Use of remote sensing in landscape-scale vegetation degradation assessment in the semi-arid areas of the Save catchment, Zimbabwe

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By

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Abstract

The deteriorating condition of land in parts of the world is negatively affecting livelihoods, especially, in rural communities of the developing world. Zimbabwe has experienced significant vegetation cover losses, particularly, in low and varied rainfall areas of the Save catchment. The concern that Save catchment is undergoing huge vegetation losses has been largely expressed, with the causes being environmental and anthropogenic. Given the magnitude of the problem, research studies have been undertaken to assess the extent of the problem in the south eastern region of Zimbabwe, which, nevertheless, have been mainly localized. The present study seeks to identify and quantify vegetation degradation at a landscape scale in the Save catchment of Zimbabwe, using remote sensing technologies. To achieve this, two objectives were set. The first objective provided a review of the application of satellite earth observations in assessing vegetation degradation, the causes, as well as associated impacts at different geographical scales. A review of literature has revealed the effectiveness of satellite information in identifying changes in vegetation condition. A second objective sought to establish the extent of vegetation degradation in the Save catchment. Moderate Resolution Imaging Spectroradiometer-Normalised Difference Vegetation Index (MODIS NDVI) datasets were used for mapping NDVI trends over the period 2000-2015. Further analysis involved application of residual trend (RESTREND) method to separate human influences from climatic signal on vegetation degradation. RESTREND results showed an increasing trend in NDVI values in about 33.6% of the Save catchment and a decreasing trend in about 18.3% from 2000 to 2015. The results of the study revealed that about 3,609,955 hectares experienced significant human induced vegetation degradation. Approximately 38.8% of the Save Catchment was significantly degraded ($p < 0.05$), 3.6%, 12.8%, and 22.4% of which were classified as severely, moderately, and lightly degraded, respectively. Severe degradation was mainly found in the central districts of the Save Catchment, mainly Bikita, Chipinge and northern Chiredzi. The results of this study support earlier reports about ongoing degradation in the catchment. Vegetation changes observed across the landscape revealed different degrees of the impacts of land use activities in altering the terrestrial ecosystems. The study demonstrated the usefulness of the RESTREND method in identifying vegetation loss due to human actions in very low rainfall areas.

Keywords: remote sensing; residual trend; NDVI; semi-arid; vegetation degradation

Preface

This research was undertaken at the School of Agricultural, Earth and Environmental Sciences, University of KwaZulu-Natal, Pietermaritzburg, South Africa, under the supervision of Professor Onisimo Mutanga and Professor Timothy Dube.

I declare that the work presented in this thesis has never been submitted in any form to any other institution. This work represents my original work except where due acknowledgements are made.

Dadirai Matarira Signed … ……………… Date…………………….

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

Prof. Onisimo Mutanga Signed………………. Date………………………...

Prof. Timothy Dube Signed… ……… Date………………………

Declaration

I, Dadirai Matarira, declare that:

1. The research reported in this thesis, except where otherwise indicated, is my original research.

2. This thesis has not been submitted for any degree or examination at any other institution.

3. This thesis does not contain other person's data, pictures, graphs or other information, unless specifically acknowledged as being sourced from other persons.

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Dedication

I dedicate this dissertation to my husband, Caxton, and my children, Tavonga and Tadiwa, for their tremendous support. To God be the glory.

Acknowledgements

Firstly, I would like to thank the Lord, Almighty, for giving me the strength to pursue this programme.

My sincere appreciation goes to my supervisor, Professor Onisimo Mutanga and co-supervisor, Professor Timothy Dube, for guiding me throughout the research process, from proposal development, to the submission of the thesis. Their advice and invaluable feedback on my submissions made it possible for me to achieve my goal.

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CHAPTER 1

General Introduction

1.1 Introduction

Terrestrial ecosystems are rapidly changing due to vegetation degradation and these changes are observed in species diversity and their geographical spread (Ndayisaba *et al*., 2017). Vegetation degradation may be described as the reduction of the capacity of land as a productive resource (Bai *et al*., 2008). Various forms of degradation include soil erosion, water quality reduction, changes in species composition and vegetation loss (Reynolds *et al*., 2007). The major drivers of the changes are largely anthropogenic, with little impact from physical factors (Vlek *et al*., 2008). These changes have made terrestrial ecosystems to be less resilient and even more vulnerable to slight disturbances, thus, reducing the generation or restoration capability. Reduction in land 's biological productivity due to natural causes and human actions leads to environmental concerns, especially, in semi-arid ecosystems whose fragile soils support the livelihood of many rural communities (Evans & Geerken, 2004).

Globally, the population depending on these fragile ecosystems exceed one billion people (Vlek *et al*., 2008), approximately 42% of whom are poor people dependant on the degraded soils for their livelihoods (Braun *et al*., 2010). Sub-Saharan Africa (SSA) experiences land deterioration the most (Nkonya et al., 2015), where, about 28% of the 924.7 million inhabitants occupy the marginal lands (Le *et al*., 2014). Tully et al. (2015) revealed that, about 75% of the rural poor living in SSA largely relies on this fragile soil resource for subsistence farming. In Kenya, for example, more than 12 million people are occupying areas that have experienced vegetation degradation (Mulinge *et al*., 2016). The "villagization" programme, initiated in Tanzania from 1973 to 1976, known as the *Ujamaa*, pushed the poorest into the most unproductive lands (Tully *et al*., 2015). In 2010, approximately 2% of the population living in communal areas of Zimbabwe occupied degraded arable land, an increase of 30% from year 2000 (Global Mechanism of the UNCCD, 2018).

There are many processes involved in the destruction of the quality of land. These processes, together with the varied assessment methods used, make the results of different studies inconsistent (De Jong *et al.,* 2011). Earlier assessments under the Global Assessment of Soil Degradation (GLASOD) project have relied mainly on expert knowledge and opinions (Nkonya et al., 2011). Their results were considered gross estimates and unreliable (Vlek *et al*., 2010). GLASOD survey results failed to distinguish between areas with degradation processes underway or where there was improvement (Nkonya *et al*., 2011), failing to provide the extent and severity of degradation at scales relevant for decision-making (Dubovyk, 2017). Field observations are an alternative method to identify vegetation degradation but are too expensive. Hence, ground based observations are still lacking globally (Ruppert *et al*., 2015). For inventorying and monitoring at catchment and national scales, objective methods capable of spatial differentiation are required (Prince, 2004). Earth observations have assisted in the development of objective techniques for quantifying levels of degradation (Wessels *et al*., 2007). Remote sensing assessment of land condition has proved to be more effective over a broad range of geographical scales (Mulinge *et al*., 2016).

In many studies, Normalised difference vegetation index (NDVI) has been applied as an indicator of degradation. It has proved to be useful in assessing the environmental condition from global, regional to local levels (Kapalanga, 2008). Fensholt *et al*. (2013) utilised the National Oceanic and Atmospheric Administration-Advanced Very High Resolution Radiometer (NOAA-AVHRR) NDVI to analyse land condition in drylands of Sahel region. That study assessed the net primary productivity (NPP) from 1982 to 2010. In another study by Forkel *et al*. (2013), a comparison was made between different techniques for quantifying vegetation productivity trends using AVHRR NDVI data in Alaska. Other authors include Tsevelmaa (2017), who assessed desertification and vegetation degradation in Steppe zone in Mongolia using trends of Moderate Resolution Imaging Spectroradiometer (MODIS) NDVI time-series. Bai *et al*. (2008) used the Global Inventory Modelling and Mapping Studies (GIMMS) to demonstrate effectiveness in using NDVI to assess degradation of ecosystems in low rainfall regions. Their studies revealed uncertainties that arise when interpreting the vegetation index for dryland environments that are characterised by sparse vegetation and high rainfall variability.

Of equal scientific importance in vegetation degradation monitoring is explanation of the causes of vegetation dynamics, as well as vegetation response to these drivers (Vlek *et al*., 2010; Tully *et al.*, 2015). In SSA, climatic disasters in the form of droughts contribute to increased pressure on the ecosystems of dry areas causing increased rate of degradation (Hermann *et al*., 2005; Vlek *et al*., 2010). Zimbabwe experienced episodes of droughts and large rainfall variations recently, altering vegetation growth patterns and leading to food shortages for the land dependant population, especially small holder farmers (Simba *et al*., 2012). Land managers and policy-makers would benefit from continuous monitoring of the quality of land condition in order to develop efficient strategies that ensure sustainable utilization of the resource and an overall ecological sustainability of drylands (Dubovyk, 2017).

Vegetation degradation, that is, reduced vegetation cover, has been characteristic of drylands in the Save Catchment (Reynolds *et al*., 2007) because of this region's vulnerability to the continued impacts of climate change. This study focuses on vegetation degradation. Since knowledge of degradation causes is essential for mapping vegetation degradation (Vlek *et al.*, 2010), understanding those causes is crucial in landscape management (Li *et al*., 2012). Several studies have used residual trend (RESTREND) technique to separate vegetation changes triggered by activities of man from productivity decline due to rainfall variations (Evans & Geerken, 2004; Li *et al*., 2012). It is this ability of the technique to isolate the influence of rainfall and predict only the role of human activities in vegetation cover dynamics that justifies its use in the Save catchment which experiences high inter-annual rainfall variability.

1.2 Aim & Objectives

The study aims to establish the location and extent of vegetation cover decline, quantify vegetation cover change and establish the underlying drivers in the context of vegetation degradation.

1.2.1 The specific objectives were to:

1. Provide a detailed overview on the application of satellite earth observations in assessing and monitoring vegetation degradation.
2. To establish the effectiveness of RESTREND method in detecting human induced vegetation degradation.

1.3 Research questions

This research aims to address the following questions:

1. To what extent are remote sensing techniques useful in detecting and mapping vegetation degradation at landscape scale?
2. Can the RESTREND method effectively detect and map the extent and severity of vegetation degradation at the Save catchment?

1.4 General structure of the thesis

Excluding the introduction and the synthesis chapters 1 and 4, the thesis comprises two research papers that answer each of the research questions in section 1.3. The literature review and methodology are entrenched within the mentioned papers. Chapter two reviews the concept of vegetation degradation and the application of remote sensing in assessing the degradation. The initial part reviews the global picture of degradation of land, the drivers and impacts, as well as key indicators of the process. Methods of mapping degradation using satellite earth observations were explored in this chapter, with main focus on utilisation of NDVI in characterising vegetation degradation. Chapter three focuses on identifying areas that are degraded and mapping their distribution in the study area. MODIS NDVI time-series images were used in the assessment of vegetation distribution patterns. RESTREND method was used to exclude the contribution of rainfall variations, which would allow the mapping of degradation which is strictly due to human influences.

CHAPTER TWO

Progress in remote sensing applications in vegetation degradation assessment and monitoring in sub-Saharan Africa

This chapter is based on a paper by:

Matarira, D., Mutanga, O. & Dube, T. 2019. Progress in remote sensing applications in vegetation degradation assessment and monitoring in sub-Saharan Africa. *Journal of Physics and Chemistry of the Earth* Manuscript ID: JPCE_2019_76 (Under review).

Abstract

The deteriorating condition of land in parts of the world has become a challenge, particularly in developing countries. It has become a threat to sustainable development since it impacts negatively on the livelihoods, agricultural output, provision of food, as well as the natural environment. The impacts of vegetation degradation are largely felt by poor communities where deforestation and inappropriate agricultural practices, are the major drivers. This study reviewed techniques that are used to determine and understand vegetation degradation, with emphasis on remote sensing technologies. This review establishes the extent, major drivers and impacts, key indicators and degree of vegetation degradation at various scales through a review of recent studies. Literature has revealed varied estimates of areal extent of vegetation degradation. Variations have mainly been due to differences in defining the process, the indicators assessed and the approaches employed in its quantification. Results from earlier assessments have been criticised for being unreliable, lacking objectivity and relying mainly on perceptions. Satellite information has proved to be effective and reliable for monitoring this process over large geographical regions. Studies that have utilized remote sensing effectively used normalised difference vegetation index (NDVI) to show where deterioration in land condition is taking place. NDVI time-series has been the most useful in determining the degradation trends. Because degradation of vegetation interacts closely with climatic fluctuations, literature revealed problems in disentangling the climate signal from the contribution of human actions in vegetation degradation assessment. Residual trend (RESTREND) method is effective in

identifying changes in vegetation status due to human actions alone by removing the contribution of rainfall.

Keywords: satellite information, normalised difference vegetation index, residual trend, time-series

2.1 Introduction

The deterioration of semi-arid and arid regions has had serious impacts on ecosystem productivity (MEA, 2005). Of paramount importance in the evaluation of vegetation degradation in the world's drylands is the ability to show the magnitude of deterioration of the land (Reynolds *et al*., 2007). Vegetation degradation tends to be applied interchangeably with desertification (Ibrahim *et al*., 2015). While definitions vary, the process relates more to the decline of ecosystem productivity (Dubovyk, 2017). According to the UNCCD (2015), the process is a result of climatic changes and human alterations of the environment. There is, however, no agreed position on what it is and no consensus with respect to the method of measuring the process, resulting in largely differing and, probably, overstated estimates of its magnitude (Safriel, 2007). Despite various efforts aimed at mapping degradation at various geographical scales (Wessels *et al*., 2007), there is no reliable estimate of the spatial extent of different kinds and degrees of vegetation degradation, globally (Dubovyk, 2017). Estimates of the magnitude and spatial extent of diminished land productivity have varied substantially. This is especially because natural vegetation in low rainfall regions has been almost ubiquitously degraded to the maximum possible extent, save and except in some protected forest lands (Ndayisaba *et al*., 2017).

Spatial information on degradation is required to address the socio-economic implications of the deterioration in land condition (Okin *et al*., 2001). However, there is a lack of agreement on the appropriate methodology to map vegetation degradation (Higginbottom & Symeonakis, 2014). The chosen approach depends on the contextual definition and the indicator used to characterise the process (Dubovyk, 2017). The assessment method also depends on the size of the area under study, specific interpretation of the process and the purpose of the monitoring (Warren, 2002). The major impact of the deterioration of land is on the sustainability of human habitation, especially where exploitation of the land resource is the source of income and food (Prince *et al*., 2009). Statistics on aspects of degradation are required for rehabilitation and remediation of degraded lands (Dube *et al*., 2017). Vegetation degradation assessments and maps are also important for decision-making and management of the ecosystems (Vagen *et al*., 2016). Shortcomings in existing global maps of vegetation degradation emanate from the fact that earlier mapping studies were mainly based on subjective expert opinion surveys without evaluation of any measurement errors (Le *et al*., 2016). Digitizing and field surveys are some of the methods used to acquire information on the distribution of degraded areas. These methods, although considered the most accurate in detecting degradation, are resource demanding so they can only be applied over a small area (Pickup, 1996).

Mankind has excelled in delimiting vegetation degradation at various spatial scales, following the development of satellite earth observation and computing systems (Vlek *et al*., 2010). Previously, scientists and policymakers found it difficult to detect the onset of vegetation degradation (Higginbottom & Symeonakis, 2014). It has since emerged that, remote sensing method is the most effective, operational, environmental monitoring approach at landscape scale (Dube *et al*., 2017). It has a demonstrated capability to collect large quantities of data in a cost-effective manner (Higginbottom & Symeonakis 2014). Among various biophysical indicators of vegetation productivity loss is the normalised difference vegetation index (NDVI) (Dubovyk, 2017), which is applied in assessing land condition because of its ability to measure patterns of vegetation greenness (Verón *et al*., 2006). The widespread reliance on the NDVI in monitoring degradation (Le *et al*., 2016) supports the link between reduction in vegetation cover over a long period and vegetation degradation (FAO, 2015). Geographic data and field measurements are used to validate the results from the analysis of remotely sensed data to infer degradation patterns (Mambo & Archer, 2007).

To date, there is limited information on the drivers of the processes associated with vegetation degradation (De Jong *et al*., 2011). This creates major obstacles in efforts aimed at reducing the process (Liniger *et al*., 2011). According to Pierre (2008), it is necessary to, first, provide information on the current degradation status and its underlying drivers in order to avert the process. In support of this view, Dubovyk *et al*. (2017) revealed that detection and characterization of vegetation change over time forms the basis of identifying the causes of degradation. Acquiring such information enables countries to develop the most appropriate, effective and sustainable actions in combatting the process. Save Catchment, being a marginal area, lacks a constant vegetation cover due to unreliable rainfall, as well as, severe pressure from human activities (Mambo & Archer, 2007). Previous research addressing vegetation degradation in the Save catchment has provided limited information on the trends and distinct causes of the observed degradation. In order to undertake a full assessment of the condition of land it becomes necessary to cover all the four themes, as follows: causes, type, degree as well as the extent of degradation (Yengoh *et al*., 2014). This chapter aims to explore the process of degradation from global to local level, its drivers, impacts and key indicators. The research reviews its assessment using remotely sensed data.

2.2 Degradation on a global scale

An early spatial assessment carried out to map vegetation degradation globally was implemented within the Global Assessment of Human-Induced Soil Degradation (GLASOD) project (Oldeman *et al*., 1990). This mapping relied on judgement by experts (Oldeman *et al*., 1990). Degree of degradation was qualitatively described as: light, moderate, strong, or extreme (Vlek *et al*., 2010). The GLASOD project only looked at the human contribution in the degradation process (De Jong *et al*., 2011), with no reference to climate change impacts, particularly in Africa (Vlek *et al*., 2008). According to the authors, there was little information on the influence of rainfall variability on land productivity during the early 1980s.

Scientific articles report varying statistics of degradation. While some record figures as low as 15%, others have degradation levels reaching 63% of the globe (Safriel, 2007). The amount of land that has been degraded in drylands has been reported to be ranging from 4% to 74% (Safriel, 2007). The GLASOD project revealed that, approximately 15% of the global area and 60% of low rainfall regions have been lost to degradation (Oldeman *et al*., 1990). Because these results were based only on informed opinions the global estimates of vegetation degradation are said to be based on poor data (Hassan *et al*., 2005).

Statistics revealed by German Technical Development Cooperation (GTZ) (2005) indicated the loss of valuable agricultural land due to degradation, each year. According to a number of studies, severe degradation is responsible for the loss of agricultural land amounting to 5-10 million ha every year (Gao & Liu, 2010). Bai *et al*. (2008) revealed that, globally, forests, cultivated lands and grasslands are very prone to degradation, 30%, 20% and 10% of which are already lost through various degradation processes, respectively. Land lost due to unsustainable agricultural activities, overgrazing and deforestation amounted to about 6 million hectares, six hundred and eighty million hectares, and 580 million hectares, respectively (GTZ, 2005). Firewood collection destroyed a further 137 million hectares, with 19.5 million hectares lost due to industries and urbanisation (Johnson *et al*., 2006). The statistics point to the human factor as a major driver of the process of vegetation degradation.

Across Africa, degradation of the environment is a challenge, with wind and water erosion claiming 25% and 22% of the land respectively (Reich *et al*., 2001). On the other hand, GEF (2006) gave 39% of the continent as being degraded and suggested that 65% of the agricultural land was prone to desertification. This agreed with the GLASOD expert survey which confirmed that 65 percent of Africa ‘s productive regions experienced a decline in the quality of land from the last century (FAO, 2015). Because of these differing statistics, information on the magnitude of the process has been unreliable, hence, no agreement on its severity (Vlek *et al*., 2010). Moreover, these studies rarely used spatially distributed data and do not identify the exact regions most affected by degradation (Vlek *et al*., 2010). This creates uncertainties with regards to the associated impacts across the African continent (Reich *et al*., 2001; GEF, 2006).

Countries in SSA, with population densities averaging 30 people /km^2 (Vlek *et al*., 2010), experience the highest rate of destruction of forests in the world. Parts of the continent lost 10% of their forest cover between 2004 and 2009 (IFAD, 2009), due to degradation. The area under cultivation in this zone is, approximately, 15% and 4% is covered by a mixture of crops and forests (FAO, 2015). In South Africa, degradation of land has become a major environmental problem, where 29% of the country degraded from 1981 to 2003 (Bai *et al*., 2008). Eighty per cent of communal areas of Zimbabwe are estimated to be degraded (Scoones, 1992). This is due to the long history of environmental and political neglect since the 1930s (Mambo & Archer, 2007). The expansion of subsistence farming in the communal areas over the years has exacerbated the problem. Approximately 21% (around 4,694,000 hectares) of Zimbabwe's forest cover was lost due to deforestation between 1990 and 2005, leading to the disappearance of all old forests (Global Mechanism of the UNCCD, 2018).

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2.3 Drivers of vegetation degradation

Degradation of land is triggered by various interconnected factors, the effects of which are modified by local conditions (Nkonya *et al*., 2016). There is, therefore, a need to carry out extensive local level studies to determine the impact of these factors, many of which depend on the scale of analysis (Camberlin, 2008). Close examination of the causes of degradation processes allows accurate interpretation of spatial distribution of the degraded lands (Dubovyk, 2017). It has since been established that environmental and human factors are the major contributors to declining land quality and alteration of terrestrial ecosystems (Hill *et al*., 2008). However, the degradation process is largely linked to human influences, making human induced vegetation degradation a key economic, security and environmental issue, worldwide (Eswaran *et al*., 2001). While overpopulation, poverty and pressure on pasture lands trigger the process of degradation, mainly, in SSA, poor management of land and ineffective resource ulitisation policies compound the problem (Dube *et al*., 2017). Biodiversity loss has resulted from such human influences on soil, water and vegetative cover, negatively affecting ecosystem structure and functions (Mambo & Archer, 2007).

The rural areas of many developing countries are experiencing rapid increases in population pressure. This has often resulted in unsustainable land use changes, mainly, due to forest clearance, with the intention of increasing agricultural production. It is largely documented that, such unsustainable land resource utilisation reduces vegetation cover and leads to soil erosion (Mambo & Archer, 2007). Most farmers in SSA have limited options and capacities to improve their land. In their pursuit to earn a living, it is postulated that, once degradation of land begins, it is highly possible that such farming communities will engage in even more degrading activities (Vlek *et al*., 2008). This eventually diminishes the productive potential of the land to an extent that it loses its capacity to restore itself (Greenland *et al*., 1994). Hoekstra *et al*. (2005) revealed that human influences on vegetation degradation could go beyond such direct land alterations, mainly by local communities, and may stretch to unsustainable international economic activities (UNEP, 2012). According to Lal and Singh (1998), hunger and famine will be a threat to many countries in Africa if vegetation degradation is not controlled.

2.4 Cost of vegetation degradation

The environmental and socio-economic impact of vegetation degradation has been highly discussed since the first attempt to map degradation globally (Nkonya *et al*., 2016). Most research efforts relied on estimates of costs associated with soil loss as being representative of degradation costs (Braun *et al*., 2010). This emanates from the reliance on estimations of soil loss as the indicator of degradation of land by earlier researchers (Vlek *et al*., 2010). This may also be due to the linkages between different vegetation degradation processes, where vegetation reduction alters the rate of soil erosion. Despite challenges involved in providing the exact figures of vegetation degradation, due to complexity of the process, many countries are cognizant of the costs of the process. It has been shown to have major impacts in developing countries (Braun *et al*. (2010). This is because of its significant effects on the ability of land in the provision of wood fuel and sustaining field crops, which are essential services for the existence of humans in poor countries (Vogt *et al*., 2011).

Statistics on negative impacts of degradation have been widely reported. According to studies by Bai *et al*. (2008), livelihoods of 1.5 billion people had been affected over the previous 25 years. Similarly, Eswaran *et al*. (2001) demonstrated equally devastating effects on 2.6 billion people due to deteriorating quality of land in 33% of global area. Worldwide, 74% of the resource-dependent, poor population, are most affected (UNCCD, 2015; Nkonya *et al*., 2016). With rising population figures in developing countries, coupled with low or no budget allocations for land management, the quality of land is bound to continuously decrease (Vlek *et al*, 2008). The United Nations puts the cost of desertification, in the form of lost income, at US$45 billion per year (Wessels, 2005), impacting adversely on sustainable development (UNCCD, 2015). The world is losing about US$10.6 trillion annually, that is, 17% of global gross domestic product, towards vegetation degradation. In Zimbabwe, approximately US$382 million, which is 6% of the country’s annual income, is lost due to deteriorating land quality (Global Mechanism of the UNCCD, 2018).

In assessing cost implications of deterioration in the quality of land, an important step in the analysis should be the distinction between on-site and offsite costs (Berry *et al*., 2003). This is because unsustainable agricultural practices may loosen the soil at a particular point, resulting in siltation of reservoirs, downstream. In mountainous regions of Northern Ethiopia, soil erosion leads to serious losses of top soil, resulting in siltation of water reservoirs (Adimassu *et al*., 2014). Deposited sediments amounting to, about, 5-20 t $ha^{-1}y^{-1}$ has been reported in small catchments of Tigray, Ethiopia (Tamene *et al*., 2017). Small dams that supply rural areas with water are also reported to be highly silted (Zimbabwe Environmental Management Agency, 2015). Studies have revealed that, in Masvingo province, Zimbabwe, 50% of 132 small dams have been regarded as silted (Dalu *et al*., 2013). Such high siltation levels also affect the aquatic ecosystems that are said to be degraded beyond restoration (Worm *et al*., 2006). The siltation of dams and waterways has a foremost impact on GDP of a country (Gore *et al*., 1992).

One million eight hundred and forty-eight thousand hectares were reported to have been subjected to erosion in Zimbabwe (Whitlow, 1988), with soil losses averaging 76 tonnes per hectare, annually (Mambo & Archer, 2007). Soil erosion is contributing immensely to decline in soil fertility in most arable lands of Zimbabwe. Nitrogen, organic matter, and phosphorus are lost to erosion with amounts reaching 1.6 million tonnes, 15.6 million tonnes and 0.24 million tonnes, respectively (Environmental Management Agency, 2015). This loss of nutrients results in decline in crop yields, affecting the wellbeing of the population whose livelihood is agriculture based. Degradation of the land leads to costs which may be reflected in diminishing carbon sequestration (Nkonya *et al*., 2011). Deforestation diminishes the ability of land to function as a carbon sink. The decline in carbon sequestration does not only have effect at a national level but its impacts are felt across the globe because such ecosystem services cross international boundaries (Global Mechanism of the UNCCD, 2018). Clearance of forests leads to increased atmospheric carbon dioxide concentrations (Kareiva *et al*., 2007). This has got impacts on climate change since the increase in greenhouse gasses may lead to global warming. Sustainable land use is therefore imperative to prevent drylands from experiencing continuous decline in productivity potential, which may culminate into desertification (Hill *et al*., 2008).

Security in ownership and tenure strongly influences management of land (Tully *et al*., 2015) since it incentivises farmers to use the land sustainably and invest in it. Without rights to ownership, land is prone to unsustainable uses and investment in land conservation will not be a priority. Where land issues depend on political expedience, deterioration of the environment is inevitable, causing vegetation degradation concerns. The political decision to decongest the communal areas of Zimbabwe, by creating resettlement areas, led to the destruction of forests by 1.41% between 1990 and year 2000 to 16.4% between year 2000 and 2005 (Dalu *et al*.,2013). During that fast track land reform programme, commercial farms were converted into small holder farms exerting pressure on lands that had been properly managed and highly productive. Such small farmlands are characterised by limited investments because there is, usually, lack of security in ownership. As a result of that land distribution exercise, forests were massively cleared. Because of improper planning on sustainable farming practices there was resultant decline in the productive capacity of most lands leading to decline in agricultural yields (Tully *et al*., 2015).

For sustainable development to be realized, the current degradation trends have to be reversed. This motive has led to the introduction of a global comprehensive framework to evaluate the financial implications of vegetation degradation (Nkonya *et al*., 2016), in view of negative changes in carbon, water resources and cultural services (Nachtergaele *et al*., 2010).

2.5 Biophysical manifestation of vegetation degradation

Remote sensing of the environment has enabled identification of physical environmental conditions that indicate improvement or degradation of ecosystems (Dubovyk, 2017). Indicators that relate to processes of vegetation degradation include changes in biological productivity, vegetation cover decline and soil erosion (Prince, 2002). These characterise vegetation degradation and allow for the delineation and mapping of degraded areas (Le *et al*., 2012). Ibrahim *et al*. (2015) used satellite information in mapping the changes in land condition, by examining the decline in vegetation productivity, whose pattern and dimension is seen without regard to the causes of change (Stellmes *et al*., 2015). The biological productivity of ecosystems is a key factor which describes the functioning of an ecosystem (Del Barrio *et al*., 2010), whose most important service is support of the primary production (MEA, 2005).

Since NDVI and vegetation productivity tend to vary with each other (Reed *et al*., 1994), a decrease in net primary productivity (NPP) can, therefore, be interpreted as vegetation degradation (Reynolds *et al*., 2007). NPP, a ratio of NDVI to rainfall, quantifies net carbon stored in vegetation (Yengoh *et al*., 2017). Several studies support the link between NDVI, a proxy for greenness, and in-situ NPP measurements (Wessels, 2007; Yengoh *et al*., 2017). NDVI correlates positively with absorbed Photosynthetic Active Radiation (APAR), which relates to the NPP (Fensholt et al., 2004). Dryland vegetation dynamics is dependent on rainfall. Therefore, rain-use efficiency (RUE), which is the ratio of NPP to rainfall, is closely related with decline in productive potential of land (Bai *et al*., 2008), hence its use in monitoring changes in land condition (Prince, 2002). However, decline in productivity can be due to factors like, climatic variability instead of loss of land capability (Bai *et al*., 2008). The component of climatic variability would have to be eliminated in order to establish productivity decline caused by degradation.

Changes in land condition can also be determined by assessing vegetation cover (Safriel, 2007). Loss of vegetation is commonly used in the characterization of vegetation degradation (Feresu, 2010) because it can easily be quantified by earth observation technologies (De Jong *et al*., 2011). Lambin & Ehrlich (1997) confirmed that vegetation cover can represent vegetation condition and, in turn, the level of degradation. However, Tucker *et al*. (2004), suggest that, occurrence of short-term droughts reduces the reliability on vegetation cover to assess the land condition. Despite this contradicting view, vegetation cover, in particular, variations in greenness, is widely used in the characterisation of degradation (Prince, 2002). Observable vegetation change is a result of vegetation degradation in semi-arid regions, hence its use as a proxy in its monitoring (Reynolds *et al*., 2007). Increase in vegetation greenness implies vegetation improvement whereas vegetation browning may indicate reduced vegetation density, a form of vegetation degradation (Ibrahim *et al*., 2015).

2.6 Remote sensing and application of NDVI in vegetation degradation assessment

The capability of remote sensing techniques to address the changes in degradation processes enhances their effectiveness in determining the rate and extent of degradation, as well as its mapping and monitoring (Burell *et al*., 2017). The satellite observation techniques have been widely utilized to map and assess vegetation degradation (De Jong *et al*., 2011) because long term data is available (Albalawi & Kumar, 2013; Bai *et al*., 2008). Time-series analysis technique assumes that degraded lands show sustained low NDVI values (Bai *et al*., 2008). Available satellite time-series data, for Africa, are available at reduced cost, cover a long period and can be subjected to statistical analysis (Vlek *et al*., 2010). When merged with global climate data, soil, topography, land use, and human demographics, analysis of remotely sensed data can reveal the underlying vegetation degradation drivers and processes at various scales (Yengoh *et al*., 2014). This enables determination of the spatial progression of vegetation development (Prince *et al*., 1998) and effective monitoring of vegetation degradation (Dubovyk, 2017). According to Rouse Jr *et al.* (1974), NDVI is obtained by subtracting red band (RED) from near-infrared band (NIR) and dividing by the sum of these two bands, as follows

$$NDVI=NIR-RED/NIR+RED \qquad (2.1)$$

Where NIR represents reflectivity in the near-infrared band and RED represents reflectivity in the red band of the visible portion.

NDVI algorithm is based on the finding that dense, healthy vegetation reflects highly in the NIR band than in the red band with the reverse being true for sparse or browning vegetation (Yengoh et al., 2015). NDVI is sensitive to such differences in reflectivity, thus, helping in detecting the presence or absence of photosynthetically active vegetation (Fensholt & Sandholt, 2005).

For satellite-based products to be useful, it is important to consider all spatial, spectral and temporal characteristics of the sensor, as well as availability and accessibility of the data (Yengoh *et al*., 2014). Remote sensing products rarely meet all the requirements. There is often, no match between spatial observation scale, and time scale of satellite imagery as well as ecological scales of vegetation degradation processes (Dubovyk, 2017). For degradation monitoring at landscape scale, imagery from high resolution satellites such as Landsat would allow detailed analysis, especially, in heterogeneous areas (Dubovyk, 2017). However, such satellites are best suited for the analysis of local environmental issues and factors and may be unsuitable for viewing a larger geographical extent (Symeonakis & Higginbottom, 2014). The use of AVHRR-derived data has been extensively covered in literature. Although its spectral resolution is low, its use in the monitoring of vegetation cover has been highly prescribed (Nemani *et al*., 2003). However, the development of the moderately high-resolution MODIS sensors, with better revisit facilities has led to improvement in environmental monitoring (De Jong *et al*., 2011). Since 2000, NDVI data derived from MODIS sensor of resolution 250m to 1000m has been applied in long term vegetation change analysis because of its time-series consistency (Yengoh *et al*., 2014). Modis sensor has narrower bands (Fensholt & Sandholt, 2005), making it more sensitive to vegetation reflectance and more accurate in vegetation cover monitoring than AVHRR data (Huete *et al*., 2002).

2.6.1. Relevance of NDVI in vegetation degradation assessment

According to Ibrahim *et al*. (2015), among 150 vegetation indices used for environmental monitoring, satellite derived NDVI has been regarded as the most appropriate in the mapping of vegetation degradation trends (Dubovyk, 2017). NDVI quantifies the amount of light absorbed and used for photosynthesis by plants, thus characterising increasing or declining photosynthetic activity (Running *et al*., 2004). High values of NDVI imply great vegetation vigour and amounts whilst low values show bare surfaces and probably, water bodies (Sokoto, 2013). This index can be directly correlated with biomass (Dubovyk, 2017). Researchers have proved the existence of a link between NDVI and vegetation productivity in the detection of the degree of, and area affected by, vegetation degradation (Jensen, 2007; Purkis & Klemas, 2011). Its ability to detect early stages of vegetation degradation makes it important in giving a warning of the process (Weiss *et al*., 2004). This index is capable of determining areas already experiencing decline in land condition and those experiencing improvement (Mambo & Archer, 2007). Through the analysis of yearly variations of NDVI, the long-term dynamics of vegetation cover in different terrestrial ecosystems can be revealed and quantified (Ndayisaba *et al*., 2017). Over the years there has been a rise in the utilisation of the long term NDVI analysis in determination of changes in vegetation coverage. Global NDVI data, available since the early 1980s (Jensen, 2007), has promoted the use of that approach. One of the most useful applications of NDVI in vegetation degradation mapping is its ability to be analysed using the time-series technique (De

Jong *et al*., 2011). Many studies have also confirmed that satellite derived NDVI data represents vegetation response to precipitation variability, particularly in dryland ecosystems.

2.6.2 Limitations of NDVI in vegetation degradation assessment

The use of NDVI in mapping the health of the ecosystem is not without limitations. According to Bai *et al*. (2008), one problem encountered when using NDVI to identify degradation is that, it does not differentiate the types of degradation occurring. The extraction of information on vegetation degradation becomes complex when the apparent increase in NDVI over long periods could be a result of change in plant species, some of which represent degradation (Pettorelli *et al*., 2005). Complexities arise due to contribution of such invasive plant species to greenness which might be interpreted as vegetation cover increase (D'Odorico *et al*., 2012). The challenge encountered when using NDVI is on accurately distinguishing greenness due to a contribution of different species (Nagendra, 2001).

Although an early warning of vegetation degradation can be provided by remotely sensed NDVI, indecisions in interpreting NDVI may be encountered in dry environments which are characterised by low NDVI values because of sparse vegetation (Weiss *et al*., 2004). Reflectances due to different soil characteristics may be interpreted as being due to vegetation, thus, presenting a major drawback in the use of NDVI in those areas (Symeonakis & Higginbottom, 2014). The sensitivity of vegetation indices to such soil background materials distorts the linearity between vegetation cover and NDVI, thereby weakening accuracy of NDVI as a proxy for condition of land (Prince, 2002). Because of this limitation, NDVI signals in savanna regions were only used to assess the association between vegetation and rainfall (Farrar *et al.*1994). Other indices, like the soil adjusted vegetation index (SAVI), the modified soil adjusted vegetation index (MSAVI) and the optimized soil-adjusted vegetation index (OSAVI) have been developed, to reduce the soil effects (Huete *et al*.,2002). The Enhanced Vegetation Index (EVI) has also been used to ensure reduction in atmospheric influences (Running *et al*., 2004).

Many environmental factors, more importantly climate, influence the health of vegetation, so a negative NDVI trend may not necessarily imply degradation (Bai & Dent, 2007). Bai & Dent

(2007)'s study revealed that factors such as rainfall variability and length of growing season may influence vegetation vigour. This is because vegetation changes reflect contributions of environmental and human factors in influencing growth patterns and performance (Yengoh *et al*., 2014). Measuring degradation, especially, in drylands has, therefore, been challenging. These regions are subjected to very little rainfall (Ruppert *et al*., 2015), as well as high year-to-year rainfall variability compared to other ecosystems (Khishigbayar *et al*., 2015). Extreme rainfall episodes are experienced over most of Africa and have increased after 1970 because of widespread and more intense droughts and floods (Ruppert *et al*., 2015) linked to the El Niño-Southern Oscillation and La Niña events, respectively. These global climatic events affect ecosystem productivity in the tropical regions (Plisnier *et al*., 2000).

For effective assessment and monitoring of vegetation degradation, there is need to disentangle such climate influences from the vegetation changes due to other human factors (Hoscilo *et al*., 2014). Utilisation of NDVI in characterising non-degraded and degraded regions may not yield effective results if the distinction between the two major drivers of vegetation degradation is not made (Yengoh *et al*., 2014).

2.7 Differentiating the climate- and human-induced drivers of vegetation degradation by RESTREND method

Distinctions between vegetation degradation due to human alteration of the landscape and that due to natural processes, is an important issue in dry regions where inter-annual climatic variations exist. Trends in vegetation changes may be correlated with trends in climate changes (Yengoh *et al*., 2014). However, it has been realised that rainfall and vegetation in arid regions exhibit year-to-year variations (Wessels *et al*., 2007). To identify regions with vegetation changes which are solely due to human activities, the rainfall factor has to be removed (Evans & Geerken, 2004). The RESTREND analysis has been used to overcome the problem of separating the effect of human activities on ecosystem productivity from those due to rainfall variability (Herrmann *et al*., 2005). The method uses the difference between predicted NDVI obtained when NDVI and rainfall are correlated in a least square model and observed NDVI (Wessels *et al*., 2007). It is a widely used technique in monitoring degradation (Higginbottom and Symeonakis, 2014), particularly in dry areas (Nemani *et al*., 2003), where ecosystem processes are subjected to water shortages (Huxman *et al*., 2004). The technique is effective in detecting vegetation condition, as well as poor land quality (Wessels *et al*., 2007). Residuals of NDVI trends (RESTREND) clearly distinguish degradation due to human activities (Ibrahim *et al*., 2015). However, according to Burell *et al*. (2017), RESTREND is more useful in situations where vegetation and rainfall exhibit a strong correlation (Bai *et al*., 2008). Data representing severe degradation, which may appear mid-way through the time-series, tends to disrupt the strong correlation, making RESTREND results inconclusive (Wessels *et al*., 2012).

2.8 Conclusions

The current study has reviewed previous studies on the use of satellite earth observations in mapping vegetation degradation. Although reliable statistics on the condition of land, globally, is lacking, there is clear indication of widespread degradation, with impacts largely experienced by the poor people occupying unproductive areas of the drylands. Remotely sensed data were reliable at revealing the land areas that have been affected at different spatial scales. Studies on the utilisation of satellite earth observations in degradation assessment have widely used satellite derived MODIS NDVI. However, sensitivity of vegetation to rainfall variations have to be considered when interpreting the results. Residual trend analysis method has been widely applied to remove the effect of the climatic component on vegetation degradation. Further research in its application for different regions is recommended.

CHAPTER THREE

Landscape scale vegetation degradation mapping in the semi- arid areas of the Save catchment, Zimbabwe

This chapter is based on a paper by

Matarira, D., Mutanga, O. & Dube, T. 2019. Landscape scale vegetation degradation mapping in the semi- arid areas of the Save catchment, Zimbabwe. South African Geographical *Journal*, (Under review).

Abstract

Vegetation degradation has become a major concern around the world, with key drivers being natural processes and human actions. The effects on the natural environment, functioning of landscapes, as well as welfare of those who depend on land for a living, have been highly documented. Although degradation of vegetation in the Save catchment of Zimbabwe impacts negatively on ecosystems productivity, quantitative data on degradation at landscape scales is scanty. This research investigates the distribution and magnitude of the problem in the Save catchment. The main objective was to map and quantify the changes in vegetation coverage due to human activities in Save catchment, using residual trend analysis (RESTREND) method. This investigation was done using the normalised difference vegetation index (NDVI) time-series data recorded using the Moderate Resolution Imaging Spectroradiometer (MODIS), and gridded precipitation datasets from Climate Research Unit, recorded between 2000 and 2015. NDVI and rainfall time-series, as well as ordinary least squares regression models used in the analysis were computed in R statistical program. Zonal statistics tool, in the Geographic Information System (GIS) environment, was used to quantify vegetation degradation trends. The study revealed that, approximately 18.3% of Save catchment experienced declining residual trends whilst increasing residual trends covered 33.6% of the area. These trends covered 1,705,910 ha and 3,129,390 ha, respectively. Approximately 3,609,955 hectares experienced significant human induced vegetation degradation during the study period. This area represents 38.8% of the Save catchment, 3.6%, 12.8%, and 22.4% of which were classified as severely, moderately, and lightly degraded, respectively. The results indicated the vulnerability of Save catchment to

human induced degradation. Severe degradation was noted in the central districts of the Save Catchment, notably Bikita, Chiredzi and most parts of Chipinge. These findings demonstrate the effectiveness of RESTREND in removing influence of precipitation changes from vegetation degradation. Based on these results, recommendation is given for the use of RESTREND method in detecting vegetation degradation that is triggered by human actions.

Keywords: normalised difference vegetation index, degradation, time-series, residual trend

3.1 Introduction

Drylands constitute 41% of our planet where over 30% of the planet's human population resides (Safriel & Adeel, 2005). These dryland ecosystems are being affected by vegetation degradation processes environmentally, socially and economically. Primary productivity of lands in these ecosystems has declined (Qureshi *et al*., 2013) and more than 60 million people live on those unproductive lands in sub-Saharan Africa (SSA) (Vlek *et al*., 2010). Zimbabwe, like most countries in SSA is subject to degradation risk, with unsustainable utilisation of land resources and climate change playing key roles in driving the processes (FAO, 2015). Accelerated loss of productive land is a major challenge in communal lands that are characterised by subsistence farming. These communal lands cover about half of the country and are inhabited by more than half of Zimbabwe's population (Waeterloos & Rutherford, 2004). Several studies have been carried out worldwide and confirmations have been made of the negative effects of the process on subsistence communities who derive their living from the land resource (Tully *et al*., 2012). South-eastern region of Zimbabwe, in particular, is experiencing widespread vegetation degradation. The fragility of terrestrial ecosystems of the Save catchment has made the region vulnerable to the driving forces of climate variations. Low annual total rainfall and its high variability, characteristic of the study area, impact on the growth of its vegetation. Apart from climatic variations, unsustainable human activities, for example, overgrazing, fuelwood collection, mineral extraction, and poor agricultural practices equally impact negatively on ecosystem productivity (Prince *et al*., 2009). These drivers were also identified by other investigators like Eswaran *et al*. (2001) who defined the process of degradation as "*decline in land quality caused by human activities*". This shows that, the influence of unsustainable uses of land and rainfall variability on the livelihood of the people and ecosystems of the Save catchment are an important characteristic of this region. The interaction of these two drivers greatly alters the status of vegetation, and their influence on vegetation growth processes has attracted widespread attention (Li *et al*., 2012).

The increased threats of degradation have made governments to be aware of the problem, hence the need to combat it through sustainable policies (Evans & Geerken, 2004). Effective implementation of conservative, preventative and/or remediation policies requires availability of statistics as evidence of the existence of degradation (Higginbottom & Symeonakis, 2014). Mapping the distribution of areas undergoing deteriorating land condition and establishment of the extent of deterioration is crucial and acts as evidence that the problem really exists (Higginbottom & Symeonakis, 2014). Knowing the degradation status and its possible causes is also a key factor in developing appropriate mitigation measures as well as sustainable strategies on the proper utilisation of the land resource (Stellmes *et al*., 2015). Remote sensing-based systems are advocated for determining the distribution of degraded areas and calculation of their area of coverage. The repetitive nature of earth observation satellites is an advantage in the quantification of degradation, given the temporal nature of the process (Yengoh *et al*., 2014). Although several studies have quantified degradation by measuring amount of greenness in drylands, complexities due to the contribution of climate have arisen. In these ecosystems, the growth of vegetation cover depends on rainfall, which is highly variable (Evans & Geerken, 2004). Normalised difference vegetation index (NDVI) trends in these regions tend to vary in direction and magnitude. Therefore, for any meaningful mapping of permanent degradation, the contribution of precipitation to degradation has to be removed (Wessels, 2007). Although separation of the two determinants of degradation is regarded as important in the management of semi-arid landscapes, it has been challenging (Li *et al*., 2015). Recent studies on vegetation degradation have advocated the use of residual trend analysis (RESTREND) method in distinguishing the two drivers (Evans & Geerken, 2004; Wessels, 2007; Ibrahim, 2017). Although several studies have been done to identify vegetation degradation in Zimbabwe, few studies have focused on NDVI trends, let alone time-series. Mambo & Archer (2007) used change detection methods to map vegetation degradation in Buhera district. Other researchers, notably, Prince *et al*. (2009), used local net production scaling technique to map vegetation degradation in Zimbabwe. Residual trend analysis, as a remote sensing technique, has not been fully explored in this region and a study mapping only human induced vegetation degradation has, to date, not been conducted. This research aims at establishing the effectiveness of RESTREND method in detecting human induced vegetation degradation.

3.2 Materials and methods

3.2.1 Description of the study area

Save catchment is part of the south-eastern region of Zimbabwe, from 17.5^0 S to 22.5^0 S, and 30^0 E to 33^0 E (figure 3.1). The region covers an area of 9,317,850 hectares. On the eastern side, the region rises to some 2,000m above sea level. The lowest point in the catchment is 500m above sea level. The mountainous region records rainfall amounts reaching up to 2,000 mm/year (FAO, 2012). This drops to an average of between 400mm and 600mm per year in the low veld which also experiences high rainfall variability (Unganai, 1996). The rainy season extends from November to April, with vegetative growth attaining its maximum between March and April. The natural vegetation in South Eastern part of Zimbabwe comprises of mainly savannah woodlands and thickets, as well as indigenous forests and open grasslands. The upper reaches of the catchment are characterised by a mountainous ecology where exotic tree plantations and the miombo woodlands are confined. This is in contrast to the low veld area which is barren, hot and dry. Dry Savannah dominates the low veld. Dominating vegetation species are *Colophospermum mopane*, *Terminalia sericea* and *Vachelia* species (Whitlow, 1988). Soils are diverse across the landscape. The soils are mainly sodic in the lowlands, which are mopane dominated, while the higher elevation sections have lateritic soils (FAO, 1978; Nyamapfene, 1991). They are, however, predominantly siallitic and sodic with parent material of the later relatively being rich in sodium and releasing weatherable minerals (Nyamapfene, 1991).

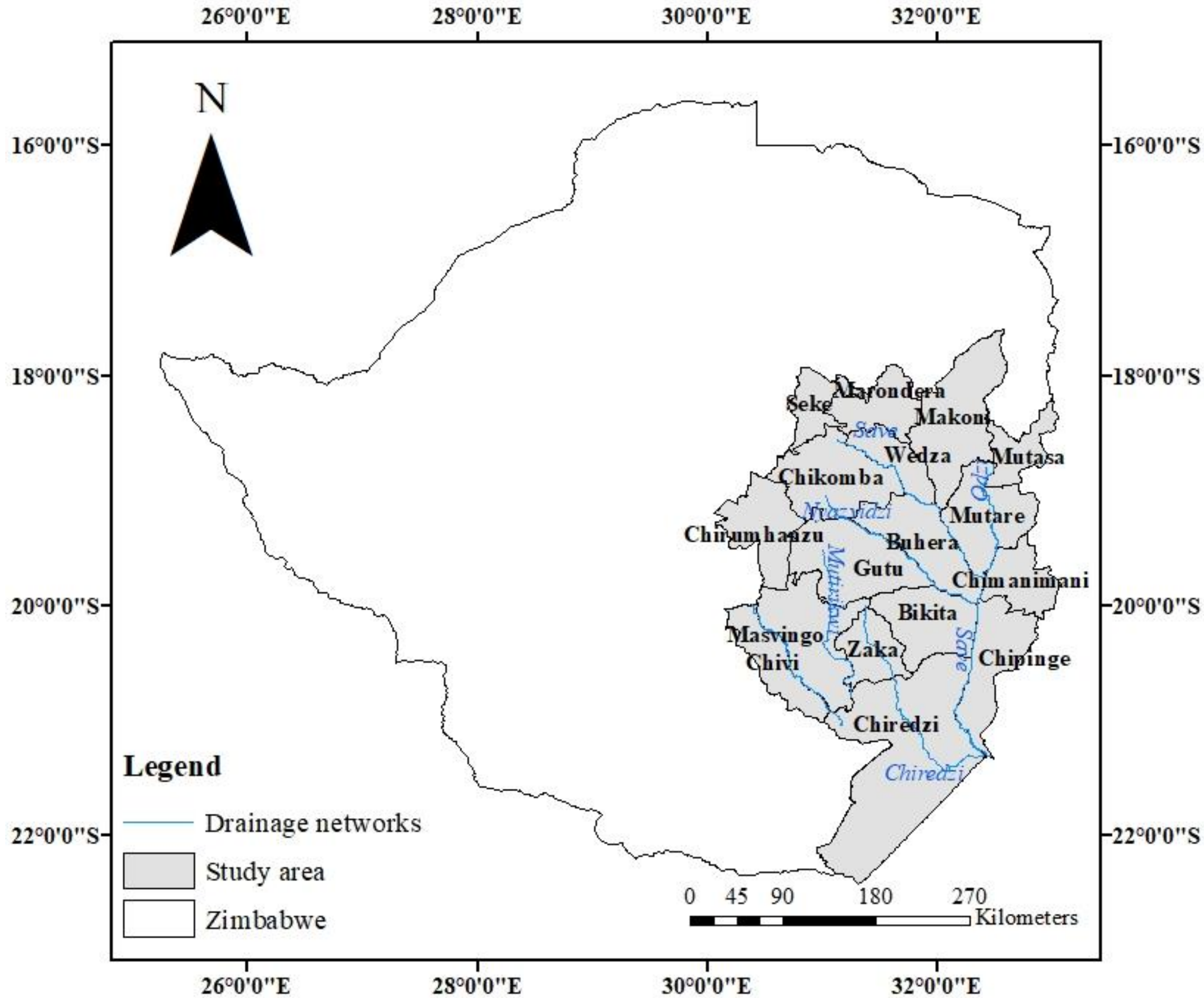

Figure 3.1 Study area- Save catchment area in Zimbabwe

3.2.2 Rainfall data processing

There are 12 synoptic weather stations in the Save Catchment (Climate handbook of Zimbabwe, 1981). The study area is made up of 17 districts, with, on average, one weather station in each district. For a study, such as this, densely distributed precipitation data are needed (Ensor & Robeson, 2008). Hence, remotely sensed precipitation data becomes the most appropriate. Therefore, gridded rainfall dataset obtained from the University of East Anglia's Climatic Research Unit (CRU) was used in this study. The advantage of using gridded datasets is that they provide a complete spatial representation of rainfall (Ensor & Robeson, 2008). Each rainfall dataset from CRU is made up of gridded monthly precipitation with a spatial grid resolution of

0.5° latitude/longitude (Harris *et al*., 2014). Rainfall data were extracted from the CRU dataset version TS 4.01 from 2000 to 2015. Cumulative monthly rainfall during the November to March rainy season was used. Grid point rainfall for 65, 0.5^0 by 0.5^0, grid points were established and captured in excel for each year. The period was from the year 2000 to 2015 growing season. The totals for each year were entered on a spreadsheet per coordinate. The files were saved as csv file format and were imported into Q-GIS, as delimited text, where yearly rainfall maps were produced. Precipitation measurements were interpolated in Q-GIS using Inverse Distance Weighting algorithm to produce spatially continuous raster images.

3.2.3 MODIS NDVI data acquisition and processing

The March remotely sensed MODIS NDVI data were used in this study. NDVI data for March was extracted from MOD13A1 V6 product. The MODIS data, which are available in Hierarchical Data Format (HDF), were downloaded as tiles. The first step was to select the tiles, time frame and product and then download them from earthexplorer.usgs.gov. In this study only end of March images were analysed. An overlay of four MODIS data tiles for a single year covered the study area. The tiles were h20v10, h20v11, h21v10, h21v11. The process involved downloading and processing 64 data tiles.

3.2.4 Data analysis

Vegetation dynamics has been assessed by other researchers using MODIS NDVI data (Lu *et al*., 2015; Fensholt & Proud, 2012; Eckert, 2015; Prince *et al*., 2009). In this study, NDVI value for March ($NDVI_{max}$) represented the total green biomass production in each year because vegetation growth is at its maximum around March. Agriculturally, this is the time of the year when biomass will be at its peak. In this study, changes in biomass production, was assessed through analysis of NDVI trend maps, with areas experiencing decline in green biomass described as degrading (Evans & Geerken, 2004). In this analysis, information on soil, vegetation cover and agro-ecological zones was useful in determining the drivers behind the variations in vegetation condition.

3.2.5 Raw NDVI trend analysis

To distinguish vegetation degraded areas from non-degraded areas in the Save Catchment, linear trend analysis (LTA) method was used. It has been applied in assessing variations in vegetation vigor, by relating vegetation index to time (year) (Vlek *et al*., 2010). Temporal trends in the NDVI datasets were evaluated using linear regression model. $NDVI_{max}$ value was regressed against time, following other studies which have explored vegetation dynamics using NDVI time-series (Fensholt & Proud, 2012). The $NDVI_{max}$ values, recorded from year 2000 to 2015 were regressed against time (year) to generate the regression equation for every pixel. Equation 3.1 is the ordinary least squares regression model which was used to determine the slope that reflected the changing trend in vegetation ($NDVI_{max}$) with time x. This allowed the generation of spatial patterns of magnitudes of change. The slope coefficient indicated the rate and magnitude of change per year (Eastman, 2009).

Yearly changes in NDVI were estimated by *A*, the slope coefficient, in the model below:

$$\mathrm{NDVI} = A \times \mathrm{Year} + \beta \tag{3.1}$$

In the above equation, β represents the intercept. *A* is the slope, an indication of the trend, which can be positive or negative. Setting the initial year (2000) to zero, β becomes the initial value of NDVI for any pixel (Vlek *et al*., 2010). The NDVI trend categories were quantified by establishing percentages of areas covered by the same trend category. Zonal statistics tool, in the GIS environment, was used to quantify the trends. The quantification of trends helped in the determination of the extent of decline in vegetation cover. In order to isolate areas with significant trends, significance testing was carried out in R at 95% significance level. This was done by identifying the probability value (p value) ($P < 0.05$).

3.2.6 Residual trend analysis method

According to Lu *et al*. (2015), trend analysis of the residual NDVI can explain magnitude of degradation processes. RESTREND method was applied in this research to isolate the role of rainfall in ecosystem productivity and detect only the influence of human activities. The residual NDVI trend, negative or positive, was used to identify regions experiencing degradation and those with improved conditions, respectively. These would be vegetation changes due to other factors different from rainfall variations (Yengoh *et al*., 2014). According to Li *et al*. (2012), climate variability and other physical phenomena do not cause a directional change in the residuals but human interference on the environment does.

RESTREND analysis involved regression of NDVI against rainfall, using ordinary least squares model, following the study by Wessels *et al*. (2007). Peak growing season NDVI ($NDVI_{max}$), and the accumulated precipitation from November to March, each year, were used. In this model, NDVI and rainfall were the dependent and independent variables, respectively (Equation 3.2). This regression also produced slopes, intercepts and R^2 values that were also useful in the analysis.

The linear regression model is:

$$Y = \propto + \beta x + \varepsilon \qquad (3.2)$$

In this equation, Y represents the dependent variable (NDVI),

x is the independent variable (rainfall),

$\propto$ is the intercept, representing the value of y when x set at 0,

$\beta =$ the slope, which is, the rate of change in y when x changes by one unit,

ε is the error term.

The method followed the following steps.

1. First, NDVI values were regressed against rainfall for each pixel.
2. A regression equation between observed NDVI and rainfall was established for each pixel.
3. Predicted values of NDVI for each pixel, were calculated from the statistical model.
4. The differences between the observed NDVI and the predicted NDVI, called *residuals*, were computed.
5. The residuals were regressed against time, pixel by pixel, and residual trends were determined.

Areas with a negative trend represented declining vegetation condition and those with positive trend indicating an improvement (Ibrahim et al., 2015). Examining residual trends allows identification of areas with human induced degradation as well as those with human induced vegetation cover improvement. Additional analysis was done to isolate areas with statistically significant negative changes. Statistical significance of the declining trends was tested in R. To capture the dynamics of decreasing green biomass, pixels without significant slopes or with significant positive slopes were not included in further analysis. The areas without significant slopes are those areas where trends in vegetation greenness are associated with trends in rainfall dynamics.

3.3 Results

3.3.1 NDVI linear trends in the Save catchment

Spatial distribution of NDVI trends in the Save catchment for the period 2000-2015 is represented in figure 3.2A. Substantial decrease in vegetation cover (- 0.6 to - 0.1 year^{-1}) characterised, mainly, the central areas. The Western part of the Save valley is the most degraded area as indicated by the dark brown colour that represents substantial decline in vegetation cover. Areas that include Buhera South, Bikita East, Mutare South, Chipinge and Chiredzi North had such strong negative trends. These are areas that extend along the Save river valley. Moderately decreasing trends have been observed in North Western Chivi, Masvingo, Mid Zaka, parts of Buhera, Gutu and parts of Chiredzi (-0.1 to -0.01 year^{-1}). Vegetation cover did not decrease much in those parts of the study region, as indicated by lower rates of change. From 2000- 2015, vegetation cover increase was characteristic of mainly the northern and eastern parts of the Save catchment. Those districts with positive trends (-0.01 to 0.6year^{-1}) include; Seke, Chikomba, Hwedza, Makoni, Mutasa, part of the Eastern Highlands and Southern Chiredzi. Some areas in Masvingo, northern Wedza, and Chirumanzu showed negative trends, interspersed between areas with positive trends.

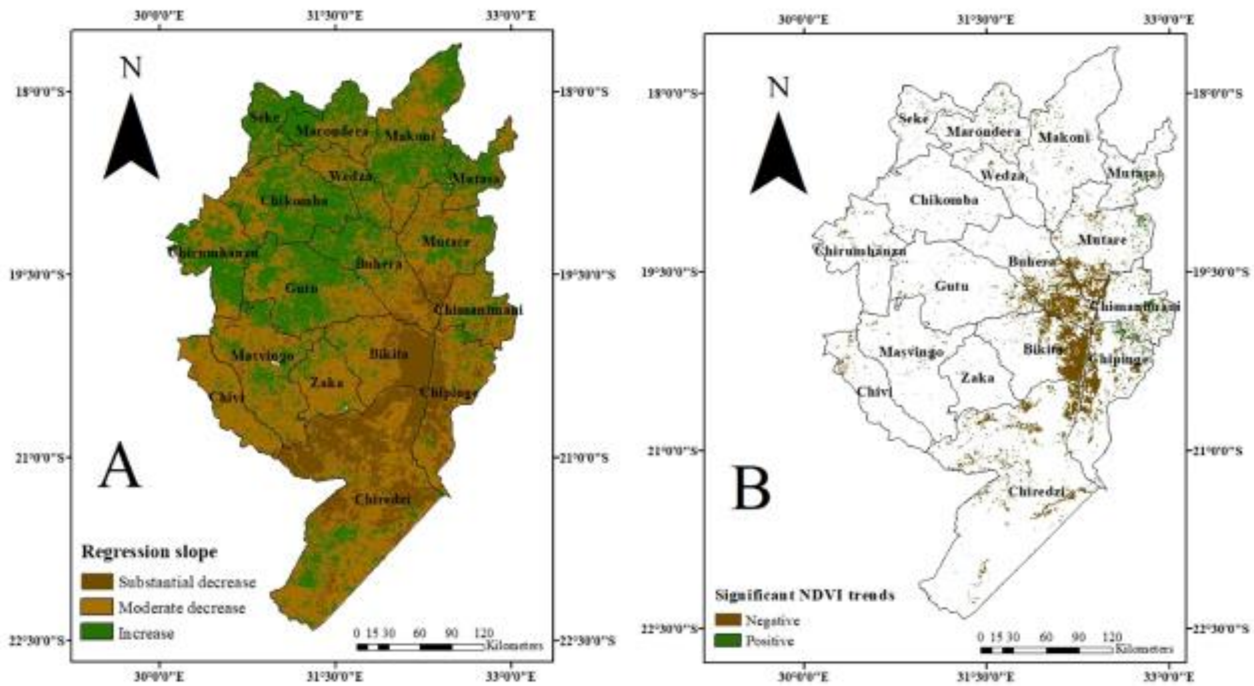

Figure 3.2 NDVI trends in the Save Catchment where A. is a rate of change in normalised difference vegetation index (NDVI) as a function of time (year) in the Save catchment of Zimbabwe and B. shows significant NDVI trends ($p<0.05$). No change areas are shown in white.

Table 3.1 shows the areal extent and percentages of NDVI trend values for each category in figure 3.2A. Areas that show substantial decrease in vegetation constitute 15% of the area. The area with increasing vegetation covers 35% of the study region. The remaining area (50%) shows moderate decrease. Therefore, 65% of the region's vegetation is degraded, from moderate degradation (50%) to substantial degradation (15%) whilst 35% of the region's vegetation showed improvement during the period of study. Spatially, land area of about 6084140 ha lost greenness over the years. This area included areas with moderate and substantial decrease. Conversely, a land area of approximately 3,233,710 ha showed an improvement in greenness from 2000-2015 (table 3.1). The area covered by decreasing trend, that is negative trend, is larger than the area showing a positive trend (table 3.1).

Table 3. 1 Spatial distribution of normalised difference vegetation index (NDVI) change trend

	Area (ha)	**% of total area**
Substantial decrease	1,438,870	` 15
Moderate decrease	4,645,270	50
Increase	3,233,710	35
Total	**9,317,850**	**100**

Negative significant slopes were also depicted during the same period (figure 3.2B) in some parts of the area, usually coinciding with the boundaries of the semi-arid regions. Significant linear regression slope values of NDVI over 2000-2015 were mapped in figure 3.2B where white areas represented statistically non-significant trends. Based on the 5% threshold ($p< 0.05$), the area with a decline in vegetation during the 16 year-period, amounts to 6,388,50 ha (about 6.9% of the study region), whereas about 90,493.7 ha (about 1% of the study region) exhibits an increase in vegetation productivity (table 3.2).

Table 3. 2 Percentage of pixels in the Save Catchment that exhibited positive and negative change trends in the normalised difference vegetation index (NDVI) dataset at 95% level of significance.

	Area (ha)	**Significant pixels (%)**
Positive trends / Increasing trend	90,493.7	1
Negative trends / Decreasing trend	638,850	6.9

Table 3.2 illustrates the percentages of significant slopes covering the Save catchment. From the table, it can be deduced that a smaller portion of the study region (about 8%) encountered significant trends. Significant negative trends covered an area of 638,850ha whilst the positive trends covered 90,493.7ha, representing 1% and 6.9% of the study area, respectively.

3.3.2 Spatial patterns of the NDVI – rainfall relationship

The per-pixel slope of NDVI against Rainfall is shown in figure 3.3. The slopes of the local regressions (figure 3.3) describe the magnitude and nature of vegetation response per unit rainfall (Evans & Geerken, 2004). The slopes were categorized into 3 classes: low increase (-0.002-0.0002), moderate increase (0.0002-0.0006), high increase (0.0006-0.002). Response of vegetation to increase in rainfall is high in areas such as Chiredzi, Chivi, western Chipinge, Eastern Bikita and south-eastern Buhera, parts of Masvingo, Zaka and Mutare. Lower slope values were mostly pronounced in some parts of Chipinge, Chimanimani, Mutare, Mutasa, Makoni and Marondera. The rest of the study area shows moderate slope values.

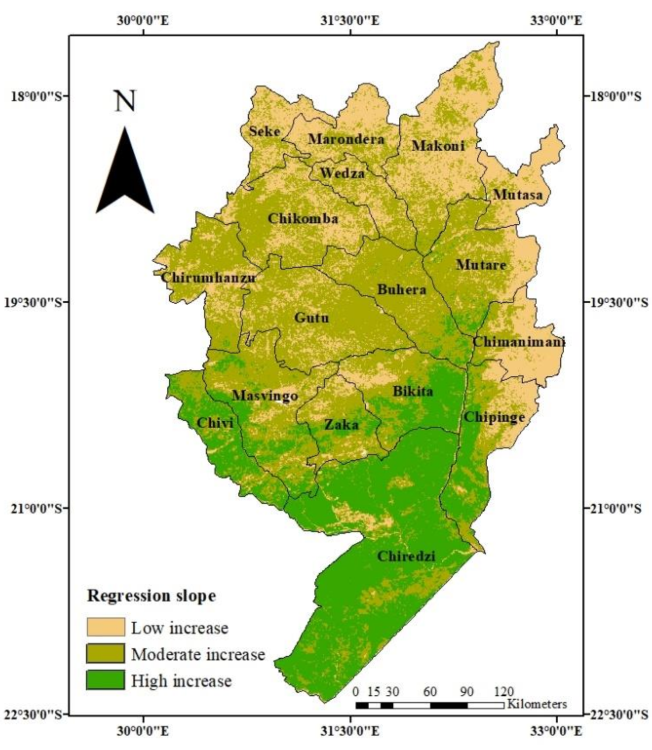

Figure 3. 3 Rate of change in normalised difference vegetation index (NDVI) as a function of rainfall in the Save catchment of Zimbabwe

To determine the percentage contribution of rainfall to NDVI variations, the coefficient of determination (R^2) was computed at each pixel (Figure 3.4). Rainfall's contribution to NDVI was weakest in the humid areas of Seke, Northern Marondera, Makoni, Chikomba, Hwedza, and the Eastern Highlands. R^2 values were low in these districts ranging from 2×10^{-9} to 0.26. Figure 3.5a and 3.5b illustrate the relationship using Marondera (grid point18.5S, 32E) and Chimanimani (grid point 20S, 32.75E) where R^2 = 0.11 and 0.05 respectively. High R^2 values are evident, mostly, in the semi-arid areas of Chipinge, Chiredzi, Chivi, Bikita, Buhera, Mutare South and Chivu. These areas portrayed stronger relationships between NDVI and rainfall. Buhera (grid point 19.5S, 32E) and Chiredzi (grid point 22S, 31.5E) are representative sites chosen to illustrate (figure 3.5c and 3.5d) that relationship in the semi- arid areas. In Buhera and Chiredzi, the values of R^2 were 0.36 and 0.31, respectively. R^2 values for the representative sites are shown in table 3.3

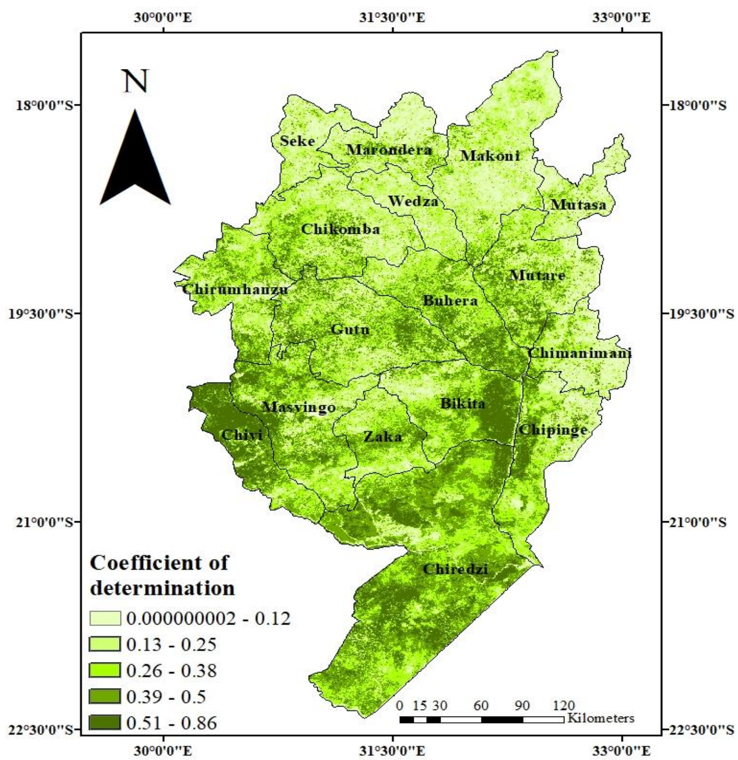

Figure 3. 4 Coefficient of determination (R^2) of NDVI –rainfall relationship

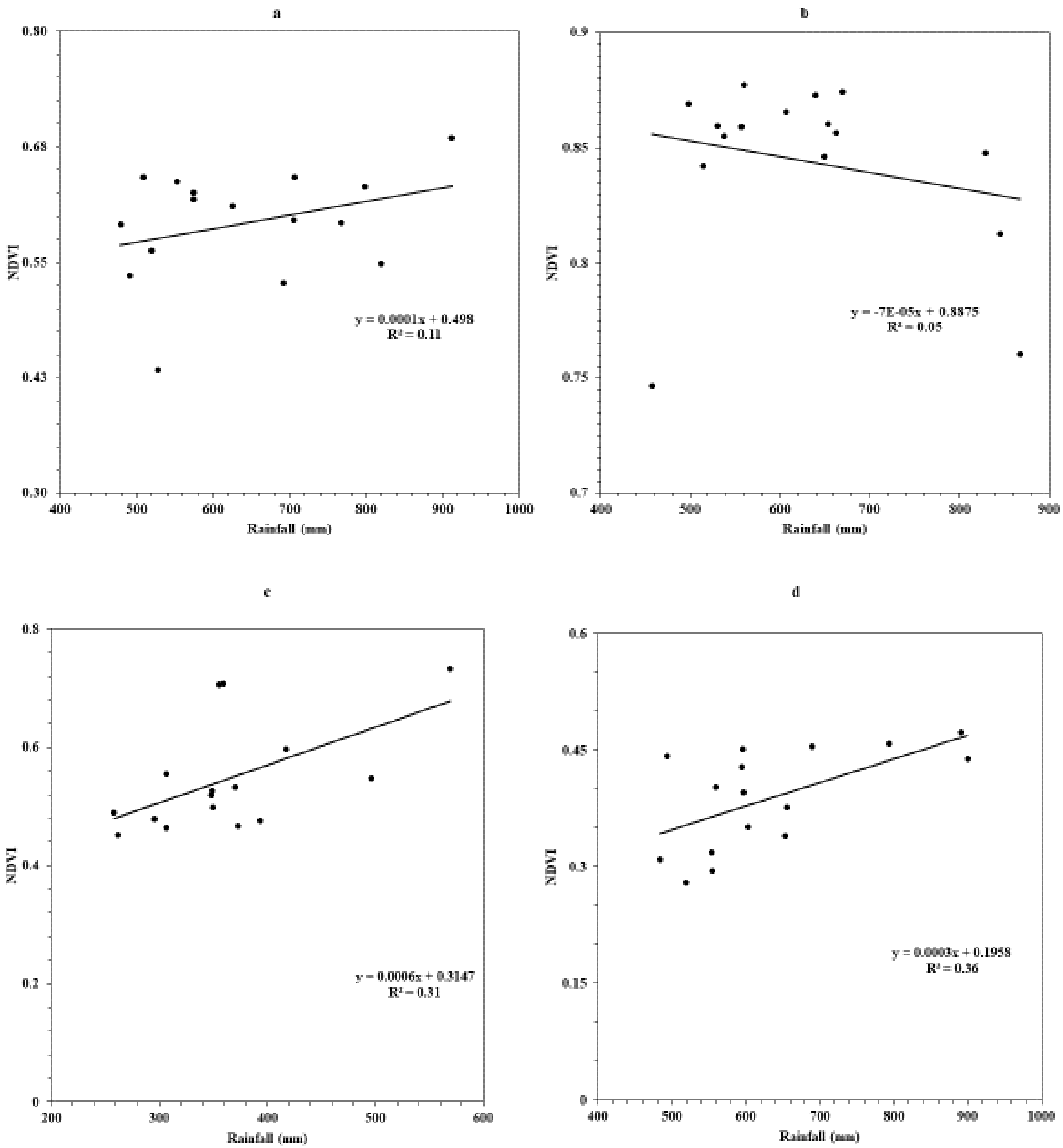

Figure 3. 5 Regressions between $NDVI_{max}$ and rainfall for (a) Marondera (grid point18.5S, 32E), (b) Chimanimani (grid point 20S, 32.75E), (c) Chiredzi (grid point 22S, 31.5E) and (d) Buhera (grid point 19.5S, 32E).

Table 3. 3 Coefficient of determination (R^2) of the relationship between rainfall and NDVI.

Station	**R^2**
Buhera	0.36
Chimanimani	0.05
Chiredzi	0.31
Marondera	0.10

The intercept (figure 3.6) indicates the NDVI value from the regression model when the rainfall amount is set at zero. The intercepts were computed to consider variations in relationships between NDVI and rainfall due to other influences, which include, different soils as well as vegetation types. The intercepts in non-degraded areas of Chipinge, Chimanimani, Mutasa, Makoni and Marondera were higher than those in degraded low rainfall areas. Intercept parameters increased from very arid to humid areas of Save Catchment. The slope parameter decreased in the same direction. Most areas with the lowest slope values when NDVI was regressed against rainfall had highest intercepts.

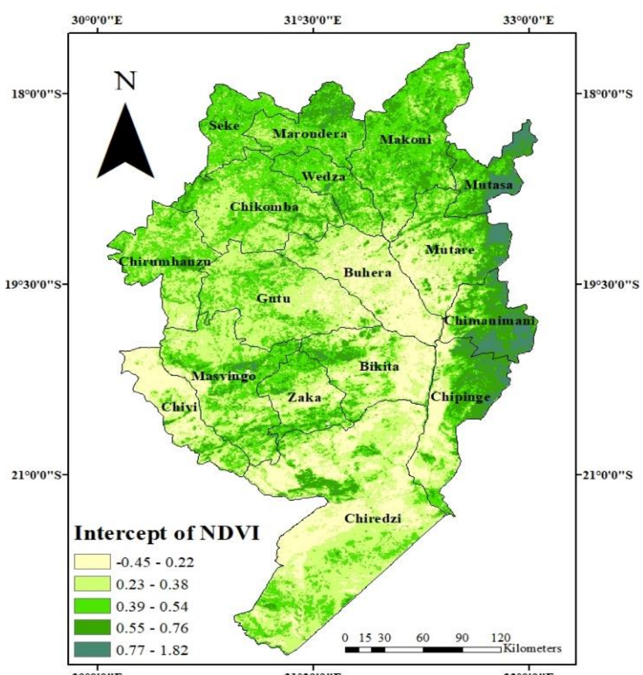

Figure 3. 6 Intercept of the relationship between NDVI and rainfall in the Save catchment of Zimbabwe

3.3.3 Spatial patterns of the NDVI residual trends

The NDVI residual trends, defined earlier as the observed minus the predicted NDVI at each pixel, was analysed using the ordinary least squares model. Figure 3.7 is a map of the spatial distribution of residual trends, showing vegetation productivity trends, which are either positive or negative, when the effect of rainfall has been removed. Higher regression slopes of residuals existed in the Northern districts (slope>0.002) of the Save Catchment. Negative trends in NDVI are clustered in the central and southern regions. Negative residual trends are in eastern Bikita, south-eastern Buhera, eastern Chipinge, south of Mutare, Chimanimani and northern Chiredzi. These areas stretch along the Save Valley.

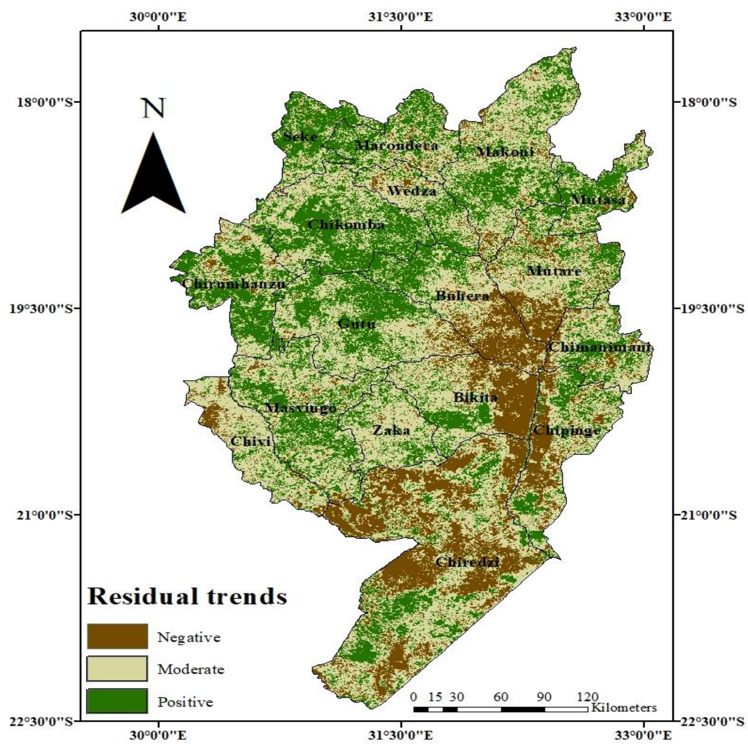

Figure 3. 7 Slope, which is the rate of change in normalised difference vegetation index (NDVI) residuals as function of time (2000-2015), in the Save catchment of Zimbabwe

Table 3. 4 Spatial distribution of normalised difference vegetation index (NDVI) residual trends

	Area (ha)	% of total area
Negative (-0.03- -0.002)	1,705,910	18.3
Moderate (-0.001-0.002)	4,469,150	48
Positive (0.003-0.04)	3,129,390	33.6

The percentages of total area representing different classes of residual trend values were calculated for every district (table 3.5). This was meant to determine the district that was mostly affected by human induced degradation. From table 3.5, the districts were arranged in descending order, from the heavily degraded to the least degraded. It can be deduced that Chiredzi experienced the most human induced degradation over the study period. 60.5% of Chiredzi district was covered by negative residual trends. The least degraded was Seke district which had 6.5% of the district area experiencing human induced degradation.

Table 3. 5 Level of human induced vegetation degradation in every district within the Save catchment of Zimbabwe

District	Total area (ha)	% of total area affected by degradation		
		Negative	Moderate	Positive
Chiredzi	1,752,562	60.5	23.8	15.8
Bikita	517,156.5	52.7	28.8	18.5
Buhera	533,419	50.4	23	26.6
Chipinge	515,900	48.3	28.7	23
Mutare	561,831	45	32.8	22.1
Chivi	354,099.7	41.5	46.2	12.3
Chimanimani	327,875	29.6	39.8	30.6
Wedza	257,524.8	25.4	41.6	33
Makoni	782,569	19.8	42.5	37.7
Zaka	309,918.3	19.4	55.2	25.4

Mutasa	251,431.3	18.2	32.9	48.8
Marondera	352,131	18.2	35	46.7
Masvingo	687,012	18	41	41
Gutu	710,437	16.8	38.9	44.3
Chirumanzu	469,187.3	14.1	31.3	54.6
Chikomba	660,868.5	7.7	34.9	57.3
Seke	253,806.3	6.5	26.8	66.7

3.3.4 Comparison of RESTREND with raw vegetation index trends

RESTREND and raw NDVI trend analysis both show considerable areas covered by greening trends (38% and 35% respectively) (table 3.6). Negative raw NDVI trends, however, covered a greater percentage of the study area (65%) than the negative residual trends (26%) although there is similarity in their spatial distribution patterns.

Table 3. 6 The percentage of pixels that increased or decreased, in the NDVI linear trend analysis and the RESTREND analysis methods

	% increasing	**% decreasing**
NDVI trend	35	65
Residual trend	38	26

3.3.5 Severity of vegetation degradation

Pixels recording significant negative residual trends ($p < 0.05$) were mapped in figure 3.8 and used to formulate different degradation classes following Vlek et al. (2008). Pixels that had a statistically significant, decreasing trend constituted 38.8% of the study area, covering 3,609,955 ha. Approximately 3.6% of the study area was severely degraded, 12.8% was moderately degraded and 22.4% was lightly degraded. The corresponding areas of significant degradation were 332,575 ha, 1,189,820 ha, and 2,087,560, respectively. Table 3.7 illustrates the geographical extent of the catchment affected by significant human-induced degradation processes.

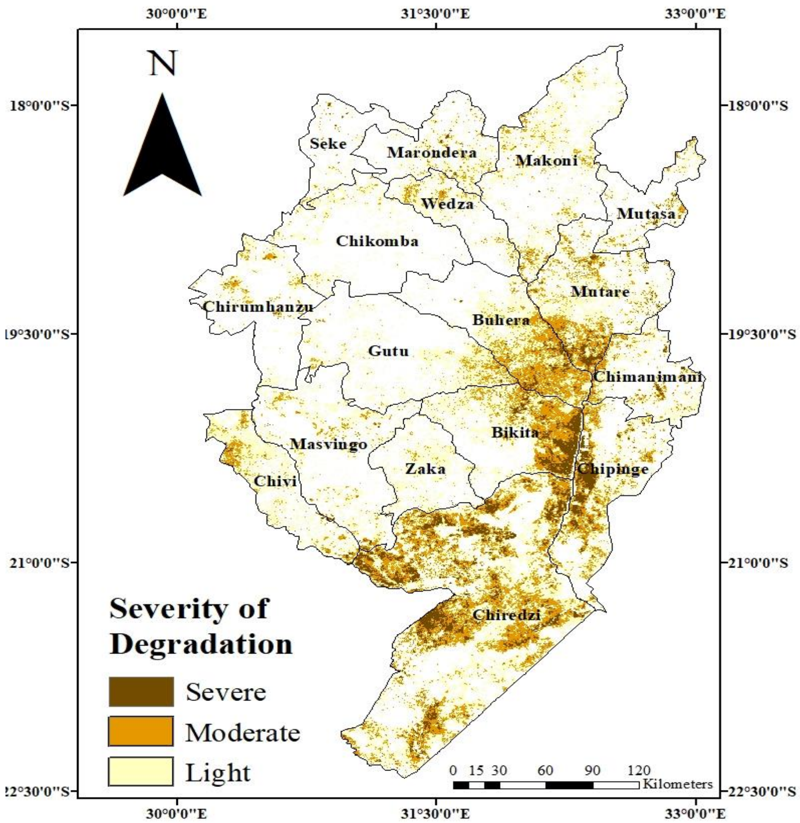

Figure 3. 8 Areas showing significant negative residual trends at 95% significance level

* Areas with non-significant changes are shown in white colour.

Table 3. 7 Degradation severity in Save catchment (percentage of area by severity class)

Degree of Degradation	Area (ha)	Percentage (%)
Severe	332,575	3.6
Moderate	1,189,820	12.8
Light	2,087,560	22.4
Total	3,609,955	38.8

3.4 Discussion

From the analysis of $NDVI_{max}$ trends, vegetation cover decline was observed in most parts of the Save Catchment, during the period 2000-2015 (figure 3.2A). Since significant negative trends were also exhibited during the same period (figure 3.2B) and considering high precipitation variability in the dry areas (Mambo & Archer, 2007), it suggests that this decrease could partly be as a result of rainfall anomalies. Buhera, Bikita, Masvingo, Chiredzi, Zaka and Chivi, and some parts of Chipinge and Chimanimani experienced wide coverage of negative NDVI trends. These are the dry regions in Zimbabwe (Vincent & Thomas, 1960). They lie in natural regions 3, 4 and 5, characterised by unreliable, low and erratic rainfall that averages between 400mm and 600mm per annum (Climate handbook of Zimbabwe, 1981). The existence of patches of degraded land interspersed between positive trends in humid areas of Chimanimani and Chipinge (fig 3.2A) can be explained in terms of vulnerability of some arid areas in the districts, given that Chipinge and Chimanimani have all the five agro-ecological regions (FAO, 2012). Zimbabwe has experienced increased frequency of drought associated with Elnino events in recent decades with, on average, 1-3 droughts experienced every 10 years. Droughts have occurred in 2001/2, 2002/3, 2004/5, 2006/7 seasons (Simba *et al*., 2012; Richardson, 2007). These drought years could have contributed to overall negative NDVI trends which are widespread in most parts of the Save Catchment because an arid climate hinders vegetation growth (Li *et al*., 2015). Tropical cyclones, a weather scenario associated with both Elnino and La Nina years also help explain strong negative trends in these semi-arid regions where associated floods caused massive vegetation destruction, mainly, in the districts of Mutare, Chimanimani, Chipinge, Chiredzi, and Zaka (FAO, 2012). Cyclone Eline, associated with extensive and disastrous floods was experienced in the year 1999/2000 and above normal mean rainfall (942mm) was recorded in those districts in that growing season (FAO, 2012). Vegetation, that included vast areas of plantations was destroyed in districts of Chimanimani and Chipinge where an estimate of 3,340 hectares of timber was damaged, which, according to the Timber Producers Association, was an equivalent of a year's harvest (Reason & Keible, 2004). Coupled with the negative impacts of drought, these destructive floods contributed immensely to the widespread negative trends in the Save Catchment. Poor soils could also have accelerated the degradation in these semi-arid regions. Most communal lands that have suffered huge biomass losses have granite derived sandy soils that are highly erodible (FAO, 2012). The communal areas of Chiredzi, characterised by sandy soils (Cunliffe *et al*., 2012) have evidence of widespread degradation, presumably, because of these poor soils.

With all the above factors pointing towards increased vegetation degradation in these areas, Chimanimani district clearly shows some positive trends in vegetation recovery. Tropical rainforests are still evident in the moist foothills of Chimanimani, with woodlands dominating the more exposed or drier sites (Timberlake *et al*., 2016). An example is the Maronga Forest Reserve. Despite the fire of 1992, the 1991/1992 drought and the effects of Cyclone Eline in 2000, which caused widespread forest destruction, the regeneration capacity of the landscape is promoting new forest growth (Timberlake *et al*., 2016). The Northern districts of the Save catchment, most of which lie in regions 2 and 3, as well as region 1 areas of the Eastern highlands, also experienced positive NDVI trends during the study period. These high rainfall areas, complemented by deep fertile soils, are characterised by high photosynthetic activity which explains vegetation improvements over the years. The distribution patterns of the raw NDVI trends follow rainfall patterns, revealing the effect of climate on terrestrial ecosystems dynamics.

According to Li *et al*. (2004), NDVI and rainfall relationships can explain ecosystem productivity variations and deterioration in land condition in dry areas. The distribution of regression slopes of NDVI against rainfall, in this study, agreed with those reported in other studies (Ibrahim, 2017; Wessels, 2007; Evans & Geerken, 2004; Lambin, 2001). The dry areas of the Save Catchment exhibited strong linear relationships as shown by high slope values in those semi-arid regions. The slopes indicate the amount of change in vegetation cover per unit change in rainfall (Ibrahim, 2017). Pixels in the semi-arid regions of Buhera, Bikita, Chipinge and Chiredzi have higher regression slope values compared to the high rainfall mountainous areas which are covered by the evergreen miombo forests. These findings indicate that vegetation in dry areas is highly responsive to the high rainfall variability (Lu *et al*., 2015; Wessels *et al*., 2007). High rainfall zones that include humid forest areas of Chimanimani and Chipinge exhibited weak responses. This is largely because annual rainfall amounts usually exceed a certain threshold, above which vegetation becomes non-responsive (Lu *et al*., 2015). Such high-altitude areas, characterised by deep loamy soils that have high water holding capacity and are not easily eroded, have sustained vegetation growth even in low rainfall regimes (FAO, 2012). Given the varied landscapes of the two districts, areas in the valleys, that are mainly in region 4 and 5 are characterised by sand to sandy loam soils that are strongly leached, have low water holding capacities and that do not sustain growth (FAO, 2012). That explains lower slope values in those semi-arid areas of the two districts. Similarities were identified in the distribution patterns of NDVI-rainfall slopes and R^2 values. Those areas receiving large amounts of rainfall and characterised by low R^2 values coincided with low responsiveness to increase in rainfall. Wetter regions exhibit low NDVI-rainfall correlation, since saturation point is attained, beyond which further greening would not occur, despite an increase in water supply (Chikore & Jury, 2010). Because Manicaland is home to indigenous forests, as well as commercial plantations of exotic trees and tea estates, proper management can help explain the low R^2 values. Most humid areas also had the highest intercepts, whilst very low rainfall areas had low intercepts, suggesting the importance of rainfall as determinant of vegetation growth in semi-arid regions (Evans & Geerken, 2004). These results reveal rainfall as highly influential in vegetation production in the Save catchment, a factor that may mask negative impacts of human-induced degradation processes (Wessels, 2007).

According to Wessels *et al*. (2007), assessing vegetation changes without removing rainfall impact has misleading implications for landscape management. This is because human beings alter the structure of landscapes, mainly through various land use practices. During the study period, considerable areas (18.3%) exhibited negative residual trends. These were mainly concentrated in Buhera, Mutare, Bikita, Chipinge, parts of Chimanimani and Chiredzi and the areas that also experienced significant degradation. Chiredzi was the most degraded district, where negative trends covered 60.5% of the district area, with the least degraded being Seke district (6.5%) (Table 3.5). Severe degradation is evident mostly in the Save Valley, with Bikita, Chipinge, Chiredzi and part of Buhera districts being the mostly affected. In agreement with these findings, Mambo & Archer (2007) also observed degradation in Buhera district with high susceptibility to the south-eastern part of the district. This study also revealed portions of severe degradation in Buhera, coinciding with almost the same areas of high susceptibility found by Mambo & Archer (2007). They also revealed a large portion of Buhera district under cultivation from 1992 data, with woodlands continuously being cleared for agricultural expansion. Prince et al. (2009) also identified degradation, reflected by local net scaling (LNS) maps, in most communal areas of the Save. Clearance of forests for the establishment or expansion of agricultural land, together with intensive fuelwood extraction is rapidly depleting communal areas of vegetation resulting in soil erosion. This breakdown in community resource management also results in siltation of water reservoirs such as the Save river, affecting the river's capacity as well as the aquatic ecosystems (Makwara & Gamira, 2012).

Degradation patterns on the RESTREND map (fig 3.7) agree with results by Prince *et al*. (2009). From their studies, commercial farms stretching through Chivu, north of Harare, Marondera and even those in Chiredzi exhibit good vegetation cover. Some degradation was detected in these commercial lands. In most of those commercial areas where rainfall is high, low NPP was related to improper agricultural practices among the neighbouring subsistence farmers (Prince *et al*., 2009). This also helps explain patches of degraded areas, mainly in some areas of Marondera, Wedza, Chimanimani and Chipinge that have vast stretches of commercial farms and plantations. Particular examples were to the southern part of Chiredzi where there is a clear distinction between greening areas of Triangle and Chisumbanje sugarcane estates and browning, communal areas of Chiredzi district. Zimbabwe has had a long history of neglected, poor degraded communal areas (Scoones, 2002).

According to Mambo & Archer (2007), investigating susceptibility to degradation requires investigation of other factors, especially the human factors (Eswaran *et al*., 1997). Mutasa district, has the highest population density of 66 persons per km^2. This area should be one of the most severely degraded regions. On the contrary, the district is lightly degraded and there are just patches of degraded land. There are more positive residual trends (48.8%) than negative residual trends (18.2%) covering Mutasa district. This supports the view that high concentration of population may not always lead to the deterioration of land condition (Eswaran *et al*., 2001). This is also in agreement with Bai *et al*. (2008), whose research results, on a global scale, show an improvement in vegetation condition in densely populated areas of SSA. Voortman *et al*. (2000) argued that, high population density in SSA characterises the most fertile areas, particularly, mountain slopes. These fertile areas would support vegetation growth. Therefore, degradation is determined by what the occupants do to the land and not just population pressure

(Eswaran *et al*., 2001).

In this study, there were areas that experienced negative correlation between population density and vegetation condition, notably, in communal areas of Chipinge district (50 persons km^{-2}) and Buhera district (46 persons km^{-2}) (https://www.citypopulation.de/php/zimbabwe-admin.php) whose negative residual trends occupied 48.3% and 50.4% of the study area (table 3.5), respectively. Excessive pressure in the overcrowded communal lands of these areas is the leading factor in the degradation process. There are also areas with low population densities that have been affected by human induced degradation. These include parts of Chiredzi district (16 persons per km^2) and Bikita district (31persons per km^2). In these areas human induced degradation was experienced in 60.5% and 52.7% of the study area (table 3.5), respectively. This agrees with Mambo & Archer (2007) who detected high indication of degradation in wards of Buhera district having the lowest population density. Most of these areas are unsuitable for agriculture because of topographical and soil constraints. Unfavorable topography and soil conditions pose inherent restrictions on exploitation and habitation (Vlek *et al*., 2008; Wang, 2016).

The interaction that takes place between humans and their environment, inevitably results in degradation, mainly because of wind and water soil erosion, chemical reactions and soil disturbance by animals. Negative land use practices (Lal, 2001) include cultivation of marginal lands like semi-arid areas, steep slopes and shallow soils. The utilisation of marginal lands is a result of an increasing number of farming communities in need of agricultural land, yet there is a decline in availability of arable land (Lal, 2000). Other factors include traditional grazing systems, deforestation and firewood collection. Further influences arise from political, socio-economic and historical backgrounds. Therefore, poor resource utilisation works hand in hand with biophysical influences like soil properties, climatic characteristics, topography and vegetation types, making the task of isolating the role of physical from anthropogenic factors more difficult (Einsele and Hinderer, 1998) .

3.5 Conclusions

Based on the findings of this study, residual trend analysis method was demonstrated to be useful in distinguishing between climatic and human induced factors as drivers of vegetation degradation in semi-arid landscapes. In this regard, this study has revealed that:

- Climate is an important factor in vegetation cover changes, particularly, in semi-arid areas. Vegetation in dry areas is responsive to rainfall variations. The responsiveness is not the same in humid areas where a weak relationship between vegetation and rainfall is observed.
- Vegetation significantly degraded in 38.8% of the Save catchment as a result of human activities.
- The degrading trend in vegetation was most severe in the central districts of the Save catchment.
- Vegetation cover decline can successfully be used as a proxy of vegetation degradation. However, it is not comprehensive in characterising vegetation degradation. As a recommendation, further studies should examine vegetation degradation using other proxies, for example, reduced soil organic carbon, wetland decline, and others.
- As a recommendation, further studies should investigate the influence of soil characteristics and topographic factors on vegetation cover in the fragile ecosystems of the Save catchment in the context of vegetation degradation.

CHAPTER FOUR: Objectives reviewed and conclusions

4.1 Introduction

This research aimed at determining the degree to which human activities influence the decline in land condition in the Save Catchment, Zimbabwe, using NDVI time-series data. This chapter evaluates the objectives presented in Chapter one against findings. Furthermore, the chapter highlights major conclusions, limitations and recommendations for future research.

4.2 Objectives reviewed

Overview of the application of satellite earth observations in assessing and monitoring vegetation degradation.

The research reviewed vegetation degradation monitoring across landscapes. The extent and rate of degradation was reviewed from planetary to local scales. Identification of the exact causes of decline in land productivity was described as challenging because of interactions between many triggering factors. However, interactions of climatic changes, unsustainable land management and land tenure systems have been regarded as major contributors to the deteriorating quality of land. Negative impacts of this degradation result in millions of dollars being lost annually. Large populations suffer from poverty and food insecurity. Literature has also revealed that, although global assessment of vegetation degradation started a long time ago (1980s), estimates of its extent and severity have not been consistent. The varied definitions regarding the process and lack of standardized method for its assessment has led to inconsistencies in interpretation of results. Early assessments have largely been questioned since the results tended to be local and relied on opinions from experts. The results lacked reliable supporting data especially in the early stages of the process. Traditional assessment methods, for example, field surveys were criticized for being costly and for failure to provide a global view of ecosystem changes. Mankind has excelled in determining vegetation degradation at various spatial scales, following the development of satellite earth observation technologies and computing systems. Remote sensing technologies, especially the use of NDVI time-series, have been advocated as the most viable way in vegetation degradation mapping. This was revealed to be because of its ability to provide up to date assessments at scales relevant for decision making. Although NDVI, a widely used proxy of vegetation degradation, was extensively applied in vegetation degradation monitoring, its use in semi-arid regions was mainly limited by rainfall variability. The application of Residual trend method in disentangling the impact of rainfall was reviewed. The method was effective in separating vegetation degradation due to human activities.

The effectiveness of RESTREND method in detecting human induced vegetation degradation.

Using ordinary least squares regression model, vegetation degradation trends were established from NDVI-time relationships. Areas experiencing vegetation improvement or loss due to both natural and anthropogenic causes were determined from this analysis. From this study, 65% of the catchment was covered by negative trends whereas 15% experienced improvement. The map of significant NDVI trends demonstrated, in part, the influence of human actions in vegetation cover growth. Regression model analysis of NDVI and rainfall showed that vegetation growth was strongly influenced by climatic variations in semi-arid areas of the Save catchment where regression slope values and R^2 values tended to be higher than in humid areas. Higher intercepts were characteristic of northern districts and mountainous areas of the eastern districts and drier areas that were largely dependent on rainfall for growth, had low intercept values. The regression slope, intercept maps and R^2 portrayed the important role played by rainfall variations in determining ecosystem productivity. Residual trend analysis method was effective in separating the influence of rainfall and human activities on degradation trends. A clear distinction between degraded areas, improved areas and areas with moderate changes was mapped using this technique. From the analysis of residual trends, 18.3% and 33.6% of the study area encountered degradation and improvement, respectively. The larger portion of negative raw NDVI trends compared to negative residual trends reflects the important role climate plays in influencing vegetation growth in very low rainfall parts of the Save catchment, sometimes masking the human influences. Statistical analysis established significantly degraded pixels, from which severity classes were produced and mapped. Severe degradation was observed to the east of Bikita, west of Chipinge and Northern Chiredzi. The drivers of the changes were suggested using information on agro-ecological zones, soil types, vegetation cover as well as population density statistics. RESTREND method effectively separated areas of degradation due to human activities.

4.3 Conclusions

The development of satellite earth observation technologies, together with computing systems, has enabled the determination of vegetation degradation at various spatial scales, because of its ability to provide up to date assessments at scales relevant for decision making. This study examined long-term MODIS NDVI data to assess changes in vegetation in Save catchment from 2000 to 2015. Time-series analysis of NDVI trends revealed large areas experiencing vegetation cover loss. Vegetation growth was strongly influenced by climatic variations. Existence of significant trends indicated the role humans play in promoting land productivity losses. RESTREND method was effective in isolating climatic influences, allowing for the mapping of alteration of the ecosystems which was a result of human activities. As a recommendation, future studies on long term vegetation changes should employ methods that consider breaks in the trend patterns, because this aspect is not handled well using the RESTREND method.

The use of MODIS data, that is available for all the years, allowing time-series analysis, is not without limitations. Its spatial resolution is relatively coarse and lacks detail required for the quantification of small-scale vegetation cover changes. Future studies should utilise higher resolution data to enhance quality of analysis results. Because some areas have been identified as severely degraded in the Save catchment, policy action is needed to rehabilitate those areas and to combat the process. Land management policies should be effectively implemented, especially in communal agricultural lands, where land tenure system does not encourage investment in the land.

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