN) Sustainable Development Goal 15 on 'Life on Land' (United Nations 2018). The condition of the vegetation, as well as its response to environmental changes, is specified in the lists of Essential Climate Variables (Bojinski et al., 2014) and Essential Biodiversity Variables (Pereira et al. 2013).

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

3.2 Research Methodology

3.2.1 Study area description

The Cape Floristic Region (CFR) is a biodiversity hotspot and part of the six floral kingdoms of the world. It has the most outstanding diversity, with 95 000 species that are endemic to the area. The region is home to 1406 of the red data book plant species, which is the largest concentration globally (Allsopp et al., 2019). This study will concentrate on a portion of the CFR, namely, the Heuningnes Catchment (Figure 3.1). Covering an area of 1403 km^2, the catchment is located in the Cape Algulhas region in the Western Cape and it is straddled by the Bredasdorp Mountains along the northern watershed (Kinoti, 2019). It is characterised by several ephemeral ponds, rivers, freshwater springs, and wetlands (riparian and non-riparian). The main rivers are the Nuwejaars and Kars Rivers, and there are several wetlands, such as the Soetendalsvlei and the Voelvlei, that are interlinked with streams. The riparian zones are infested by invasive plant species such as *acacia longifolia* (Geartner *et al*., 2012). The geology is distributed into three main groups, namely, the Table Mountain Group (TMG), which consists of quartzic sandstone, while shale and siltstone dominate the north-western parts of the catchment. The TMG is affected by deformation, which has resulted in a fractured secondary aquifer. The Bokkeveld Group overlies the TMG and occupies the eastern and middle parts of the catchment in the Elim and Soetendalsvlei areas. The shales of the Bokkeveld Group have notable fractures and faults and saline groundwater. The Bredasdorp Group, which consists of shallow Cenozoic marine aeolian deposits, overlies the TMG and Bokkeveld Group (Mkunyana et al., 2019; Mokoena, 2019). The characteristic lithology of calcified dunes and coastal limestone are found in the southern coastal regions of the catchment. The groundwater flow is heavily influenced by the underlying geology and structural characteristics, and therefore follows the topography. The groundwater is characterised by both primary and secondary aquifers (Mkunyana et al., 2019), and the region has primarily fractured aquifer types, with several springs distributed along the catchment. However, the lower part of the catchment is characterised by an intergranular aquifer with low-yielding shale (Mokoena, 2019). The groundwater in the area is used for livestock farming and domestic use. The land cover is mainly natural, with dominant shrubland fynbos, which is in demand for the ornamental industry and for pharmaceuticals (Turpie et al., 2003). Natural eco-tourism contributes to the economy by means of the two conservation areas, namely, the De Mond Nature Reserve and the Algulhas

National Park. The major land uses are agricultural, with mainly wheat and livestock farming, as well as a few vineyards (Thamaga and Dube, 2018) and pine plantations (Kinoti, 2019). Since the economic activities rely on water, there is a fundamental challenge to support economic development and social redress, while also ensuring the environmental functioning of the water-dependent ecosystems. This is exacerbated by the competing demands of agriculture, the ecology and invasive plants that may be utilizing the environmental water reserves.

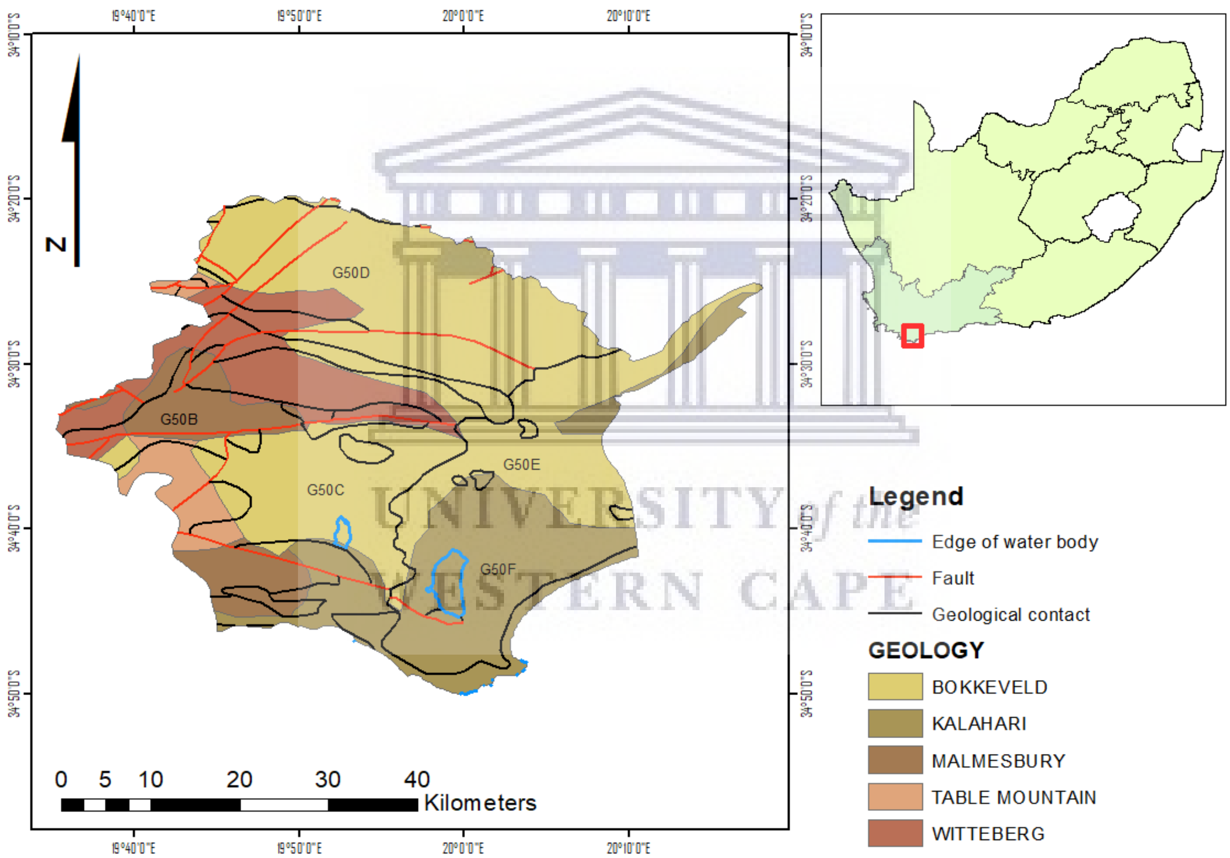


Figure 3. 1 The Heuningnes Catchment study area and its geology in the Western Cape region of South Africa

3.2.2 Data acquisition

3.2.2.1 Floristic survey

Field data were collected to map and validate the groundwater dependent vegetation within the Heuningnes Catchment. The vegetation data were acquired from reference data and a floristic survey conducted during the wet and flowering seasons for easy plant identification. Plot sizes of 10 m x 10 m were delineated to collect the Global Positioning System (GPS) coordinates where the vegetation was sampled. The dominant vegetation, plant phenology and other land cover types in the area were noted. Overall, there were 12 sampling points within the G50B quaternary catchment, with the dominant vegetation species being identified and recorded in each of them. Species locations were recorded by using the eTrex 10 Garmin GPS, with an error margin of 3 m (Garmin, 2019). Samples of the dominant vegetation within the sample plots were collected, including their pictures, and these were for further species identification by using the SANBI iNaturalist Plant Identification application. The application uses crowd-sourced data and artificial intelligence identification algorithm that provides the real time identification of the organisms posted.

3.2.2.2 Satellite data

The study sought to compare the Sentinel 2- and Landsat 8-derived models to map the potential distribution of the GDV. These models were produced from bio-indicators (vegetation productivity), landcover, as well as the topographic features, including the slope and surface curvature (Brodie et al., 2002; Münch and Conrad, 2007). The L8 Level 1C satellite dataset was downloaded from the online USGS Earth Explorer Earth Observation database (https://earthexplorer.usgs.gov/). Satellite images from the dry season were specifically selected to exploit the impacts of water scarcity on the vegetation. Groundwater dependent vegetation with access to groundwater has a higher vegetation productivity than the surrounding vegetation when surface water resources are limited. The images were mainly for the year 2017. A single L8 scene, which was acquired on the 15th of January, covered the entire expanse of the study area. Two S2 Level 1C products with minimal cloud cover (<2%) were obtained from the 11th and 08th of January 2017. The images were acquired on different dates because of the need for cloud-free images. It is assumed that land cover changes were negligible within that period. The Shuttle Radar Topography Mission (SRTM) void-filled image, with a 30 m spatial resolution, was also downloaded from the USGS online resource. The landcover map was obtained from the Department of Forestry, Fisheries and Environment database (https://egis.environment.gov.za/gis_data_downloads). The acquired map had an overall classification accuracy of 90.14%. Multi-seasonal Sentinel 2 images were used to generate the landcover map, which was useful for extracting the areas with natural vegetation that are suitable for GDV.

3.2.3 Data processing and classification

Level 1C products for L8 and S2 are radiometrically and geometrically corrected, with spatial registration and ortho-rectification (Suhet, 2015). The Top of Atmosphere (TOA) reflectance was used for determining the vegetation indices, as Emelyanova et al. (2018) demonstrated that the TOA and Atmospheric Correction (AC) reflectance are equally appropriate for GDV mapping. The L8 and S2 images were re-projected to the WGS84 UTM zone 34S geographical co-ordinate system. The Normalised Difference Vegetation Index (NDVI) and Soil Adjusted Vegetation Index (SAVI) were used as a proxy for vegetation productivity. The NDVI has been extensively used in literature (Doody et al., 2017; Jovanovic et al., 2011; Liao et al., 2020; Münch and Conrad, 2007; Thamaga et al., 2018; G. Zhang et al., 2020), with great results for GDV mapping. The SAVI minimises the influence of soil brightness on the vegetation spectral reflectance, which is suitable for areas with a low vegetation cover (Huete, 1988; Rhyma et al., 2020). The relevant bands required for calculating the SAVI and NDVI were processed further by clipping them to fit the extent of the study area. The vegetation indices (VI) were then calculated (Equations 1 and 2) by using the map algebra tool from the spatial analyst tools in ARMAP 10.8.

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

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

The VI spatial layers were also classified by using the IsoData Unsupervised Classification technique. There were a total of five classes, ranging from 1 to 5. VI Class 5 represented the highly productive vegetation associated with water availability, while Classes 1-4 characterized vegetation with limited access to groundwater. Therefore, the first four classes were masked out, leaving Class 5, which represented the areas with the highest potential for groundwater dependence. Vegetation with an above-average productivity indicates that it has access to surface water resources. The landcover dataset was resampled to fit the study area. From the landcover layer, only the wetland and natural vegetation classes are suitable for GDV; therefore, the other classes were masked out.

The SRTM void-filled dataset was also clipped and used to calculate the slope and profile curvature. The rules for selecting the areas with topographic characteristics suitable for GDV were set as the areas with a gentle slope of less than 3%, and a positive profile curvature value (depressions) has a high potential for GDV (Münch and Conrad, 2007). Figure 3.2 summarized the steps for potential GDV distribution mapping. The land cover, slope, profile curvature and VI layers were reclassified into two classes. The class with the pixel value of 1 represents the pixels with a high potential for GDV and 0 represents those pixels with no potential. The four layers (landcover, slope, vegetation productivity and surface curvature) were integrated by using the weighted sum overlay tool, with pixel values above three indicating the potential GDV, and those below three being masked out, as they did not satisfy the criteria. The final outputs were four potential GDV maps, which were derived by using the different indices from the two sensors (L8(SAVI), L8(NDVI), S2(SAVI) and S2(NDVI)). The area extent of the GDV and non-GDV classes was computed to estimate the percentage coverage of GDV within the Heuningnes Catchment.

The validity of the four binary classified maps was assessed on a reference Google Earth image with a 5m resolution. The landcover characteristics at the time were obtained from the Google Earth image. There were 196 randomly generated accuracy assessment points (40 for the GDV class and 156 for the non-GDV class). These were overlaid on the January 2017 image to assess the quality of information derived from the classified models. The 196 points were created because the area is relatively small and sample point allocation per class unbalanced because the binary classification is unbalanced (Foody, 2002; Stehman, 2009, 2000). The classification accuracy was assessed through binary confusion matrix to compute the producers, users, and overall accuracies. Cohen's Kappa Coefficient indicating the level of agreement between the reference image and the classified images was computed. The allocation of omission and commission errors was determined following Olofsson et al., (2013). The commission errors are determined by deducting the producer's accuracy from the total percentage of pixels to indicate overestimation. Omission errors are determined by deducting the User's accuracy from the total percentage of pixels to indicate underestimation. The McNemar's test was performed to find out if there were any significant differences in the overall performance of the classified images.

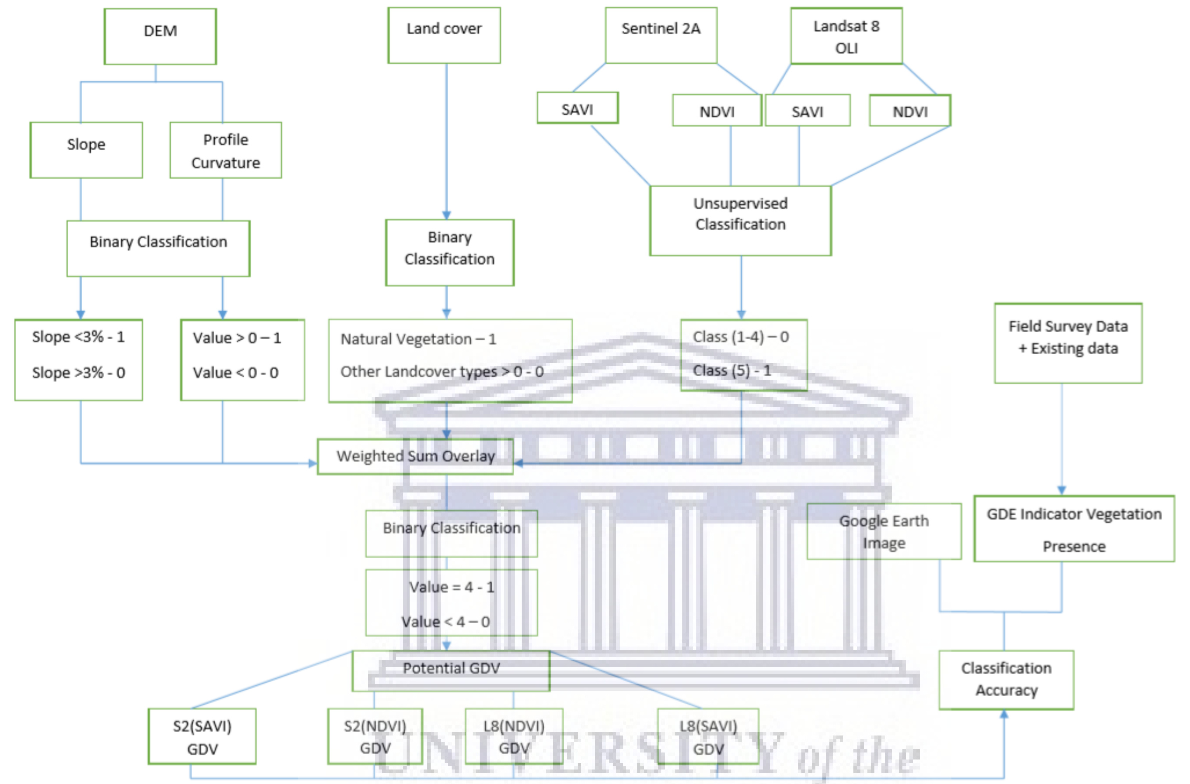


Figure 3. 2 Flow chart summarizing the critical analysis steps for mapping the potential distribution of GDV

3.1 Results

3.1.1 Potential GDV model classification assessment

Overall, the S2(SAVI) model produced the best results for identifying the potential GDV, with an Overall Accuracy OA of 97% and the highest level of agreement (93%). Table 3.1 shows the GDV and Non-GDV classification accuracies for the Heuningnes Catchment, with overall accuracies ranging from 92% to 97%. The GDV classification has better User Accuracy (UA) than Producer Accuracy (PA), while the opposite is true for the non-GDV classification (Table 3.1). When looking at the L8 models, the L8(SAVI) model performed better than the L8(NDVI) model, in terms of the PA, the UA and the OA. This shows that, when using L8, the SAVI is the better-performing index for determining bio-indicators. This is also true for the S2-derived maps, where the SAVI maps had a higher PA (93%) and UA (95%) compared to the NDVI PA (88%) and UA (90%) for the GDV classification. When looking at the sensors, S2(SAVI) outperformed L8(SAVI) by 1%, and by 3% for the NDVI model. Overall, the results reveal S2 performs better than L8 when evaluating the capability for detecting and mapping the potential distribution of GDV and areas with limited GDV potential.

Table 3. 1 Accuracy assessment results for the binary classification of potential GDV for the Heuningnes Catchment

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

The level of agreement and disagreement for the four models is shown on Figure 3.3. The level of agreements is higher than the level of disagreement (errors of commission and omission) for both classes. However, the error of omission is high for the GDV class, while the non-GDV class has a higher error of commission. The L8(NDVI) performed the least, with a high level of disagreement (35%), mainly from the high omission error (20.45%) for the GDV class. The classification from S2(SAVI) had an overall disagreement (4%) equally contributed by the commission and the omission errors for the GDV class. The performance difference between the sensors indicated that potential GDV can be more accurately detected when using Sentinel 2 within the Heuningnes Catchment. The McNemar statistical test (p>0.05) revealed that there were no significant differences in the performance of the classifications.

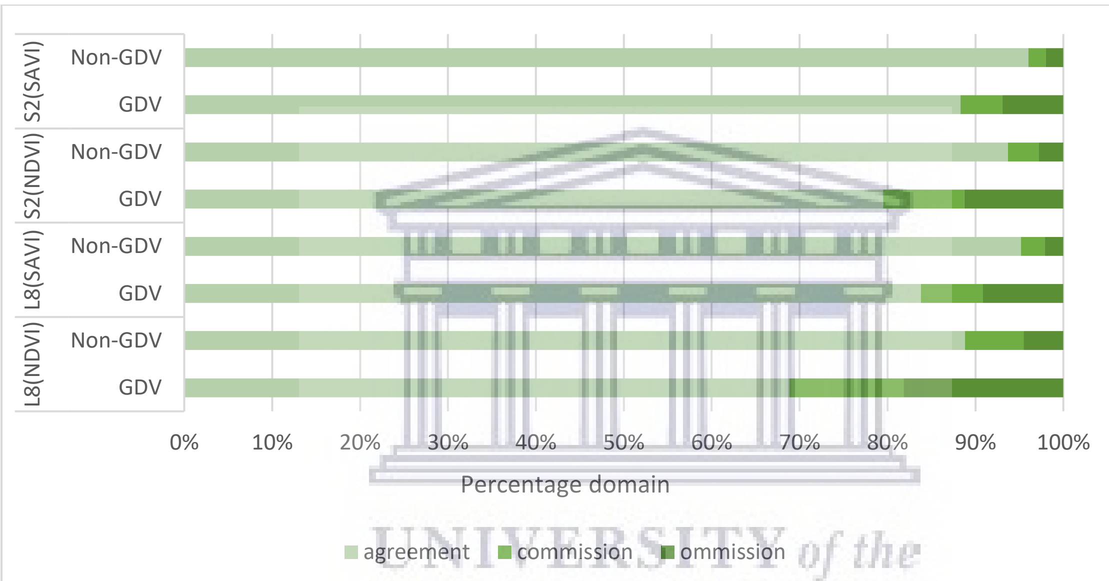


Figure 3. 3 Allocation of agreement, commission, and omission errors for the four potential GDV maps

3.1.2 Vegetation species as an indicator of GDV occurrence

Vegetation that is known to be dependent on groundwater can be used to assess the GDV classification, and if the known GDV is found in the identified areas, the classification is validated (le Maitre et al., 1999; Páscoa et al., 2020). Since the north-western regions have a high-density potential for GDV, the G50B quaternary catchment was chosen for the floristic survey. The dominant vegetation within the quaternary catchment consisted of the *Acacia pycnatha, Poacea (grasses), Acacia longifolia, Acacia saligna, Helichrysum petiolare, Restionaceae, Ornithogalum thrrsoids, Diospyros glabra* and *Pinus*. The report by le Maitre et al. (1999) produced a provincial list of GDV, based on the vegetation setting. The *Acacia, Thyrsoides* and *Diospyros* species were included in the list for the Western Cape. Studies on the impact of the *Acacia* species have revealed that it has led to a reduction in the water table and that its water use exceeds the rainfall (Shoko et al., 2020; Groengroeft *et al.,* 2018; Khanzada et al., 1998). Groundwater is important on the quaternary sands on the western, south-eastern coasts and on the limestone laterites of the Algulhas coastal plain (Scott and le Maitre, 1998).

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

The southern regions of the catchment are characterised by gentle slopes, when compared to the northern regions, while the surface depressions are evenly spread within the catchment. Natural vegetation dominates the catchment and the L8 and S2 vegetation indices indicate similar results for areas with a high vegetation productivity. The catchment areas with Class 1 are characterised by gentle slopes of less than 3%, depression areas, natural vegetation and highly productive vegetation. Class 0 areas do not have potentially suitable characteristics for GDV potential (Figure 3.4).

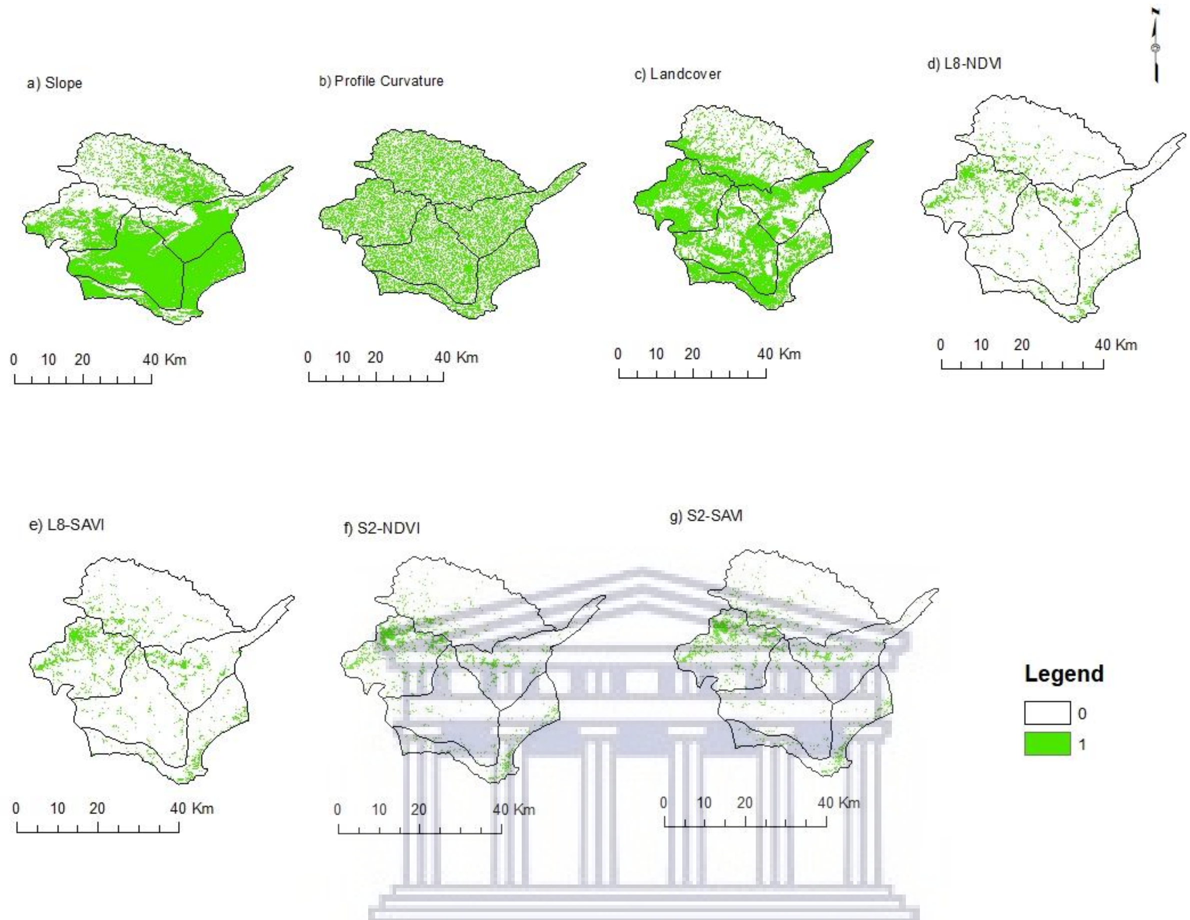


Figure 3. 4 The binary classification of indicator variables used in producing the four potential GDV indices; Class 1 indicates the areas with GDV suitability, with Class 0 indicating the unsuitable areas

A visual description of the potential GDV, as well as its distribution within the catchment, is presented in Figure 3.5. The four models produced visually similar results on the distribution of GDV. This is in line with the quantitative results, where the L8 models show about 2.6% of the area is suitable for GDV, when compared to the S2(SAVI) and S2(NDVI), which determine that 2.4% and 2.34% of the area has GDV potential, respectively. The north-western region of the catchment has a higher potential for GDV, when compared to the other lower parts of the catchment, were the GDV is widely spread and sporadic. The GDV in the north-western region seems to be riparian vegetation where the groundwater level is close to the surface. The GDV in the south of the catchment taps into the shallow primary aquifer of the Bredasdorp Group. The

GDV communities are not only distributed along the riparian zone, but they are also found in areas further away from the streams.

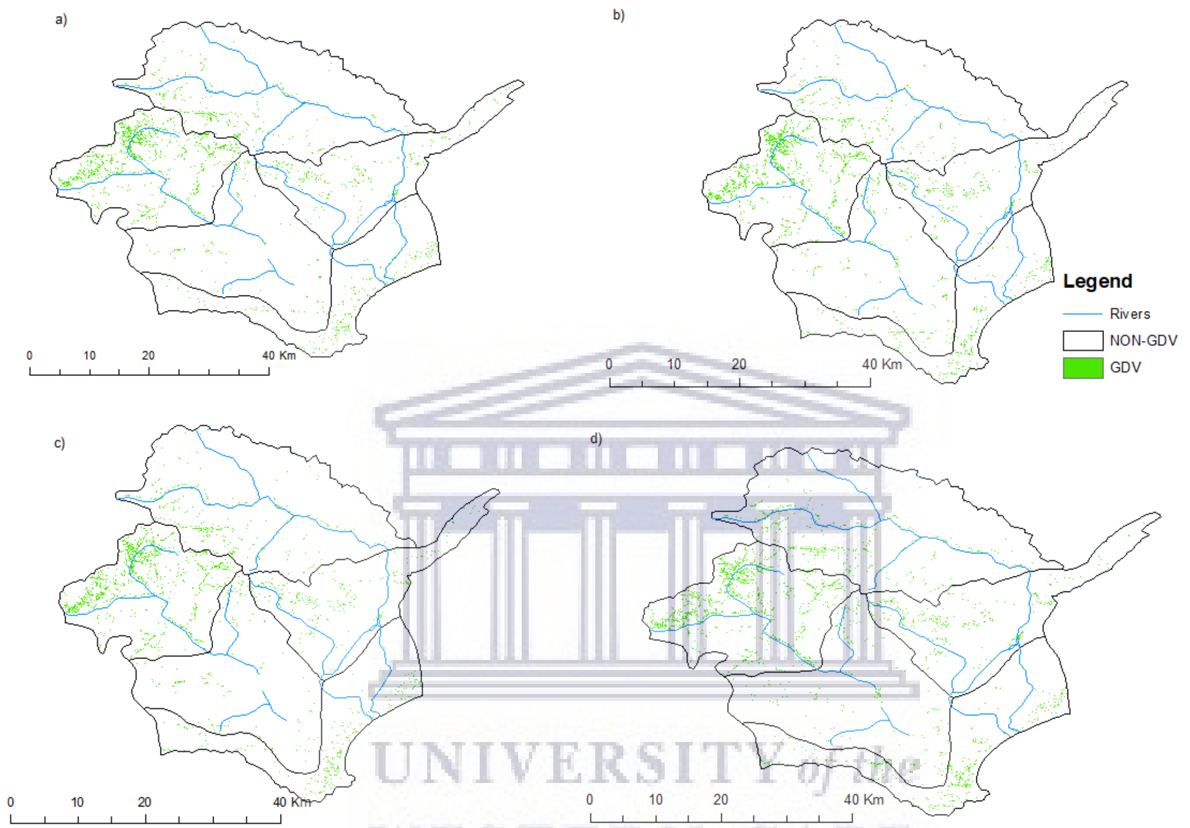


Figure 3. 5 Distribution of potential GDV within the Heuningnes Catchment derived from the GDV indices: a) S2(SAVI), b) L8(SAVI), c) S2(NDVI) and d) L8(NDVI)

3.2 Discussion

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

The occurrence of vegetation that is known to be associated with groundwater use has been used as a qualitative verification method for GDV/GDE mapping in previous studies (Dzikiti et al., 2013; Páscoa et al., 2020; Scott and le Maitre, 1998). This study found a high potential for GDV occurrence in the north-western region of the Heuningnes Catchment. The identified vegetation species were the native and alien invasive species. The endemic plants belong to the Renosterveld of the South Coast Centre and Mountain Centre vegetation and have been indicated to be xeric (Colvin et al., 2003; Rutherford et al., 2006). The renosterveld shrubs may develop deep roots, where possible, but have limited interaction because of the hard shales. Groundwater may play a critical role in the quaternary sands on the western, southern and south-eastern coasts, as well as on the limestones on the laterites of the Agulhas-Riversdale coastal plain (le Maitre et al., 1999). The north-western region of the catchment has a secondary fractured aquifer (Mokoena, 2019), and it is possible that these vegetation communities may be maintained by springs. This study revealed that both endemic and invasive vegetation potentially rely on the groundwater within the catchment. Invasive GDV threatens the endemic GDV, as it can out-compete the endemic GDV and is more resilient to the decreasing groundwater levels (Maitre et al., 1996; Rouget et al., 2003; van Wilgen et al., 2008; Jovanovic et al., 2013). Not only do invasive vegetation and GDV exploit the groundwater resources, but they also reduce the groundwater recharge, which limits the available water for the endemic GDV.

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

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

3.2 Conclusion

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

CHAPTER FOUR

Multispectral remote sensing of vegetation responses to groundwater variability in the Greater Floristic Region of the Western Cape, South Africa

Abstract

The interaction of groundwater and vegetation during the drought period, from June 2017 to July 2018, was investigated for riparian and hillslope environments, using multispectral remote sensing data (MODIS-NDVI). In addition, the relationship between the vegetation productivity, the rainfall and the temperature was analysed. Specifically, the vegetation and groundwater depth correlation were tested for immediate and lagged interactions. A time series analysis and linear regression indicated that the groundwater depth is strongly associated with the 1-month lagged R(-0.54--0.71), compared to the non-lagged R(-0.45--0.62). The hillslope vegetation was observed to be more sensitive to groundwater than the riparian vegetation. This was evidenced by the larger gain/loss range in the NDVI, with variations in the groundwater level. However, these responses varied significantly between the sites under study. Generally, the groundwater depth variability is a function of the seasonal changes, which induces a response in the productivity of vegetation. For instance, the water table is higher in the wet months; therefore, the vegetation productivity is higher, when compared to the dry season, when the water table is deeper. In contrast, temperature was a significant ($p < 0.05$) contributing factor to the hillslope vegetation dynamics. The rainfall and groundwater depth had a minimal impact on vegetation productivity, except for riparian vegetation, which demonstrated a strong association with rainfall. Overall, high NDVI (>0.6) values were observed throughout the monitoring period, despite it being a drought period. This chapter highlighted the value of remote sensing datasets and statistical analysis methods for understanding the prevalent groundwater-vegetation interactions in semi-arid environments.

Keywords: Climate factors, Invasive vegetation, MODIS, semi-arid, groundwater resource management

4.1 Introduction

Vegetation plays a significant role by providing crucial ecosystem services, such as carbon sequestration, providing biodiverse habitats and the regulation of climate systems (Gauthier et al., 2015; Ndehedehe et al., 2019). However, these functions may be compromised when the vegetation is degraded. In semi-arid environments, vegetation is vulnerable to water shortages caused by unsustainable land-use practices, rapid socio-economic development and the impacts of climate change (Elmore et al., 2006, Xia et al., 2017). Managing the competing uses of freshwater resources is a challenge for the future development and management of water resources. Moreover, the impacts of drought are a growing concern (Froend and Sommer, 2010; Kath et al., 2014). Droughts that are related to climate change result in an over-reliance on groundwater resources, which affects the vegetation growth patterns. This is of great concern for water resource managers and ecologists.

Groundwater variability is significant for determining the availability of water for Groundwater Dependent Vegetation (GDV). Although the relationship between vegetation and natural groundwater variability is well understood, there is still a need to understand the response of the vegetation to groundwater variability during a drought period. This is of significance in a Mediterranean climate environment, which is characterised by wet winters, when there is a low evaporative demand, and dry summers, when there is a high evaporative demand (Gasith and Resh, 1999; Swift et al., 2008). Furthermore, numerous studies focus on riparian vegetation, with limited attention being given to hillslope and mountain groundwater dependent vegetation. For instance, Froend and Sommer (2010) investigated the long-term riparian vegetation responses to climate- and abstraction-induced groundwater draw-down at a plant community level, and they found dissimilarities, as well as changes, in the floristic composition in areas with a high draw-down rate. Furthermore, GDV is assimilated to a specific groundwater depth range; therefore, not all GDV responds to a decline in the groundwater in the same way. At greater depths to groundwater, vegetation response may be mediated by soil moisture. The plants extensive roots may tap soil water instead of water from an aquifer (Zencich et al., 2002). In addition, most studies have been conducted in temperate ecosystems, thus there is a need to elucidate the seasonal vegetation responses to groundwater dynamics within an arid Mediterranean environment (Shafroth et al., 2000; Naumburg et al., 2005; Scott and le Maitre, 1998). The majority of these studies also used indirect physiological variables (stomatal conductance, stem diameter, abundance, composition and basal area) as indicators for vegetation productivity (Froend and Sommer, 2010; Hoogland et al., 2010; Kath et al., 2014; Martinetti et al., 2021; Shafroth et al., 2000; Silva Mota et al., 2018; Zencich et al., 2002). For example, Froend and Sommer (2010) collated the 7-year tree condition data that was acquired from field surveys to determine the non-linear vegetation responses to the decline in groundwater. Acquiring *in-situ* vegetation data is inefficient and labour-intensive, and it limits the spatial and temporal scope of a study. In addition, the upscaling of *in-situ* measurements, from a plant and stand level to a larger scale, is challenging because of the heterogeneity of the vegetation characteristics. These studies also concentrated on the physiological structure of the vegetation, whereas hydrologists, water engineers and geoscientists are focused on ecosystem restoration and the catchment water balance; thus, transpiration and photosynthesis are the main components of interest (Orellana et al., 2012). Remote sensing mitigates the limitations of *in-situ* measurements by providing an archive of vegetation and climate data that may not be available for study in inaccessible and data-scarce areas. Moreover, remote sensing presents the transpiration and vegetation health estimates over large areas, with a high spatial coverage and temporal frequencies, and at a low cost. Vegetation indices derived from multispectral data may be used as proxies for vegetation productivity, to investigate the vegetation dynamics and their relationship to hydrology and the climate variables. The Normalised Difference Index (NDVI) defines the absorbed photosynthetic active radiation because the mesophyll of healthy vegetation strongly reflects near infrared radiation, while leaf chlorophylls and other pigments largely absorb visual red radiation (Wang et al., 2003). NDVI has been extensively used to investigate green biomass (Northcote and Atagi, 1997; Shoko et al., 2016) and patterns of productivity (Chávez and Clevers, 2012; Jin et al., 2014; Lv et al., 2013; Mtengwana et al., 2020). Environmental factors, such as the hydrology, climate and land use, influence the health of the vegetation, which influences the NDVI. Thus, the NDVI has been widely employed for investigating vegetation dynamics in response to climate factors (Bhatt et al., 2020; Dlikilili, 2019; Graw et al., 2017; Morsy et al., 2017; Yang et al., 2012). Furthermore, Moderate Resolution Imaging Spectrometer (MODIS)-derived transpiration and the NDVI have been successfully employed to investigate the hydraulic link between vegetation and the groundwater table (Adams et al., 2015; Gow et al., 2010; Jin et al., 2011; Sommer et al., 2016). A simple linear regression and Mann Kendall test are reliable and useful analysis methods for examining the relationship between groundwater and the vegetation health (Gow et al., 2010; Graw et al., 2017; Shafroth et al., 2000a). For instance, Shafroth et al. (2000) determined the response of woody riparian vegetation to changing alluvial water table regimes by using a simple regression. Previous studies have indicated that the response of vegetation to a groundwater regime change is related to the previous groundwater regime adaptation. Moreover, plants that have access to shallow groundwater are more sensitive to a groundwater decline than those with a variable groundwater regime (Shafroth et al., 2000; Adams et al., 2015). Therefore, a knowledge of natural groundwater regime adaptation provides water resource managers with critical information for determining the vegetation response to climate change and abstraction (Froend and Sommer, 2010). Knowledge of the extent and degree of groundwater influence on the vegetation productivity is still required. Therefore, this paper assesses the inter-annual vegetation response to natural groundwater variability between the riparian and hillslope vegetation. Furthermore, the strength of the relationship between the NDVI and the groundwater depth, rainfall and temperature will be quantified. The acquired information will help to develop water resource management and planning that does not compromise groundwater dependent vegetation, and subsequently, it will contribute to achieving the SDG 15 for life on earth.

4.2 Research Methodology

4.2.1 Study site

The study area has a Mediterranean climate, with hot dry summers and with 60-75% of the rainfall occurring on the winter months. The annual average rainfall range is 445 mm/yr in the east and 540 mm/yr in the west (Kraaij et al., 2009). This study focused on the 5G0B, which forms the quaternary catchment of the Nuwejaars Catchment within the Heuningnes Catchment (Figure 4.1). The major river flowing in this catchment is the Nuwejaars River, which has three main tributaries, namely, the Jan Swartskraal, Koue and Pietersielieskloof Rivers. The headwater environment for these rivers is in the mountainous areas, and wetlands are found in the lowlands of the catchment. The Jan Swartskraal River is 18.3 km long at an elevation of 534 m; it has an average slope of 3.9 degree and a maximum slope of 30.8 degrees in the mountainous regions. The Koue River is 18.9 km in length at an elevation of 527 m, with an average slope of 2.4 m and 20.7 m in the mountainous regions. The Pietersielieskloof River is 14.7 km long and has an elevation of 365 m at its source and 27 m at its confluence with the Nuwejaars River. The average slope along this river is 2.9°, with a maximum of 27.5° in the mountainous region. The Nuwejaars (Moddervlei) wetland forms at the confluence of the Jan Swartskraal, Koue and Pietersielieskloof Rivers (Mehl, 2019).

The Nuwejaars Catchment is mostly cultivated with woodlands in the mountainous regions. There are pine plantations in the mountainous regions and fynbos and protea flower farms in the Jan Swartskraal, Koue and Pietersielieskloof river sub-catchments. The main agricultural activities are livestock, wheat and canola farming. There are also vineyards in the Moddervlei and Pietersielieskloof sub-catchments. The geology of the coastal mountains of the Nuwejaars Catchment consists of Cape Fold Belt sandstone, which is overlaid with limestone. The area is largely underlain with the Palaeozoic sediments of the Cape Supergroup and sandstone, and the low mountains and coastal ridges are comprised of quartzite of the Table Mountain Group (TMG). The soils produced from these rocks are acidic and mostly infertile. Fynbos vegetation occurs naturally in the catchment. According to Mazvimavi (2017), a connection exists between the groundwater and surface water in the upper regions of the catchment. The source of the constant base flow for the Koue, Pietersielieskloof and Jan Swartskraal tributaries are the upstream springs. The catchment consists of both primary and secondary aquifers. The primary aquifers are characterised by unconsolidated sediments that were deposited during sea level changes and occur at a depth of 8 m and 30 m. The secondary aquifers consist of fractured bedrock, which is semi-confined. Groundwater flow within the catchment is controlled by the recharge areas that are underlain by the TMG formations and existing fault systems. Springs occur upstream within the TMG region of the catchment and are closely linked to the fault systems. They supply the town of Elim with water for domestic and agricultural purposes (Mazvimavi, 2017). The area is heavily invaded by the acacia species and black wattle; however, the northern parts of Jan Swartskraal are being rehabilitated by the planting of natural fynbos.

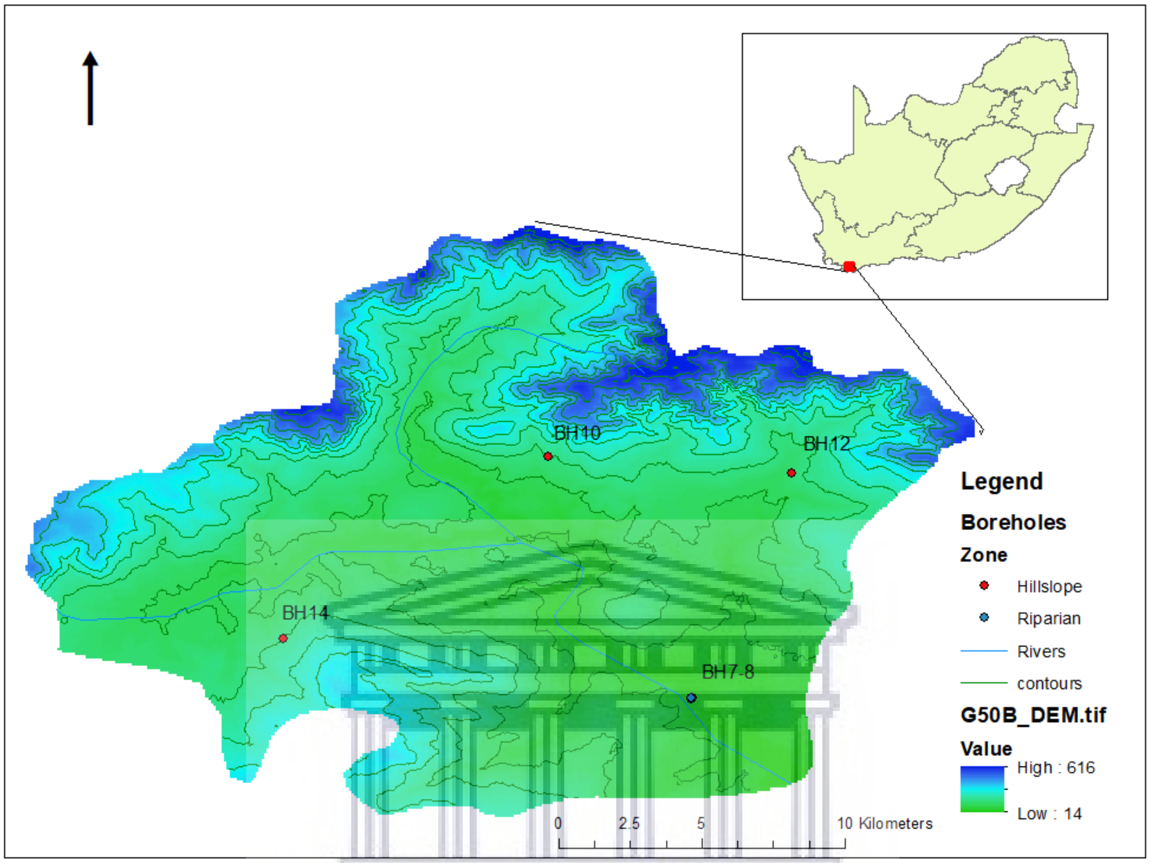


Figure 4. 1 Location of the G50B quaternary catchment and study sites within the Heuningnes Catchment

4.2.2 Data acquisition

The daily groundwater level data were obtained from an ongoing hydrological monitoring program at the University of the Western Cape, which has been monitoring groundwater levels from the Nuwejaars River Catchment. The data range was from 22/06/2017 to 24/07/2018. The daily groundwater levels were converted to monthly averages, in order to correspond with the remotely sensed NDVI. The data of five shallow boreholes distributed around the G50B quaternary catchment were selected, based on their consistent availability and the occurrence of individual pixels for vegetation data (Table 4.1). The groundwater data that covered riparian and hillslope areas were used to investigate the effects of elevation and the distance from the surface water. Forty-seven atmospherically corrected scenes of MODIS NDVI data were downloaded from https://ladsweb.modaps.eosdis.nasa.gov/search/. The MODIS NDVI, with a 16-day temporal resolution, was suitable for a time series analysis. The 250 m resolution had no effect on the acquiring vegetation data since each sampling point was on a specific pixel. The mean daily temperature data for the G50B were downloaded from https://app.climateengine.org/climateEngine/. The vegetation data were extracted at each sampling point on ArcMap 10.8, which covers the study period, and these values were averaged, to determine the monthly averages.

Table 4. 1 Location of sampling points and borehole depth

Name	Location	Latitude	Longitude	Borehole depth (m)	Zone	Elevation
BH 7	Moddervlei	-34.60561	19.79753	20	Riparian	<150
BH 8	Moddervlei	-34.60531	19.79741	8	Riparian	<150
BH 10	Spanjaardskloof	-34.52961	19.75252	20	Hillslope	>150
BH 12	Boskloof	-34.53485	19.8291	20	Hillslope	>150
BH 14	Uitsig	-34.58694	19.66944	20	Mountain	>200

4.2.3 Data analysis

The NDVI, groundwater depth, temperature and rainfall data underwent an exploratory data analysis. The Shapiro-wilk test for normality revealed that all four variables were parametric. Therefore, the Bayesian Pearson correlation and multiple linear regression were used to investigate the relationship between the NDVI and the three independent variables. The temporal trends in vegetation productivity and groundwater depth were evaluated by using the time series plot. A time series analysis is a statistical method that utilises past data within a certain period, to predict the future. It is comprised of an arrangement of data at equal intervals, and in this instance, the monthly interval was used. A time series analysis helps to determine the trends, seasonality, and heteroscedasticity. Further the gain/loss plot determined the monthly differences in the groundwater depth and NDVI from the monthly averages.

The Pearson coefficient correlation determines the strength of the linear relationship between the mean monthly depth of the groundwater and the mean monthly NDVI. The strength of the relationship between the two variables is determined by using the correlation coefficient (r^2). The results of the perfect negative and positive relationships are indicated by the values 1 and -1, respectively. The values between 1 and -1 describe the degree of linear independence between the variables. The r^2 value of zero indicates a non-linear relationship between the variables (Dodhia, 2005; Laar, 2018). In addition, the Bayes Factor (BF) summarizes the strength of the evidence in the study, which supports or goes against the null hypothesis. A multiple regression analysis was also used to determine the correlation and significance of the groundwater depth, temperature and rainfall effects on the NDVI.

4.3 Results

4.3.1 NDVI and groundwater depth trend during the study period

The groundwater depth was influenced by seasonality; the lower depths (min- 1.35) were associated with the wet season (May-Aug) and the higher depths (max- 2.67) were associated with the dry months. Figure 4.2a shows the time series plot of the mean groundwater depth and NDVI during the study period. The trend displayed an inverse relationship between the groundwater and NDVI. The average NDVI value was 0.59 and average groundwater depth was 2.06 m during the study period. Figure 4.2b shows the monthly deviations from the average NDVI and average groundwater depth. With a few exceptions, there was a clear trend, where an increase in the groundwater depth is associated with a decrease in NDVI in the riparian environment (Figure 4.2b).

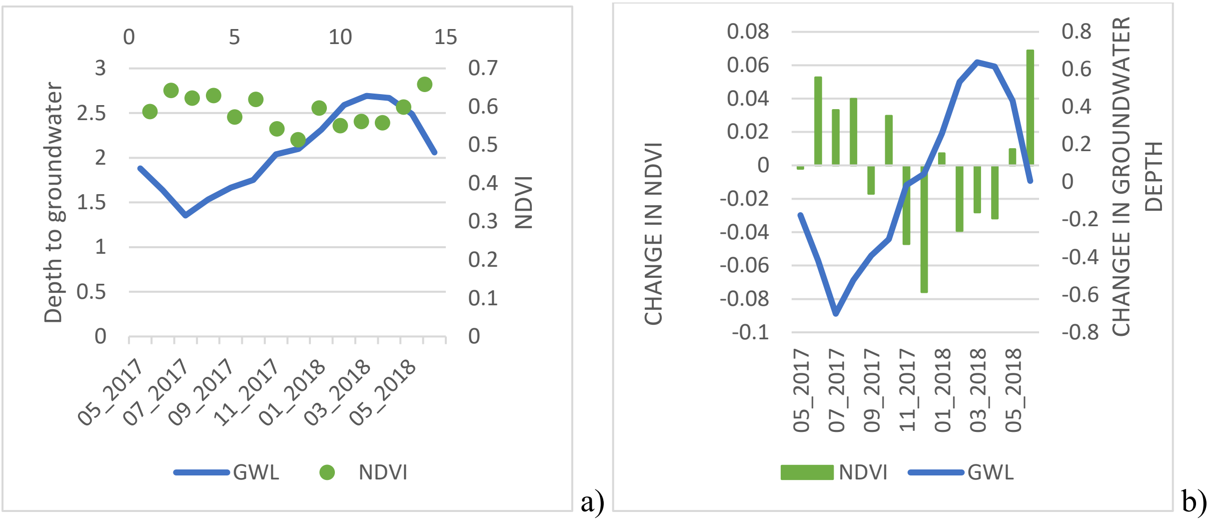
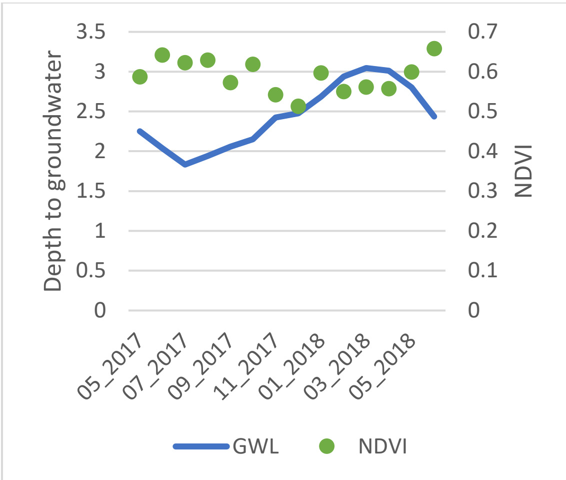
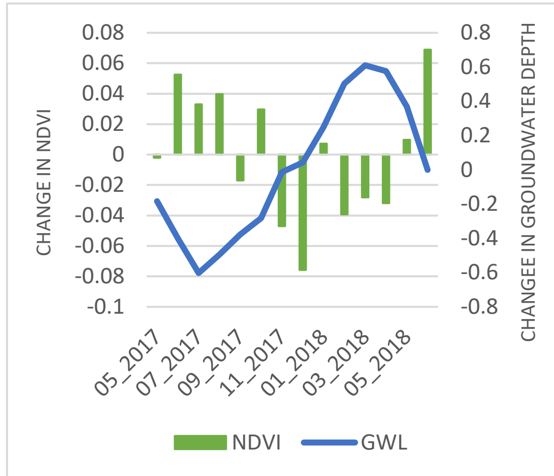


Figure 4. 2 a) Monthly time series of groundwater depth and vegetation greenness for the study period for vegetation around Bh7; and b) Groundwater depth and NDVI deviation from their annual average for vegetation around Bh7. The 0-line is the mean NDVI and groundwater depth throughout the study period

Bh8 is a deeper shallow borehole within the riparian zone. Figures 4.3a and b describe the relationship between the mean groundwater depth and vegetation productivity. The time series plot of the mean groundwater depth and the NDVI revealed that the annual trend of the NDVI increased with a decrease in the groundwater depth. Groundwater levels peaked at 1.8 m in July and were the deepest, at 3.05 m, in March. The NDVI also followed a similar trend, with high values (0.64) in June/July and low values (0.5) in Jan/Feb. The groundwater variability followed a similar trend as in Bh7; however, it had a slightly deeper groundwater level. Figure 4.3b shows the NDVI and groundwater depth deviations from their annual average. The NDVI trends followed the same pattern as those around Bh7, as they fall on the same pixel. However, the groundwater table peak was 0.10 m lower than Bh7 during the 2017 wet season.



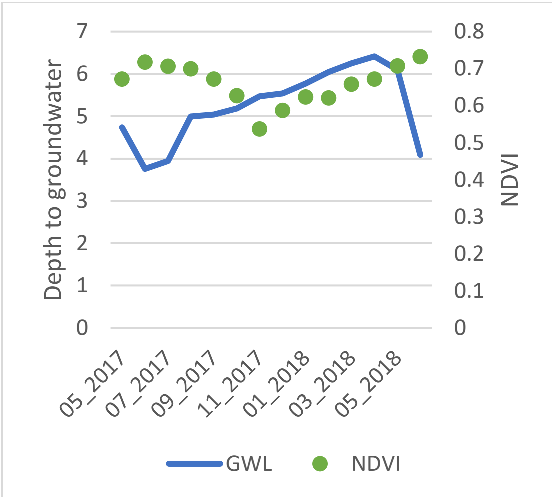
a)



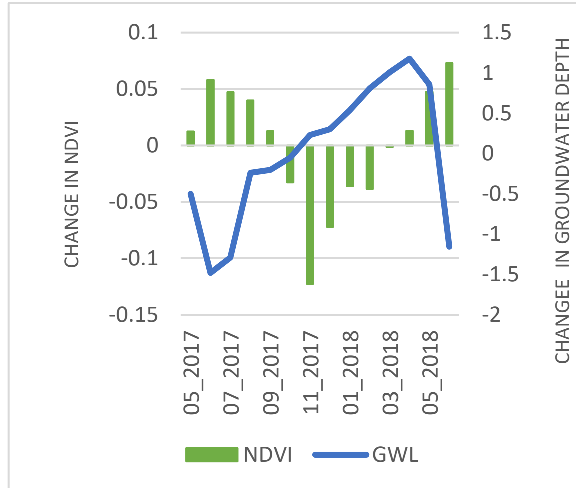
b)

Figure 4. 3 a) Monthly time series of groundwater depth and vegetation greenness for the study period for vegetation around Bh8; and b) Groundwater depth and NDVI deviation from their annual average for vegetation around Bh8. The 0-line is the mean NDVI and groundwater depth throughout the study period

The NDVI is affected by seasonality, with it peaking at 0.72 in the wet season and then plummeting to 0.54 during the dry months (Figure 4.4a). The groundwater depth increases steadily throughout the study period, with low groundwater depths (3.76 and 3.95) in the wet months Jun/July. During the 2017 wet season, the NDVI values are associated with a lower groundwater depth; however, during the dry season, the NDVI increases with the groundwater depth, until the beginning of the wet season 2018. This suggests that there is a strong relationship between NDVI and groundwater depth during the wet period. Figure 4.4b displays the seasonal differences from the mean NDVI (0.66) and groundwater depth (5.24 m). The increased NDVI range (0.01-0.06) in the wet months of 2017 was associated with a 0.1 m increase in the water table.



a)



b)

Figure 4. 4 a) Monthly time series of groundwater depth and vegetation greenness for the study period for vegetation around Bh10; and b) Groundwater depth and NDVI deviation from their annual average for vegetation around Bh10. The 0-line is the mean NDVI and groundwater depth throughout the study period

The time series plot of the groundwater depth and NDVI is displayed in Figure 4.5a. The depths to the groundwater were the lowest in the Aug/Sept (9.26) months and gradually increased, until they plummeted to 11.47 m in the next dry season. The NDVI values changed with the seasons, with high values (0.67) in the wet months of May-Sept, which then decreased during the early dry season to 0.55 in the mid-dry season and picked up again from autumn (Fig. 4.5a). The average groundwater depth (9.94 m) and NDVI (0.62) are displayed in Figure 4.5b. The groundwater depth deviation ranged from -0.70 to 1.53 m, and the inverse relationship with the NDVI was pronounced during the 2017 wet season.

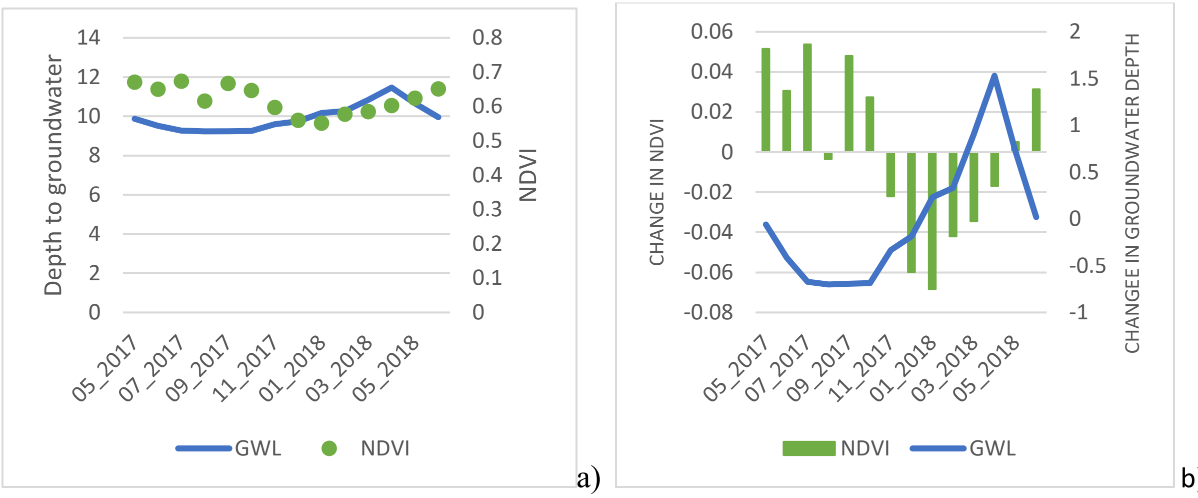


Figure 4. 5 a) Monthly time series of groundwater depth and vegetation greenness for the study period for vegetation around Bh12; and b) Groundwater depth and NDVI deviation from their annual average for vegetation around Bh12. The 0-line is the mean NDVI and groundwater depth throughout the study period

The time series plot of the monthly mean groundwater depth and NDVI are displayed in Figure 4.6a. The depth to the groundwater was the lowest in July (0.72) and decreased during spring, to a low (0.45) in the dry season. The groundwater levels increased from the mid-dry season to the next wet season. The seasonal variability in the groundwater depth was pronounced in this area. This is evidenced by the shallow depth (2.34) in the wet season and the deep-water table (5.12) at the end of the dry season (Fig. 4.6a). The average groundwater depth (3.50 m) and NDVI (0.57) are displayed in Fig. 4.6b. The differences between the mean NDVI and groundwater depth emphasised the seasonal inverse relationship between the two variables. The groundwater depth deviation ranged from -1.46 to 1.63, and 0.15 to -0.12, from the wet to the dry seasons.

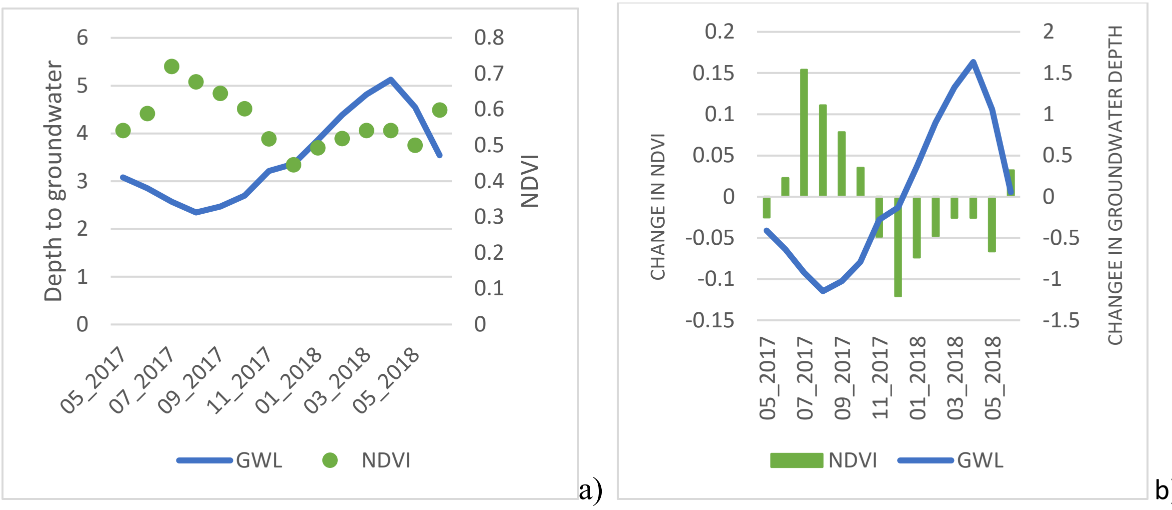


Figure 4. 6 a) Monthly time series of groundwater depth and vegetation greenness for the study period for vegetation around Bh14; and b) Groundwater depth and NDVI deviation from their annual average for vegetation around Bh14. The 0-line is the mean NDVI and groundwater depth throughout the study period

4.3.2 Quantitative relation between groundwater and NDVI

The relationship between the vegetation and the groundwater depth were quantified by using the Bayesian Pearson correlation. The vegetation and groundwater depth correlation were tested for immediate and lagged interactions, and the results are summarised in Table 4.2. The productivity of the riparian vegetation has a negative moderate (r^2 = -0.51) correlation with groundwater depth, which increases (r^2 = -0.65) with the lagged vegetation response. The hillslope vegetation indicated a weaker immediate correlation to the groundwater depth, when compared to the riparian vegetation. However, the NDVI of the hillslope vegetation found in the vicinity of Bh14 suggests that there is a strong relationship between the two variables. The Bayes Factor (BF) summarises the strength of evidence for the association between the NDVI and groundwater depth, and it (BF<1) indicates anecdotal evidence that supports the null hypothesis. Therefore, there is no significant evidence to accept or reject that there is a correlation between groundwater depth and vegetation productivity.

Table 4. 2 Summary of the Bayesian correlation for the groundwater depth and NDVI

	0-month lag		1-month lag	
	R square	Bayes Factor	R square	Bayes Factor
Bh7	-0.51	0.89	-0.65	0.27
Bh8	-0.51	0.85	-0.65	0.28
Bh10	-0.47	1.15	-0.54	0.76
Bh12	-0.45	1.37	-0.70	0.19
Bh14	-0.62	0.31	-0.71	0.17

4.3.3 Mean temperatures and monthly mean rainfall for the study period

The mean daily temperatures within the G50B catchment are affected by seasonality (Figure 4.7). The temperatures begin to decrease (May-Sep) and then intensify in the spring/summer months (Oct-Mar) and decrease again in May. A minimum mean temperature was experienced in winter, July 2017 (12.38°C) and it peaked in January 2018 (20.99°C). The mean monthly temperature is 16.42 for the study period, with a standard deviation of 0.80.

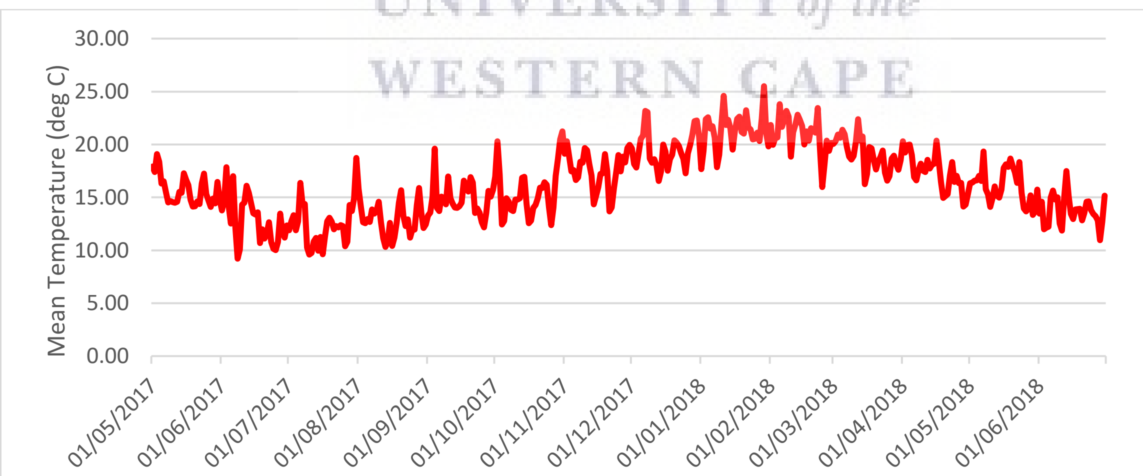


Figure 4. 7 Mean daily temperature for the study period

The average monthly rainfall figures are compared in Figure 4.8. The average rainfall for the four sites was 34.61 mm, 38.96 mm, 37.41 mm, 36.37 mm for Bh7, Bh8, Bh10, Bh12 and Bh14, respectively. Bh7 and Bh8 are in the same rainfall area. Figure 4.8 demonstrates that December 2017 was the driest month, with an average rainfall of 10.49 mm, and that June 2018 was the wettest month, with 85.83 mm. The riparian sites received slightly lower rainfall than the hillslope sites, with the areas around Bh10 receiving the most rainfall. The rainfall trend shows that most months received rainfall below the average of 50 mm, which indicates that this was a period of low precipitation (Fig. 4.8). The Coefficient of Variation (CV) was used to measure the variability of the rainfall for the period, and the areas displayed a moderate average rainfall variability (56.46%).

Figure 4. 8 Mean monthly rainfall for the four study sites within the G60B catchment

4.3.4 Quantitative relation between NDVI with groundwater depth, rainfall and temperature

A multiple regression analysis was computed to demonstrate the impacts of rainfall, groundwater depth and temperature on the vegetation productivity of riparian and hillslope vegetation. The results indicate that 63.1% of the NDVI variability was determined by the three variables. For the hillslope area, rainfall, groundwater depth and temperature account for 67.1% of the NDVI variability, while the vegetation around Bh12 was significantly influenced by these variables. This is indicated by the r square values in Table 4.3. The three variables (groundwater depth, rainfall, and temperature) had a significant influence ($p<0.05$) on riparian and hillslope vegetation productivity, which may not be true for the vegetation around Bh10 ($p>0.05$).

Table 4. 3 Multiple Regression model summary

		Test for sign. Dif.	R square
Riparian	Bh7	0.02	0.63
	Bh8	0.02	0.63
Hillslope	Bh10	0.06	0.50
	Bh12	0.00	0.75
	Bh14	0.01	0.67

The unstandardised coefficients and p-values, as summarised in Table 4.4, indicate the contributing factors of rainfall, groundwater depth and temperature on the monthly NDVI variability. In the riparian region, the NDVI has no significant relationship with the three variables ($p>0.05$). However, the relationship is stronger with the rainfall, followed by the temperature, but it is limited with the groundwater depth. The hillslope area revealed a weak relationship between NDVI and the three variables; however, the vegetation around Bh12 and 14 displayed a significant relationship between the NDVI and temperature ($p<0.05$). Rainfall plays a more significant role in NDVI for the vegetation around Bh10 and Bh12, while the vegetation close to Bh14 is influenced more by the groundwater depth than by the rainfall.

Table 4. 4 The correlation and level of significance of the relationship of the NDVI with rainfall, groundwater depth and temperature

		Rainfall		GWL		Temp	
	Site	coefficients	p-value	coefficients	p-value	coefficients	p-value
Riparian	Bh7	0.00	0.14	-0.00	0.95	-0.01	0.24
	Bh8	0.00	0.14	-0.00	0.90	-0.01	0.25
Hillslope	Bh10	0.00	0.47	0.02	0.54	-0.01	0.07
	Bh12	0.00	0.42	0.00	0.96	-0.01	0.00
	Bh14	0.00	0.97	-0.02	0.45	-0.02	0.04

4.4 Discussion

4.4.1 Relational trends between the groundwater depth and the NDVI

This study examined the spatial and temporal strength of the relationship between the groundwater depth and the NVDI. The results demonstrated a general pattern, showing that the groundwater levels increase during the onset of the wet season and decrease in the dry season. In the riparian area, the water table was shallow (<3 m), but it was slightly higher around Bh7 than around Bh8. Moreover, there was a stronger groundwater depth correlation with 1-month lag NDVI, compared to the 0-month NDVI. This suggests that the vegetation condition has a delayed response to groundwater variability within this area. No significant differences were observed between the vegetation responses within the riparian sites. The response of the vegetation to the groundwater dynamics is subtle; for example, the lowered water table may prevent seedling recruitment and photosynthetic activity, with little obvious impact in the short-term (le Maitre et al., 1999). The vegetation around Bh7 was slightly more sensitive to the groundwater depth variations, when compared to the vegetation close to Bh8. Because the two sites fell on the same pixel, contrasting the riparian NDVI-depth to groundwater relationship was compromised.

The riparian area is dominated by invasive acacia species, such as *Acacia longifolia* and *Acacia Saligna* (le Maitre et al., 2000). *Acacia longifolia* (long-leafed wattle) were introduced in South Africa in 1864 and are evergreen shrubs with yellow flowers that sprout from August to October (Mkunyana et al., 2019; Richardson et al., 2004). Endemic vegetation, such as *Ornithogalum thysoids*, *Restionaceae* and *Kiggelaria Africana*, are present. The hillslopes have also been invaded by *A. Longifolia*, *A. Saligna,* and *P. pinaster,* as well as the native vegetation *helichrysum petiolare* and *diospyros glabria* species. Invasive species that are found in the hillslope environment have smaller and shorter stems than those found in riparian environments (Dzikiti et al., 2013; le Maitre et al., 2000; Mazvimavi, 2018; Mkunyana et al., 2019). The hillslope water table is deeper than the riparian water table, namely <7 m, <12 m and <6 m for Bh10, Bh12 and Bh14, respectively. Therefore, the NDVI relates variably with the groundwater depth in the hillslope environment. The relationship between the groundwater table and the NDVI increased from Bh10, Bh14 to Bh12, as indicated by the high negative r^2-values. These findings corroborate those of Martinetti et al. (2021), where vegetation from the deep groundwater table (Bh12) was more sensitive to the groundwater level dynamics, compared to the riparian vegetation. The correlation coefficients for the groundwater depth and NDVI indicated a moderate association. Moreover, the Bayes Factors (-1> BF<1) showed that there is no strong evidence to reject/accept there is any correlation between the NDVI and depth to the groundwater.

4.4.2 Relational trends between NDVI, groundwater depth, rainfall, and temperature

A multiple regression analysis was carried out to understand the influence of the groundwater depth, rainfall, and temperature on the vegetation productivity. The results indicate that vegetation productivity was strongly linked to the three variables ($p<0.05$), compared to the water table ($p>0.05$). Climate factors play an important role in the dynamics of vegetation productivity (Dlikilili, 2019; Graw et al., 2017; Martinetti et al., 2021; Yang et al., 2012; W. Zhang et al., 2020).The variables had a significant impact on the NDVI for both the riparian and hillslope vegetation ($p<0.05$), except for the hillslope area around Bh10. The results also demonstrated that temperature plays a significant role in vegetation productivity, compared to the other variables for the hillslope environments (Bh12 and Bh14). Rainfall plays an important role in riparian vegetation productivity; however, it is not statistically significant. These results are in accordance with the findings of Dlikilili (2019), who indicated that vegetation productivity in the Touws River Catchment in South Africa had a stronger relationship with temperature than with rainfall. Furthermore, Mkunyana et al. (2019) examined the water use of riparian and hillslope invasive species at the study site, and their findings indicated that temperature and wind speed are important factors that influence the transpiration rate. They also observed a close link between water use and the soil moisture content of the vegetation. During the dry summer months, soil moisture is high in the riparian areas, compared to the dry hillslopes. Moreover, Mkunyana et al. (2019) found that a decrease in soil moisture resulted in reduced water use, which is contrary to the belief that the vegetation would tap into the groundwater. Despite the drought period and seasonal dynamics in vegetation productivity, the NDVI values remained high in both the riparian and hillslope sites. While the riparian vegetation may have water available from moisture in the soil, the hillslope vegetation is physiologically adapted to survive dry periods, based on its height and stem size (Koirala et al., 2017; Mkunyana et al., 2019; Rodriguez-Iturbe and Porporato, 2005; Scott and le Maitre, 1998). For example, Koirala et al. (2017) determined the relationship between gross primary productivity of the vegetation and the groundwater depth. Their results indicated that the vegetation characteristics are more closely linked to soil moisture than to differences in the climate and surface variables. This suggests that vegetation productivity may be influenced by other factors that have not been included in this study. Therefore, more information can be gained from assessing additional factors on vegetation productivity. It is expected that temperatures in Africa will increase by 3-6°C, by the end of the century. This means that southern Africa will experience a sharp increase in temperatures and frequent drought events (IPCC, 2014). Excluding the pressures of groundwater abstraction and incompatible land use and land cover, such as the proliferation of invasive species, this will result in a lower NDVI for endemic vegetation (Sommer et al., 2016). Therefore, this study demonstrates the capabilities of remote sensing data for determining the response of vegetation to variabilities in the groundwater table, and more specifically, for acquiring baseline data in data-scarce areas. This will be useful for ecological resources management, planning and vulnerability assessments, and it is in line with SDG Goal 15, which aims to protect, restore, and promote the sustainable use of terrestrial ecosystems.

4.5 Limitations and recommendations

In this chapter, remote sensing data were utilised to quantify the influence of the groundwater depth, rainfall, and temperature on vegetation productivity. MODIS-NDVI, with a 250 m spatial resolution, could accurately quantify the vegetation dynamics between riparian and hillslope environments. However, the riparian sample sites fell within the same pixel, thus compromising the vegetation dynamics. It is therefore recommended that the potential of moderate-resolution satellite datasets (Sentinel 2A and Landsat 8 OLI) be explored for investigating the response of the vegetation to groundwater variability at a community level. Furthermore, the area displays a heterogeneity, in terms of its species composition, such as invasive and endemic vegetation, and the use of Unmanned Aerial Vehicles (AUVs) and hyperspectral satellite datasets could provide species-specific responses to the groundwater dynamics. This study examined the relationship between vegetation productivity and the three dependent variables over a period of 13 months, by using the available groundwater level data. The phenological trends may vary slightly from year to year; therefore, a more comprehensive understanding of groundwater depth-vegetation interaction could be gained from long-term studies. Finally, it should be noted that the results presented in this paper represent the aggregates for a 16-day MODIS-NDVI, and therefore, the vegetation dynamics possess substantial uncertainties; however, the methodology was impartial.

4.6 Conclusion

Multispectral remote sensing data were used to determine the response of vegetation to the variability in the groundwater level in a Mediterranean climate region. The impact of climate variables was also investigated. The depth to groundwater is affected by seasonality given that during dry periods groundwater resources are limited and this has an impact on vegetation health. Therefore, water resource managers and biodiversity conservationists should ensure the sustainable use of groundwater resources during these periods. Further, hillslopes are invaded by alien species which uses both surface water and groundwater resources. This emphasises the need for invasive plant clearing to conserve water. Overall, the study revealed the power of remote sensing as an efficient preliminary investigation tool into hydrological and ecological interactions, which is critical for sustainable water resource management. Significant information can be obtained when we compare the vegetation-groundwater depth dynamics of the normal and dry periods. Therefore, it is recommended that a long-term study be conducted, and that moderate and hyperspectral remote sensing data be used to determine the vegetation dynamics, in response to groundwater variability. This is critical for catchments such as the Heuningnes Catchment, which has heterogeneous vegetation of both invasive and endemic species.

CHAPTER FIVE

Multispectral remote sensing of vegetation responses to groundwater variability in the Greater Floristic Region of the Western Cape, South Africa: Synthesis

5.1 Summary of the Study Findings

This study aimed to assess the spatial distribution of groundwater dependent vegetation and their responses to groundwater variability within the Heuningnes Catchment. The specific objectives were to determine the spatial distribution of GDV, characterise the dominant vegetation within the catchment and assess riparian and hill-slope vegetation responses to groundwater variability to achieve the study aim. The following finding were obtained:

First, an extensive literature review was conducted to provide the background on GDV and the current state of knowledge. The progress of GIS and remote sensing techniques for GDV mapping and monitoring was also assessed. Groundwater resources are rapidly deteriorating because of global change and increased reliance on groundwater (Kløve et al., 2014; Morsy et al., 2017; Richards et al., 1975). Water scarcity threatens vegetation health and productivity, which induces several vegetation responses such as reduced photosynthetic rates, plant productivity, change in species composition and abundance. The study has showed that sustainable groundwater resource development with limited consideration of ecological impacts has become a concern. Therefore, research on GDV has increased over the past twenty years (Chiloane et al., 2021; Davies et al., 2016; Kløve et al., 2011; Morsy et al., 2017; Hoyos et al., 2016). GIS and remote sensing techniques have emerged as popular methods for GDV mapping and monitoring because of their efficiency, unique spatial, spectral, and temporal characteristics that allow GDV assessments at multiple scales. GDV assessments have used MODIS and the Landsat series datasets extensively, because of the large historical archive, which is suitable for long-term studies (Barron et al., 2014; Doody et al., 2017; Glanville et al., 2016a; Münch and Conrad, 2007). New generation sensors such as Landsat 8 OLI and Sentinel 2A with improved temporal and spatial resolutions and Machine Learning Algorithms have the potential to improve the identification and monitoring of GDV. However, there is still a need to assess the potential for the new remote sensing techniques.

Secondly, Sentinel 2A and Landsat 8 OLI derived potential GDV distribution models based on SAVI and NDVI were compared. GDV distribution was determined, based on the assumption that vegetation, which remains green during dry periods, on gentle slopes (<3%), surface depressions and are naturally occurring, are likely to be groundwater dependent potential. The study determined that ~ 3% of the area was suitable for GDV, and their distribution was dense in the north-western regions and sporadic in the south-eastern regions of the catchment. Vegetation within the Heuningnes Catchment is heterogeneous with both endemic and invasive plant species. Therefore, invasive, and endemic vegetation competes for groundwater resources. The study demonstrates that moderate resolution satellite data has a high potential for mapping the potential distribution of GDV with high overall accuracies > 90%. Moreover, S2(SAVI) model outperformed the other models, a result of the differences in sensor spatial resolution and the enhanced ability for the SAVI to discriminate healthy vegetation from soil.

Lastly, an assessment of vegetation responses to groundwater variability during the drought period from June 2017 to July 2018 was done. The time series and gain/loss plots were used to assess the temporal dynamics of depth to groundwater and NDVI. The results showed that groundwater dynamics are influenced by seasonality, which induces a response to NDVI. Groundwater depth-vegetation interactions are more pronounced during the wet season and hillslope vegetation is more sensitive to groundwater variability than to riparian vegetation. The strength of NDVI and depth to groundwater associations was evaluated using the Bayesian Pearson Correlation. Further, results show a moderate to low negative association; however, the lagged vegetation response to groundwater depth reveals a stronger negative correlation. Move over, the Bayes Factor (-1 > BF < 1) shows there is no firm evidence to accept/ reject the hypothesis that there is a correlation between groundwater depth and NDVI within the study sites. A multiple regression was computed to determine the impact of groundwater depth, rainfall, and temperature on vegetation. The results showed no significant impact of the three variables on NDVI in riparian environments. However, temperature had a significant negative impact on NDVI for hillslope vegetation. Rainfall plays an important role in riparian NDVI, while hillslope NDVI is more sensitive to groundwater variability.

5.2 Conclusions

- The study predicted that GDV occupies ~3% of the Heuningnes Catchment, however, that is reliant on the predictor variables used. Groundwater dependent vegetation communities are unevenly distributed within the catchment. They occur densely in the north-western regions and distributed sporadically in the south and eastern regions of the catchment.
- Sentinel 2 and Landsat 8 performed well for detecting the spatial distribution of GDV. However, S2 has improved detection capabilities with a less overestimation of GDV than L8 data. The higher spectral and spatial resolution of S2 reduces the generalization of features as compared to L8. Moreover, L8 has an extensive archive of earth observation data than S2 and can play a complementary role.
- Dominant vegetation within this area is both endermic and invasive plants. These included; *Acacia pycnatha, Poacea (grasses), Acacia longifolia, Acacia saligna, Helichrysum petiolare, Restionaceae, Ornithogalum thrrsoids, Diospyros glabra* and *Pinus pinaster*. The proliferation of invasive species is a challenge in this area. Therefore, the results emphasize the need for invasive species eradication as they compete with endemic vegetation for groundwater resources.
- MODIS-NDVI provides accurate data for assessing the spatio-temporal dynamics of vegetation health. Showing that satellite derived indices provide valuable information for monitoring vegetation-groundwater interactions.
- Vegetation responses are likely lagged within this area. However, NDVI values remained relatively high during the study period. This is attributed to the physiological characteristics of the vegetation and the nature of MODIS-NDVI to be saturated.
- Temperature was a significant contributor factor on NDVI for hillslope vegetation, therefore there is a need to investigate the long-term effects of climate on GDV.
- Overall, the findings of the study provide valuable baseline data for determining groundwater restrictions that ensure the sustainability of groundwater dependent vegetation and highlight the significance of remote sensing data for assessing and routine monitoring of GDV.

5.3 Recommendations

- There is a need to assess GDV long-term responses to groundwater and climate dynamics at species level.
- Although the study demonstrated the capabilities of moderate resolution data for detecting and monitoring GDV over space and time, their performance is limited in heterogenous vegetation communities. Therefore, hyperspectral remote sensors, such as Sentinel 1, Worldview 2 and AUVs with unique sensing characteristics, require consideration.
- Groundwater dependent vegetation detection and monitoring can be improved by integrating robust machine learning algorithms and cloud computing platforms, such as Google Earth Engine (GEE).
- There is a need to incorporate ecologically meaningful remotely sensed variables for detecting the potential distribution of GDV.

References

Adams, M., Smith, P.L., Yang, X., 2015. Assessing the effects of groundwater extraction on coastal groundwater-dependent ecosystems using satellite imagery. Mar. Freshw. Res. https://doi.org/10.1071/MF14010. Available at: https://www.publish.csiro.au/mf/MF14010

Albano, C.M., Mcgwire, K.C., Hausner, M.B., Mcevoy, D.J., Morton, C.G., Huntington, J.L., 2020. Drought sensitivity and trends of riparian vegetation vigor in Nevada, USA (1985-2018). Remote Sens. 12, 1–26. https://doi.org/10.3390/RS12091362. Available at: https://www.mdpi.com/700714

Ali, S., Alandjani, G., 2019. Mapping Land Cover Damages in Mega Floods through Integration of Remote Sensing and GIS Techniques. 3C Tecnol. innovación Apl. a la pyme 8, 258–275. https://doi.org/10.17993/3ctecno.2019.specialissue2.258-275. Available at: http://ojs.3ciencias.com/index.php/3c-tecnologia/article/view/779

Allsopp, N., Slingsby, J.A., Esler, K.J., 2019. Identifying research questions for the conservation of the Cape Floristic Region. S. Afr. J. Sci. 115, 1–8. https://doi.org/10.17159/sajs.2019/5889. Available at: http://www.scielo.org.za/scielo.php?pid=S0038-23532019000500017&script=sci_arttext&tlng=es.

Anderson, W.P., Emanuel, R.E., 2008. Effect of interannual and interdecadal climate oscillations on groundwater in North Carolina. Geophys. Res. Lett. 35, 1–4. https://doi.org/10.1029/2008GL036054. Available at: https://agupubs.onlinelibrary.wiley.com/doi/abs/10.1029/2008GL036054

Antunes, C., Chozas, S., West, J., Zunzunegui, M., Diaz Barradas, M.C., Vieira, S., Máguas, C., 2018. Groundwater drawdown drives ecophysiological adjustments of woody vegetation in a semi-arid coastal ecosystem. Glob. Chang. Biol. 24, 4894–4908. https://doi.org/10.1111/gcb.14403. Available at: https://onlinelibrary.wiley.com/doi/abs/10.1111/gcb.14403

Barron, O., Froend, R., Hodgson, G., Ali, R., Dawes, W., Davies, P., Mcfarlane, D., 2014. Projected risks to groundwater-dependent terrestrial vegetation caused by changing climate and groundwater abstraction in the Central Perth Basin, Western Australia. Hydrol. Process. 28, 5513–5529. https://doi.org/10.1002/hyp.10014. Available at: https://www.sciencedirect.com/science/article/pii/S0022169412001412.

Barron, O., Silberstein, R., Ali, R., Donohue, R., McFarlane, D.J., Davies, P., Hodgson, G., Smart, N., Donn, M., 2012. Climate change effects on water-dependent ecosystems in south-western Australia. J. Hydrol. 434–435, 95–109. https://doi.org/10.1016/j.jhydrol.2012.02.028. Available at: https://onlinelibrary.wiley.com/doi/abs/10.1002/hyp.10014.

Barron, O. V., Emelyanova, I., Van Niel, T.G., Pollock, D., Hodgson, G., 2014. Mapping groundwater-dependent ecosystems using remote sensing measures of vegetation and moisture dynamics. Hydrol. Process. 28, 372–385. https://doi.org/10.1002/hyp.9609. Available at: https://onlinelibrary.wiley.com/doi/abs/10.1002/hyp.9609.

Bertrand, G., Goldscheider, N., Gobat, J.M., Hunkeler, D., 2012. Review: From multi-scale conceptualization to a classification system for inland groundwater-dependent ecosystems. Hydrogeol. J. 20, 5–25. https://doi.org/10.1007/s10040-011-0791-5. Available at: https://link.springer.com/article/10.1007/s10040-011-0791-5.

Bhatt, D., Kundu, A., Mall, R., Raju, K.P., 2020. Dynamics of Vegetation Response to Seasonal

Rainfall in the Gomati River Basin (India) using Earth Observation Data Sets. J. Sci. Res. 64, 20–31. https://doi.org/10.37398/jsr.2020.640103. Available at: http://www.mceccr.in/document/2020/10.pdf.

Blevins, E. and Aldous, A. (2011) 'Biodiversity Value of Groundwater-dependent Ecosystems', Methods, (June), pp. 18–24. Available at: https://www.conservationgateway.org/ConservationByGeography/NorthAmerica/UnitedStates/oregon/freshwater/Documents/GW_Blevins%20and%20Aldous_2011_WSP.pdf

Bojinski, S., Verstraete, M., Peterson, T.C., Richter, C., Simmons, A., Zemp, M., 2014. The concept of essential climate variables in support of climate research, applications, and policy. Bull. Am. Meteorol. Soc. 95, 1431–1443. https://doi.org/10.1175/BAMS-D-13-00047.1

Boulton, A.J., Hancock, P.J., 2006. Rivers as groundwater-dependent ecosystems: A review of degrees of dependency, riverine processes and management implications. Aust. J. Bot. 54, 133–144. https://doi.org/10.1071/BT05074.

Bowman, D.M.J.S., 2000. Rainforests and Flame Forests: the Great Australian Forest Dichotomy. Aust. Geogr. Stud. 38, 327–331. https://doi.org/10.1111/1467-8470.00120

Brodie, R.S., Green, R., Graham, M., 2002. Mapping groundwater-dependent ecosystems: A case study in the fractured basalt aquifers of the Alstonville Plateau, New South Wales, Australia, in: Balancing the Groundwater Budget. Available at: https://citeseerx.ist.psu.edu/viewdoc/download?doi=10.1.1.498.3208&rep=rep1&type=pdf

Cartwright, I., Weaver, T., Cendón, D.I., Swane, I., 2010. Environmental isotopes as indicators of inter-aquifer mixing, Wimmera region, Murray Basin, Southeast Australia. Chem. Geol. 277, 214–226. https://doi.org/10.1016/j.chemgeo.2010.08.002

Cernusak, L.A., Haverd, V., Brendel, O., Le Thiec, D., Guehl, J.M., Cuntz, M., 2019. Robust Response of Terrestrial Plants to Rising CO2. Trends Plant Sci. 24, 578–586. https://doi.org/10.1016/j.tplants.2019.04.003

Chambers, J., Nugent, G., Sommer, B., Speldewinde, P., Neville, S., Beatty, S., Chilcott, S., Eberhard, S., Mitchell N, D'Souza, F., Barron, O., McFarlane, D., Braimbridge, M., Robson, B., Close, P., Morgan, D., Pinder, A., Froend, R., Horwitz, P., Davies, P., 2013. Adapting to climate change: a risk assessment and decision making framework for managing groundwater dependent ecosystems with declining water levels: Development and Case Studies. Final Report. Available at: https://researchrepository.murdoch.edu.au/id/eprint/22283/

Chapman, J.B., Lewis, B., Litus, G., 2003. Chemical and isotopic evaluation of water sources to the fens of South Park, Colorado. Environ. Geol. 43, 533–545. https://doi.org/10.1007/s00254-002-0678-9.

Chávez, R., Clevers, J.G.P.W., 2012. Object-based analysis of 8-bands WorldView2 imagery for assessing health condition of desert trees. CGI Rep. 2012-001 15.

Colvin, C., Le Maitre, D., Hughes, S., 2003. Assessing terrestrial groundwater dependent ecosystems in South Africa, Water Research Commission. Available at: http://www.wrc.org.za/wp-content/uploads/mdocs/1090-2-2-031.pdf

Colvin, C., Maitre, D. Le, Saayman, I., Hughes, S., 2007. An Introduction to Aquifer Dependent Ecosystems in South Africa. Natural Resources and the Environment, Water Research.

Cooper, M., 2010. Advanced Bash-Scripting Guide An in-depth exploration of the art of shell scripting Table of Contents.5.3(1), 2267–2274. https://doi.org/10.1002/hyp.

Costanza, R., de Groot, R., Sutton, P., van der Ploeg, S., Anderson, S.J., Kubiszewski, I., Farber, S., Turner, R.K., 2014. Changes in the global value of ecosystem services. Glob. Environ. Chang. 26, 152–158. https://doi.org/10.1016/j.gloenvcha.2014.04.002

Currie, B., Milton, S.J., Steenkamp, J.C., 2009. Cost-benefit analysis of alien vegetation clearing for water yield and tourism in a mountain catchment in the Western Cape of South Africa. Ecol. Econ. 68, 2574–2579. https://doi.org/10.1016/j.ecolecon.2009.04.007. Available at: https://www.sciencedirect.com/science/article/pii/S0921800909001359

Davies, T., Everard, M., Horswell, M., 2016. Community-based groundwater and ecosystem restoration in semi-arid north Rajasthan (3): Evidence from remote sensing. Ecosyst. Serv. 21, 20–30. https://doi.org/10.1016/j.ecoser.2016.07.007. Available at: https://www.sciencedirect.com/science/article/pii/S2212041616301681

de Klerk, A.R., de Klerk, L.P., Chamier, J., Wepener, V., 2012. Seasonal variations of water and sediment quality parameters in endorheic reed pans on the Mpumalanga Highveld. Water SA 38, 663–672. https://doi.org/10.4314/wsa.v38i5.3.

DeFries, R., Bounoua, L., 2004. Consequences of land use change for ecosystem services: A future unlike the past. GeoJournal 61(4), 345–351. https://doi.org/10.1007/s10708-004-5051-y.

Dlikilili, S., 2019. Investigating the Groundwater Dependence and Response To Rainfall Variability of Vegetation in the Touws River and Catchment Using. University of the Western Cape. Available at: https://etd.uwc.ac.za/handle/11394/6955

Dodhia, R.M., 2005. A Review of Applied Multiple Regression/Correlation Analysis for the Behavioral Sciences (3rd ed.) . J. Educ. Behav. Stat. 30(2), 227–229. https://doi.org/10.3102/10769986030002227. Available at: https://journals.sagepub.com/doi/pdf/10.3102/10769986030002227

Doody, T.M., Barron, O. V., Dowsley, K., Emelyanova, I., Fawcett, J., Overton, I.C., Pritchard, J.L., Van Dijk, A.I.J.M., Warren, G., 2017. Continental mapping of groundwater dependent ecosystems: A methodological framework to integrate diverse data and expert opinion. J. Hydrol. Reg. Stud. 10(2017), 61–81. https://doi.org/10.1016/j.ejrh.2017.01.003. Available at: https://www.sciencedirect.com/science/article/pii/S2214581817300319

Dresel, P.E., Clark, R., Cheng, X., Reid, M., Terry, A., Fawcett, J., Cochrane, D., 2010a. Mapping Terrestrial Groundwater Dependent Ecosystems : Method Development and Example Output. Available at: https://www.researchgate.net/profile/P-Dresel/publication/266023005_Mapping_Terrestrial_Groundwater_Dependent_Ecosystems_Method_Development_and_Example_Output/links/55ee585908ae199d47bef355/Mapping-Terrestrial-Groundwater-Dependent-Ecosystems-Method-Development-and-Example-Output.pdf

Dresel, P.E., Clark, R., Cheng, X., Reid, M., Terry, A., Fawcett, J., Cochrane, D., 2010b. Mapping Terrestrial Groundwater Dependent Ecosystems : Method Development and Example Output. Victoria Department of Primary Industries, Melbourne. Available at: https://www.researchgate.net/profile/P-Dresel/publication/266023005_Mapping_Terrestrial_Groundwater_Dependent_Ecosystems_Method_Development_and_Example_Output/links/55ee585908ae199d47bef355/Mapping-Terrestrial-Groundwater-Dependent-Ecosystems-Method-Development-and-Example-Output.pdf

Dube, T., Mutanga, O., Shoko, C., Samuel, A., BangiraTsitsi, 2016. Remote sensing of aboveground forest biomass: A review. Trop. Ecol. *57*(2), pp.125-132. Available at: https://tropecol.com/pdf/open/PDF_57_2/1%20Timothy%20et%20al..pdf.

Dube, T., Pandit, S., Shoko, C., Ramoelo, A., Mazvimavi, D., Dalu, T., 2019. Numerical assessments of leaf area index in tropical savanna rangelands, South Africa using Landsat 8 OLI derived metrics and in-situ measurements. Remote Sens. 11(7). 829-843.

https://doi.org/10.3390/rs11070829. Available from: https://www.mdpi.com/441344
Dzikiti, S., Schachtschneider, K., Naiken, V., Gush, M., Le Maitre, D., 2013. Comparison of water-use by alien invasive pine trees growing in riparian and non-riparian zones in the Western Cape Province, South Africa. For. Ecol. Manage. 293, 92–102. https://doi.org/10.1016/j.foreco.2013.01.003. Available at: https://www.sciencedirect.com/science/article/pii/S0378112713000285.
Eamus, D., 2009. Identifying groundwater dependent ecosystems A guide for land and water managers, Australian Government Land & Water Australia. Braddon.
Eamus, D., Froend, R., Loomes, R., Hose, G., Murray, B., 2006. A functional methodology for determining the groundwater regime needed to maintain the health of groundwater-dependent vegetation. Aust. J. Bot. 54(2), 97–114. https://doi.org/10.1071/BT05031. Available at: https://www.publish.csiro.au/bt/bt05031.
Eamus, D., Zolfaghar, S., Villalobos-Vega, R., Cleverly, J., Huete, A., 2015a. Groundwater-dependent ecosystems: recent insights, new techniques and an ecosystem-scale threshold response. Hydrol. Earth Syst. Sci. Discuss. 12(5), 4677–4754. https://doi.org/10.5194/hessd-12-4677-2015. Available at: https://hess.copernicus.org/preprints/12/4677/2015/hessd-12-4677-2015.pdf.
Eamus, D., Zolfaghar, S., Villalobos-Vega, R., Cleverly, J., Huete, A., 2015b. Groundwater-dependent ecosystems: Recent insights from satellite and field-based studies. Hydrol. Earth Syst. Sci. 19(10), 4229–4256. https://doi.org/10.5194/hess-19-4229-2015. Available at: https://hess.copernicus.org/articles/19/4229/2015/
Eamus, D.A., Froend, R.B., 2006. Groundwater-dependent ecosystems : the where , what and why of GDEs. Aust. J. Bot. 54(2), 91–96. Available at: https://www.academia.edu/download/53995873/_.pdf
Elmore, A.J., Manning, S.J., Mustard, J.F., Craine, J.M., 2006. Decline in alkali meadow vegetation cover in California: The effects of groundwater extraction and drought. J. Appl. Ecol. 43(4), 770–779. https://doi.org/10.1111/j.1365-2664.2006.01197.x. Available at: https://besjournals.onlinelibrary.wiley.com/doi/abs/10.1111/j.1365-2664.2006.01197.x
Emelyanova, I., Barron, O., Alaibakhsh, M., 2018a. A comparative evaluation of arid inflow-dependent vegetation maps derived from LANDSAT top-of-atmosphere and surface reflectances. Int. J. Remote Sens. 39(20), 6607–6630. https://doi.org/10.1080/01431161.2018.1463114. Available at: https://www.tandfonline.com/doi/abs/10.1080/01431161.2018.1463114
Emelyanova, I., Barron, O., Alaibakhsh, M., 2018b. A comparative evaluation of arid inflow-dependent vegetation maps derived from LANDSAT top-of-atmosphere and surface reflectances. Int. J. Remote Sens. 39(20), 6607–6630. https://doi.org/10.1080/01431161.2018.1463114. Available at: https://www.tandfonline.com/doi/abs/10.1080/01431161.2018.1463114.
Fang, X., Chen, Z., Guo, X., Zhu, S., Liu, T., Li, C., He, B., 2019. Impacts and uncertainties of climate/CO2 change on net primary productivity in Xinjiang, China (2000–2014): A modelling approach. Ecol. Modell. 408(2019), 108742. https://doi.org/10.1016/j.ecolmodel.2019.108742. Available at: https://www.sciencedirect.com/science/article/pii/S0304380019302509
FAO, ITPS, 2015. The role of soils in ecosystem processes., Status of the World's Soil Resources - Main Report. p650. Rome, Italy.
Foody, G.M., 2002. Status of land cover classification accuracy assessment. Remote Sens. Environ.

80(1), 185–201. https://doi.org/10.1016/S0034-4257(01)00295-4. Available at: https://www.sciencedirect.com/science/article/pii/S0034425701002954

Franklin, J., Serra-Diaz, J.M., Syphard, A.D., Regan, H.M., 2016. Global change and terrestrial plant community dynamics. Proc. Natl. Acad. Sci. U. S. A. 113(14), 3725–3734. https://doi.org/10.1073/pnas.1519911113

Froend, R., Sommer, B., 2010. Phreatophytic vegetation response to climatic and abstraction-induced groundwater drawdown: Examples of long-term spatial and temporal variability in community response. Ecol. Eng. 36, 1191–1200. Washington, United States https://doi.org/10.1016/j.ecoleng.2009.11.029. Available at: https://www.pnas.org/content/113/14/3725.short

Gasith, A., Resh, V.H., 1999. Streams in Mediterranean climate regions: Abiotic influences and biotic responses to predictable seasonal events. Annu. Rev. Ecol. Syst. 30(1), 51–81. https://doi.org/10.1146/annurev.ecolsys.30.1.51. Available at: https://www.annualreviews.org/doi/abs/10.1146/annurev.ecolsys.30.1.51

Gauthier, S., Bernier, P., Kuuluvainen, T., Shvidenko, A.Z., Schepaschenko, D.G., 2015. Boreal forest health and global change. Science 349(6250), 819–822. Washington DC, United States. https://doi.org/10.1126/science.aaa9092

Gerten, D., Schaphoff, S., Haberlandt, U., Lucht, W., Sitch, S., 2004. Terrestrial vegetation and water balance - Hydrological evaluation of a dynamic global vegetation model. J. Hydrol. 286(1-4), 249–270. https://doi.org/10.1016/j.jhydrol.2003.09.029. Availabel at: https://www.sciencedirect.com/science/article/pii/S0022169403003901

Gholami, V., Chau, K.W., Fadaee, F., Torkaman, J., Ghaffari, A., 2015. Modeling of groundwater level fluctuations using dendrochronology in alluvial aquifers. J. Hydrol. 529(3), 1060–1069. https://doi.org/10.1016/j.jhydrol.2015.09.028

Glanville, K., Ryan, T., Tomlinson, M., Muriuki, G., Ronan, M., Pollett, A., 2016a. A Method for Catchment Scale Mapping of Groundwater-Dependent Ecosystems to Support Natural Resource Management (Queensland, Australia). Environ. Manage. 57(2), 432–449. https://doi.org/10.1007/s00267-015-0612-z

Gou, S., Gonzales, S., Miller, G.R., 2015. Mapping Potential Groundwater-Dependent Ecosystems for Sustainable Management. Groundwater 53(1), 99–110. https://doi.org/10.1111/gwat.12169. Availabelhttps://ngwa.onlinelibrary.wiley.com/doi/abs/10.1111/gwat.12169 https://ngwa.onlinelibrary.wiley.com/doi/abs/10.1111/gwat.12169

Gow, L., Brodie, R.S., Green, R., Punthakey, J., Woolley, D., Redpath, P., Bradburn, A., 2010. Identification and monitoring GDEs using MODIS time series: Hat Head National Park – a case study. Groundw. 2010 Chall. Sustain. Manag. Available at: https://www.academia.edu/download/46147749/Identification_and_monitoring_GDEs_using20160601-14244-m5zm5y.pdf

Graw, V., Ghazaryan, G., Dall, K., Gómez, A.D., Abdel-Hamid, A., Jordaan, A., Piroska, R., Post, J., Szarzynski, J., Walz, Y., Dubovyk, O., 2017. Drought dynamics and vegetation productivity in different land management systems of Eastern Cape, South Africa-A remote sensing perspective. Sustain. 9(10), 1728 https://doi.org/10.3390/su9101728

Griffiths, P., Nendel, C., Hostert, P., 2019. Intra-annual reflectance composites from Sentinel-2 and Landsat for national-scale crop and land cover mapping. Remote Sens. Environ. 220(2019), 135–151. https://doi.org/10.1016/j.rse.2018.10.031

Gu, Y., Brown, J.F., Verdin, J.P., Wardlow, B., 2007. A five-year analysis of MODIS NDVI and

NDWI for grassland drought assessment over the central Great Plains of the United States. Geophys. Res. Lett. 34(6). https://doi.org/10.1029/2006GL029127
Gurdak, J.J., Hanson, R.T., McMahon, P.B., Bruce, B.W., McCray, J.E., Thyne, G.D., Reedy, R.C., 2007. Climate Variability Controls on Unsaturated Water and Chemical Movement, High Plains Aquifer, USA. Vadose Zo. J. 6(3), 533–547. https://doi.org/10.2136/vzj2006.0087
Gxokwe, S., Dube, T., Mazvimavi, D., 2020. Multispectral remote sensing of wetlands in semi-arid and arid areas: A review on applications, challenges and possible future research directions. Remote Sens. 12(24), 1–19. https://doi.org/10.3390/rs12244190
Han, L., He, D., 2020. Leafing intensity decreases with increasing water table depth and plant height in Populus euphratica, a desert riparian species. Acta Oecologica 109(2020), 103672. https://doi.org/10.1016/j.actao.2020.103672
Hancock, P.J., Hunt, R.J., Boulton, A.J., 2009. Preface: Hydrogeoecology, the interdisciplinary study of groundwater dependent ecosystems. Hydrogeol. J. 17(1), 1–3. https://doi.org/10.1007/s10040-008-0409-8. Available at: https://link.springer.com/article/10.1007/s10040-008-0409-8
Hatton, T., Evans, R., 1998. Dependence of Ecosystems on Groundwater and its Significance to Australia. L. Water Resour. 12/98, 77. Canberra, Australia. Availavle at: https://library.dbca.wa.gov.au/static/FullTextFiles/018743.pdf
Hausner, M.B., Huntington, J.L., Nash, C., Morton, C., McEvoy, D.J., Pilliod, D.S., Hegewisch, K.C., Daudert, B., Abatzoglou, J.T., Grant, G., 2018. Assessing the effectiveness of riparian restoration projects using Landsat and precipitation data from the cloud-computing application ClimateEngine.org. Ecol. Eng. 120(2018), 432–440. https://doi.org/10.1016/j.ecoleng.2018.06.024
Havril, T., Tóth, Á., Molson, J.W., Galsa, A., Mádl-Szőnyi, J., 2018. Impacts of predicted climate change on groundwater flow systems: Can wetlands disappear due to recharge reduction? J. Hydrol. 563(2018), 1169–1180. https://doi.org/10.1016/j.jhydrol.2017.09.020
Hoffman, M.T., Cowling, R.M., 1990. Vegetation change in the semi-arid eastern Karoo over the last 200 years: an expanding Karoo - fact or fiction? S. Afr. J. Sci. 86(7), 286–294. Available at: https://journals.co.za/doi/abs/10.10520/AJA00382353_4489
Hoogland, T., Heuvelink, G.B.M., Knotters, M., 2010. Mapping water-table depths over time to assess desiccation of groundwater-dependent ecosystems in the Netherlands. Wetlands 30(1), 137–147. https://doi.org/10.1007/s13157-009-0011-4
Huang, F., Chunyu, X., Zhang, D., Chen, X., Ochoa, C.G., 2020. A framework to assess the impact of ecological water conveyance on groundwater-dependent terrestrial ecosystems in arid inland river basins. Sci. Total Environ. 709(1), 136155. https://doi.org/10.1016/j.scitotenv.2019.136155. Available at: https://www.sciencedirect.com/science/article/pii/S0034425716302619
Huang, F., Zhang, Y., Zhang, D., Chen, X., 2019. Environmental groundwater depth for groundwater-dependent terrestrial ecosystems in arid/semiarid regions: A review. Int. J. Environ. Res. Public Health 16(5). 763. https://doi.org/10.3390/ijerph16050763. Available at: https://www.mdpi.com/421046
Huang, J., Zhou, Y., Wenninger, J., Ma, H., Zhang, J., Zhang, D., 2016. How water use of Salix psammophila bush depends on groundwater depth in a semi-desert area. Environ. Earth Sci. 75(7), 556. https://doi.org/10.1007/s12665-016-5376-0Available at: https://link.springer.com/content/pdf/10.1007/s12665-016-5376-0.pdf
Huete, A.R., 1988. A soil-adjusted vegetation index (SAVI). Remote Sens. Environ. 25(3), 295–309.

https://doi.org/10.1016/0034-4257(88)90106-X.Available at: https://www.sciencedirect.com/science/article/pii/003442578890106X

Hunink, J.E., Contreras, S., Soto-García, M., Martin-Gorriz, B., Martinez-Álvarez, V., Baille, A., 2015a. Estimating groundwater use patterns of perennial and seasonal crops in a Mediterranean irrigation scheme, using remote sensing. Agric. Water Manag. 162, 47–56. https://doi.org/10.1016/j.agwat.2015.08.003. Available at: https://www.sciencedirect.com/science/article/pii/S037837741530069X

Huntington, J., McGwire, K., Morton, C., Snyder, K., Peterson, S., Erickson, T., Niswonger, R., Carroll, R., Smith, G., Allen, R., 2016. Assessing the role of climate and resource management on groundwater dependent ecosystem changes in arid environments with the Landsat archive. Remote Sens. Environ. 185, 186–197. https://doi.org/10.1016/j.rse.2016.07.004. Available at: https://www.sciencedirect.com/science/article/pii/S0034425716302619

Huss, M., Hock, R., Bauder, A., Funk, M., 2010. 100-year mass changes in the Swiss Alps linked to the Atlantic Multidecadal Oscillation. Geophys. Res. Lett. 37. https://doi.org/10.1029/2010GL042616

IPCC, 2014. Climate Change 2014: Impacts, Adaptation, and Vulnerability. Summary for Policymakers, Climate Change 2014: Impacts, Adaptation and Vulnerability - Contributions of the Working Group II to the Fifth Assessment Report. https://doi.org/10.1016/j.renene.2009.11.012

Ismail, M.H., 2009. Evaluating supervised and unsupervised techniques for land cover mapping using remote sensing data. Geogr. Malaysian J. Soc. Sp. 5, 1–10.Avilable at: http://journalarticle.ukm.my/917

Jin, X.M., Guo, R.H., Zhang, Q., Zhou, Y.X., Zhang, D.R., Yang, Z., 2014. Response of vegetation pattern to different landform and water-table depth in Hailiutu River basin, Northwestern China. Environ. Earth Sci. 71, 4889–4898. https://doi.org/10.1007/s12665-013-2882-1.Available at: https://link.springer.com/article/10.1007/s12665-013-2882-1

Jin, X.M., Schaepman, M.E., Clevers, J.G.P.W., Su, Z.B., Hu, G.C., 2011. Groundwater depth and vegetation in the Ejina area, China. Arid L. Res. Manag. 25, 194–199. https://doi.org/10.1080/15324982.2011.554953.Available at: https://www.tandfonline.com/doi/abs/10.1080/15324982.2011.554953

Johansen, O.M., Andersen, D.K., Ejrnæs, R., Pedersen, M.L., 2018. Relations between vegetation and water level in groundwater dependent terrestrial ecosystems (GWDTEs). Limnologica 68, 130–141. https://doi.org/10.1016/j.limno.2017.01.010. Available at: https://www.sciencedirect.com/science/article/pii/S0075951117300452

Jones, C., Stanton, D., Hamer, N., Denner, S., Singh, K., Flook, S., Dyring, M., 2020. Field investigation of potential terrestrial groundwater-dependent ecosystems within Australia's Great Artesian Basin. Hydrogeol. J. 28, 237–261. https://doi.org/10.1007/s10040-019-02081-1. Availabe at: https://link.springer.com/article/10.1007/s10040-019-02081-1

Jovanovic, N., Bugan, R.D.H., Israel, S., 2013. Rainfall, Soil Water Content, and Groundwater Levels at the Riverlands Nature Reserve (South Africa). Dataset Pap. Geosci. 2013, 1–14. https://doi.org/10.7167/2013/724819. Available at: https://www.hindawi.com/archive/2013/724819/sup/

Jovanovic, N.Z., Jarmain, C., de Clercq, W.P., Vermeulen, T., Fey, M. V., 2011. Total evaporation estimates from a renosterveld and dryland wheat/fallow surface at the Voëlvlei nature reserve (South Africa). Water SA 37, 471–482. https://doi.org/10.4314/wsa.v37i4.5. Available at:

https://www.ajol.info/index.php/wsa/article/view/71424
Kalbus, E., Reinstorf, F., Schirmer, M., 2006. Measuring methods for groundwater - Surface water interactions: A review. Hydrol. Earth Syst. Sci. 10, 873–887. https://doi.org/10.5194/hess-10-873-2006. Available at: https://hess.copernicus.org/articles/10/873/2006/
Kaneko, K., Nohara, S., 2014. Review of Effective Vegetation Mapping Using the UAV (Unmanned Aerial Vehicle) Method. J. Geogr. Inf. Syst. 06, 733–742. https://doi.org/10.4236/jgis.2014.66060. Available at: https://www.scirp.org/html/13-8401417_52721.htm
Kath, J., Reardon-Smith, K., Le Brocque, A.F., Dyer, F.J., Dafny, E., Fritz, L., Batterham, M., 2014. Groundwater decline and tree change in floodplain landscapes: Identifying non-linear threshold responses in canopy condition. Glob. Ecol. Conserv. 2, 148–160. https://doi.org/10.1016/j.gecco.2014.09.002. Available at: https://www.sciencedirect.com/science/article/pii/S2351989414000286
Klausmeyer, K., Howard, J., Keeler-wolf, T., Davis-fadtke, K., Hull, R., 2018. Mapping indicators of groundwater dependent ecosystems in California: Methods report. Ventura.
Klausmeyer, K.R., Biswas, T., Rohde, M.M., Schuetzenmeister, F., 2019. GDE Pulse : Taking the Pulse of Groundwater Dependent Ecosystems with Satellite Data.. Available at: https://groundwaterresourcehub.org/public/uploads/pdfs/iGDE_data_paper_20180423.pdf
Kløve, B., Ala-aho, P., Bertrand, G., Boukalova, Z., Ertürk, A., Goldscheider, N., Ilmonen, J., Karakaya, N., Kupfersberger, H., Kvœrner, J., Lundberg, A., Mileusnić, M., Moszczynska, A., Muotka, T., Preda, E., Rossi, P., Siergieiev, D., Šimek, J., Wachniew, P., Angheluta, V., Widerlund, A., 2011. Groundwater dependent ecosystems. Part I: Hydroecological status and trends. Environ. Sci. Policy 14, 770–781. https://doi.org/10.1016/j.envsci.2011.04.002Available at: https://www.sciencedirect.com/science/article/pii/S1462901111000517
Kløve, B., Ala-Aho, P., Bertrand, G., Gurdak, J.J., Kupfersberger, H., Kværner, J., Muotka, T., Mykrä, H., Preda, E., Rossi, P., Uvo, C.B., Velasco, E., Pulido-Velazquez, M., 2014. Climate change impacts on groundwater and dependent ecosystems. J. Hydrol. 518, 250–266. https://doi.org/10.1016/j.jhydrol.2013.06.037. Available at: https://www.sciencedirect.com/science/article/pii/S0022169413004800
Koirala, S., Jung, M., Reichstein, M., de Graaf, I.E.M., Camps-Valls, G., Ichii, K., Papale, D., Ráduly, B., Schwalm, C.R., Tramontana, G., Carvalhais, N., 2017. Global distribution of groundwater-vegetation spatial covariation. Geophys. Res. Lett. 44, 4134–4142. https://doi.org/10.1002/2017GL072885. Available at: https://agupubs.onlinelibrary.wiley.com/doi/abs/10.1002/2017GL072885
Kraaij, T., Hanekom, N., Russell, I.A.A., Randall, R.M.M., 2009. Agulhas National Park-State of Knowledge. South African Natl. Park. 14, 1–16. Available at: http://wildcompany.co.za/docs/conservation/scientific/coastal/Agulhas/ANP_SOK_Mar2009.pdf
Krause, S., Heathwaite, A.L., Miller, F., Hulme, P., Crowe, A., 2007. Groundwater-dependent wetlands in the UK and Ireland: Controls, functioning and assessing the likelihood of damage from human activities. Water Resour. Manag. 21, 2015–2025. https://doi.org/10.1007/s11269-007-9192-x. Available at: https://link.springer.com/article/10.1007/s11269-007-9192-x
Kreamer, D.K., Stevens, L.E., Ledbetter, J.D., 2015. Groundwater Dependent Ec osystems –Science, Challanges, and Policy Directions. Groundwater 13, 206–229.Available at:

https://www.novapublishers.com/wp-content/uploads/2019/03/978-1-63321-759-1_ch9.pdf
Krogulec, E., 2018. Evaluating the risk of groundwater drought in groundwater-dependent ecosystems in the central part of the Vistula River Valley, Poland. Ecohydrol. Hydrobiol. 18, 82–91. https://doi.org/10.1016/j.ecohyd.2017.11.003. Available at: https://www.sciencedirect.com/science/article/pii/S1642359317302136

Kumar, C.P., 2013. Recent Studies on Impact of Climate Change on Groundwater Resources. Int. J. Phys. Soc. Sci. 3, 189–221.Available at: https://www.indianjournals.com/ijor.aspx?target=ijor:ijpss&volume=3&issue=11&article=017

Kundzewicz, Z.W., Döll, P., 2009. Will groundwater ease freshwater stress under climate change? Hydrol. Sci. J. 54, 665–675. https://doi.org/10.1623/hysj.54.4.665.Available at: https://www.tandfonline.com/doi/abs/10.1623/hysj.54.4.665

Laar, C., 2018. Application of Environmental & Hydrochemical Analysis to Characterize Flow Dynamics in the Sakumo Wetland, Ghana. University of the Western Cape.Available at: https://etd.uwc.ac.za/handle/11394/6328

Laio, F., Tamea, S., Ridolfi, L., D'Odorico, P., Rodriguez-Iturbe, I., 2009. Ecohydrology of groundwater-dependent ecosystems: 1. Stochastic water table dynamics. Water Resour. Res. 45, 1–13. https://doi.org/10.1029/2008WR007292. Available at: https://agupubs.onlinelibrary.wiley.com/doi/abs/10.1029/2008WR007292

Le Maitre, D.C., Scott, D.F., Colvin, C., 1999. A review of information on interactions between vegetation and groundwater. Water SA 25, 137–152.Available at: http://researchspace.csir.co.za/dspace/handle/10204/524

Le Maitre, D.C., Versfeld, D.B., Chapman, R.A., 2000. The impact of invading alien plants on surface water resources in South Africa: A preliminary assessment. Water SA 26, 397–408.Available at: http://researchspace.csir.co.za/dspace/handle/10204/2121

Liao, S., Xue, L., Dong, Z., Zhu, B., Zhang, K., Wei, Q., Fu, F., Wei, G., 2020. Cumulative ecohydrological response to hydrological processes in arid basins. Ecol. Indic. 111, 106005. https://doi.org/10.1016/j.ecolind.2019.106005. Available at: https://www.sciencedirect.com/science/article/pii/S1470160X19310003

Liu, H.H., 2011. Impact of climate change on groundwater recharge in dry areas: An ecohydrology approach. J. Hydrol. 407, 175–183. https://doi.org/10.1016/j.jhydrol.2011.07.024. Available at: https://www.sciencedirect.com/science/article/pii/S002216941100480X

Loheide, S.P., Butler, J.J., Gorelick, S.M., 2005. Estimation of groundwater consumption by phreatophytes using diurnal water table fluctuations: A saturated-unsaturated flow assessment. Water Resour. Res. 41, 1–14. https://doi.org/10.1029/2005WR003942. Available at: https://agupubs.onlinelibrary.wiley.com/doi/abs/10.1029/2005wr003942

Loomes, R., Froend, R., Sommer, B., 2013. Response of wetland vegetation to climate change and groundwater decline on the swan coastal plain, Western Australia: Implications for management, in: Groundwater and Ecosystems. pp. 207–219. https://doi.org/10.1201/b15003-22. Available at: https://books.google.com/books?hl=en&lr=&id=9vjI2HxM9Z0C&oi=fnd&pg=PA207&dq=Response+of+wetland+vegetation+to+climate+change+and+groundwater+decline+on+the+swan+coastal+plain,+Western+Australia:+Implications+for+management,+in:+Groundwater+and+Ecosystems&ots=EuG00pIaBA&sig=1P-0P5_gvkdtCTcCZDcDc0h2JTI

Lurtz, M.R., Morrison, R.R., Gates, T.K., Senay, G.B., Bhaskar, A.S., Ketchum, D.G., 2020. Relationships between riparian evapotranspiration and groundwater depth along a semiarid irrigated river valley. Hydrol. Process. 34, 1714–1727. https://doi.org/10.1002/hyp.13712. Available at: https://onlinelibrary.wiley.com/doi/abs/10.1002/hyp.13712

Lv, J., Wang, X.S., Zhou, Y., Qian, K., Wan, L., Eamus, D., Tao, Z., 2013. Groundwater-dependent distribution of vegetation in Hailiutu River catchment, a semi-arid region in China. Ecohydrology 6, 142–149. https://doi.org/10.1002/eco.1254. Available at: https://onlinelibrary.wiley.com/doi/abs/10.1002/eco.1254

Macintyre, P., van Niekerk, A., Mucina, L., 2020. Efficacy of multi-season Sentinel-2 imagery for compositional vegetation classification. Int. J. Appl. Earth Obs. Geoinf. 85, 101980. https://doi.org/10.1016/j.jag.2019.101980. Available at: https://www.sciencedirect.com/science/article/pii/S0303243419301242

MacKay, H., 2006. Protection and management of groundwater-dependent ecosystems: Emerging challenges and potential approaches for policy and management. Aust. J. Bot. 54, 231–237. https://doi.org/10.1071/BT05047. Available at: https://www.publish.csiro.au/bt/bt05047

Maitre, D.C. Le, Wilgen, B.W. Van, Chapman, R.A., McKelly, D.H., 1996. Invasive Plants and Water Resources in the Western Cape Province, South Africa: Modelling the Consequences of a Lack of Management. J. Appl. Ecol. 33, 161. https://doi.org/10.2307/2405025. Available at: https://www.jstor.org/stable/2405025

Marques, I.G., Nascimento, J., Cardoso, R.M., Miguéns, F., Teresa Condesso De Melo, M., Soares, P.M.M., Gouveia, C.M., Kurz Besson, C., 2019. Mapping the suitability of groundwater-dependent vegetation in a semi-arid Mediterranean area. Hydrol. Earth Syst. Sci. 23, 3525–3552. https://doi.org/10.5194/hess-23-3525-2019. Available at: https://pdfs.semanticscholar.org/66d7/f4de425b92fad2d18f860a5df1a9978fcfc6.pdf

Martinetti, S., Fatichi, S., Floriancic, M., Burlando, P., Molnar, P., 2021. Field evidence of riparian vegetation response to groundwater levels in a gravel-bed river. Ecohydrology 14, 1–17. https://doi.org/10.1002/eco.2264. Available at: https://onlinelibrary.wiley.com/doi/abs/10.1002/eco.2264

Mawdsley, J.R., O'Malley, R., Ojima, D.S., 2009. A review of climate-change adaptation strategies for wildlife management and biodiversity conservation. Conserv. Biol. 23, 1080–1089. https://doi.org/10.1111/j.1523-1739.2009.01264.x

Mazvimavi, D., 2018. Finding "new" water to address conflicting and competing water demands in the Nuwejaars Catchment, Cape Agulhas. Cape Town. Water Research Commission Report. Pretoria, South Africa.

McDowell, C., Moll, E., 1992. The influence of agriculture on the decline of west coast renosterveld, south-western Cape, South Africa. J. Environ. Manage. 35, 173–192. https://doi.org/10.1016/S0301-4797(05)80118-5. Available at: https://www.sciencedirect.com/science/article/pii/S0301479705801185

Mehl, D.J.G., 2019. An Assessment of the River Flow Contributions of Tributaries ans the Effects of Floodplain Wetlands on Spatio-temporal Variations of River Flows in the Nuwejaars River Catchment, Cape Agulhas. University of the Western Cape. Bellville, South Africa Available at: https://etd.uwc.ac.za/handle/11394/7031

Meinzer, O.E., 1927. Plants as Indicators of Ground water, The Journal of Geology. 64. US Government Printing Office. Washington, United States https://doi.org/10.1086/623671. Available at: https://books.google.com/books?hl=en&lr=&id=E8UvAAAAYAAJ&oi=fnd&pg=PA1&dq=Plants+as+Indicators+of+Ground+water&ots=wwO7Tle97q&sig=BvBbFgmNHMsP2Vfc2Ne5Zzu7lOg

Miller, G.R., Chen, X., Rubin, Y., Ma, S., Baldocchi, D.D., 2010. Groundwater uptake by woody vegetation in a semiarid oak savanna. Water Resour. Res. 46(10), 1–14. https://doi.org/10.1029/2009WR008902. Available at: https://agupubs.onlinelibrary.wiley.com/doi/abs/10.1029/2009WR008902

Mkunyana, Y.P., Mazvimavi, D., Dzikiti, S., Ntshidi, Z., 2019. A comparative assessment of water use by Acacia longifolia invasions occurring on hillslopes and riparian zones in the Cape Agulhas region of South Africa. Phys. Chem. Earth Parts A/B/C. 112, 255–264. https://doi.org/10.1016/j.pce.2018.10.002. Available at: https://www.sciencedirect.com/science/article/pii/S1474706518301529

Mokoena, P.L., 2019. Novel Approach Of Uising Hydrogeochemistry, Hydrogeologic And Hydrostratigraphic Techniques In Evaluating Coastal Aquifers In Heuningnes Catchment, South Africa. University of th Western Cape. Bellville, South Africa Available at: https://etd.uwc.ac.za/handle/11394/7960

Móricz, N., 2010. Water balance study of a groundwater-dependent oak forest. Acta Silv. Lignaria Hungarica 6, 49–66. Available at: http://real-j.mtak.hu/17059/1/ASLH_Vol_6_2010.pdf#page=47

Morsy, K.M., Alenezi, A., Alrukaibi, D.S., 2017. Groundwater and dependent ecosystems: Revealing the impacts of climate change. Int. J. Appl. Eng. Res. 12(13), 3919–3926. Available at: https://www.researchgate.net/profile/Karim-Morsy/publication/318929478_Groundwater_and_Dependent_Ecosystems_Revealing_the_Impacts_of_Climate_Change/links/59861e2245851560584a379b/Groundwater-and-Dependent-Ecosystems-Revealing-the-Impacts-of-Climate-Change.pdf

Mountrakis, G., Im, J., Ogole, C., 2011. Support vector machines in remote sensing: A review. ISPRS J. Photogramm. Remote Sens. 66(3), 247–259. https://doi.org/10.1016/j.isprsjprs.2010.11.001. Available at: https://www.sciencedirect.com/science/article/pii/S0924271610001140

Mtengwana, B., Dube, T., Mkunyana, Y.P., Mazvimavi, D., 2020. Use of multispectral satellite datasets to improve ecological understanding of the distribution of Invasive Alien Plants in a water-limited catchment, South Africa. Afr. J. Ecol. 58(4), 709–718. https://doi.org/10.1111/aje.12751. Available at: https://onlinelibrary.wiley.com/doi/abs/10.1111/aje.12751

Münch, Z., Conrad, J., 2007. Remote sensing and GIS based determination of groundwater dependent ecosystems in the Western Cape, South Africa. Hydrogeol. J. 15(1), 19–28. https://doi.org/10.1007/s10040-006-0125-1. Availabe at: https://link.springer.com/content/pdf/10.1007/s10040-006-0125-1.pdf

Muñoz-Reinoso, J.C., 2001. Vegetation changes and groundwater abstraction in SW Doñana, Spain. J. Hydrol. 242(3-4), 197–209. https://doi.org/10.1016/S0022-1694(00)00397-8. Available at: https://www.sciencedirect.com/science/article/pii/S0022169400003978

Mutanga, O., Kumar, L., 2019. Google earth engine applications. Remote Sens. 11(5), 591. https://doi.org/10.3390/rs11050591. Available at: https://www.mdpi.com/2072-4292/11/5/591/htm

Robinson, T.W., 1958. Phreatophytes. United States, Geological Survey. Water-Supply Paper, 1423 pp. 84. Washington, United States. https://doi.org/10.1017/s001675680006622x.

Naumburg, E., Mata-Gonzalez, R., Hunter, R.G., McLendon, T., Martin, D.W., 2005. Phreatophytic vegetation and groundwater fluctuations: A review of current research and application of ecosystem response modeling with an emphasis on great basin vegetation. Environ. Manage.

35(6), 726–740. https://doi.org/10.1007/s00267-004-0194-7. Available at: https://link.springer.com/content/pdf/10.1007/s00267-004-0194-7.pdf

Ndehedehe, C.E., Ferreira, V.G., Agutu, N.O., 2019. Hydrological controls on surface vegetation dynamics over West and Central Africa. Ecol. Indic. 103, 494–508. https://doi.org/10.1016/j.ecolind.2019.04.032. Available at: https://www.sciencedirect.com/science/article/pii/S1470160X19302791

Noone, K.J., Nobre, C., Seitzinger, S., 2011. The International Geosphere-Biosphere Programme's (IGBP) Scientific Research Agenda for Coping with Global Environmental Change, in: Hexagon Series on Human and Environmental Security and Peace,Coping with Global Environmental Change, Disasters and Security. pp. 1249–1256. Springer, Berlin, Heidelberg. https://doi.org/10.1007/978-3-642-17776-7_77. Available at: https://link.springer.com/chapter/10.1007/978-3-642-17776-7_77

Northcote, T.G., Atagi, D.Y., 1997. Ecological interactions in the flooded littoral zone of reservoirs: the importance and role of submerged terrestrial vegetation with special reference to fish, fish habitat and fisheries in the Nechako Reservoir of British Columbia, Canada 71. Available at: http://www.neef.ca/uploads/library/169_NorthcoteAtagi1997_SubmergedTrees.pdf

O'connor, J., Santos, M.J., Rebel, K.T., Dekker, S.C., 2019. The influence of water table depth on evapotranspiration in the Amazon arc of deforestation. Hydrol. Earth Syst. Sci. 23, 3917–3931. https://doi.org/10.5194/hess-23(9)-3917-2019. Available at: https://hess.copernicus.org/articles/23/3917/2019/

Olofsson, P., Foody, G.M., Stehman, S. V., Woodcock, C.E., 2013. Making better use of accuracy data in land change studies: Estimating accuracy and area and quantifying uncertainty using stratified estimation. Remote Sens. Environ. 129, 122–131. https://doi.org/10.1016/j.rse.2012.10.031. Available at: https://www.sciencedirect.com/science/article/pii/S0034425712004191

Orellana, F., Verma, P., Loheide, S.P., Daly, E., 2012. Monitoring and modelling water-vegetation interactions in groundwater dependent ecosystems. Reviews of Geophysics, 50(3). https://doi.org/10.1029/2011RG000383.1. Available at: https://agupubs.onlinelibrary.wiley.com/doi/abs/10.1029/2011RG000383

Osmond, C.B., Austin, M.P., Berry, J.A., Billings, W.D., Boyer, J.S., Dacey, J.W.H., Nobel, P.S., Smith, S.D., Winner, W.E., 1987. Stress Physiology and the Distribution of Plants. Bioscience 37(1), 38–48. https://doi.org/10.2307/1310176. Available at: https://www.jstor.org/stable/1310176

Paola, J.D., Schowengerdt, R.A., 1995. A review and analysis of backpropagation neural networks for classification of remotely-sensed multi-spectral imagery. Int. J. Remote Sens. 16(16), 3033–3058. https://doi.org/10.1080/01431169508954607. Available at: https://www.tandfonline.com/doi/abs/10.1080/01431169508954607

Parker, B.M., Sheldon, F., Phinn, S., Ward, D., 2018. Changes in foliage projective cover and its implications for mapping groundwater dependent vegetation across a precipitation gradient. Ecohydrology 11(4), 1–9. https://doi.org/10.1002/eco.1937. Available at: https://onlinelibrary.wiley.com/doi/abs/10.1002/eco.1937

Páscoa, P., Gouveia, C.M., Kurz-Besson, C., 2020. A simple method to identify potential groundwater-dependent vegetation using NDVI MODIS. Forests 11(12), 147. https://doi.org/10.3390/f11020147. Available at: https://www.mdpi.com/627290

Pereira, H.M., Ferrier, S., Walters, M., Geller, G.N., Jongman, R.H.G., Scholes, R.J., Bruford, M.W., Brummitt, N., Butchart, S.H.M., Cardoso, A.C. and Coops, N.C., 2013. Essential biodiversity

variables. Science, 339(6117), pp.277-278 . https://doi.org/10.1126/science.1229931. Available at: https://science.sciencemag.org/content/339/6117/277.summary
Pérez Hoyos, I., Krakauer, N., Khanbilvardi, R., 2016. Estimating the Probability of Vegetation to Be Groundwater Dependent Based on the Evaluation of Tree Models. Environments 3(2), 9. https://doi.org/10.3390/environments3020009. Available at: https://www.mdpi.com/134916
Pérez Hoyos, I.C., Krakauer, N.Y., Khanbilvardi, R., Armstrong, R.A., 2016. A review of advances in the identification and characterization of groundwater dependent ecosystems using geospatial technologies. Geosci. 6(2). https://doi.org/10.3390/geosciences6020017. Available at: https://www.mdpi.com/133038
Peters, J., De Baets, B., Samson, R., C. Verhoest, N.E., 2008. Modelling groundwater-dependent vegetation patterns using ensemble learning. Hydrol. Earth Syst. Sci. 12(2), 603–613. https://doi.org/10.5194/hess-12-603-2008. Available at: https://hess.copernicus.org/articles/12/603/2008/
Peters, J., De Baets, B., Verhoest, N.E.C., Samson, R., Degroeve, S., Becker, P. De, Huybrechts, W., 2007. Random forests as a tool for ecohydrological distribution modelling. Ecol. Modell. 207(2-4), 304–318. https://doi.org/10.1016/j.ecolmodel.2007.05.011. Available at: https://www.sciencedirect.com/science/article/pii/S0304380007002931
Poiani, K.A., Johnson, W.C., Swanson, G.A., Winter, T.C., 1996. Climate change and northern prairie wetlands: Simulations of long-term dynamics. Limnol. Oceanogr. 41(5), 871–881. https://doi.org/10.4319/lo.1996.41.5.0871. Available at: https://aslopubs.onlinelibrary.wiley.com/doi/abs/10.4319/lo.1996.41.5.0871
Raczko, E., Zagajewski, B., 2017. Comparison of support vector machine, random forest and neural network classifiers for tree species classification on airborne hyperspectral APEX images. Eur. J. Remote Sens. 50(1), 144–154. https://doi.org/10.1080/22797254.2017.1299557. Available at: https://www.tandfonline.com/doi/abs/10.1080/22797254.2017.1299557
Rhyma, P.P., Norizah, K., Hamdan, O., Faridah-Hanum, I., Zulfa, A.W., 2020. Integration of normalised different vegetation index and Soil-Adjusted Vegetation Index for mangrove vegetation delineation. Remote Sens. Appl. Soc. Environ. 17, 100280. https://doi.org/10.1016/j.rsase.2019.100280. Available at: https://www.sciencedirect.com/science/article/pii/S2352938519301661
Richards, P.W., Walter, H., Wieser, J., 1975. Vegetation of the Earth in Relation to Climate and the Eco-Physiological Conditions. J. Ecol. 63, 1014. https://doi.org/10.2307/2258632. Available at: https://www.cabdirect.org/cabdirect/abstract/19770754008
Richardson, D.M., Kruger, F.J., 1990. Water relations and photosynthetic characteristics of selected trees and shrubs of riparian and hillslope habitats in the south-western Cape Province, South Africa. South African J. Bot. 56(2), 214–225. https://doi.org/10.1016/s0254-6299(16)31089-4. Available at: https://www.sciencedirect.com/science/article/pii/S0254629916310894
Richey, A.S., Thomas, B.F., Lo, M.H., Reager, J.T., Famiglietti, J.S., Voss, K., Swenson, S., Rodell, M., 2015. Quantifying renewable groundwater stress with GRACE. Water Resour. Res. 51, 5217–5237. https://doi.org/10.1002/2015WR017349. Available at: https://agupubs.onlinelibrary.wiley.com/doi/abs/10.1002/2015WR017349
Rodriguez-Iturbe, I., Porporato, A., 2005. Ecohydrology of water-controlled ecosystems: Soil moisture and plant dynamics, Ecohydrology of Water-Controlled Ecosystems: Soil Moisture and Plant Dynamics. Cambridge University Press https://doi.org/10.1017/CBO9780511535727. Available at: https://www.sciencedirect.com/science/article/pii/S0309170802000581

Rohde, M.M., Froend, R., Howard, J., 2017a. A Global Synthesis of Managing Groundwater Dependent Ecosystems Under Sustainable Groundwater Policy. Groundwater 55(53), 293–301. https://doi.org/10.1111/gwat.12511. Available at: https://ngwa.onlinelibrary.wiley.com/doi/abs/10.1111/gwat.12511

Rouget, M., Richardson, D.M., Cowling, R.M., Lloyd, J.W., Lombard, A.T., 2003. a. Biol. Conserv. 112(1-2), 63–85. https://doi.org/10.1016/S0006-3207(02)00395-6. Available at: https://www.sciencedirect.com/science/article/pii/S0006320702003956

Roy, D.P., Kovalskyy, V., Zhang, H.K., Vermote, E.F., Yan, L., Kumar, S.S., Egorov, A., 2016. Characterization of Landsat-7 to Landsat-8 reflective wavelength and normalized difference vegetation index continuity. Remote Sens. Environ. 185, 57–70. https://doi.org/10.1016/j.rse.2015.12.024. Available at: https://www.sciencedirect.com/science/article/pii/S0034425715302455

Rozenstein, O., Karnieli, A., 2011. Comparison of methods for land-use classification incorporating remote sensing and GIS inputs. Appl. Geogr. 31(2), 533–544. https://doi.org/10.1016/j.apgeog.2010.11.006. Available at: https://www.sciencedirect.com/science/article/pii/S0143622810001517

Rutherford, M.C., Mucina, L., Rebelo, A.G., Boucher, C., Helme, N., 2006. Fynbos Biome, in: Vegetation Map of South Africa, Lesotho and Swaziland. Strelitzia, pp. 55–206. South Africa, Pretoria.

Sabat-Tomala, A., Raczko, E., Zagajewski, B., 2020. Comparison of support vector machine and random forest algorithms for invasive and expansive species classification using airborne hyperspectral data. Remote Sens. 12(3). 516. https://doi.org/10.3390/rs12030516. Available at: https://www.mdpi.com/633974

Scanlon, B.R., Keese, K.E., Flint, A.L., Flint, L.E., Gaye, C.B., Edmunds, W.M. and Simmers, I., 2006. Global synthesis of groundwater recharge in semiarid and arid regions. Hydrological Processes: An International Journal, 20(15), pp.3335-3370. https://doi.org/10.1002/hyp

Scibek, J., Allen, D.M., 2006. Modeled impacts of predicted climate change on recharge and groundwater levels. Water Resour. Res. 42(11). https://doi.org/10.1029/2005WR004742. Availavle at: https://agupubs.onlinelibrary.wiley.com/doi/abs/10.1029/2005wr004742

Scott, D.F., le Maitre, D.C., 1998. The interaction between vegetation and groundwater: research priorities for South Africa Water Research Commission. South Africa, Pretoria.

Seyler, H., 2017. Opportunities for Groundwater use in the Western Cape Overview of Groundwater Resources Common groundwater myths.Green Cape. South Africa, Cape Town. Available at: https://www.greencape.co.za/assets/Uploads/GreeCape-desk-GW-event-20171208.pdf

Shafroth, P.B., Stromberg, J.C., Patten, D.T., 2000a. Woody Riparian Vegetation Response to Different Alluvial Water Table Regimes. West. North Am. Nat. 60, 66–76. Available at: https://www.jstor.org/stable/41717015

Shoko, C., Mutanga, O., Dube, T., 2016. Progress in the remote sensing of C3 and C4 grass species aboveground biomass over time and space. ISPRS J. Photogramm. Remote Sens. 120, 13–24. https://doi.org/10.1016/j.isprsjprs.2016.08.001. Available at: https://www.sciencedirect.com/science/article/pii/S0924271616302118

Silva Mota, G., Luz, G.R., Mota, N.M., Silva Coutinho, E., das Dores Magalhães Veloso, M., Fernandes, G.W., Nunes, Y.R.F., 2018. Changes in species composition, vegetation structure, and life forms along an altitudinal gradient of rupestrian grasslands in south-eastern Brazil. Flora Morphol. Distrib. Funct. Ecol. Plants 238, 32–42. https://doi.org/10.1016/j.flora.2017.03.010. Availabel at:

https://www.sciencedirect.com/science/article/pii/S0367253017331663
Sommer, B., Boggs, D.A., Boggs, G.S., van Dijk, A., Froend, R., 2016. Spatio-temporal patterns of evapotranspiration from groundwater-dependent vegetation. Ecohydrology 9(8), 1620–1629. https://doi.org/10.1002/eco.1752. Available at: https://onlinelibrary.wiley.com/doi/abs/10.1002/eco.1752
Song, X., Duan, Z., Jiang, X., 2012. Comparison of artificial neural networks and support vector machine classifiers for land cover classification in Northern China using a SPOT-5 HRG image. Int. J. Remote Sens. 33(10), 3301–3320. https://doi.org/10.1080/01431161.2011.568531
Stehman, S. V., 2009. Sampling designs for accuracy assessment of land cover. Int. J. Remote Sens. 30(20), 5243–5272. https://doi.org/10.1080/01431160903131000. Available at: https://www.tandfonline.com/doi/abs/10.1080/01431160903131000
Stehman, S. V., 2000. Practical implications of design-based sampling inference for thematic map accuracy assessment. Remote Sens. Environ. 72(1), 35–45. https://doi.org/10.1016/S0034-4257(99)00090-5. Available at: https://www.sciencedirect.com/science/article/pii/S0034425799000905
Swift, C.C., Jacobs, S.M., Esler, K.J., 2008. Drought induced xylem embolism in four riparian trees from the Western Cape Province: Insights and implications for planning and evaluation of restoration. South African J. Bot. 74(3), 508–516. https://doi.org/10.1016/j.sajb.2008.01.169
Taylor, R., Tindimugaya, C., 2011. The impacts of climate change and rapid development on weathered crystalline rock aquifer systems in the humid tropics of sub- Saharan Africa: Evidence from south- western Uganda, in: Climate Change Effects on Groundwater Resources: A Global Synthesis of Findings and Recommendations. pp. 17–32. https://doi.org/10.1201/b11611-6
Thamaga, K.H., Dube, T., 2018. Remote sensing of invasive water hyacinth (Eichhornia crassipes): A review on applications and challenges. Remote Sens. Appl. Soc. Environ. 10, 36–46. https://doi.org/10.1016/j.rsase.2018.02.005.Available at: https://www.sciencedirect.com/science/article/pii/S2352938517302148
Thamaga, K.H., Dube, T., Shoko, C., 2021. Advances in satellite remote sensing of the wetland ecosystems in Sub-Saharan Africa. Geocarto Int. 1-23. https://doi.org/10.1080/10106049.2021.1926552. Available at: https://www.tandfonline.com/doi/abs/10.1080/10106049.2021.1926552
Thamaga, K.H., Dube, T., Thamaga, K.H., 2018. Testing two methods for mapping water hyacinth (Eichhornia crassipes) in the Greater Letaba river system , South Africa : discrimination and mapping potential of the polar-orbiting Sentinel-2 MSI and Landsat 8 OLI sensors. Int. J. Remote Sens. 39(22), 8041–8059. https://doi.org/10.1080/01431161.2018.1479796. Available at: https://www.tandfonline.com/doi/abs/10.1080/01431161.2018.1479796
Turpie, J.K., Heydenrych, B.J., Lamberth, S.J., 2003. Economic value of terrestrial and marine biodiversity in the Cape Floristic Region: Implications for defining effective and socially optimal conservation strategies. Biol. Conserv. 112(1-2), 233–251. https://doi.org/10.1016/S0006-3207(02)00398-1. Available at: https://www.sciencedirect.com/science/article/pii/S0006320702003981
United Nations, 2017. The Sustainable Development goal Report 2017. Available at: https://sustainabledevelopment.un.org/aboutmajorgroups.html.https://unstats.un.org/sdgs/files/report/2017/TheSustainableDevelopmentGoalsReport2017.pdf
van Wilgen, B.W., Reyers, B., Le Maitre, D.C., Richardson, D.M., Schonegevel, L., 2008. A biome-

scale assessment of the impact of invasive alien plants on ecosystem services in South Africa. J. Environ. Manage. 899(4), 336–349. https://doi.org/10.1016/j.jenvman.2007.06.015
Van Wilgen, B.W., Richardson, D.M., 2012. Three centuries of managing introduced conifers in South Africa: Benefits, impacts, changing perceptions and conflict resolution. J. Environ. Manage. 106, 56–68. https://doi.org/10.1016/j.jenvman.2012.03.052. Available at: https://www.sciencedirect.com/science/article/pii/S0301479712001776
Vaux, H., 2011. Groundwater under stress: The importance of management. Environ. Earth Sci. 629(1), 19–23. https://doi.org/10.1007/s12665-010-0490-x. Available at: https://link.springer.com/article/10.1007/s12665-010-0490-x
Wada, Y., Van Beek, L.P.H., Van Kempen, C.M., Reckman, J.W.T.M., Vasak, S., Bierkens, M.F.P., 2010. Global depletion of groundwater resources. Geophys. Res. Lett. 37(20), 1–5. https://doi.org/10.1029/2010GL044571. Available at: https://agupubs.onlinelibrary.wiley.com/doi/abs/10.1029/2010gl044571
Wang, J., Rich, P.M., Price, K.P., 2003. Temporal responses of NDVI to precipitation and temperature in the central Great Plains, USA. Int. J. Remote Sens. 24(11), 2345–2364. https://doi.org/10.1080/01431160210154812. Available at: https://www.tandfonline.com/doi/abs/10.1080/01431160210154812
Wang, Q., Dong, S., Wang, H., Yang, J., Zhao, C., Dong, X., Wang, T., 2020. Effects of Groundwater Table Decline on Vegetation Transpiration in an Arid Mining Area: A Case Study of the Yushen Mining Area, Shaanxi Province, China. Mine Water Environ. 39(4), 839–850. https://doi.org/10.1007/s10230-020-00714-6
Wang, X., Xie, S., Zhang, X., Chen, C., Guo, H., Du, J., Duan, Z., 2018. A robust Multi-Band Water Index (MBWI) for automated extraction of surface water from Landsat 8 OLI imagery. Int. J. Appl. Earth Obs. Geoinf. 68, 73–91. https://doi.org/10.1016/j.jag.2018.01.018
Wattendorf, P., Niederberger, J., Ehrmann, O., Konold, W., 2010. Consequences of climate change on the water balance of fen peatlands in Baden-Wuerttemberg. Hydrol. Und Wasserbewirtschaftung 54(5), 293–303.
Wessels, K.J., Pretorius, D.J., Prince, S.D., 2008. The reality of rangeland degradation mapping with remote sensing: the South African experience, in: 14th Australasian Remote Sensing and Photogrammetry Conference. pp. 1–7. Australia, Darwin. Available at: http://researchspace.csir.co.za/dspace/handle/10204/3266
Williams, S., 2018. Perceptions of wetland ecosystem services in a region of climatic variability. University of the Western Cape. South Africa, Bellville. Available at: https://etd.uwc.ac.za/handle/11394/6599
Wu, Y., Liu, T., Paredes, P., Duan, L., Pereira, L.S., 2015. Water use by a groundwater dependent maize in a semi-arid region of Inner Mongolia: EVAPOTRANSPIRATION partitioning and capillary rise. Agric. Water Manag. 152, 222–232. https://doi.org/10.1016/j.agwat.2015.01.016. Available at: https://www.sciencedirect.com/science/article/pii/S0378377415000256
Xia, J., Ning, L., Wang, Q., Chen, J., Wan, L., Hong, S., 2017. Vulnerability of and risk to water resources in arid and semi-arid regions of West China under a scenario of climate change. Clim. Change 144(3), 549–563. https://doi.org/10.1007/s10584-016-1709-y. Available at: https://link.springer.com/article/10.1007/s10584-016-1709-y
Xia, P., Yin, S., Jiang, J., 2012. Pinus Aiwanensis Tree-Ring Chronology and Its Response to Climate. Procedia Environ. Sci. 13, 307–315. https://doi.org/10.1016/j.proenv.2012.01.029. Available at: https://www.sciencedirect.com/science/article/pii/S1878029612000308

Xu, Y., Beekman, H.E., 2003. Groundwater Recharge Estimation in Southern Africa, UNESCO IHP Series No 64. https://doi.org/10.3109/00016486709127791. Available at: https://www.researchgate.net/profile/Gregory-Hughes/publication/303013881_TECHNIQUES_FOR_ESTIMATING_GROUNDWATER_RECHARGE_AT_DIFFERENT_SCALES_IN_SOUTHERN_AFRICA/links/57356a8708ae298602df1053/TECHNIQUES-FOR-ESTIMATING-GROUNDWATER-RECHARGE-AT-DIFFERENT-SCALES-IN-SOUTHERN-AFRICA.pdf

Yang, Y., Xu, J., Hong, Y., Lv, G., 2012. The dynamic of vegetation coverage and its response to climate factors in Inner Mongolia, China. Stoch. Environ. Res. Risk Assess. 26(3), 357–373. https://doi.org/10.1007/s00477-011-0481-9

Yates, M.J., Anthony Verboom, G., Rebelo, A.G., Cramer, M.D., 2010. Ecophysiological significance of leaf size variation in Proteaceae from the Cape Floristic Region. Funct. Ecol. 24(3), 485–492. https://doi.org/10.1111/j.1365-2435.2009.01678.x. Available at: https://besjournals.onlinelibrary.wiley.com/doi/abs/10.1111/j.1365-2435.2009.01678.x

Zencich, S.J., Froend, R.H., Turner, J. V., Gailitis, V., 2002. Influence of groundwater depth on the seasonal sources of water accessed by Banksia tree species on a shallow, sandy coastal aquifer. Oecologia 131(1), 8–19. https://doi.org/10.1007/s00442-001-0855-7

Zhang, G., Su, X., Singh, V.P., 2020. Modelling groundwater-dependent vegetation index using Entropy theory. Ecol. Modell. 416, 108916. https://doi.org/10.1016/j.ecolmodel.2019.108916. Available at: https://www.sciencedirect.com/science/article/pii/S0304380019304247

Zhang, W., Zhao, L., Yu, X., Zhang, L., Wang, N., 2020. Estimation of Groundwater Evapotranspiration Using Diurnal Groundwater Level Fluctuations under Three Vegetation Covers at the Hinterland of the Badain Jaran Desert. Adv. Meteorol. 2020. https://doi.org/10.1155/2020/8478140. Available at: https://www.hindawi.com/journals/amete/2020/8478140/

Zhao, X., Zhou, D., Fang, J., 2012. Satellite-based Studies on Large-Scale Vegetation Changes in China. J. Integr. Plant Biol. 54(10), 713–728. https://doi.org/10.1111/j.1744-7909.2012.01167.x

Zhaoming, W., 2020. A Theoretical Review of Vegetation Extraction Methods Based on UAV. IOP Conf. Ser. Earth Environ. Sci. 546(3). 032019. IOP Publishing. https://doi.org/10.1088/1755-1315/546/3/032019

Zhu, Z., 2017. Change detection using landsat time series: A review of frequencies, preprocessing, algorithms, and applications. ISPRS J. Photogramm. Remote Sens. 130. 370-384. https://doi.org/10.1016/j.isprsjprs.2017.06.013. Available at: https://www.sciencedirect.com/science/article/pii/S092427161730103X