

**Mapping Land Degradation using remote sensing data and an
unsupervised Clustering Algorithm in the eThekweni Metropolitan
Area**

by

Philasande Shange

212509422



**Submitted in fulfillment of the academic requirements for the degree of
Master of Science in the Discipline of Geography in the
School of Environmental Sciences, Faculty of Science and Agriculture.
University of KwaZulu-Natal, Pietermaritzburg**

January 2020


Abstract

Land degradation is a major environmental problem facing South Africa and many other countries around the world. For proper management and adoption of best rehabilitation strategies, a compendious regional-scale assessment approach is needed to attain the full extent of the impairment. The aim of this study was to assess the spatial extent of land degradation with the use of GIS and remote sensing techniques in the eThekweni Metropolitan Area (EMA), KwaZulu-Natal, South Africa. The first objective was to review the status of land degradation in South Africa, as well as tracking of emerging trends in remote sensing and Geographic Information Systems research. Historically, in South Africa, land degradation has been associated with poverty and rurality. While conducting studies was also a challenge, demanding high human and economic resources. Although these studies were accurate and invaluable, most of them were too localized and highly difficult to replicate. The introduction of remote sensing has bought a new dimension with a timely spatial mapping of land degradation at regional scales. As a result, there thus been a sharp increase in remote sensing-based land degradation studies, this is also accompanied by the recent improvements in capabilities of remote sensors and associated GIS platforms. However, there is still a challenge of accessibility, especially for financial constricted regions such as the sub-Sahara of Africa. Most of the cutting-edge remote sensing data such as the hyperspectral and high spatial resolution imagery are highly expensive and therefore inaccessible to those not affording. However, the use of new-age medium resolution sensors is a potential solution. The second objection of this study was to detect and map the spatial distribution of land degradation in the EMA through use of Sentinel-2 derived vegetation indices (VIs) in conjunction with a hierarchical clustering algorithm. Data from Sentinel-2 was used to derive VIs used in this study, these are namely; NDVI, RVI, SAVI; and SARVI. The framework using Ward's hierarchical clustering performed relatively good to produce 6 clusters that achieved an overall classification accuracy (OA) of 88.81% when mapping land-cover including land degradation. In this regard, land degradation achieved the highest classification accuracy of up to 100%, while water achieved the lowest at 63.33%. Although there was quite a significant difference in accuracies between different land-cover classes, overall, the results were still reasonably good with an error rate of 0.14 and Kappa Coefficient of 0.86. The results from this study, therefore, suggest that Ward's unsupervised clustering approach is a suitable tool for mapping of complex land-cover classes, particularly land degradation.


Keywords: Land degradation, Sentinel-2, Geographical Information Systems, Hierarchical Clustering, vegetation indices

Declaration

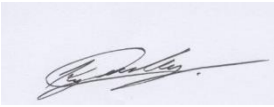
This research was undertaken in fulfilment of the requirements within the School of Agriculture, Earth and Environmental Sciences and represents original work of the author. Work or ideas taken from other sources have been duly acknowledged in a form of citation and reference list.

Signature (Student): 
Philasande Shange

Date: 04 August 2020

Signature (Supervisor): 
Dr Romano Trent Lottering

Date: 04 August 2020


Signature (Co-Supervisor): 
Dr Kabir Peerbhay

Date: 04 August 2020

Plagiarism Declaration

I, Philasande Shange declare that;

1. The research reported in this thesis, except where otherwise indicated is my original work.
2. This thesis has not been submitted for any degree or examination at any other university.
3. This thesis does not contain other persons' data, pictures, graphs or other information, unless specifically acknowledged as being sourced from other persons.
4. This thesis does not contain other persons' writing, unless specifically acknowledged as being sourced from other researchers. Where other written sources have been quoted, then:
 - a. Their words have been re-written, and the general information attributed to them has been referenced.
 - b. Where their exact words have been used, then their writing has been placed in italics and inside quotation marks, and referenced.
5. This thesis does not contain text, graphics or tables copied and pasted from the internet, unless specifically acknowledged, and the source being detailed in the thesis and reference sections.

Signed: 

Declaration for Publications

Details of contribution to publications that form part of and/or include research presented in this thesis (includes publications in progress, submitted and published and give details of the contributions of each author of each publication).

Publication 1: Shange, P., Lottering, R., and Peerbhay, K. Y. A Review of the status of land degradation in South Africa as well as tracking emerging trends in remote sensing and GIS research.

Publication 2: Shange, P., Lottering, R., and Peerbhay, K. Y. Mapping of Land Degradation using Unsupervised Learning Approaches in an Urban Environment.

The work was done by the first author under the guidance and supervision of the second and third authors.



04/08/2020

Signature: Student

Date

Philasande Shange



04/08/2020

Signature: Supervisor

Date

Dr Romano Trent Lottering

Table of Contents

Abstract	ii
Declaration	iv
Plagiarism Declaration	v
Declaration for Publications	vi
Table of Contents	vii
List of Tables	x
List of Figures	xi
1 General Introduction	1
1.1 Introduction	1
1.2 Research Problem.....	3
1.3 Aim and Objectives	3
1.4 General Structure of the Thesis	4
2 Chapter Two: A Review of the status of land degradation in South Africa as well as tracking emerging trends in remote sensing and GIS research	6
Abstract	6
2.1 Introduction	7
2.2 Land Degradation in South Africa	9
2.2.1 Population Growth.....	10
2.2.2 Land-Use Change.....	11
2.3 Mapping of Land Degradation	12
2.3.1 Traditional Methods of estimating Land Degradation.....	12
2.3.2 The use of Remote Sensing and GIS in estimating land degradation.....	13

2.3.3	Current and Possible Future Trends in Land Degradation Mapping	22
2.4	Lessons Learnt.....	25
2.5	Conclusion.....	26
3	Chapter Three: Mapping of Land Degradation using Unsupervised Learning Approaches in the eThekweni Metropolitan Area	28
	Abstract.....	28
3.1	Introduction	29
3.2	Methodology	31
3.2.1	Study Area	31
3.2.2	Field verification data	32
3.2.3	Image Acquisition and Pre-processing	33
3.2.4	Spectral Vegetation Indices	34
3.2.5	Use of the Ward’s hierarchical clustering algorithm	35
3.2.6	Accuracy assessment	36
3.3	Results	37
3.3.1	Ward’s Hierarchical Clustering using Sentinel-2 Vegetation Indices	37
3.3.2	Vegetation Indices Confusion Matrix.....	39
3.3.3	Ward’s Hierarchical Clustering using Sentinel-2 Spectral Bands Combined with Vegetation Indices	40
3.3.4	Analysis of Classification Map Derived from Selected Best Method	40
3.4	Discussion	43
3.4.1	Distribution of Land Degradation in the EMA.....	44
3.4.2	Mapping Land Degradation using Sentinel-2 and Vegetation Indices	44
3.4.3	Ward’s Hierarchical Clustering Algorithm and Unsupervised Mapping	45
3.5	Conclusions	46
4	Chapter Four	48

4.1	Aim and Review of objectives	48
4.2	Conclusion.....	49
References		51

List of Tables

Table 2. 1: Comparison of different satellite imagery providers.....	17
Table 2. 2: Summary of remote sensing applications in land degradation mapping in Africa.....	18
Table 3.1: Sentinel-2A Satellite Sensor Specifications	34
Table 3.2: Comparison of different vegetation indices used for land-cover and soil erosion mapping.....	36
Table 3.3: Classification accuracies derived using vegetation indices as an independent dataset	39
Table 3.4: Classification accuracies derived using a combination of bands and vegetation indices	40
Table 3.5: Cluster make-up detailing the percentages of contributing classes and number of data points per cluster	42

List of Figures

Figure 3.1: The map of South Africa (A), KwaZulu-Natal showing location of the study area (B) and study area (C).	32
Figure 3.2: Dendrogram representing a hierarchy of clusters and a cut-off line (in red) at six clusters	38
Figure 3.3: Land-cover classes in the study area as modelled by the hierarchical clustering algorithm.	38
Figure 3.4: Sentinel-2 vegetation indices derived classification maps of EMA showing (A) spatial distribution of major land-covers, and (B) showing the distribution of land degradation.....	41

1 General Introduction

1.1 Introduction

Most developing countries primarily depend on the natural environment for provision of livelihoods; these are countries that largely practice subsistence agriculture, fishing, and forestry (Blum, 2005; Lambin et al., 2001; Wessels, Prince, Frost, & Van Zyl, 2004). In addition to that, they also depend on land for residential purposes which are usually manifested through housing developments. However, due to increased demands, augmented pressure has been put on the environment leading to inevitable exploitation and accelerated land degradation. The problem of land degradation is well documented and is recognized as a major environmental problem; threatening food security, water resources and biodiversity (Wessels, Prince, Carroll, & Malherbe, 2007). Many researchers have labelled land degradation as one of the most critical environmental issues, affecting over 250 million people around the world (Aggarwal et al., 2010; M. T. Hoffman & Todd, 2000; T. Hoffman, Todd S., Ntoshona Z., and Turner S, 1999; UNCCD, 2014). It is estimated that up to 22 percent of all global cropland, pastures, and forests have been lost since the turn of the century (Oldeman, Hakkeling, & Sombroek, 2017; Pimentel, 2006).

One of the most cited factors of land degradation is land-cover change (Hudson & Alcántara-Ayala, 2006). The accelerated conversion of natural land for human use is mostly related to agricultural and residential purposes. Subsistence farming is a popular practice among developing countries and is linked with rural areas, usually without sustainable conservation techniques, thus leading to accelerated soil erosion (Jacobus Johannes Le Roux, Newby, & Sumner, 2007). As a result, land degradation is regarded as one of the most serious environmental problems in South Africa. In the South African context, the problem of land degradation has been well documented and various efforts have been instigated by both the public and private sectors to address this problem (M. T. Hoffman & Todd, 2000; T. Hoffman, Todd S., Ntoshona Z., and Turner S, 1999; Wessels et al., 2004; Wessels, Prince, Malherbe, et al., 2007). However, one of the major setbacks to these efforts is the lack of aggregation and limited explicit information on its spatial distribution (Jacobus Johannes Le Roux et al., 2007). In order to successfully combat this problem, it is imperative to have full knowledge of its spatial extent and severity (Seutloali, Beckedahl, Dube, & Sibanda, 2016).

In order to make informed decisions and formulate suitable strategies, there must be reliable and up to date information displaying the extent of land degradation (Bartlett & Smith, 2004). In the past, most land degradation studies adopted the traditional assessment strategies such as the Universal Soil Loss Equation (USLE) and its modified versions for soil erosion estimation, while others used methods such as field observations and community surveys (Wessels et al., 2004). Even though these types of approaches can be very accurate, they also comprise of shortcomings such as being very localized, time-consuming and tedious (K. Lee & Lunetta, 1996; Meyer & Turner, 1994; J. O. Odindi, Adam, Ngubane, Mutanga, & Slotow, 2014). However, the use of satellite remote sensing data and the advancement of Geographical Information Systems (GIS) has made it easier to conduct land degradation assessment studies at regional to large scales, with acceptable levels of accuracy in an efficient manner.

A substantial number of studies have successfully used remotely sensed imagery for mapping of land surface features across different disciplines (Bangamwabo, 2009; Boardman & Lorentz, 2000; J. Odindi, Mutanga, Abdel-Rahman, Adam, & Bangamwabo, 2017; Peerbhay, Mutanga, Lottering, & Ismail, 2016). Traditionally, most remote sensing studies were based on the mapping of changes in land-use and mainly focused on urbanization, vegetation and ecological studies (Luleva, Van Der Werff, Van Der Meer, & Jetten, 2012). The adoption of this approach for land degradation studies has been relatively recent (Sobrino & Raissouni, 2000). The open-access imagery from providers such as Sentinel and Landsat has proven to be highly beneficial for the earth mapping community. As a result, there is now a significant amount of successful studies adopting remote sensing datasets. For example, a study by Phinzi and Ngetar (2017) successfully mapped soil erosion distribution in rural Limpopo using Landsat-8 while Makaya, Mutanga, Kiala, Dube, and Seutloali (2019) used Sentinel-2 for mapping gullies in rural KwaZulu-Natal.

The success of remote sensing has also been aided by the recent advancements in GIS, these include the adoption of newer techniques such as the unsupervised machine learning algorithms. Owing to that, numerous studies have thus used machine learning techniques for various earth mapping purposes, these include a study by E. M. Adam and Mutanga (2012) who used random forest to estimate high-density biomass. While Makaya et al. (2019) also successfully used Support Vector Machines to map gully erosion. The number of studies utilizing these approaches has exponentially increased, while the conjunction of GIS with programming languages such as r and

python has opened up endless possibilities. These include the adoption of Ward's hierarchical clustering algorithm which can be used as an unsupervised mapping approach. This algorithm has been successful used in other disciplines, such as life sciences and economics but has not been used for remote sensing purposes and thus requires further investigation.

The recent advancements in satellite remote sensing and GIS have highly improved the field of earth observation research. However, there is still a shortage of studies mapping the spatial distribution of land degradation at regional scales across South Africa. Nonetheless, the adoption and improvements of the latest approaches have yielded impressive results and also demonstrate high potential success for future studies.

1.2 Research Problem

Durban is the South Africa's third largest city with regional economic importance. The metro is no exception and is also facing a challenges of land degradation. The metropolitan municipality is located on an ecologically sensitive area as it falls within the biodiversity rich Maputaland-Pondoland Albany (MPA). MPA has a total of nine vegetation types while most of it lies in on the KwaZulu-Natal Sandstone Sour-veld (KZNSS), which is classified as a savanna type vegetation endemic to KZN (CEPF, 2015; Boon, 2016). This region is highly species rich and has more than 7000 species of vascular vegetation plants of which 25% of them are endemic to the region (Van Wyk and Smith, 2001). Although the metro sits on a highly sensitive biodiversity region, it however, has sadly experienced major land-use modifications over the past decades. These activities have been rapid and thus resulted into severe land degradation in the region. Although the problem of land degradation is highly recognized and has received extensive coverage in South Africa over the years. There is still a deficit in coverage and understanding of the true intensity at regional scales. It is, therefore, highly important to continuously improve our knowledge through development and adoption of the new techniques remote sensing and unsupervised learning approaches.

1.3 Aim and Objectives

The aim of this study is to assess the spatial distribution of land degradation in the eThekweni Metropolitan Area with the use of remote sensing techniques, and also investigate and contribute

to new emerging trends in GIS and Remote Sensing. This will be achieved through the following objectives:

- (1) To review the status of land degradation in South Africa as well as the tracking of emerging trends in remote sensing and GIS research.
- (2) To test Sentinel-2 derived vegetation indices in the mapping of spatial distribution and analysis of land degradation in the EMA using the hierarchical clustering algorithm and discussion of the distribution of land degradation across the EMA.

Key research questions:

1. What are the emerging trends in mapping land degradation using remote sensing and GIS?
2. Can the hierarchical algorithm effectively detect land degradation?
3. How is land degradation distributed across the EMA area?

1.4 General Structure of the Thesis

This thesis is made up of four chapters, the first chapter is made of the general introduction and includes the main aim and objectives. The second and third chapters are comprised of two publishable stand-alone research papers. Then lastly, the fourth chapter is a brief summary of the study and is made up of the synthesis and conclusions. Below is a brief summary of chapters two and three.

Chapter two is the first publishable research paper which reviews the status of land degradation in South Africa. This includes land degradation spatial trends and the main contributing factors to this phenomenon. This followed by a special focus on the emerging trends in remote sensing and GIS. These include the adoption of newer freely available remote sensing data providers and the use of machine learning algorithms for remote sensing and GIS purposes.

Chapter three makes up the second publishable research paper, this chapter focuses on spatially mapping land degradation in EMA. This is done with the use of sentinel-2 derived indices in conjunction with an unsupervised machine learning approach, the Wards hierarchical clustering

algorithm. The choice of this technique was partly done to assess the potential of this clustering approach for purposes of land degradation mapping.

2 Chapter Two: A Review of the status of land degradation in South Africa as well as tracking emerging trends in remote sensing and GIS research

Abstract

Land degradation is one of the major environmental problems facing South Africa and many other countries around the world. This is also demonstrated by the wide range of research studies for monitoring, assessing and managing this phenomenon. Previous literature has evidenced that the process of mapping and rehabilitating affected areas is still a challenge for most sub-Saharan African countries. However, the use of remotely sensed satellite imagery data has proven to be highly important in improving the knowledge base of this challenge. As a result, there has been a sharp increase in remote sensing-based land degradation studies across the world, this is also accompanied by the recent improvements in capabilities of remote sensing data by providers and computer technologies, specifically GIS. This increase has occurred even though there is still a challenge of accessibility, especially for financially constricted regions such as sub-Saharan Africa. Most of the cutting-edge remote sensing data such as hyperspectral and high spatial resolution imagery are highly expensive and therefore inaccessible to financially constrained regions. The studies of land degradation assessment have thus been limited to the freely available medium to high spectral and spatial resolution data sources. Remote sensing data providers such as Landsat and Sentinel have demonstrated high potential and proved to be suitable for mapping the complex spectral characteristics of land degradation such as soil erosion. These studies have also benefited from the adoption of advanced classification approaches such as the SVMs and FR algorithms, which also improved the detection and mapping of land degradation features. However, the overall trends from the latest scientific studies revealed that although there still is a challenge in mapping land degradation features, the utilization coupled with the latest improvements of free and readily available data from providers such as Landsat and Sentinel has proven to be highly significant.

Keywords: Land degradation, Remote Sensing, Geographic Information Systems, Vegetation Indices, Hierarchical clustering.

2.1 Introduction

The land is one of the most important natural resources and is responsible for the survival and sustenance of many terrestrial and aquatic ecosystems (FAO, 1999). For millenniums, the land has been the backbone of human livelihoods through the provision of food, shelter and numerous other essentials. Although its importance has never been in doubt, human activities have altered and degraded the environment resulting in negative effects, which may also boomerang to endanger humans themselves. These impacts have been highly exponential, coupled with the exponential human population growth and increasing resource demand in the 20th and 21st centuries (Bongaarts, 2009; Parry, Rosenzweig, Iglesias, Livermore, & Fischer, 2004; Steffen et al., 2011).

Land degradation has had numerous definitions from different individuals and organizations. This is partly due to the nature of this phenomenon itself as it has no single-readily identifiable feature. The United Nations Convention to Combat Desertification (UNCCD) defines land degradation as “any reduction or loss in the biological or economic productive capacity of the land resource base. It is generally caused by human activities, exacerbated by natural processes, and often magnified by and closely intertwined with climate change and biodiversity loss” (UNCCD, 2014).

The occurrence and impacts of land degradation are well known as they have been widely documented, with literature extending from multiple global organizations to academic publications around the world. This phenomenon has a global prevalence, with most severe cases having been reported in underdeveloped and developing regions from literature (FAO, 1999; M. T. Hoffman & Todd, 2000; UNCCD, 2014). These regions are traditionally more prone and vulnerable to this phenomenon, largely due to their direct dependence on land for the provision of food and shelter. This is true for most developing countries including South Africa, where it has been reported that most land degradation is located in rural areas and is coupled by numerous social issues that are prevalent in these regions (M. T. Hoffman & Todd, 2000; T. Hoffman, Todd S., Ntoshona Z., and Turner S, 1999; Palmer, 2002).

Poor rural communities have the least adaptive capacity, mostly due to their lack of knowledge and resources, which makes them more vulnerable to environmental impacts of land (IPCC, 2001). The most common forms of land degradation in these regions are associated with soil erosion processes including sheet, rill and gully erosion. These have been strongly linked to rapid population growth; poor agricultural and land management activities, while they also co-exist with

natural factors such as climate change, making this a complex process (Jacobus Johannes Le Roux et al., 2007; Meyer & Turner, 1994; Poesen, Nachtergaele, Verstraeten, & Valentin, 2003; Prosser et al., 2001).

The impact of land degradation has challenged and threatened the lives of millions of people around the world, partly due to its complex nature. It is important to note that this impact has been very dynamic and there is no universal global solution to it. In order to combat land degradation, it is essential to attain a better understanding of its spatial trends and extents. Traditionally, tedious methods involving the collection of field data at high financial and human resource costs made the implementation of land degradation assessment studies a challenge. Although such studies were relatively accurate, they are difficult to replicate and are limited to small localized scales (J. Odindi et al., 2017).

There is now enough evidence from previous literature showing that such studies cannot provide an adequate assessment of land degradation, especially due to some areas being inaccessible, particularly remote mountainous areas that are hard to reach (Mehner, 2004; J. O. Odindi et al., 2014). The introduction of remotely sensed data in combination with Geographic Information Systems (GIS) provide a convenient alternative, which is both cheaper and timely. This method also has a far wider reach, making it possible to map and assess land degradation at regional to global scales. There has since been a large number of land degradation studies utilizing remote sensing techniques around the world (Khaledian, Kiani, Ebrahimi, Brevik, & Aitkenhead-Peterson, 2017; Maitima et al., 2009; Metternicht, Zinck, Blanco, & del Valle, 2010; Symeonakis, Karathanasis, Koukoulas, & Panagopoulos, 2016); including South Africa (Bangamwabo, 2009; Graw et al., 2017; Kakembo, 2001; Jacobus J Le Roux & Sumner, 2013; Makaya et al., 2019; Mbambo & Archer, 2007; Phinzi & Ngetar, 2017).

This paper serves to review the historical and current trends in land degradation mapping through remote sensing techniques. This will be achieved through a review of the state of land degradation in South Africa with special attention to remote sensing techniques through analysis of previous and current literature. Firstly, this paper will assess the national trends in the distribution of land degradation within South Africa, including key drivers of this phenomenon in this region. Secondly, the study will compare the use and performance of two medium resolution image providers, namely Sentinel-2 MSI and Landsat 8 OLI. The study then goes on to further highlight

current trends in GIS with a discussion of emerging trends in image processing and analysis. This includes a focus on the hierarchical clustering algorithm and object-orientated techniques that have not been previously extensively used nor reviewed for properties of land degradation mapping in South Africa.

2.2 Land Degradation in South Africa

Land degradation is a global threat, affecting millions of people around the world. With most severe cases being reported in developing countries, South Africa is no exception since it has one of the highest rates of land degradation (M. T. Hoffman & Todd, 2000; T. Hoffman, Todd S., Ntoshona Z., and Turner S, 1999; Wessels et al., 2004). The problem of land degradation in South Africa is well recognized, this is demonstrated by the considerable amount of research that has taken place during the last few decades. This is also reaffirmed by the country's commitment to strategies of combating this challenge, these include taking part and being in the forefront of global efforts such as the United Nations Conference on Desertification (UNCD) and participation in the United Nations Convention to Combat Desertification (UNCCD) (M. T. Hoffman & Todd, 2000). According to T. Hoffman, Todd S., Ntoshona Z., and Turner S (1999), more than 90% of South Africa's land area has been classified as affected drylands by UNCCD. Although there is a presence of different forms of land degradation, Critchley and Netshikovhela (1998) recognized soil erosion as one of the greatest threats. According to previous research, up to 70% of the country's total land area is affected by soil erosion at varying intensities (Abbas, 2007; Critchley & Netshikovhela, 1998; Garland, Hoffman, & Todd, 2000). This is in agreement with findings by Jacobus Johannes Le Roux et al. (2007) who reported that 50% (61 million ha) of South African land has a moderate to severe soil erosion potential, while 20% (26 million ha) is classified as having a moderate to severe rate of soil erosion risk.

According to numerous studies, the problem of land degradation in South Africa is highly biased, with most degradation and severe cases reported in areas mainly associated with poverty and rurality (M. T. Hoffman & Todd, 2000; T. Hoffman, Todd S., Ntoshona Z., and Turner S, 1999; Wessels et al., 2004). This has resulted in land degradation problems being labeled as spatially, geographically and socially biased. T. Hoffman, Todd S., Ntoshona Z., and Turner S (1999) states

that most land degradation in South Africa occurs in crowded communal lands, where about 80% of the total population share only 13% of the total land surface. This may somewhat be predictable since these areas were previously neglected by the government and thus have one of the highest poverty and unemployment rates. In most cases rural communities tend to depend primarily on land for food and income, this is usually through subsistence agricultural practices.

A number of studies by M. T. Hoffman and Todd (2000), and Palmer (2002) have reported that much of land degradation in South Africa is located in the Eastern Cape, KwaZulu-Natal and Limpopo Provinces; which are predominantly rural (Hoffman, 2000; Phinzi, 2017; Sepuru, 2018). This trend has therefore been attributed to the high population densities, extensive overgrazing, high levels of poverty and communal land tenure practices in these regions. The problem may worsen in the future, this is mainly due to the exponential growth of the human population, changes in land-use and land-cover and the inevitable impact of climate change. These three factors have been the driving forces of global land degradation, with population growth being labeled as the driving force for both changes in land-use and climate.

2.2.1 Population Growth

Population growth is often labeled as the key driver of global change, as it is the primary trigger for most changes in the earth's main systems (Steffen et al., 2011). The increase in the global population has put pressure on the earth's finite resources. This has resulted in increased demand for food, fuel, and energy, shelter and water that has to be satisfied by the earth's finite resources (Parry et al., 2004; Steffen et al., 2011; Steffen et al., 2006).

Much of the global population growth took place in the twentieth century, from an estimated 2 billion in 1930 to approximately 6.5 billion in 2005 (Cohen, 1995). What is even more concerning, is the continuous exponentially increasing rate as the global human population is projected to reach 9.2 billion by 2050 (Bongaarts, 2009). South Africa is no exception to the threat of the population boom, as South Africa's population has been increasing at its fastest rate in recorded history. It is estimated that the country's population has been growing by an average of approximately two-thirds of a million for the past decade and a half (StatsSA, 2018). The country's population grew from 45.8 million in 2002 to 56.5 million in 2017 (StatsSA, 2018). As a result, South Africa is

experiencing a long-term high urbanization rate, which is due to both natural growth and also a high rural to urban migration rate. This trend puts enormous pressure on urban infrastructure and resources (DEA, 2017).

2.2.2 Land-Use Change

Land-use change is regarded as the single most significant causal factor of environmental change leading to land degradation. The impact of land-use change is well documented and is highly linked to land degradation. Global change studies gained much popularity during the late 1990s and early 2000s and have confirmed the negative impacts of changing land-use on the environment (Abbas, 2007; Lu, Mause, Brondizio, & Moran, 2004; Turner et al., 2015; Warburton, Schulze, & Jewitt, 2012; Xulu, 2014). A study by Meyer and Turner (1994) highlighted changes such as intensification of urban (increase in magnitude through modification of new areas for purposes of urbanization) areas as the major cause of land-cover changes, demonstrating how humans are central and contribute significantly to land degradation.

Agriculture has often also been cited among the most significant causes of land-cover changes (Houghton, 1994; Kumar, Denis, Singh, Szabó, & Suryavanshi, 2018; Van Vliet et al., 2012). The demand for food to feed the growing global population has led to extensive global agricultural intensification (increase in magnitude of both total areas modified and productivity per acre). As a result, millions of hectares of rangeland, forests, and wetlands have been lost. This has led to a loss of many ecological ecosystems and biodiversity hot-spots, through such impacts humans have changed the environment and altered the systems that drive it (Maitima et al., 2009). According to the Food and Agricultural Organisation (2016), agriculture occupies about 1.5 billion ha of arable land, which equals approximately 11% of the global land surface. Although the impact of agriculture is labeled as the most significant, it is not the only land-cover change factor; the development of new residential and industrial areas has also significantly contributed.

Pacione (2013) defines urbanization as the increase in the proportion of the total population that lives in urban areas. According to this definition, urbanization is not only viewed as the increasing total number of the urban population, but it is also described by its proportion to the total population. Traditionally, South Africa's urbanization was historically shaped by policies to control the movement of people to urban areas (Todes, Kok, Wentzel, Van Zyl, & Cross, 2010). The proportion of the urban population in South Africa is growing, due to both natural growth and

rural to urban migration. Although urbanization is usually described by population size, it is characterized as an economic base, lifestyle, employment opportunities and infrastructure that make these areas so desirable (Lambin et al., 2001) In order to cater for the growing population, urban areas are therefore associated with intensification of residential settlements and industrialization. This, in turn, influences the outward expansion of these areas, leading to excessive land-cover changes and in-turn land degradation (Cakir et al., 2008).

2.3 Mapping of Land Degradation

There is no universal method of mapping land degradation, as a result, various researchers have adopted different techniques for basement mapping of land degradation around the world (Jacobus J Le Roux & Sumner, 2013). There are different techniques used for monitoring and management, choice of the technique might depend on factors such as financial costs, availability of skill and knowledge; the purpose of study, availability of required tools or resources. The most commonly used techniques can be categorized as traditional field surveys and modern remote sensing techniques.

2.3.1 Traditional Methods of estimating Land Degradation

Traditionally, field surveys were used for land degradation studies, but with the advancement of technology, their content reduced in light of the newer techniques that make use of air-borne photography and later, remotely sensed satellite images. The traditional techniques relied heavily on intensive fieldwork with ancillary data analysis, visual observation and estimation of features that were highly labor-intensive (K. Lee & Lunetta, 1996). This is sometimes not applicable, especially since it becomes time-consuming and usually costly, on top of that some areas might be remote and therefore not be accessible. One of the most popular traditional techniques is the Universal Soil Loss Equation and its revised version the Revised Universal Soil Loss Equation, which were developed by Wischmeier (1965) and Wischmeier (1978), respectively.

RUSLE is an empirical model that uses field-collected data. It is an improved version of the USLE model, comprising of some adjustments its parameters. Although improved, since it is based on the old USLE which was originally designed for evaluating sheet and rill erosion on short slopes; it is therefore still limited to six factors, namely: rainfall erosivity (R); soil erodibility (K); slope

length (L); slope steepness (S); soil use and management (C); and support practices (P). This limitation makes them unreliable when used on larger scales. This is because the model might leave out many processes that occur on larger scales but are negligible on smaller ones. This results in changes in the model's empirical relationships, making its results invalid (Jahun, Ibrahim, Dlamini, & Musa, 2015; Meyer & Turner, 1994; Anton Vrieling, 2006). Another limitation is the fact that the model in its original form does not provide any spatial distribution of soil erosion, but rather only absolute soil loss values. However, this weakness can be eliminated with the use of GIS and RS (Fistikoglu & Harmancioglu, 2002).

2.3.2 The use of Remote Sensing and GIS in estimating land degradation

The development of remote sensing and GIS is admired for its practicality and efficiency and has been adopted for various earth mapping purposes. This is due to the wide coverage and repeatability offered by remote sensing, providing a means for change detection of land features at larger scales (Shaikh, Green, & Cross, 2001). Although remote sensing has gained so much popularity, it is important to note that these techniques still have their own advantages and disadvantages (Phiri & Morgenroth, 2017).

The use of remotely sensed data has brought about an ability to map the entire planet in an efficient manner. The temporal aspect of the sensors has also made it possible to detect surface changes in a timely manner (Mansour, Mutanga, Adam, & Abdel-Rahman, 2016). Over the past few decades, this approach has gained wide acceptance across different research domains as the tool of choice for observing and understanding the changing and dynamic nature of earth at different spatial scales (Xulu, 2014). The frequency of remotely sensed imagery in conjunction with relatively high spatial and spectral resolutions makes them highly suitable for capturing of earth features at intervals that probably match the pace of land-use or environmental change (Phiri & Morgenroth, 2017). Remote sensing has thus been the prevailing tool for the indication of “what’s happening where” and “how much”; while also helping for studying historical trends through the long imagery archive extending back to 1972 (Turner et al., 2015; Xulu, 2014).

Over the years, improvements in remote sensors coupled with new technological advancements, particular in computer science and GIS, have led to improved earth observing capabilities,

including mapping of spatially distributed phenomena such as land degradation (Makaya et al., 2019; Mansour et al., 2016; Phinzi & Ngetar, 2017). Through maximization of sensor's spectral, spatial and temporal resolutions, it is now possible to map land degradation with less expert knowledge in a timely and cost-effective manner; especially mapping of remote environments where intensive methods are not feasible (Seutloali et al., 2016; Wilkie, Finn, & Finn, 1996). There are numerous studies that used remotely sensed imagery to detect and map land degradation processes such as soil erosion, desertification, deforestation and flooding around the world. In South Africa, remote sensing has received extensive use for mapping of land-use and assessment of the spatial distribution of land degradation (Wessels et al., 2004; Wessels, Prince, Malherbe, et al., 2007).

A significant quantity of research has focused on mapping the spread, intensity, and causes of land degradation around the country. Studies by Botha and Fouche (2000); Wessels et al. (2004); Jacobus J Le Roux and Sumner (2013); Phinzi and Ngetar (2017), have all successfully used remote sensing approaches in the assessment of land degradation and soil erosion in particular. Wessels et al. (2004), derived NDVI from a 1 km Advanced Very High-Resolution Radiometer (AVHRR) to assess the effect of human-induced land degradation in homelands of northern South Africa. This study was successful in determining human impacts on ecosystem functioning; however, the use of a 1 km spatial resolution sensor was deemed too coarse in extracting soil erosion characteristics.

Mbambo and Archer (2007) used Landsat 5 TM and Landsat 7 ETM for assessment of land degradation in a large catchment in Zimbabwe, and they were able to classify and categorize it into five levels of susceptibility. While, Taruvinga (2009) successfully used Landsat TM derived vegetation indices for mapping of gully erosion in KZN and concluded that Landsat TM has the greatest potential in gully mapping in South Africa. In this study, they compared the accuracy of Landsat imagery with that of a higher spatial resolution SPOT 5 image. In a similar study, Phinzi and Ngetar (2017) used Landsat8 OLI derived vegetation indices for mapping of soil erosion distribution; they achieved acceptable levels of accuracy with all overall classification accuracies above 80%. While a study by Floras and Sgouras (1999), achieved an overall classification accuracy of 83.94% for identifying eroded areas, land-cover and sloping using Landsat TM through the Gaussian maximum likelihood classifier.

Another important factor of the Landsat8 OLI is the availability of the higher spatial resolution 15 m panchromatic band. This is a crucial factor since a coarser spatial resolution may fail to effectively represent erosion features. There are a number of high spatial resolution imagery providers, which have gained extensive use. These include WorldView-2, SPOT, QuickBird, and IKONOS, due to their higher spatial resolution, the use of an object-oriented approach is possible (Mayr, Rutzinger, Bremer, & Geitner, 2016). The use of higher spatial resolution imagery improves the classification since it can detect and map soil erosion features better. Mapping of land degradation features such as gullies is sometimes limited by the use of coarse resolution imagery. Bocco and Valenzuela (1993) and Dwivedi, Kumar, and Tewari (1997) found the higher resolution SPOT-5 imagery to be better at classifying soil erosion in comparison to Landsat, however, it is also important to point out that they found the higher spectral resolution of Landsat to be better suited for classifying surrounding land-cover and land-use over SPOT (Bocco & Valenzuela, 1993; Servenay & Prat, 2003).

Apart from sensor capability, another key factor that separates the image data providers is their accessibility. Although the higher spatial resolution images are more desirable than those offered by the moderate resolution Landsat platform, they are not easily accessible due to their high acquisition costs, while in contrast, Landsat imagery is freely available. According to Anton Vrieling (2006), despite its limitations, the Landsat TM has the greatest potential of mapping gully erosion, due to its ability to discriminate eroded areas from surrounding land-cover. While Hansen and Loveland (2012) and Turner et al. (2015) hail its importance and nature of constant improvements through the launch of new sensors.

In addition to Landsat, the recently launched Sentinel-2 MSI has received overwhelming acceptance, with a number of studies pointing to its high potential in land degradation research. This is highly due to it serving to bridge the gap between the high spatial resolution data sources and the medium-resolution Landsat. One of its most important attributes is its free availability coupled with its relatively higher spatial and spectral resolutions in comparison to the Landsat's latest offering as seen in Table 2.1. A number of studies have proved Sentinel-2 to be highly capable of mapping most land degradation features. Makaya et al. (2019) achieved an overall classification and gully classification accuracy of 94% and 77%, respectively, using Sentinel-2 MSI in Okhombe Valley in the KZN province of South Africa. Several comparison studies with

Landsat8 OLI have demonstrated Sentinel-2 MSI to be more superior (Forkuor, Dimobe, Serme, & Tondoh, 2018; Sibanda, Mutanga, & Rouget, 2016a). Table 2.2 provides a summary of some studies that have utilized remote sensing techniques for land degradation mapping in the sub-Saharan Africa region.

The launch of the freely available Sentinel-2 in 2015 brings great opportunities for the remote sensing research community, while the longevity and constant improvements of Landsat are some of the reasons why it still appeals better to most land-cover mapping researchers.

Table 2. 1: Comparison of different satellite imagery providers.

SPOT5 HRG		Landsat8 OLI		WorldView-2 (at Nadir)		Sentinel-2 MSI	
		Band 1	30m Coastal/Aerosol	Band 1	0.46m Panchromatic	Band 1	60m Coastal/aerosol
		Band 2	30m Blue	Band 2	1.84m Coastal/Aerosol	Band 2	10m Blue
Band 1	10m Green	Band 3	30m Green	Band 3	1.84m Blue	Band 3	10m Green
Band 2	10m Red	Band 4	30m Red	Band 4	1.84m Green	Band 4	10m Red
Band 3	10m NIR	Band 5	30m RIR	Band 5	1.84m Yellow	Band 5	20m Veg red edge
Band 4	20m SWIR	Band 6	30m SWIR-1	Band 6	1.84m Red	Band 6	20m Veg red edge
		Band 7	30m SWIR-2	Band 7	1.84m Red-Edge	Band 7	20m Veg red edge
Band 5	2.5m Panchromatic	Band 8	15m Panchromatic	Band 8	1.84m NIR-1	Band 8	10m RIR
		Band 9	30m Cirrus	Band 9	1.84m NIR-2	Band 8A	20m Narrow NIR
		Band 10	100m TIR-1			Band 9	60m Water Vapor
		Band 11	100m TIR-2			Band 10	60m SWIR- Cirrus
						Band 11	60m SWIR
						Band 12	60m SWIR
Swat Width	60 Km	Swat Width	185 Km	Swat Width	16.4 Km	Swat Width	290 Km
Revisit	16 days	Revisit	26 days	Revisit	1.1 days	Revisit	5 days
Cost	Moderate	Cost	Free	Cost	High	Cost	Free

Table 2. 2: Summary of remote sensing applications in land degradation mapping in Africa.

Study Application	Sensor and Methodology	Results	Reference
<i>The study compared and explored the synergistic use of Landsat8 and Sentinel-2 in land-cover mapping</i>	Landsat8 and Sentinel-2 Used RF, SGB, and SVMs.	All Classification overall accuracies were above 90%, except for SGB on Landsat8. While Sentinel-2 outperformed L-8.	(Forkuor et al., 2018)
<i>The study tested the ability of landsat8 and sentinel-2 in mapping eroded areas across wet and dry seasons.</i>	Landsat8 and Sentinel-2 Used Discriminant Analysis (DA). Classification ensemble	OAs ranging between 80% to 81.90% for S-2 and 75.71%–80.95% for L8 were derived for the wet and dry season, respectively.	(Sepuru & Dube, 2018)
<i>The study evaluates the potential of Sentinel-2 in mapping the spatial distribution of gullies.</i>	Sentinel-2 Uses semi-automatic Support Vector Machine algorithm (SVM).	OA land-cover classification of 94% and OA classification of 77% for gullies.	(Makaya et al., 2019)
<i>Assessing rangeland degradation using WorldView-2 imagery in Okhombe, KZN.</i>	WorldView-2 Used Random Forest Algorithm	Achieved OA of 82.6% which increased to 90% when using a subset of vegetation indices.	(Mansour, Mutanga, & Everson, 2012)
<i>Using multispectral remote sensing imagery for mapping of grassland degradation in Cathedral Peak.</i>	SPOT-5 Used Random Forest Algorithm	OA of 75.3% and improved to 88.6% with the integration of multispectral data and soil-related variables.	(Mansour et al., 2016)
<i>Mapping of soil erosion in the Eastern Cape with the use of Landsat8 imagery derived indices.</i>	Landsat8 Used ArcMap for selecting Index soil erosion thresholds	SAVI at 83% was more accurate in comparison to 81% by NDVI and SARVI. While Kappa statistics was at 64%, 60%, and 59% respectively.	(Phinzi & Ngetar, 2017)

2.3.2.1 Soils Spectral Characteristics

The complexity of mapping land degradation features with the use of remote sensing largely depends on the spectral characteristics of the target features themselves (King, Baghdadi, Lecomte, & Cerdan, 2005). Soil erosion is one of the major problems of land degradation in South Africa. There is a direct correlation between soil erosion and the spectral reflectance values, this distinction allows for the detection and mapping of soil erosion features and their intensity (King et al., 2005; Price, 1993). It is, therefore, highly important to understand the spectral characteristics of soil erosion features and their surroundings.

The spectral signatures of bare soil characterizing soil erosion and its levels of severity are highly influenced by features such as mineral composition, soil texture, soil moisture and organic matter content (Barnes & Baker, 2000; Sujatha, Dwivedi, Sreenivas, & Venkataratnam, 2000). Soil particle size influences the porosity, which directly affects both soil moisture and color. The differences in spectral curves of sandy and clay soils relate directly to soil texture. Sandy soils have larger particles and are usually drier, which results in a strong reflectance across the visible and NIR portions of the spectrum in comparison to clay (S. A. Bowers & S. J. Smith, 1972; Hoffer & Johannsen, 1969). Clay, on the other hand, is fine and smooth and it absorbs most of the incoming light. Since texture largely influences soil moisture, clay soils are able to retain most of its moisture and are thus usually wetter. If the soil moisture content increases, the soil's spectral reflectance will decrease and become similar to that of water. According to studies by S. Bowers and S. Smith (1972) and Matinfar, Alavipanah, and Sarmadian (2006), soil moisture has the highest effect on the spectral reflectance of soil.

Another important characteristic of soil moisture is the presence of absorption bands around 1.4 μm and 1.9 μm of which dry soils do not have (S. Bowers & S. Smith, 1972). The last factor influencing the soil spectral signatures is the presence of minerals and organic matter. The presence of organic matter highly influences soil color. An increase in organic matter content will decrease the spectral reflectance of soil, as the soils will appear darker (Stoner & Baumgardner, 1981). Organic matter is controlled by plants decomposition content and is usually a good indicator of land degradation. The removal of organic content leads to increased soil albedo, resulting in high spectral reflectance (Taruvunga, 2009).

As discussed in the preceding paragraphs, the distinction of soil features from its surroundings; including vegetation cover, built-up areas, cultivated areas, and water bodies; largely depends on the spectral heterogeneity of soil erosion features due to the highly complex spectral properties of the surroundings (Alejandro & Omasa, 2007). Soil usually does not occur in isolation; it is thus highly important to understand the characteristics of its spectral signatures both in isolation and also relative to its surroundings. According to Wegmuller, Strozzi, Farr, and Werner (2000) and A Vrieling, Rodrigues, Bartholomeus, and Sterk (2007), vegetation and moisture change are a major cause of spectral decorrelation when mapping soil erosion. In order to attain accurate soil mapping estimates, it is therefore important to capture soil's distinction in both isolation and relative to its surrounding environment.

2.3.2.2 The Use of Image Spectral Indices in Soil Erosion Mapping

Vegetative spectral indices utilize the correlation between the land-cover features and the spectral reflectance values for purposes of detection and mapping. This method has been used for more than four decades as one of the primary remote sensing methods for quick and simple land-cover mapping (King et al., 2005). Spectral indices rely on the spectral heterogeneity of the land-cover features for mapping. For example, using the spectral contrast between vegetation and bare soil to detect soil erosion. This is usually done through the use of the linear relationship between the visible red and infrared bands.

The combination of the visible red and NIR bands results in a distinct separation of vegetation from other surfaces. This is because vegetation reflects very low in the visible red band, while in contrast, it reflects very high in the NIR band. Spectral indices can thus be used as an indicator of the presence or lack of vegetation biomass. Some studies have used the assumption of lack of vegetation or bareness as an indicator of soil erosion (Phinzi & Ngetar, 2017). These studies have used different indices that are suitable for an accurate representation of vegetation on the ground (Vaidyanathan, Sharma, Sinha, & Dikshit, 2002).

The spectral indices have been utilized in numerous studies around the globe for various purposes including land-use and land-cover change studies such as Pickup and Nelson (1984); Price (1993); Zha, Gao, and Ni (2003); Sinha, Verma, and Ayele (2016) and Rasul et al. (2018). While they have

also been used for land degradation and soil erosion mapping in particular by Phinzi and Ngetar (2017); (Taruvinga, 2009) in South Africa. Two of the earliest and most popular spectral indices are the Ratio Vegetation Index (RVI) and Normalized Difference Vegetation Index (NDVI), which have received extensive use around the world for decades. Many studies have preferably used NDVI for mapping of land-use change. For example, Marsh, Walsh, Lee, Beck, and Hutchinson (1992) successfully used NDVI derived from SPOT and AVHRR for mapping of land-cover dynamics in the West African Sahel and achieved good temporal assessment of semi-arid vegetation dynamics. Tappan, Tyler, Wehde, and Moore (1992) also studied a series of three NDVI images from AVHRR data for monitoring seasonal vegetation conditions of the Sahel and Sudan rangeland and found them to be particularly valuable in differentiating seasonal fluctuations from long term production characteristics.

Other studies include Ray, Farr, Blom, and Crippen (1993) who studied land degradation after abandonment using NDVI from Airborne Synthetic Aperture Radar and airborne visible/infrared spectrometer images and found out that abandoned land supported less vegetation in comparison to occupied land. Some studies have also proven that the use of NDVI goes beyond quantifying biomass. For example, Kawamura et al. (2005) used NDVI for monitoring of forage quantity and quality in inner Mongolia and concluded that NDVI can reliably detect phenology and forage quality of grassland steppe areas. The extensive use of NDVI is also found in South Africa, where there is a number of successful studies.

Studies by Wessels et al. (2004); Wessels, Prince, Malherbe, et al. (2007), are some of the most referenced land degradation studies in South Africa, these studies successfully used the NDVI for mapping of land degradation features in the semi-arid parts of the country. In the first study, Wessels et al. (2004) used NDVI to assess human-induced effects of land degradation in the former homelands of northern South Africa; while in the second study Wessels, Prince, Malherbe, et al. (2007) used NDVI to distinguish human-induced land degradation from that of rainfall variability. Although there are only a few land degradation mapping studies that have used NDVI in South Africa, the index has been used extensively for other land-cover mapping purposes.

It is important to note that with all its success and popularity, NDVI also has its own shortfalls, some arising from its high sensitivity to both soil background and atmospheric effects. As a result, there are numerous modified versions including the Soil Adjusted Vegetation Index (SAVI) and

Soil and Atmospheric Resistance Vegetation Index (SARVI). A study by Taruvinga (2009) used NDVI in combination with SAVI and SARVI derived from Landsat TM images for mapping of gully erosion in KZN. While Phinzi and Ngetar (2017) in a similar study used Landsat8 OLI for mapping of soil erosion in the Eastern Cape, where SAVI was found to be more accurate in comparison to NDVI and SARVI. Huete and Liu (1994) used NDVI, SAVI and SARVI indices for error and sensitivity analysis and found both SAVI and SARVI outperformed NDVI, while the SARVI produced the best results.

There have also been numerous other modifications proposed and used by numerous researchers. A study by Price (1993) found a strong correlation between the NIR band and soil erosion using Landsat TM in the Pinyon-Jupiler woodlands. While Pickup and Nelson (1984) successfully used band ratios green/NIR and red/NIR from Landsat MSS to map different levels of soil erosion in arid rangelands of Australia.

2.3.3 Current and Possible Future Trends in Land Degradation Mapping

Over the past decades, significant developments have been achieved in both computer-aided image analysis algorithms and earth mapping satellite sensors. As a result, current satellite sensors are capable of mapping large surfaces of the earth with high accuracy using high spatial, spectral and temporal resolutions. While with the latest developments in computer and GIS capability, researchers are now able to detect and map earth features with a high degree of precision and accuracy. However, there is still a lot of potential and aspects that have yet to be elucidated in the mapping of land degradation using RS.

2.3.3.1 Recent Improvements in Remote Sensors

Recent improvements in remote sensor capabilities have been grasped with the developments of a number of satellite sensors comprising of higher spatial, spectral and temporal resolutions. Due to such high capability features, fine spatial and hyperspectral imagery has been effectively used in various remote sensing applications including land-cover mapping. The discrimination of degraded areas has long been challenging, largely due to the complexities arising from similarities in spectral characteristics of bare soil and those of mixed areas comprising of vegetation and water surfaces. However, the development of the newer superior sensors has brought about the new potential for mapping these features with high accuracy.

It is, worth noting that although the use of such sensors has increased and their importance is also invaluable, their adoption in resource-scarce regions such as sub-Saharan Africa remains hindered, due to their high cost which repels their accessibility (J. O. Odindi et al., 2014). There is still a shortage in the utilization of higher resolution sensors. As a result, there is still a need for a robust hyperspectral and high spatial resolution research in the assessment of land degradation in South Africa.

A large number of studies have utilized free and readily available satellite imagery from providers such as Landsat and Sentinel, who provide reasonably high-resolution multispectral images. This trend is also expected to continue in the near future since these image providers have also been constantly improving their offerings. This is reaffirmed with the launch of Landsat8 OLI back in 2013 and the launch of Sentinel-2 MSI in June 2015. Numerous studies have been conducted in the sub-Saharan Africa region with these sensors and have achieved a high success rate (Makaya et al., 2019; Matongera, 2016; Phinzi & Ngetar, 2017). A number of studies have also focused on the comparative assessment of these two sensors with the Sentinel-2 MSI proving to be superior to Landsat8 OLI in the mapping of both urban and land degradation features (Forkuor et al., 2018; Pesaresi et al., 2016; Sibanda, Mutanga, & Rouget, 2016b). These studies suggest that the use of Sentinel-2 MSI provides great potential for mapping of land-cover features and might prove to be highly important for future studies.

2.3.3.2 Emerging Trends in Remote Sensing

There is a common belief that the quality of imagery used is more important than the method of the algorithm used in classification results. However, the image classification approaches are also highly important and can also dictate the classification outcome. A large number of recent studies are drifting away from the traditional supervised and unsupervised classification approaches such as the Maximum Likelihood Classification and ISO cluster unsupervised classification to newer and more logical and accurate approaches. These include the robust machine learning algorithms such as Support Vector Machine (SVM) and Random Forest (RF) (EM Adam, Mutanga, Rugege, & Ismail, 2012; Adelabu & Dube, 2015; Makaya et al., 2019; J. O. Odindi et al., 2014).

EM Adam et al. (2012) successfully used RF techniques to estimate high-density biomass from WorldView-2 imagery. J. O. Odindi et al. (2014) also used RF for mapping of bracken fern plant using WorldView-2 and SPOT-5 imagery and achieved overall accuracies (OA) of 91.67 and

82.33%, respectively. In another study, Adelabu and Dube (2015) used RF to discriminate tree species from QuickBird imagery and produced an OA of 79.86 and 88.78 for resampled and actual images, respectively. Makaya et al. (2019) also used SVM for mapping the spatial distribution of gullies. While Elhadi Adam, Mutanga, Odindi, and Abdel-Rahman (2014) used both RF and SVMs to evaluate the performance of Rapid Eye bands, where RF achieved a comparably higher accuracy of 93.07%, while achieved SVMs 91.8% with the Kappa coefficients also coming out the same at 0.92.

Other popular unsupervised learning algorithms include cluster analysis, which have been used for various data manipulation purposes including; classification, interactive user-interface, storage and retrieval; and pattern recognition of complex datasets (Giraldo, Delicado, & Mateu, 2012; Kraskov, Stögbauer, Adrsejak, & Grassberger, 2003; Meyer & Turner, 1994; Murtagh & Contreras, 2012; Zhao & Karypis, 2002; Zhao, Karypis, & Fayyad, 2005). This approach is used for grouping of data into homogenous clusters, such that data within one cluster share similar characteristics (Anderberg, 2014). The approach is also suited for separating spatial data into multiple classes of similar characteristics. In the case of imagery data, this method can be used to classify and merge pixels that have the highest probability of being members of the same class (S. Lee & Crawford, 2005). Two of the most popular clustering methods are the hierarchical clustering and partitional clustering methods, which have received widespread use across different disciplines.

The hierarchical clustering method is a bottom-up agglomerative approach, where initially each individual data point is assigned to its own cluster and the two closest clusters are iteratively clustered together until all data belong to the same cluster (Giraldo et al., 2012; Kraskov et al., 2003; Zhao & Karypis, 2002; Zhao et al., 2005). While in contrast, the partitional algorithm methods adopt a top to the bottom approach where there is a single cluster containing all data points, the cluster is then partitioned into a certain number of smaller clusters (Zhao et al., 2005).

Hierarchical clustering is useful for analyzing and grouping of data, especially when working with categorical data where similarity measures can be defined accordingly. However, this approach also has a number of limitations such as the selection and merging of wrong clusters, due to factors such as distance and interconnectivity (Karypis, Han, & Kumar, 1999). While it also has challenges when dealing with clustered data such as images, as it has difficulties in the selection

of a correct distance matrix to use. It also does not define any probabilities related to the data used, therefore making it hard to establish the quality of the cluster and to compare it with other models (Heller, 2005). The clustering algorithms have found limited use in the remote sensing and land-cover classification space, but their successful use in disciplines such as life and physical sciences demonstrate high potential in complex data classification (Arbeitman et al., 2002; J.-G. Lee, Han, Li, & Gonzalez, 2008; Sanges, Cordero, & Calogero, 2007; Sasson et al., 2003).

The adoption of some of these approaches has not been widely accepted by the remote sensing community, due to different factors such as lack of appropriate software and overall complex workarounds (Waske et al., 2012). While recently, development and application of various algorithms have been on the rise and in combination with the adoption of newer satellite image sensors their adoption may produce more accurate land-use maps. The development of high spatial and spectral images has also brought more possibilities and an increased potential in the adoption of methods that were not feasible in the past, such as the object-based image analysis.

Over the past two decades, the object-based image analysis has been recognized as an emerging approach in the analysis of high spatial resolution images. The unique features of this approach take advantage of features such as shape, texture and contextual features to improve the delineation of the target (Chen, Weng, Hay, & He, 2018). Some latest development proposals for this approach also seek to maximize mapping through the representation of target features in a three-dimensional (3D) format with the development of Geographic Object-Based Image Analysis. A successful development of such an approach could be a highly important breakthrough, especially in the mapping of urban areas, which usually comprise of 3D structures. This can also aid in explicit mapping tree species and gullies, which are sometimes not suitably represented in two-dimensional images. The generation of land-cover maps in 3D would be a more accurate representation of the real world. According to Wang (2013), 3D image scenes can be achieved with the constant improvements in computer technology coupled with the fusion of LiDAR and optical data.

2.4 Lessons Learnt

One of the most notable takings from literature is the utmost severity of land degradation in South Africa. This had emerged as a serious environmental problem, while the lack of information with

regards to its spatial extent remains a key limitation. Therefore, there is an urgent need to improve knowledge through regional land degradation mapping and assessment studies, such as those carried out with GIS and remote sensing techniques. However, this review has also demonstrated the country's extensive quantity of remote sensing research, the adoption of latest techniques has been highly useful and is ministered by the recent advancements in computer and image sensor technologies. Furthermore, the adoption of the latest imagery from sensors such as Sentinel-2 and Landsat-8 is now coupled with the use of new-age machine learning techniques such as RF and SVMs, which have highly improved detection and mapping of land degradation features, producing results of high accuracy.

The study also finds that despite the introduction of fine spatial and hyperspectral imagery, in the context of a resource-scarce country such as South Africa, it is the cheap, free and readily available imagery data providers that have and are still expected to play an important role. It is therefore expected that the adoption of newer superior sensors such as Sentinel-3 MSI and Landsat8 OLI, in conjunction with improved classification algorithms, will highly improve the country's potential for future land degradation studies.

Lastly, the review also discovered that the adoption of techniques such as the hierarchical clustering algorithm and object-orientated approaches, which were previously lacking is now possible with the latest advancements in image sensors and computer technology. Therefore, there is a need to continuously improve our knowledge, especially through the improvement of already existing approaches and adoption of the latest techniques, including those that were previously not explored.

2.5 Conclusion

According to literature, there has been a drastic increase in the amount of research content on land degradation using remote sensing methods. The use of remotely sensed imagery has proven to be highly efficient, by virtue of both its user convenience and superior accurate results. The past two decades had a significant improvement in the development and use of various remote sensing techniques around the world. The improvements in sensor technology have led to the availability of higher spatial and spectral capabilities, which provide more accurate and reliable land degradation mapping estimates. However, although such sensors have a highly recognized potential and capacity, they are still not readily available to most African countries due to their

high costs. It is, therefore, the freely and readily available medium resolution multispectral sensors such as Landsat and Sentinel that have the highest potential in this region. This is more so with the constant update and launching of improved sensor versions from these imagery providers. Literature has demonstrated how the improvements in these sensors have led to more accurate detection and mapping of land degradation features. The inclusion of the red-edge bands in the Sentinel-2 MSI has improved the discrimination of land degradation features from other land-cover features. It is also notable that even though these sensors have accurately detected and mapped land degradation features, they still have some limitations. This is primarily due to their spatial resolutions sometimes deemed too coarse for mapping of some land degradation features such as rill and gully erosion, especially when used at local scales for qualitative purposes. The classification of land degradation features is still a challenge, but literature proves that the constant improvements of offerings by the remotely sensed data providers, coupled with the adoption of new classification approaches such as machine learning algorithms have played an important role in the advancement of land degradation research, especially within the resource-constrained sub-Saharan Africa region. It is also highly important to continuously improve and adopt the latest techniques, approaches such as hierarchical clustering and object-based image classification, which now have high potential especially with the rapid advancements in GIS and imagery sensor technologies.

3 Chapter Three: Mapping of Land Degradation using Unsupervised Learning Approaches in the eThekweni Metropolitan Area

Abstract

This study seeks to automatically map land degradation with the use of remotely sensed imagery through unsupervised clustering in a complex urban environment in the eThekweni Metropolitan Area, KwaZulu-Natal, South Africa. Data from Sentinel-2 Multispectral Instrument was used to derive vegetation indices used in this study, these were namely; Normalized Difference Vegetation Index, Ratio Vegetation Index, Soil Adjusted Vegetation Index; and Soil and Atmospheric Resistance Vegetation Index. The framework using Ward's hierarchical clustering performed relatively well to produce 6 clusters that achieved an overall classification accuracy (OA) of 88.81% when mapping land-cover including land degradation. In this regard, land degradation achieved the highest classification accuracy of up to 100%, while water achieved the lowest at 63.33%. Although there was quite a significant difference in accuracy between different land-cover classes, overall the results were still reasonably good with an error rate of 0.14 and Kappa Coefficient of 0.86. The results from this study, therefore, suggest that Ward's unsupervised clustering approach is suitable for mapping of complex land-cover classes and land degradation in particular.

Keywords: Land degradation, Sentinel-2, Hierarchical Clustering, vegetation indices.

3.1 Introduction

The distribution of land degradation in Southern Africa is alarming, with South Africa being reported as one of the most susceptible regions to soil erosion in the world (Wessels et al., 2004). Land degradation is a threat to biodiversity, as it disturbs ecosystem functioning and also causes great implications to an already scarce water resource. It has also led to the destruction of large portions of natural biomes, which in turn threatens food security through the loss of fertile soil, whilst also leading to a reduction of water reserves through sedimentation (J. Le Roux, 2011; Onyando, Kisoyan, & Chemelil, 2005; Peng, Xu, Cai, & Xiao, 2011). This is a similar case with the eThekweni Metropolitan Area (EMA), where most of the natural veld biome has been lost, largely due to human activities (Onyango, 2014). The region is experiencing rapid fragmentation, mainly from pressures of land-cover changes arising from high urbanization rates and other factors such as the inevitable and often uncontrollable effects of climate change, which results in further dynamism and uncertainty (Warburton, Schulze, & Jewitt, 2010). There have been a number of strategies implemented to combat degradation, such as the Durban Metro Open Space System (D'MOSS) aimed to protect and manage all land significant to biodiversity and supply of ecosystem services to EMA (Boon et al., 2016; Davids, Rouget, Boon, & Roberts, 2016).

It is therefore important to obtain information and better our understanding of the extent of land degradation in this region, in order to adopt the best management and rehabilitation strategies. Traditionally, field surveys were used for such studies, these techniques relied heavily on intensive fieldwork with ancillary data analysis, visual observation and estimation of features which were highly labor-intensive (K. Lee & Lunetta, 1996). Remote sensing has emerged as a highly reliable approach for detecting and mapping of land degradation features. This technology provides up to date spatial data, which is necessary for showcasing the spread and intensity of this phenomenon at a regional scale (Senanayake, Welivitiya, & Nadeeka, 2013). Recently, many studies have focused on exploiting newly launched open access multispectral data such as Landsat-8 and Sentinel-2, particularly from regions with constrained financial resources (Forkuor et al., 2018; Makaya et al., 2019; Phinzi & Ngetar, 2017; Sepuru & Dube, 2018).

In this context, Makaya et al. (2019) used Sentinel-2 imagery to map the spatial distribution of gullies in Okhombe, a village in KwaZulu-Natal, achieving an overall accuracy (OA) of 94% using a Support Vector Machine algorithm and a 77% class accuracy for gullies. Sepuru and Dube (2018)

also successfully used Sentinel-2 and Landsat-8 in mapping eroded soils in the Limpopo Province using a combination of spectral bands and vegetation indices (VIs). Results from this study indicated that Sentinel-2 had superior capabilities in the mapping of soil erosion features compared to Landsat-8. Similarly, Forkuor et al. (2018) used three machine-learning algorithms (random forest, stochastic gradient boosting, and support vector machines) to compare Sentinel-2 and Landsat-8 in mapping land-use and land-cover in rural Burkina Faso. They found the classification of Sentinel-2 to be more accurate in comparison to that of Landsat-8. The OA from all Sentinel-2 bands and that from Sentinel-2 bands shared with Landsat-8 produced 5% and 4% improvements in land-use and land-cover mapping respectively in comparison to Landsat-8. They also noted that classification from Sentinel-2 red-edge bands alone was up to 3% superior to that of Landsat-8 and was comparable to the other Sentinel-2 bands. Sibanda et al. (2016a) also compared the utility of these two sensors using discriminant analysis and found Sentinel-2 to have improved spectral capabilities in mapping rangeland management practices. In a subsequent study, Sibanda et al. (2016b) found the performance of Sentinel-2 (red-edge, Near-Infrared and Short Wave Infrared) to be comparable to that of a Hyperspectral Infrared Imager (red-edge, NIR, and SWIR) in assessing and monitoring of rangeland management practices.

The performance of Sentinel-2 has demonstrated improved capabilities in the detection and mapping of heterogeneous land-cover classes, especially with the addition of the three vegetation-red-edge bands. While this sensor also comprises reasonably fine spatial bands, with resolutions of up to 10 m for the visible region of the electromagnetic spectrum, Makaya et al. (2019) also noted that the visible region, SWIR, and red-edge make Sentinel-2 highly suitable for mapping of land degradation features such as gullies using the Support Vector Machine (SVM) algorithm. Additionally, Sepuru and Dube (2018) mentioned NIR, red-edge, and SWIR as the most optimal bands for detecting degraded soils amongst other land-covers using discriminant analysis. The use of VIs derived from such remotely sensed imagery has also gained substantial success and popularity. There is a substantial number of studies which have adopted this technique in the southern African region for land degradation mapping. These include studies by Wessels et al. (2004); (Wessels, Prince, Carroll, et al., 2007); and newer studies by Phinzi and Ngetar (2017); (Seutloali et al., 2016; Taruvinga, 2009); which utilized Landsat-8 and Landsat-7, respectively. To the best of our knowledge, there are currently no studies that have utilized Sentinel-2 derived VIs for mapping land degradation in southern Africa using an unsupervised approach.

Unsupervised mapping approaches require no training data information, thus demanding less human interference, reducing human error and saving time (Le Hegarat-Masclé, Bloch, & Vidal-Madjar, 1997; Zhong, Zhang, Huang, & Li, 2006). Such approaches have yielded major success from recent studies using remotely sensed datasets (Lottering, Mutanga, & Peerbhay, 2018; Makaya et al., 2019; Peerbhay, Mutanga, Lottering, Agjee, & Ismail, 2019; Peerbhay et al., 2016). This study adopts the Ward's hierarchical clustering algorithm which has previously not been explored for purposes of mapping land degradation using remote sensing. Whereas, it has found success in disciplines such as life and health sciences where Seo and Shneiderman (2002) used it for the identification of co-regulated genes. It has also been adopted in marketing and finance for many decades as Srivastava, Leone, and Shocker (1981) successfully used it for market structure analysis through product usage. While it has also been used for image analysis and segmentation (S. Lee & Crawford, 2005).

The main objective of this study was therefore twofold; firstly, to automatically detect the spatial distribution of land degradation in the study area using Sentinel-2 derived VIs and a combination of VIs and image spectral bands; and secondly, to assess the potential of Ward's hierarchical clustering algorithm for purposes of detecting and mapping land degradation from complex land-cover classes.

3.2 Methodology

3.2.1 Study Area

The study was conducted in the eThekweni Metropolitan Area (EMA), located on the eastern shoreline of the KwaZulu-Natal (KZN) Province in South Africa (Figure 3.1). EMA lies between 29° 55' 23.46" to 29° 47' 33.64" south latitudes, and between 30° 37' 39.07" to 30° 47' 30.45" east longitudes. EMA is South Africa's third-largest urban region with an estimated total population of 3.7 million (StatsSA, 2018). The Metro covers an area of 2297 km² which gives it a moderate population density of 1611.8 people/Km² (Breetzke, 2009). Although EMA is dominated by urban areas, it also falls within a global biodiversity hotspot. The city of Durban is located within the MPA Hotspot and lies on the KZNSS, which is classified as a savanna type vegetation endemic to KZN (Boon et al., 2016; CEPF, 2005). This region is highly species-rich and has more than 7000

species of vascular vegetation plants of which 25% of them are endemic to the region (Van Wyk & Smith, 2001).

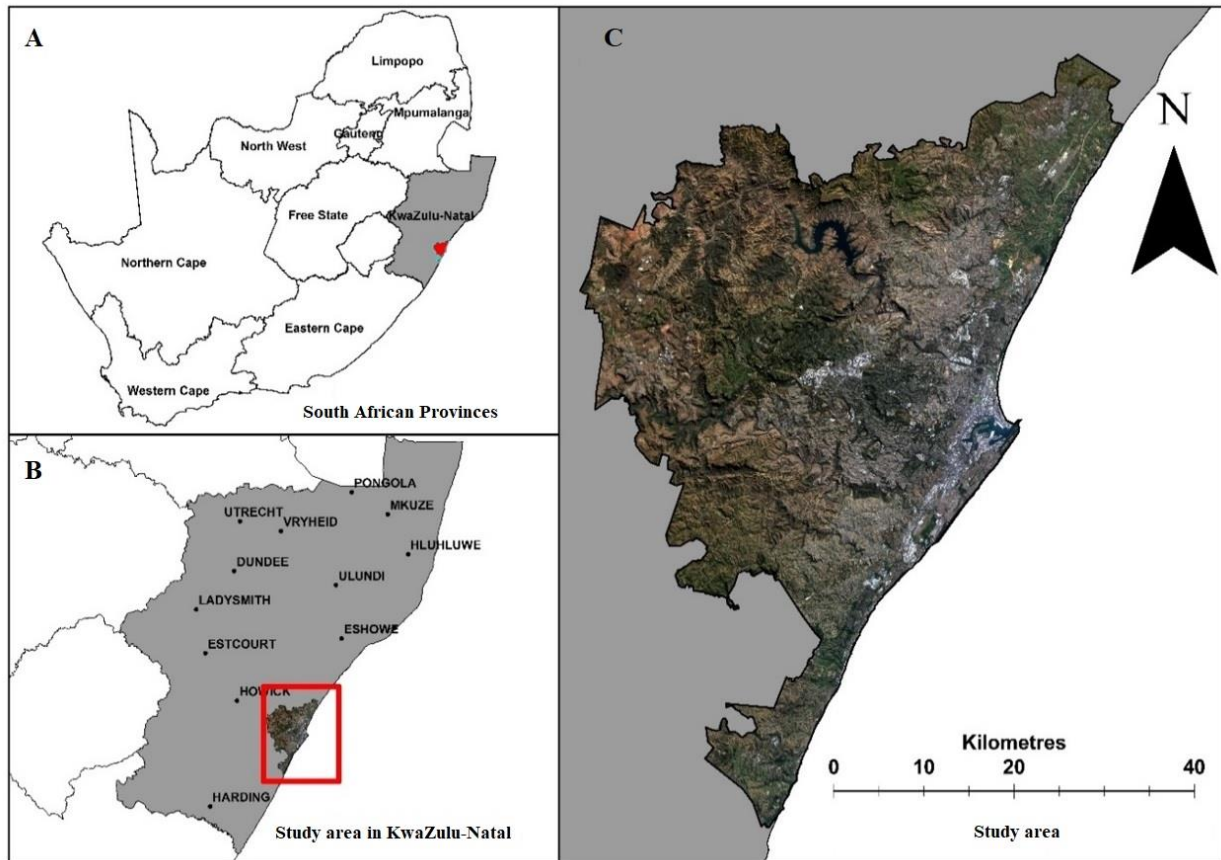


Figure 3.1: The map of South Africa (A), KwaZulu-Natal showing location of the study area (B) and study area (C).

3.2.2 Field verification data

It is highly essential to qualitatively assess the accuracy of remote sensing classification results. This is helpful for both the producer and the user of the map, as it evaluates and shows how the source of data and model choice affects the result. One of the most popular accepted methods for this process includes the use of unbiased ground reference samples. In this study, a total of 268 polygon ground samples were created using the “Training sample manager tool” in ArcMap10.4. These samples were spread across all major land-cover classes within the boundary of the study area. These samples were then converted to keyhole markup language (kml) format and imported into Google Earth Pro for purposes of ground-truthing, where the date was set to April 2016 in

order to match the date of image acquisition. Since most land degradation features are small, most ground reference samples sat on non-land degradation features. To cater to that, if close enough, random points were then assigned to the closest adjacent land degradation features on Google Earth Pro, using a method similar to that of Phinzi and Ngetar (2017). Out of the 268 samples created only 55 samples were assigned to land degradation, with the rest being assigned to the remaining identified major land-cover classes of the study area.

3.2.3 Image Acquisition and Pre-processing

For this study, two image scenes of the Sentinel-2 sensor covering the entire study area were sourced from the United States Geological Survey's (USGS) Earth Observation and Science (EROS) website (<http://earthexplorer.usgs.gov/>). The study area covered the entire boundary of EMA and the Sentinel-2 sensor used in this study consist of a single Multispectral Instrument with 13 spectral bands in the visible, near-infrared (NIR) and short wave infrared spectral range (SWIR). The sensor has a swath width of 290 km and a revisit time of 5 days. Please refer to Table 3.1 for image and sensor details and specifications.

The images were then individually rectified for preprocessing through radiometric correction. This process was carried out with the use of Sentinel Application Platform version 5.0 (SNAP) software that has a Sen2Cor atmospheric correction toolbox, which is an external plugin algorithm. After completion of the radiometric correction, the image scenes then went through a process of resampling, where the band's variable spatial resolution were all resampled to 10 m. This was then followed by a process of sub-setting and mosaicking the image, which was done with the use of ArcMap 10.4. This was required in order to merge the different scenes into a single image that was then clipped to the boundaries of the study area.

Table 3.1: Sentinel-2A Satellite Sensor Specifications

Sentinel-2A MSI bands	Spatial Resolution	Central wavelength (nm)
Band 1	60m Coastal/aerosol	442.2
Band 2	10m Blue	492.4
Band 3	10m Green	559.8
Band 4	10m Red	664.6
Band 5	20m Veg red edge	704.1
Band 6	20m Veg red edge	740.5
Band 7	20m Veg red edge	782.8
Band 8	10m RIR	832.8
Band 8A	20m Narrow NIR	864.7
Band 9	60m Water Vapor	945.1
Band 10	60m SWIR- Cirrus	1373.5
Band 11	60m SWIR	1610.4
Band 12	60m SWIR	2185.7
Swat Width	290 Km	

3.2.4 Spectral Vegetation Indices

The use of VIs forms a major part of this study, with the adoption of a combination of Ratio Vegetation Index (RVI), Normalized Difference Vegetation Index, Soil Adjusted Vegetation Index; and Soil and Atmospheric Resistance Vegetation Index for mapping of land degradation within the study area. These VIs were combined to produce a weighted average, where each VI contributed a quarter to the overall output. The use of VIs requires extensive use of the red and near-infrared bands, which are probably the two most important bands in the calculation of VIs. This study uses the assumption that areas that lack vegetation cover and comprise of bare surfaces are eroded areas. All processing of VIs in this study was carried out with the use of the ArcGIS, where a Sentinel-2 image of the study area was used to derive the VIs through a raster calculation tool in ArcMap 10.4. The extraction of index values was then carried out for land degradation and all other major land-cover classes identified in the study area, these were namely; water, forests, grasslands, suburban (built-up) and industrial (built-up) areas. The RVI is one of the earliest

successful VIs, developed in the early 1970s by Pearson and Miller (1972). It is one of the simplest VIs to effectively enhance the contrast between the ground and the vegetation cover and is not highly affected by the sun's illumination. However, it is highly sensitive to ground optical conditions (Baret & Guyot, 1991). RVI is simply expressed as a ratio of the visible red and the NIR spectral bands as illustrated in Table 3.2. The second VI used in this study is the NDVI, which is the most commonly used VI and is formulated as illustrated in Table 3.2. The success and importance of NDVI is invaluable and well documented, however, due to its high sensitivity to atmospheric effects and other non-vegetative surfaces, there have thus been various modifications and development of newer improved indices (Govaerts & Verhulst, 2010). SAVI and SARVI are two of the most widely used VIs in vegetation and soil research and were mainly developed to cater to the shortcomings of NDVI. The SAVI successfully describes the soil-vegetation system, and its formula is very similar to that of NDVI with only a minor addition and was proposed by Huete (1988) as seen in Table 3.2. The SARVI was then later developed by Huete and Liu (1994) and generally uses the traditional combination of visible red and NIR bands with an introduction of a visible blue band B and γ which is a constant that stabilizes the index for atmospheric aerosol content.

3.2.5 Use of the Ward's hierarchical clustering algorithm

The ward's hierarchical clustering algorithm is a useful tool used for analysis and grouping of data. This approach is used in this study as an unsupervised mapping approach where similar data is grouped together into clusters (Zhao et al., 2005). Initially, a single dataset containing all data points is partitioned into a certain number of clusters (Zhao et al., 2005). The number of data points is the sample of field land-cover data which is divided classes, in this approach each cluster is a representative of a particular land-cover class.

There were 268 points representing six major land-cover classes identified in the study area, each data point was represented by four spectral values to represent four VIs. These were uploaded to the model (hierarchical clustering algorithm) to produce results of individual and various combinations of these VIs. For purposes of comparison, a second dataset was also tested. This dataset included a combination of VIs and six Sentinel-2 bands.

Table 3.2: Comparison of different vegetation indices used for land-cover and soil erosion mapping

ABBV	Full Name	Equation	Accuracy	References
1	EVI Enhanced Vegetation Index	$2.5 \frac{NIR - R}{(NIR + 6 * R - 7.5 * B + 1)}$	R ² = 0.74; R ² = 0.72	(Kawamura et al., 2005; Matsushita, Yang, Chen, Onda, & Qiu, 2007)
2	RVI Ratio Vegetation Index	$\frac{NIR}{RED}$	R ² = 75; K= 63%	(Kaufman & Tanre, 1992; Stenberg, Rautiainen, Manninen, Voipio, & Smolander, 2004)
3	NDVI Normalised Difference Vegetation Index	$\frac{NIR - RED}{NIR + RED}$	R ² = 0.77- 0.83; OA= 81%	(Kawamura et al., 2005; Meyer & Turner, 1994; Phinzi & Ngetar, 2017)
4	ARVI Atmospherically Resistant Vegetation Index	$\frac{NIR - [R - \gamma(B - R)]}{NIR + [R - \gamma(B - R)]}$	R ² = 0.74 – 0.89	(Eastwood, Yates, Thomson, & Fuller, 1997)
5	SAVI Soil Adjusted Vegetation Index	$\frac{NIR - RED}{NIR + RED} (1 + L) *$	OA= 83%; K= 60%	(Huete, 1988; Phinzi & Ngetar, 2017)
6	SARVI Soil and Atmospherically Resistance Vegetation Index	$\frac{(1 + L) * (NIR - R_{RB})^{**}}{(NIR + R_{RB} + L)}$	OA= 81%; K= 59%	(Phinzi & Ngetar, 2017)

3.2.6 Accuracy assessment

A confusion matrix was created for testing the model classification output for Sentinel-2 derived VIs and a combination of both VIs and image spectral bands. The confusion matrix included four

levels of accuracy, namely the producer's accuracy, user's accuracy, overall accuracy, and the kappa statistic. The confusion matrix was chosen for this study because of its simplicity and its ability to examine the relationship between ground reference data and the corresponding model output results. The confusion matrix is one of the most popular methods used for accuracy assessment and is widely used for image classification accuracy (Lillesand, Kiefer, & Chipman, 2015; Phinzi & Ngetar, 2017; Taruvinga, 2009). The study then adopts the Kappa coefficient which includes overall statistic agreement of the error matrix when assessing classification accuracy output (Lu & Weng, 2007). The Kappa coefficient is a reliable measure of the difference between the actual agreement and the chance agreement (Congalton, 1991; Taruvinga, 2009).

3.3 Results

3.3.1 Ward's Hierarchical Clustering using Sentinel-2 Vegetation Indices

The Ward's hierarchical clustering algorithm produced a dendrogram that visually represents the decisions used to allocate sample pixels to their resultant clusters. The dendrogram represents a hierarchy of clusters from a single cluster at the top to the desired number of clusters. As illustrated from Figure 3.2, the dendrogram tree was cut at six clusters in order to complement the number of classes based on the similarity of pixels. Each of the six resultant clusters highly resembles a land-cover class that may make up its majority.

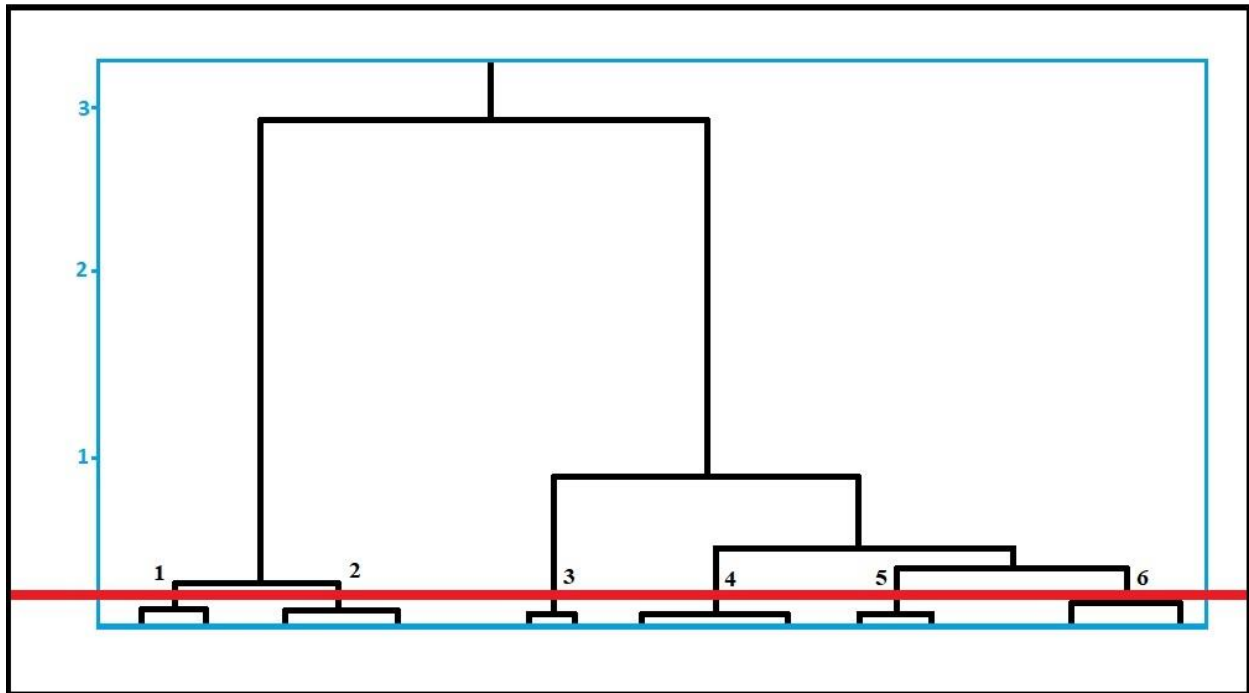


Figure 3.2: Dendrogram representing a hierarchy of clusters and a cut-off line (in red) at six clusters

Figure 3.3 shows the alignment of land-cover pixel similarities with the 6 unsupervised clusters derived from VIs using Wards clustering. For instance, 238 out of 268 data points were correctly assigned to each of the respective classes.

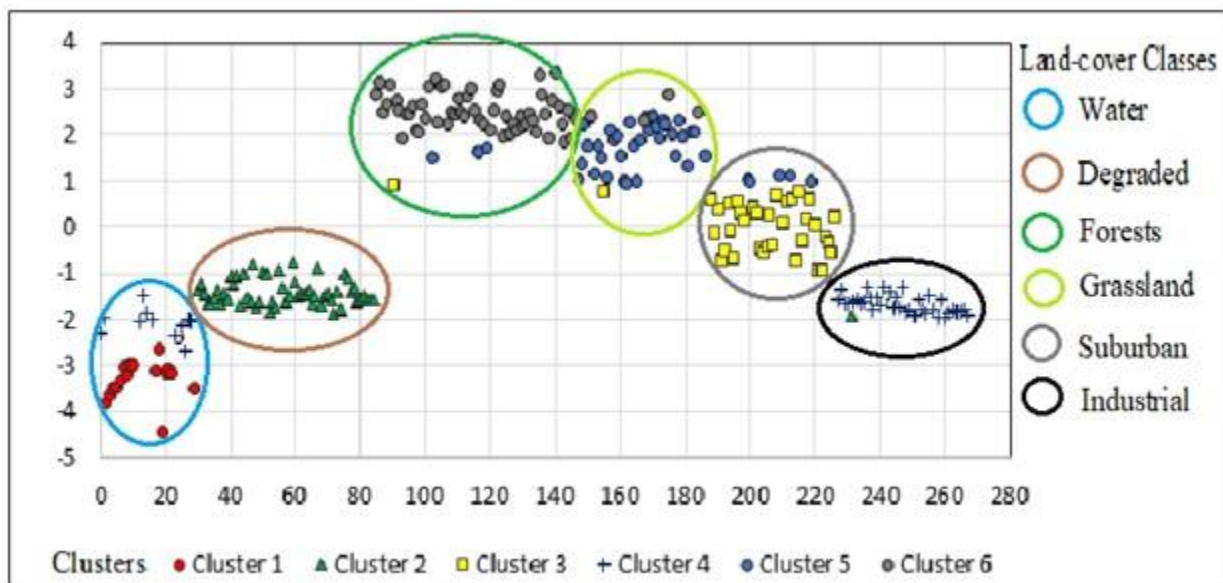


Figure 3.3: Land-cover classes in the study area as modelled by the hierarchical clustering algorithm.

3.3.2 Vegetation Indices Confusion Matrix

The use of the Sentinel-2 derived VIs as an independent test dataset produced a high OA of 88.81% and a Kappa coefficient of 0.86. This dataset also produced the highest accuracy when classifying degraded areas, achieving a prodigious producer's accuracy of 100% and a user's accuracy of 94.83%. The high producer's accuracy indicates the algorithm's impressive ability to correctly classify degraded areas when using the VIs, this can also be used as a measure of the error of omission. While the high user's accuracy indicates that there were only a few non-degraded areas identified as degraded, which represents the algorithms low error of commission.

Table 3.3: Classification accuracies derived using vegetation indices as an independent dataset

Land-Cover Name	Producer Accuracy (%)	User Accuracy (%)
Waters	63.33	100.00
Degraded	100.00	94.83
Forests	93.55	90.63
Grassland	82.50	80.49
Suburban	87.50	94.59
Industrial	92.68	77.55
Overall Accuracy (%)	88.81	Kappa 0.86

As shown in Table 3.3, out of all six clusters, the land degradation class achieved the highest land-cover/cluster correlation. All degraded areas were found in cluster 2, where they made up 94.8% of the cluster, while the remaining 5.2% was made up of the industrial land-cover class. The rest of the landuse classes were also highly correlated with the clusters, however, there was some notable mixing in clusters 4, 5 and 6 as shown in Table 3.3.

3.3.3 Ward’s Hierarchical Clustering using Sentinel-2 Spectral Bands Combined with Vegetation Indices

The use of the VIs in combination with Sentinel-2 bands produced a classification performance with an OA of 79.47% and a Kappa coefficient of 0.752. Although such numbers might indicate a relatively good classification accuracy, however, the classification results of degraded areas were second-lowest out of all land-cover classes, narrowly bettering that of industrial areas. Degraded areas registered a very weak classification, achieving a modest producer’s accuracy of 56.36%, while the user’s accuracy was significantly higher at 79.48%. Forests achieved the highest classification accuracy with producer’s and user’s accuracies both commanding 96.77%.

Table 3.4: Classification accuracies derived using a combination of bands and vegetation indices

Land-Cover Name	Producer Accuracy (%)	User Accuracy (%)	
Waters	100.00	71.43	
Degraded	56.36	79.49	
Forests	96.77	96.77	
Grassland	80.00	96.97	
Suburban	100.00	78.43	
Industrial	48.78	48.78	
Overall Accuracy (%)	79.47	Kappa	0.752

As illustrated in Table 3.3 and Table 3.4, the use of VIs as an independent test dataset achieved superior classification results in comparison to the combination of spectral bands and VIs. For instance, the analysis of VIs yielded a high OA of 88.81% in comparison to 79.47% obtained when using the combination of spectral bands and VIs. The analysis of VIs also produced the highest classification accuracy for degraded areas; while in contrast, the combination of bands and VIs produced a lower accuracy, which was the second-lowest out of all six land-cover classes. For this reason, the results from the analysis of VIs independently was then selected as the best method to automatically detect and map land degradation using Wards Hierarchical Clustering in this study. These were then selected for further analysis and derivation of classification maps in the following section.

3.3.4 Analysis of Classification Map Derived from Selected Best Method

Figure 3.4 illustrates the derived classification maps, while Table 3.3 details the classification results obtained from the use of VIs as an independent test dataset. Figure 3.3(A) showcases the

spatial distribution of land-cover in EMA, while Figure 3.3(B) shows the distribution of mapped degraded areas.

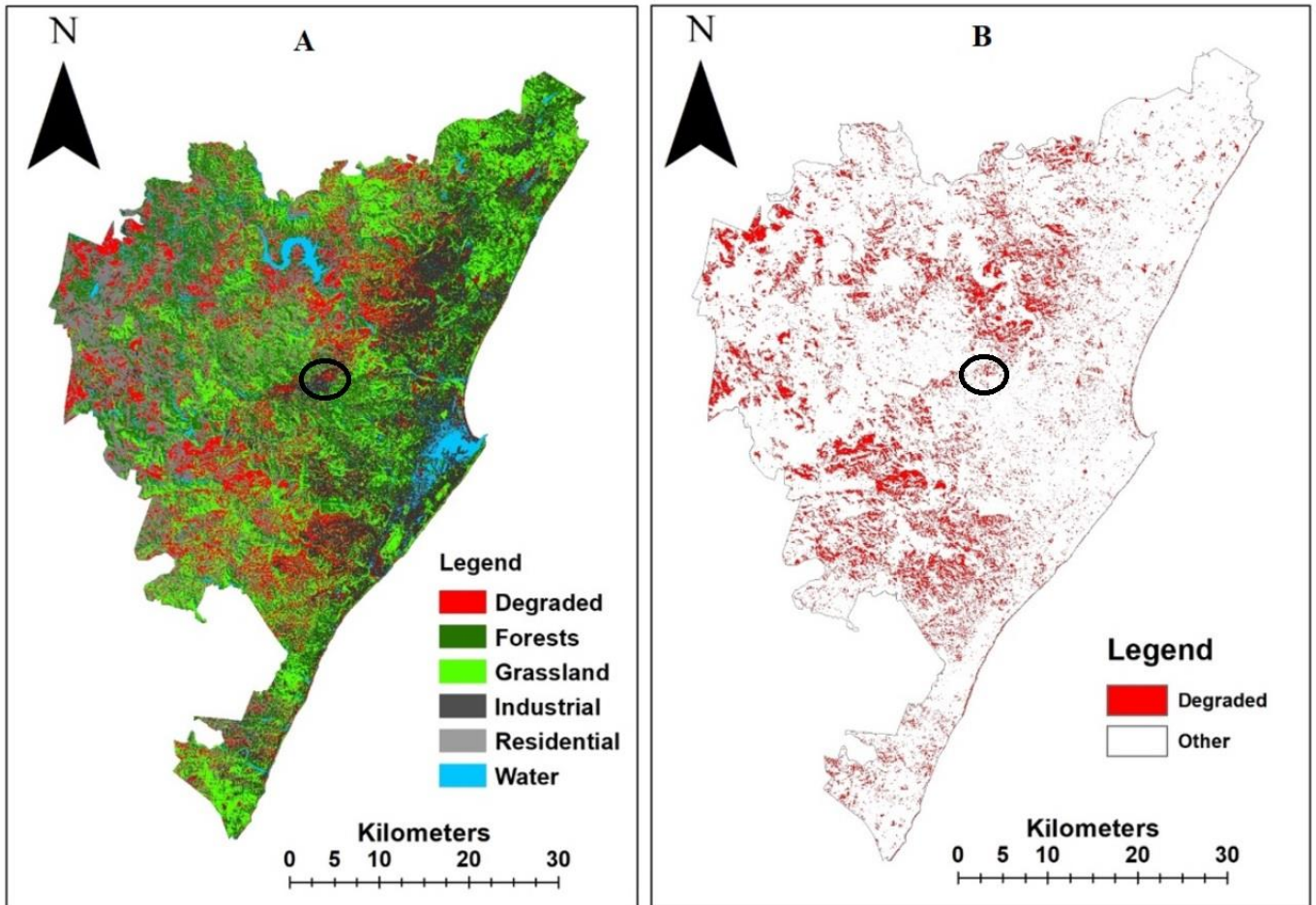


Figure 3.4: Sentinel-2 vegetation indices derived classification maps of EMA showing (A) spatial distribution of major land-covers, and (B) showing the distribution of land degradation.

Table 3.5: Cluster make-up detailing the percentages of contributing classes and number of data points per cluster

Cluster 1			Cluster 2			Cluster 3		
Examples [7.1%] 19			Examples [21.6%] 58			Examples [13.8%] 37		
Class name	% of Class	% of Cluster	Class name	% of Class	% of Cluster	Class name	% of Class	% of Cluster
Water	63	100	Degraded	100	94.8	Residential	87.5	94.6
Grassland	0	0	Industrial	7.3	5.2	Grassland	2.5	2.7
Residential	0	0	Residential	0	0	Forests	1.7	2.7
Industrial	0	0	Grassland	0	0	Industrial	0	0
Degraded	0	0	Residential	0	0	Degraded	0	0
Forests	0	0	Forests	0	0	Forests	0	0
Cluster 4			Cluster 5			Cluster 6		
Examples [18.3%] 49			Examples [15.3%] 41			Examples [23.9%] 64		
Class name	% of Class	% of Cluster	Class name	% of Class	% of Cluster	Class name	% of Class	% of Cluster
Industrial	92.7	77.6	Grassland	82.5	80.5	Forests	93.5	90.6
Water	36.7	22.4	Residential	12.5	12.2	Grassland	15	9.4
Residential	0	0	Forests	4.8	7.3	Residential	0	0
Grassland	0	0	Industrial	0	0	Industrial	0	0
Degraded	0	0	Degraded	0	0	Degraded	0	0
Forests	0	0	water	0	0	Water	0	0

From Figure 3.4(B) it can be observed that most degradation is located in the inner western part of the EMA away from the coast. Extensive levels of land degradation can be observed from both south-west and north-west, even stretching towards far-west. It is also visible from Figure 3.4(A) that most land degradation occurs on the outskirts away from the city and prominent affluent suburbs. In addition, most detected degradation is located near or mixed with residential areas, these are mostly township areas in the south-west and rural areas on the north-western part of the metro. This is also indicative of degradation caused by anthropogenic activities in these areas.

There's also evidence of land degradation located adjacent industrial areas. As seen in Table 3.5, about 7.3% of all industrial areas were included into one cluster with the degraded areas. While 100% of degraded areas were found to be within one cluster. This is indicative of a good detection of the degraded areas by the Wards Hierarchical Clustering algorithm, even though it also classified minor parts of industrial areas as degradation. It was rather industrial areas that had higher levels of classification error, 77.6% of all industrial areas were actually industrial areas with the remaining 22.4% being actually water bodies. This was also visually observable in Figure 3.4(A), where most of the peninsula was classified as water, while it was actually a harbor, which is an industrial area.

3.4 Discussion

The main objective of this paper was to automatically detect the spatial distribution of land degradation in the study area using Sentinel-2 derived VIs and a combination of VIs and image spectral bands; and to also assess the potential of Ward's hierarchical clustering algorithm as a mapping tool.

In this paper, the description of land degradation included all exposed and bare land types located within the EMA, which is one of the most actively changing regions in southern Africa. The results from this study demonstrate the success of the Ward's hierarchical clustering approach to produce reliable levels of accuracies for mapping land degradation in a complex environment. The use of Sentinel-2 derived vegetation indices and bands performed reasonably well and demonstrated high capabilities to detect and map land degradation from other land-cover classes.

3.4.1 Distribution of Land Degradation in the EMA

The distribution of land-use and their changes often plays a major role in the occurrence and distribution of land degradation. In this study, it was discovered that most land degradation in EMA occurs on the outskirts of the metro. The high degradation intensification in the EMA peripheries is also directly linked to the intensification of land transformation in these areas. This is a typical phenomenon and has been reported in different parts of the world. According to Jensen and Cowen (1999) land-use change is a direct cause of habitat fragmentation and land degradation on urban peripheries. In the EMA there are a number of reasons which might have led to this outcome, some are typical of developing cities while some are uniquely South African.

Traditionally, the townships; located in these areas are often characterized by high population densities accompanied by a lack of resources (Crankshaw & Parnell, 1996). The demand for new settlements in these areas thus creates a rapid transformation of green spaces into impervious surfaces and is often associated with land degradation (Onyango, 2014). The high population growth of EMA has thus expanded the human settlements beyond historical extents, this can also be illustrated by the government's efforts such as housing provision initiatives like the Reconstruction and Development Programme (RDP). It has also been reported that the RDP has led to land degradation in many urban areas, creating a steady decline in green spaces ((McConnachie & Shackleton, 2010; Pillay & Sebake, 2008) . The results from this study are thus in line with findings from other similar studies, which point land degradation intensification with urban outskirts and rurality (Crankshaw & Parnell, 1996; M. T. Hoffman & Todd, 2000; T. Hoffman, Todd S., Ntoshona Z., and Turner S, 1999; McConnachie & Shackleton, 2010; Onyango, 2014; Pillay & Sebake, 2008).

3.4.2 Mapping Land Degradation using Sentinel-2 and Vegetation Indices

The use of VIs as an independent dataset produced a high OA of 88.81% and a Kappa coefficient of 0.86. While the combination of spectral bands and VIs yielded a relatively weaker OA at 79% and a Kappa coefficient of 0.75. Such a significant difference between accuracies can be an outcome of different factors. Factors such as the bands inability to discriminate these land cover classes, since different bands are more diverse in comparison to VIs, or simply the model's difficulties in dealing with highly diverse spectral bands. However; in this study, it was notable that the algorithm had difficulties in discriminating degraded areas from built-up areas when using Sentinel-2 bands. This was especially notable in the visible

range of the electromagnetic spectrum, where both the degraded and built-up industrial areas had a higher average reflectance in comparison to other land-cover classes. Nonetheless, both sets of results were reasonably good, denoting a successful classification.

A high OA demonstrates a good classification accuracy; however, it can also be misleading since most of the study area is made up of non-land degradation land-cover classes. However, from the confusion matrix, land degradation also achieved the highest classification accuracy when using VIs, which showed the algorithm's ability to detect degradation from their surroundings. Since land degradation does not occur in isolation, it was imperative to map them with other major land-cover classes that are found in the study area. These results represent a relatively high accuracy classification, especially when comparing them to other similar studies that have used VIs to map land degradation in South Africa. A study by Taruvinga (2009) produced Kappa statistics of between 50% and 56% using similar VIs to map land degradation in KZN. While Phinzi and Ngetar (2017) achieved OA range of 59% to 83% with Kappa statistics ranging from 59% to 64% also using similar VIs in the Eastern Cape. The results from the aforementioned studies are moderate to moderately high. This makes the results from this study imposing, especially since the study area comprised of a highly complex environment, while, the algorithm was still able to map them into reasonably high accuracy levels.

The algorithm was able to detect and classify all six major land-cover classes into six corresponding clusters. This also demonstrated the ability to detect and map land degradation by the Sentinel-2 sensor. The sensor comprises of recently improved spatial and spectral resolutions. It has thus received quite a substantial amount of success and praise for its ability to discriminate degraded areas from other land-cover classes (Makaya et al., 2019; Sepuru & Dube, 2018). This is highly attributed to its bands located at the near infra-red and red-edge portions of the electromagnetic spectrum, in addition to its reasonably high spatial resolutions of up to 10m (Forkuor et al., 2018; Sibanda et al., 2016a, 2016b).

3.4.3 Ward's Hierarchical Clustering Algorithm and Unsupervised Mapping

These results also demonstrate a high potential of Ward's hierarchical clustering algorithm in land-cover mapping, particularly land degradation areas. Although it has previously not been extensively tested for purposes of image classification, Ward's hierarchical clustering algorithm has shown the potential to discriminate between complex land-cover classes using spectral information. In addition to that, the algorithm is very repeatable since it is easy to use and is also supported by numerous data handling platforms. The algorithm's classification

success can also be illustrated by its extensive adoption in other research areas, these include disciplines such as life and health sciences, image (object) segmentation and; marketing and finance management (S. Lee & Crawford, 2005; Punj & Stewart, 1983; Zhao & Karypis, 2003). Results from this study are also in line with those found in other studies that adopted unsupervised learning for land-cover mapping. A study by Forkuor et al. (2018) achieved a high classification performance with OAs of between 88.9 and 94.3 and Kappa coefficients range of 0.87 and 0.93 for land-cover mapping using RS, SVM and Stochastic Gradient Boosting in Burkina Faso. Peerbhay et al. (2016) also successfully used RF for mapping of bugweed in forests, open spaces and riparian zones to accuracies of 91.33%, 85.08 and 67.90%, respectively. In a separate study, Peerbhay et al. (2019) yielded an improved OA of 83% for mapping of riparian bugweed using AISA Eagle hyperspectral data (393 nm–994 nm) in combination with height derived from LiDAR on RF and Anselin Local Moran's I clustering.

Although the results from this study show good potential, it is worth saying that one of the major shortfalls of the algorithm in this study was the poor ability to discriminate degraded areas from built-up areas when using Sentinel-2 bands as an independent dataset or in combination with VIs. This was especially notable in the visible range of the electromagnetic spectrum, where both the degraded and built-up industrial areas have a higher average reflectance in comparison to other land-cover classes. Nonetheless, this study has demonstrated the algorithm's good qualities to detect and discriminate complex land-cover classes, the use of VIs showed great abilities especially when detecting degraded areas. The Ward's hierarchical clustering algorithm can, therefore, provide a suitable alternative method for mapping land degradation and other land-cover classes especially when coupled with Sentinel-2 derived VIs.

3.5 Conclusions

The main aim of this study was to detect and map land degradation from complex land-cover classes in an urban environment, using Sentinel-2 VIs and Ward's hierarchical clustering algorithm. The results have demonstrated successful mapping of land degradation and also confirmed the abilities of the Sentinel-2 sensor for purposes of detecting and mapping of land degradation from diverse land-cover classes. The study achieved an OA of 88% while land degradation achieved a high classification accuracy of up to 100%. The use of VIs produced the best classification performance with the highest accuracy, however; the use of Sentinel-2

bands as an independent test dataset produced a relatively weaker performance. The study further demonstrated the potential of Ward's hierarchical clustering algorithm as a tool for mapping land degradation features from remotely sensed imagery. Despite achieving a good overall performance, the algorithm had challenges with discriminating between degraded areas and industrial areas when using the bands in the visible range of the electromagnetic spectrum. Nonetheless, the findings from this study clearly confirm Ward's hierarchical clustering algorithm as a suitable remote sensing mapping tool with great potential.

4 Chapter Four

This chapter serves to review and evaluate the success of the study in fulfilling the aim and objectives established in the first chapter. This chapter also includes the conclusions and recommendations pertaining to this study.

4.1 Aim and Review of objectives

The main aim of this study was to assess the state of land degradation in South Africa with a focus on the eThekweni Metropolitan Area as a study area. Two objectives were established in order to fulfill this aim.

Objective One:

To review the status of land degradation in South Africa as well as tracking emerging trends in remote sensing and GIS research.

Evidence from previous literature shows land degradation as a major problem facing the Southern African region. One of the most cited limitations has been the lack of detailed information with regards to the location of land degradation at regional scales. This, in turn, creates a major hindrance in terms of planning and implementation of management and rehabilitation measures. The study critically reviewed the state of land degradation in South Africa, discussing the country's land degradation patterns and highlighting some of the major causal factors. In addition to that, the study reviewed some of the current and emerging trends in land degradation research. Remote sensing has emerged as a highly reliable tool and has been adopted by researchers in numerous disciplines for various purposes including land degradation research. The open availability of medium resolution imagery from providers such as Landsat and Sentinel has also highly contributed to remote sensing popularity, this is particularly true even in resource-constrained regions such as South Africa. Additionally, the review also found the recent advancements in Geographic Information Systems and computer sciences as another key factor contributing to land degradation research. This is evidenced by the rapid development and adoption of machine learning languages for purposes of remote sensing and GIS. This has also highly improved the accuracy of land degradation mapping studies.

Objective Two:

Use of Sentinel-2 derived vegetation indices to map the spatial distribution of land degradation in the EMA through the use of the wards hierarchical clustering algorithm.

For successful implementation of suitable environmental management and rehabilitation strategies, there is a need for detailed information on the state of the environment, explicitly displaying the spatial extent of land degradation at regional scales. The aim of this study was to detect and map land degradation features in the EMA using Sentinel-2 derived spectral signatures and vegetation indices through the Ward's hierarchical clustering algorithm. Furthermore, this was to aid in testing and evaluation of the algorithm's capabilities for land degradation mapping. The two sets of data used in this study both produced positive results. However, the use of VIs as an independent test dataset produced superior results with an overall classification accuracy of 88.81%. In that regard, out of six land-cover classes, the degraded areas also achieved the highest classification accuracy of up to 100%. The use of a combination of VIs and spectral bands produced a relatively lower classification accuracy with an OA of 79.48. Although the OA might seem to represent a relatively good classification, the classification of degraded areas had the second-lowest accuracy at between 56.36 and 79.49%. One of the identified factors which contributed to such a significant difference in results from the two datasets was the model's poor ability to discriminate degraded and built-up areas. The spectral signatures of degraded and built-up areas are fairly similar in the mid-infrared region of the electromagnetic spectrum, the introduction of these bands, therefore, resulted in a mixed classification of these particular land-cover classes. With regard to the spread of degraded areas in the study area, their distribution was more severe in the rural areas and townships away from the CBD of the EMA. It was also attributed to the rapid transformation of green spaces for residential purposes, this is due to the high demand for human settlement leading to the expansion of the surrounding townships beyond original extents. Overall, the use of Sentinel-2 derived indices and spectral indices demonstrated its ability to detect and map land degradation features, while the results also confirm the Ward's hierarchical clustering algorithm as a suitable earth mapping tool with great potential.

4.2 Conclusion

The primary aim of this study was to assess the spatial extent of land degradation with the use of a Sentinel-2 remotely sensed dataset, through an unsupervised machine learning approach, Ward's hierarchical clustering algorithm in the eThekweni Metropolitan Area. Findings from

this study have revealed the state of land degradation in South Africa. This study was able to adequately determine the spatial extent of land degradation in the EMA despite some difficulties in spectral discrimination, the Ward's hierarchical clustering algorithm produced a relatively high accuracy classification. The conclusions below are thus a consolidation of the study's findings which are presented in this thesis and responds to the research questions posed in Chapter 1.

What are the emerging trends in mapping land degradation using remote sensing and GIS?

The recent advancements in remote sensing and GIS have highly improved the potential of land degradation studies. These have led to improvements in results accompanied by an easy and convenient workaround. This study and numerous others have successfully used new-generation medium resolution sensors and achieved high accuracy results for various earth mapping purposes including land degradation. The improvements in results are also fueled by the adoption of unsupervised machine learning approaches such as RF and SVM.

Can the hierarchical algorithm effectively detect land degradation?

This study adopted Ward's hierarchical clustering algorithm approach, which has previously not been used for purposes of remote sensing land degradation mapping. This algorithm can provide a suitable alternative unsupervised mapping approach that is quick and easy to use. The best results from this study achieved an OA of 88.88 and Kappa coefficient of 0.86, which denote a highly accurate classification. Such results demonstrate great potential for the hierarchical clustering algorithm in the mapping of earth surface features. Even though the algorithm has some limitations, especially when discriminating between features of bright spectral signatures. Overall, it was able to map all land-cover classes identified in the study areas with acceptable results.

What is the Distribution of Land Degradation Across the Study Area?

Land degradation is distributed across the entire study area, with some areas having more severity than others. The study discovered that the highest land degradation intensification is located in the peripheries of the metro, particularly in townships and rural areas away from the central district and suburbs. This is a typical scenario since townships are usually the most susceptible to such phenomenon, largely due to their lack of resources and rapid transformation.

References

- Abbas, I. (2007). An overview of land cover changes in Nigeria, 1975-2005. *Journal of Geography and Regional Planning*, 2(4), 062-065.
- Adam, E., Mutanga, O., Odindi, J., & Abdel-Rahman, E. M. (2014). Land-use/cover classification in a heterogeneous coastal landscape using RapidEye imagery: evaluating the performance of random forest and support vector machines classifiers. *International journal of remote sensing*, 35(10), 3440-3458.
- Adam, E., Mutanga, O., Rugege, D., & Ismail, R. (2012). Discriminating the papyrus vegetation (*Cyperus papyrus* L.) and its co-existent species using random forest and hyperspectral data resampled to HYMAP. *International journal of remote sensing*, 33(2), 552-569.
- Adam, E. M., & Mutanga, O. (2012). *Estimation of high density wetland biomass: combining regression model with vegetation index developed from Worldview-2 imagery*. Paper presented at the Remote Sensing for Agriculture, Ecosystems, and Hydrology XIV.
- Adelabu, S., & Dube, T. (2015). Employing ground and satellite-based QuickBird data and random forest to discriminate five tree species in a Southern African Woodland. *Geocarto International*, 30(4), 457-471.
- Aggarwal, P. K., Baethegan, W., Cooper, P., Gommers, R., Lee, B., Meinke, H., . . . Sivakumar, M. (2010). Managing climatic risks to combat land degradation and enhance food security: key information needs. *Procedia Environmental Sciences*, 1, 305-312.
- Alejandro, M., & Omasa, K. (2007). Estimation of vegetation parameter for modeling soil erosion using linear Spectral Mixture Analysis of Landsat ETM data. *ISPRS Journal of Photogrammetry and Remote Sensing*, 62(4), 309-324.
- Anderberg, M. R. (2014). *Cluster analysis for applications: probability and mathematical statistics: a series of monographs and textbooks* (Vol. 19): Academic press.
- Arbeitman, M. N., Furlong, E. E. M., Imam, F., Johnson, E., Null, B. H., Baker, B. S., . . . White, K. P. (2002). Gene Expression During the Life Cycle of *Drosophila melanogaster*. *Science*, 297(5590), 2270-2275. doi:10.1126/science.1072152
- Bangamwabo, V. M. (2009). Spatial and temporal extents of land degradation in a communal landscape of KwaZulu-Natal, South Africa.
- Baret, F., & Guyot, G. (1991). Potentials and limits of vegetation indices for LAI and APAR assessment. *Remote Sensing of Environment*, 35(2-3), 161-173.
- Barnes, E., & Baker, M. (2000). Multispectral data for mapping soil texture: possibilities and limitations. *Applied Engineering in Agriculture*, 16(6), 731.
- Bartlett, D., & Smith, J. (2004). *GIS for coastal zone management*: CRC press.
- Blum, W. E. (2005). Functions of soil for society and the environment. *Reviews in Environmental Science and Bio/Technology*, 4(3), 75-79.
- Boardman, J., & Lorentz, S. (2000). The GCTE soil erosion network and model evaluation studies. *South African Geographical Journal*, 82(3), 154-156.
- Bocco, G., & Valenzuela, C. (1993). Integrating satellite-remote sensing and geographic information systems technologies in gully erosion research. *Remote sensing reviews*, 7(3-4), 233-240.
- Bongaarts, J. (2009). Human population growth and the demographic transition. *Philosophical Transactions of the Royal Society of London B: Biological Sciences*, 364(1532), 2985-2990.
- Boon, R., Cockburn, J., Douwes, E., Govender, N., Ground, L., Mclean, C., . . . Slotow, R. (2016). Managing a threatened savanna ecosystem (KwaZulu-Natal Sandstone Sourveld) in an urban biodiversity hotspot: Durban, South Africa. *Bothalia-African Biodiversity & Conservation*, 46(2), 1-12.

- Botha, J., & Fouche, P. (2000). An assessment of land degradation in the Northern Province from satellite remote sensing and community perception. *South African Geographical Journal*, 82(2), 70-79.
- Bowers, S., & Smith, S. (1972). Spectrophotometric Determination of Soil Water Content 1. *Soil Science Society of America Journal*, 36(6), 978-980.
- Bowers, S. A., & Smith, S. J. (1972). Spectrophotometric Determination of Soil Water Content1. *Soil Science Society of America Journal*, 36(6), 978-980. doi:10.2136/sssaj1972.03615995003600060045x
- Breetzke, K. (2009). From conceptual frameworks to quantitative models: Spatial planning in the Durban metropolitan area, South Africa—the link to housing and infrastructure planning. *Unpublished case study prepared for the Global Report on Human Settlements*.
- Cakir, G., Ün, C., Baskent, E., Köse, S., Sivrikaya, F., & Keleş, S. (2008). Evaluating urbanization, fragmentation and land use/land cover change pattern in Istanbul city, Turkey from 1971 to 2002. *Land Degradation & Development*, 19(6), 663-675.
- CEPF. (2005). Critical Ecosystem Partnership Fund, Maputaland-Pondoland-Albany.
- Chen, G., Weng, Q., Hay, G. J., & He, Y. (2018). Geographic Object-based Image Analysis (GEOBIA): Emerging trends and future opportunities. *GIScience & remote sensing*, 55(2), 159-182.
- Cohen, J. E. (1995). Population growth and earth's human carrying capacity. *Science*, 269(5222), 341-346.
- Congalton, R. G. (1991). A review of assessing the accuracy of classifications of remotely sensed data. *Remote Sensing of Environment*, 37(1), 35-46.
- Crankshaw, O., & Parnell, S. (1996). *Housing provision and the need for an urbanisation policy in the new South Africa*. Paper presented at the Urban Forum.
- Critchley, W. R., & Netshikovhela, E. M. (1998). Land degradation in South Africa: conventional views, changing paradigms and a tradition of soil conservation. *Development Southern Africa*, 15(3), 449-469.
- Davids, R., Rouget, M., Boon, R., & Roberts, D. (2016). Identifying ecosystem service hotspots for environmental management in Durban, South Africa. *Bothalia-African Biodiversity & Conservation*, 46(2), 1-18.
- DEA. (2017). *Compilation of the 3rd South Africa Environment, Outlook Report*. Department of Environmental Affairs. Pretoria.
- Dwivedi, R., Kumar, A., & Tewari, K. (1997). The utility of multi-sensor data for mapping eroded lands. *International journal of remote sensing*, 18(11), 2303-2318.
- Eastwood, J., Yates, M., Thomson, A., & Fuller, R. (1997). The reliability of vegetation indices for monitoring saltmarsh vegetation cover. *International journal of remote sensing*, 18(18), 3901-3907.
- FAO, U. (1999). The future of our Land—Facing the Challenge, Guidelines for Integrated Planning for Sustainable Management of Land Resources. *Food and Agriculture Organization, Rome, Italy*.
- Fistikoglu, O., & Harmancioglu, N. B. (2002). Integration of GIS with USLE in assessment of soil erosion. *Water Resources Management*, 16(6), 447-467.
- Floras, S. A., & Sgouras, I. D. (1999). Use of geoinformation techniques in identifying and mapping areas of erosion in a hilly landscape of central Greece. *International Journal of Applied Earth Observation and Geoinformation*, 1(1), 68-77.
- Forkuor, G., Dimobe, K., Serme, I., & Tondoh, J. E. (2018). Landsat-8 vs. Sentinel-2: examining the added value of sentinel-2's red-edge bands to land-use and land-cover mapping in Burkina Faso. *GIScience & remote sensing*, 55(3), 331-354.

- Garland, G., Hoffman, M., & Todd, S. (2000). Soil degradation. *A National Review of Land Degradation in South Africa*. South African National Biodiversity Institute, Pretoria, South Africa, 69-107.
- Giraldo, R., Delicado, P., & Mateu, J. (2012). Hierarchical clustering of spatially correlated functional data. *Statistica Neerlandica*, 66(4), 403-421.
- Govaerts, B., & Verhulst, N. (2010). The normalized difference vegetation index (NDVI) Greenseeker (TM) handheld sensor: toward the integrated evaluation of crop management part A: concepts and case studies: CIMMYT.
- Graw, V., Ghazaryan, G., Dall, K., Delgado Gómez, A., Abdel-Hamid, A., Jordaan, A., . . . Walz, Y. (2017). Drought dynamics and vegetation productivity in different land management systems of Eastern Cape, South Africa—A remote sensing perspective. *Sustainability*, 9(10), 1728.
- Hansen, M. C., & Loveland, T. R. (2012). A review of large area monitoring of land cover change using Landsat data. *Remote Sensing of Environment*, 122, 66-74.
- Heller, K. A., and Ghahramani, Z. . (2005). *Bayesian hierarchical clustering*. In *Proceedings of the 22nd international conference on Machine learning* (pp. 297-304). ACM.
- Hoffer, R. M., & Johannsen, C. J. (1969). Ecological potentials in spectral signature analysis. *Remote sensing in ecology*, 1-16.
- Hoffman, M. T., & Todd, S. (2000). A national review of land degradation in South Africa: the influence of biophysical and socio-economic factors. *Journal of Southern African Studies*, 26(4), 743-758.
- Hoffman, T., Todd S., Ntoshona Z., and Turner S. (1999). *Land degradation in South Africa*. Cape Town, South Africa: Cape Town National Botanical Institute.
- Houghton, R. A. (1994). The worldwide extent of land-use change. *BioScience*, 44(5), 305-313.
- Hudson, P. F., & Alcántara-Ayala, I. (2006). Ancient and modern perspectives on land degradation. *Catena (Giessen)*, 65(2), 102-106.
- Huete, A. R. (1988). A soil-adjusted vegetation index (SAVI). *Remote Sensing of Environment*, 25(3), 295-309.
- Huete, A. R., & Liu, H. Q. (1994). An error and sensitivity analysis of the atmospheric-and soil-correcting variants of the NDVI for the MODIS-EOS. *IEEE Transactions on Geoscience and Remote Sensing*, 32(4), 897-905.
- IPCC. (2001). *Climate change 2001: Impacts, adaptation and vulnerability*. Intergovernmental Panel on Climate Change.
- Jahun, B., Ibrahim, R., Dlamini, N., & Musa, S. (2015). Review of soil erosion assessment using RUSLE model and GIS. *J Biol Agric Healthcare*, 5(9), 36-47.
- Jensen, J. R., & Cowen, D. C. (1999). Remote sensing of urban/suburban infrastructure and socio-economic attributes. *Photogrammetric engineering and remote sensing*, 65, 611-622.
- Kakembo, V. (2001). Trends in vegetation degradation in relation to land tenure, rainfall, and population changes in Peddie district, Eastern Cape, South Africa. *Environmental Management*, 28(1), 39-46.
- Karypis, G., Han, E.-H. S., & Kumar, V. (1999). Chameleon: Hierarchical clustering using dynamic modeling. *Computer*(8), 68-75.
- Kaufman, Y. J., & Tanre, D. (1992). Atmospherically resistant vegetation index (ARVI) for EOS-MODIS. *IEEE Transactions on Geoscience and Remote Sensing*, 30(2), 261-270.
- Kawamura, K., Akiyama, T., Yokota, H. o., Tsutsumi, M., Yasuda, T., Watanabe, O., & Wang, S. (2005). Comparing MODIS vegetation indices with AVHRR NDVI for monitoring the forage quantity and quality in Inner Mongolia grassland, China. *Grassland Science*, 51(1), 33-40.

- Khaledian, Y., Kiani, F., Ebrahimi, S., Brevik, E. C., & Aitkenhead-Peterson, J. (2017). Assessment and monitoring of soil degradation during land use change using multivariate analysis. *Land Degradation & Development*, 28(1), 128-141.
- King, C., Baghdadi, N., Lecomte, V., & Cerdan, O. (2005). The application of remote-sensing data to monitoring and modelling of soil erosion. *Catena*, 62(2-3), 79-93.
- Kraskov, A., Stögbauer, H., Adrsejak, R., & Grassberger, P. (2003). Hierarchical clustering based on mutual information. *arXiv preprint q-bio/0311039*.
- Kumar, M., Denis, D. M., Singh, S. K., Szabó, S., & Suryavanshi, S. (2018). Landscape metrics for assessment of land cover change and fragmentation of a heterogeneous watershed. *Remote Sensing Applications: Society and Environment*, 10, 224-233.
- Lambin, E. F., Turner, B. L., Geist, H. J., Agbola, S. B., Angelsen, A., Bruce, J. W., . . . Folke, C. (2001). The causes of land-use and land-cover change: moving beyond the myths. *Global environmental change*, 11(4), 261-269.
- Le Hegarat-Masclé, S., Bloch, I., & Vidal-Madjar, D. (1997). Application of Dempster-Shafer evidence theory to unsupervised classification in multisource remote sensing. *IEEE Transactions on Geoscience and Remote Sensing*, 35(4), 1018-1031.
- Le Roux, J. (2011). Monitoring soil erosion in South Africa at a regional scale. *Agricultural Research Council-Institute for Soil, Climate and Water, Pretoria*.
- Le Roux, J. J., Newby, T., & Sumner, P. (2007). Monitoring soil erosion in South Africa at a regional scale: review and recommendations. *South African Journal of Science*, 103(7-8), 329-335.
- Le Roux, J. J., & Sumner, P. D. (2013). Water erosion risk assessment in South Africa: a proposed methodological framework. *Geografiska Annaler: Series A, Physical Geography*, 95(4), 323-336.
- Lee, J.-G., Han, J., Li, X., & Gonzalez, H. (2008). TraClass: trajectory classification using hierarchical region-based and trajectory-based clustering. *Proc. VLDB Endow.*, 1(1), 1081-1094. doi:10.14778/1453856.1453972
- Lee, K., & Lunetta, R. (1996). *Wetland and environmental application of GIS*: Lewis Publishers, New York.
- Lee, S., & Crawford, M. M. (2005). Unsupervised multistage image classification using hierarchical clustering with a Bayesian similarity measure. *IEEE Transactions on Image Processing*, 14(3), 312-320.
- Lillesand, T., Kiefer, R. W., & Chipman, J. (2015). *Remote sensing and image interpretation*: John Wiley & Sons.
- Lottering, R., Mutanga, O., & Peerbhay, K. (2018). Detecting and mapping levels of *Gonipterus scutellatus*-induced vegetation defoliation and leaf area index using spatially optimized vegetation indices. *Geocarto International*, 33(3), 277-292.
- Lu, D., Mausel, P., Brondizio, E., & Moran, E. (2004). Change detection techniques. *International journal of remote sensing*, 25(12), 2365-2401.
- Lu, D., & Weng, Q. (2007). A survey of image classification methods and techniques for improving classification performance. *International journal of remote sensing*, 28(5), 823-870.
- Luleva, M. I., Van Der Werff, H., Van Der Meer, F., & Jetten, V. (2012). Gaps and opportunities in the use of remote sensing for soil erosion assessment. *Chemistry*, 21(5), 748-764.
- Maitima, J. M., Mugatha, S. M., Reid, R. S., Gachimbi, L. N., Majule, A., Lyaruu, H., . . . Mugisha, S. (2009). The linkages between land use change, land degradation and biodiversity across East Africa. *African Journal of Environmental Science and Technology*, 3(10).

- Makaya, N. P., Mutanga, O., Kiala, Z., Dube, T., & Seutloali, K. E. (2019). Assessing the potential of Sentinel-2 MSI sensor in detecting and mapping the spatial distribution of gullies in a communal grazing landscape. *Physics and Chemistry of the Earth, Parts A/B/C*.
- Mansour, K., Mutanga, O., Adam, E., & Abdel-Rahman, E. M. (2016). Multispectral remote sensing for mapping grassland degradation using the key indicators of grass species and edaphic factors. *Geocarto International*, 31(5), 477-491.
- Mansour, K., Mutanga, O., & Everson, T. (2012). Remote sensing based indicators of vegetation species for assessing rangeland degradation: opportunities and challenges. *African Journal of Agricultural Research*, 7(22), 3261-3270.
- Marsh, S., Walsh, J., Lee, C., Beck, L., & Hutchinson, C. (1992). Comparison of multi-temporal NOAA-AVHRR and SPOT-XS satellite data for mapping land-cover dynamics in the west African Sahel. *International journal of remote sensing*, 13(16), 2997-3016.
- Matinfar, H., Alavipanah, S., & Sarmadian, F. (2006). Soil spectral properties of arid region, Kashan area, IRAN. *Desert*, 11(1), 9-17.
- Matongera, T. N. (2016). *Remote sensing applications for monitoring the spatial distribution of Bracken fern (Pteridium) in the Cathedral Peak: Drakensberg, South Africa*.
- Matsushita, B., Yang, W., Chen, J., Onda, Y., & Qiu, G. (2007). Sensitivity of the enhanced vegetation index (EVI) and normalized difference vegetation index (NDVI) to topographic effects: a case study in high-density cypress forest. *Sensors*, 7(11), 2636-2651.
- Mayr, A., Rutzinger, M., Bremer, M., & Geitner, C. (2016). MAPPING ERODED AREAS ON MOUNTAIN GRASSLAND WITH TERRESTRIAL PHOTOGRAMMETRY AND OBJECT-BASED IMAGE ANALYSIS. *ISPRS Annals of Photogrammetry, Remote Sensing & Spatial Information Sciences*, 3(5).
- Mbambo, J., & Archer, E. (2007). An assessment of land degradation in the Save catchment of Zimbabwe. *Area*, 39(3), 380-391.
- McConnachie, M. M., & Shackleton, C. M. (2010). Public green space inequality in small towns in South Africa. *Habitat International*, 34(2), 244-248.
- Mehner, H., Cutler, M., Fairbairn, D., & Thompson, G. . (2004). Remote sensing of upland vegetation: the potential of high spatial resolution satellite sensors. *Global ecology and biogeography*, 13(4), 359-369.
- Metternicht, G., Zinck, J., Blanco, P. D., & del Valle, H. F. (2010). Remote sensing of land degradation: Experiences from Latin America and the Caribbean. *Journal of environmental quality*, 39(1), 42-61.
- Meyer, & Turner. (1994). *Changes in land use and land cover: a global perspective* (Vol. 4): Cambridge University Press.
- Murtagh, F., & Contreras, P. (2012). Algorithms for hierarchical clustering: an overview. *Wiley Interdisciplinary Reviews: Data Mining and Knowledge Discovery*, 2(1), 86-97. doi:10.1002/widm.53
- Odindi, J., Mutanga, O., Abdel-Rahman, E. M., Adam, E., & Bangamwabo, V. (2017). Determination of urban land-cover types and their implication on thermal characteristics in three South African coastal metropolitans using remotely sensed data. *South African Geographical Journal*, 99(1), 52-67.
- Odindi, J. O., Adam, E. E., Ngubane, Z., Mutanga, O., & Slotow, R. (2014). Comparison between WorldView-2 and SPOT-5 images in mapping the bracken fern using the random forest algorithm. *Journal of Applied Remote Sensing*, 8(1), 083527.

- Oldeman, L. R., Hakkeling, R., & Sombroek, W. G. (2017). *World map of the status of human-induced soil degradation: an explanatory note*: International Soil Reference and Information Centre.
- Onyando, J., Kisoyan, P., & Chemelil, M. (2005). Estimation of potential soil erosion for river perkerra catchment in Kenya. *Water Resources Management*, 19(2), 133-143.
- Onyango, O. C. (2014). *Multi-temporal mapping and projection of urban land-use-land-cover change: implication on urban green spaces*.
- Organisation, F. a. A. (2016). Crop production and natural resource use. Retrieved from Crop production and natural resource use
- Pacione, M. (2013). *Urban geography: A global perspective*: Routledge.
- Palmer, A. a. A., A. . (2002). *Country pasture/forage resources profile: South Africa. Rome: Plant Production and Protection Division. United Nations Food and Agriculture Organisation*.
- Parry, M. L., Rosenzweig, C., Iglesias, A., Livermore, M., & Fischer, G. (2004). Effects of climate change on global food production under SRES emissions and socio-economic scenarios. *Global environmental change*, 14(1), 53-67.
- Pearson, R. L., & Miller, L. D. (1972). *Remote mapping of standing crop biomass for estimation of the productivity of the shortgrass prairie*. Paper presented at the Remote sensing of environment, VIII.
- Peerbhay, K., Mutanga, O., Lottering, R., Agjee, N. e., & Ismail, R. (2019). Improving the unsupervised mapping of riparian bugweed in commercial forest plantations using hyperspectral data and LiDAR. *Geocarto International*, 1-16.
- Peerbhay, K., Mutanga, O., Lottering, R., & Ismail, R. (2016). Mapping *Solanum mauritianum* plant invasions using WorldView-2 imagery and unsupervised random forests. *Remote Sensing of Environment*, 182, 39-48.
- Peng, J., Xu, Y., Cai, Y., & Xiao, H. (2011). Climatic and anthropogenic drivers of land use/cover change in fragile karst areas of southwest China since the early 1970s: a case study on the Maotiaohe watershed. *Environmental Earth Sciences*, 64(8), 2107-2118.
- Pesaresi, M., Corbane, C., Julea, A., Florczyk, A., Syrris, V., & Soille, P. (2016). Assessment of the added-value of Sentinel-2 for detecting built-up areas. *Remote Sensing*, 8(4), 299.
- Phinzi, K., & Ngetar, N. S. (2017). Mapping soil erosion in a Quaternary catchment in Eastern Cape using Geographic information system and remote sensing. *South African Journal of Geomatics*, 6(1), 11-29.
- Phiri, D., & Morgenroth, J. (2017). Developments in Landsat land cover classification methods: A review. *Remote Sensing*, 9(9), 967.
- Pickup, G., & Nelson, D. (1984). Use of Landsat radiance parameters to distinguish soil erosion, stability, and deposition in arid central Australia. *Remote Sensing of Environment*, 16(3), 195-209.
- Pillay, D., & Sebake, M. (2008). Assessing post apartheid settlement growth patterns using remote sensing and GIWS: A case study of Cape Town metropolitan area.
- Pimentel, D. (2006). Soil erosion: a food and environmental threat. *Environment, development and sustainability*, 8(1), 119-137.
- Poesen, J., Nachtergaele, J., Verstraeten, G., & Valentin, C. (2003). Gully erosion and environmental change: importance and research needs. *Catena*, 50(2-4), 91-133.
- Price, K. P. (1993). Detection of soil erosion within pinyon-juniper woodlands using Thematic Mapper (TM) data. *Remote Sensing of Environment*, 45(3), 233-248.
- Prosser, I. P., Rutherford, I. D., Olley, J. M., Young, W. J., Wallbrink, P. J., & Moran, C. J. (2001). Corrigendum to: Large-scale patterns of erosion and sediment transport in river networks, with examples from Australia. *Marine and Freshwater Research*, 52(5), 817-817.

- Punj, G., & Stewart, D. W. (1983). Cluster analysis in marketing research: Review and suggestions for application. *Journal of marketing research*, 20(2), 134-148.
- Rasul, A., Balzter, H., Ibrahim, G., Hameed, H., Wheeler, J., Adamu, B., . . . Najmaddin, P. (2018). Applying Built-Up and Bare-Soil Indices from Landsat 8 to Cities in Dry Climates. *Land*, 7(3), 81.
- Ray, T., Farr, T., Blom, R., & Crippen, R. (1993). Monitoring land use and degradation using satellite and airborne data.
- Sanges, R., Cordero, F., & Calogero, R. A. (2007). oneChannelGUI: a graphical interface to Bioconductor tools, designed for life scientists who are not familiar with R language. *Bioinformatics*, 23(24), 3406-3408. doi:10.1093/bioinformatics/btm469
- Sasson, O., Vaaknin, A., Fleischer, H., Portugaly, E., Bilu, Y., Linial, N., & Linial, M. (2003). ProtoNet: hierarchical classification of the protein space. *Nucleic Acids Research*, 31(1), 348-352. doi:10.1093/nar/gkg096
- Senanayake, I., Welivitiya, W., & Nadeeka, P. (2013). Remote sensing based analysis of urban heat islands with vegetation cover in Colombo city, Sri Lanka using Landsat-7 ETM+ data. *Urban Climate*, 5, 19-35.
- Seo, J., & Shneiderman, B. (2002). Interactively exploring hierarchical clustering results [gene identification]. *Computer*, 35(7), 80-86.
- Sepuru, T. K., & Dube, T. (2018). Understanding the spatial distribution of eroded areas in the former rural homelands of South Africa: Comparative evidence from two new non-commercial multispectral sensors. *International Journal of Applied Earth Observation and Geoinformation*, 69, 119-132.
- Servenay, A., & Prat, C. (2003). Erosion extension of indurated volcanic soils of Mexico by aerial photographs and remote sensing analysis. *Geoderma*, 117(3-4), 367-375.
- Seutloali, K. E., Beckedahl, H. R., Dube, T., & Sibanda, M. (2016). An assessment of gully erosion along major armoured roads in south-eastern region of South Africa: a remote sensing and GIS approach. *Geocarto International*, 31(2), 225-239.
- Shaikh, M., Green, D., & Cross, H. (2001). A remote sensing approach to determine environmental flows for wetlands of the Lower Darling River, New South Wales, Australia. *International journal of remote sensing*, 22(9), 1737-1751.
- Sibanda, M., Mutanga, O., & Rouget, M. (2016a). Comparing the spectral settings of the new generation broad and narrow band sensors in estimating biomass of native grasses grown under different management practices. *GIScience & remote sensing*, 53(5), 614-633.
- Sibanda, M., Mutanga, O., & Rouget, M. (2016b). Discriminating rangeland management practices using simulated hySPIRI, landsat 8 OLI, sentinel 2 MSI, and VEN μ s spectral data. *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing*, 9(9), 3957-3969.
- Sinha, P., Verma, N. K., & Ayele, E. (2016). Urban built-up area extraction and change detection of Adama municipal area using time-series Landsat images. *International Journal of Advanced Remote Sensing and GIS*, 5(8), 1886-1895.
- Sobrino, J., & Raissouni, N. (2000). Toward remote sensing methods for land cover dynamic monitoring: Application to Morocco. *International journal of remote sensing*, 21(2), 353-366.
- Srivastava, R. K., Leone, R. P., & Shocker, A. D. (1981). Market structure analysis: hierarchical clustering of products based on substitution-in-use. *Journal of Marketing*, 45(3), 38-48.
- StatsSA. (2018). *Mid-year population estimates for 2017*. Pretoria, South Africa.

- Steffen, W., Persson, Å., Deutsch, L., Zalasiewicz, J., Williams, M., Richardson, K., . . . Gordon, L. (2011). The Anthropocene: From global change to planetary stewardship. *Ambio*, 40(7), 739.
- Steffen, W., Sanderson, R. A., Tyson, P. D., Jäger, J., Matson, P. A., Moore III, B., . . . Turner, B. L. (2006). *Global change and the earth system: a planet under pressure*: Springer Science & Business Media.
- Stenberg, P., Rautiainen, M., Manninen, T., Voipio, P., & Smolander, H. (2004). Reduced simple ratio better than NDVI for estimating LAI in Finnish pine and spruce stands.
- Stoner, E. R., & Baumgardner, M. (1981). Characteristic Variations in Reflectance of Surface Soils 1. *Soil Science Society of America Journal*, 45(6), 1161-1165.
- Sujatha, G., Dwivedi, R., Sreenivas, K., & Venkataratnam, L. (2000). Mapping and monitoring of degraded lands in part of Jaunpur district of Uttar Pradesh using temporal spaceborne multispectral data. *International journal of remote sensing*, 21(3), 519-531.
- Symeonakis, E., Karathanasis, N., Koukoulas, S., & Panagopoulos, G. (2016). Monitoring sensitivity to land degradation and desertification with the environmentally sensitive area index: The case of Iesvos island. *Land Degradation & Development*, 27(6), 1562-1573.
- Tappan, G. G., Tyler, D. J., Wehde, M. E., & Moore, D. G. (1992). Monitoring rangeland dynamics in Senegal with advanced very high resolution radiometer data. *Geocarto International*, 7(1), 87-98.
- Taruvinga, K. (2009). *Gully mapping using remote sensing: Case study in KwaZulu-Natal, South Africa*. University of Waterloo.
- Todes, A., Kok, P., Wentzel, M., Van Zyl, J., & Cross, C. (2010). *Contemporary South African urbanization dynamics*. Paper presented at the Urban forum.
- Turner, W., Rondinini, C., Pettorelli, N., Mora, B., Leidner, A. K., Szantoi, Z., . . . Herold, M. (2015). Free and open-access satellite data are key to biodiversity conservation. *Biological Conservation*, 182, 173-176.
- UNCCD. (2014). *Land degradation neutrality: resilience at local, national and regional levels*. United Nations Convention to Combat Desertification, Bonn, Germany.
- Vaidyanathan, N., Sharma, G., Sinha, R., & Dikshit, O. (2002). Mapping of erosion intensity in the Garhwal Himalaya. *International journal of remote sensing*, 23(20), 4125-4129.
- Van Vliet, N., Mertz, O., Heinemann, A., Langanke, T., Pascual, U., Schmook, B., . . . Leisz, S. (2012). Trends, drivers and impacts of changes in swidden cultivation in tropical forest-agriculture frontiers: a global assessment. *Global environmental change*, 22(2), 418-429.
- Van Wyk, A. E., & Smith, G. F. (2001). *Regions of floristic endemism in southern Africa: a review with emphasis on succulents*: Umdaus press.
- Vrieling, A. (2006). Satellite remote sensing for water erosion assessment: A review. *Catena*, 65(1), 2-18.
- Vrieling, A., Rodrigues, S., Bartholomeus, H., & Sterk, G. (2007). Automatic identification of erosion gullies with ASTER imagery in the Brazilian Cerrados. *International journal of remote sensing*, 28(12), 2723-2738.
- Wang, R. (2013). 3D building modeling using images and LiDAR: A review. *International Journal of Image and Data Fusion*, 4(4), 273-292.
- Warburton, M. L., Schulze, R. E., & Jewitt, G. P. (2010). Confirmation of ACRU model results for applications in land use and climate change studies. *Hydrology and Earth System Sciences*, 14(12), 2399.
- Warburton, M. L., Schulze, R. E., & Jewitt, G. P. (2012). Hydrological impacts of land use change in three diverse South African catchments. *Journal of Hydrology*, 414, 118-135.

- Waske, B., van der Linden, S., Oldenburg, C., Jakimow, B., Rabe, A., & Hostert, P. (2012). ImageRF—A user-oriented implementation for remote sensing image analysis with Random Forests. *Environmental Modelling & Software*, 35, 192-193.
- Wegmuller, U., Strozzi, T., Farr, T., & Werner, C. L. (2000). Arid land surface characterization with repeat-pass SAR interferometry. *IEEE Transactions on Geoscience and Remote Sensing*, 38(2), 776-781.
- Wessels, K. J., Prince, S., Frost, P., & Van Zyl, D. (2004). Assessing the effects of human-induced land degradation in the former homelands of northern South Africa with a 1 km AVHRR NDVI time-series. *Remote Sensing of Environment*, 91(1), 47-67.
- Wessels, K. J., Prince, S., Malherbe, J., Small, J., Frost, P., & VanZyl, D. (2007). Can human-induced land degradation be distinguished from the effects of rainfall variability? A case study in South Africa. *Journal of Arid Environments*, 68(2), 271-297.
- Wessels, K. J., Prince, S. D., Carroll, M., & Malherbe, J. (2007). Relevance of rangeland degradation in semiarid northeastern South Africa to the nonequilibrium theory. *Ecological Applications*, 17(3), 815-827.
- Wilkie, D. S., Finn, J. T., & Finn, J. (1996). *Remote sensing imagery for natural resources monitoring: a guide for first-time users*: Columbia University Press.
- Wischmeier, W. H. (1965). Predicting rainfall erosion losses from cropland east of the Rocky Mountain. *Agriculture handbook*, 282, 47.
- Wischmeier, W. H. (1978). Predicting rainfall erosion losses: a guide to conversation planning. *USDA Agr. Handbook*.
- Xulu, S. (2014). *Land degradation and settlement intensification in Umhlathuze Municipality*. Stellenbosch: Stellenbosch University.
- Zha, Y., Gao, J., & Ni, S. (2003). Use of normalized difference built-up index in automatically mapping urban areas from TM imagery. *International journal of remote sensing*, 24(3), 583-594.
- Zhao, Y., & Karypis, G. (2002). *Evaluation of hierarchical clustering algorithms for document datasets*. Paper presented at the Proceedings of the eleventh international conference on Information and knowledge management.
- Zhao, Y., & Karypis, G. (2003). Clustering in life sciences *Functional Genomics* (pp. 183-218): Springer.
- Zhao, Y., Karypis, G., & Fayyad, U. (2005). Hierarchical clustering algorithms for document datasets. *Data mining and knowledge discovery*, 10(2), 141-168.
- Zhong, Y., Zhang, L., Huang, B., & Li, P. (2006). An unsupervised artificial immune classifier for multi/hyperspectral remote sensing imagery. *IEEE Transactions on Geoscience and Remote Sensing*, 44(2), 420-431.