CHINHOYI UNIVERSITY OF TECHNOLOGY
SCHOOL OF WILDLIFE AND ENVIRONMENTAL SCIENCES
DEPARTMENT OF GEOINFORMATICS AND ENVIRONMENTAL CONSERVATION

GEOSPATIAL ASSESSMENT OF HABITAT DISTURBANCE AND LAND COVER CHANGE IN A HUMAN-MEDIATED ECOSYSTEM, MIDLANDS BLACK RHINO CONSERVANCY, ZIMBABWE.

By
Kunedzimwe Francisca

A thesis submitted in fulfilment of the requirements for the degree of
Doctor of Philosophy in **Environmental Conservation and Geoinformatics** in the School of Wildlife and Environmental Sciences at Chinhoyi University of Technology, Chinhoyi, Zimbabwe.

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The undersigned declare that they have supervised, read and recommended to the School of Wildlife, and Environmental science Chinhoyi University of Technology, for approval; a thesis titled, **"GEOSPATIAL ASSESSMENT OF HABITAT DISTURBANCE AND LAND COVER CHANGE IN A HUMAN-MEDIATED ECOSYSTEM, MIDLANDS BLACK RHINO CONSERVANCY, ZIMBABWE"**
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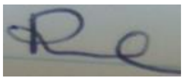
DECLARATION

I, Francisca Kunedzimwe, do hereby declare that this thesis is the result of my own work, except to the extent indicated in the acknowledgements, references and by comments included in the body of the report, and that it has not been submitted in part or in full for any other degree to any other university.

Signature…  …………………………Date…16…… June 2023

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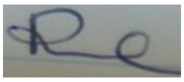
SIGNED ………… 

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DEDICATION

This research is dedicated to my family, Tinaye, Tinevimbo and Calisto. My siblings, Chipo, Annatoria, Jameson, Collen and Raymond, my parents Mr and Mrs Severino Kunedzimwe.

ABSTRACT

The main purpose of the research was to assess the extent of disturbance and land cover changes using geospatial technology in the Midlands Black Rhino Conservancy, Kwekwe, Zimbabwe which is a human mediated environment. Recent research has established that conservancies are undergoing structural changes mainly characterized by changes in land cover commonly referred to as patch dynamics. There is little knowledge as to how this global phenomenon is being understood (extent and consequences of patch dynamics). This research aims to fill the currently outlined gap in innovative geo-technological ways to determine and assess the occurrence of this disturbance and quantify its extent. An analysis of trends was done and land use land cover maps from 1980, 1990, 2000,2010 and 2020 were created from remotely sensed images. The generated images were classified to detect changes that occurred over time in the human mediated environment where mining activities, agriculture and some other activities are taking place. Patch analyst was used for the landscape assessment and characteristic determination; land use land cover statistics were generated for each land cover map for a specific year. Net primary production was estimated using remote sensed imagery to determine the changes in vegetation productivity. The overall transformations in the area of study showed a decrease in forest cover, lake, grassland and increased bare land as well as an increase in the areas occupied by human activities such as agriculture and mining among others. The changes that were detected were predominantly derived by the indiscriminate logging for mining and agricultural purposes. The decrease in habitat sizes resulted in the decrease in habitat richness, heterogeneity, fragmentation and the complexity of form and increased land use intensity. A decrease in net primary productivity was also detected through the computing of NDVI. There is a beneficial trade off that is provided by the approach of this research work especially between very expensive ground surveys and the low-priced image processing analysis. Results of this research further the understanding of spatial dynamics in a protected area and its key drivers.

Key words: Change, habitat, geo-technology, disturbance, land use, land cover

LIST OF ABBREVIATIONS AND ACRONYMS

GIS	Geographic Information Systems
RS	Remote Sensing
LANDSAT	Land Satellite System
ZIMPARKS	Zimbabwe Parks and Wildlife Management
ZINWA	Zimbabwe National Water Authority
QGIS	Quantum Geographic Information Systems
LC	Land Cover
SPSS	Statistical Package for Social sciences
ILWIS	Integrated Land and Water Information System
NDVI	Normalized Vegetation Index
NPP	Net Primary Productivity
GPP	Gross Primary Productivity
MK	Mann Kendall
ENVI	Image Processing and Analysis Software Solution
CCKP	Climate Change Knowledge Portal
UTM	Universal Transverse Mercator
SRS	Simple Random Sampling
SIR	Simple Linear Regression
CA	Cellular Automata

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CHAPTER 1
GENERAL INTRODUCTION

1.1 Background to the study

Geospatial assessment entails the application of science and spatial technology in the utilization and monitoring of natural resources as well as in the determination of habitat disturbance and land cover change (Hussain et al., 2020). Globally, geospatial tools have emerged as effective tools for the execution of spatial data for decision making purposes in several management areas including the environment (Das Chatterjee & Chatterjee, 2016; S. Hussain et al., 2020). This study used geospatial tools to assess the extent of habitat disturbance in a protected area conservancy.

Geographic Information Systems (GIS) and Remote sensing (RS) are some of the geospatial techniques that are used for biodiversity assessment and management. GIS and Remote Sensing are powerful tools in the ecology of the landscape as they are used in the mapping disturbance zones in ecosystem, quantifying its impact on the biodiversity and detecting land cover changes over a period of time (Pöhlker et al., 2019; Skaloš et al., 2011; Weber et al., 2007). To understand the consequences of disturbance on the habitats, a spatio temporal analysis on land cover change is desired (Antwi, 2009; Homer et al., 2015). Several research has shown that biodiversity of terrestrial ecosystem is expected to be mainly affected by land use changes within the next 100 years (Braimoh & Osaki, 2010; Caldas et al., 2015; Chapin Iii et al., 2000).

Limited studies have looked at empirical methods of assessing disturbance and land cover in mining environments hence the need to use geospatial technology because it can analyze big data at different spatiotemporal scales (Zerbe, 2023). For instance, a review which was done on evaluating alternate post-mining land-uses, concluded that only empirical methods were being used for the assessment of rehabilitation progress in a post mining environment (Mborah, Bansah, & Boateng, 2016). The results of the study showed no research that used spatial technology for assessing impact of mining on the environment with respect to protected areas where mining is being undertaken. Their focus was on highlighting the impacts of mining on the environment through empirical methods only, for instance, use of quantitative surveys for assessing post mining rehabilitation progress. Another review was done on evaluating the environmental and economic impact of mining for post-mined land restoration and land-use Worlanyo & Jiangfeng, 2021.

Spatial technology such as GIS and RS can predict, assess risk, and identify hazardous locations of natural resources (Shokr, 2020; Venkatramanan, Viswanathan, & Chung, 2019). The technology can further integrate the spatial and non-spatial data to enable better understanding of emergency conditions (Paramasivam, 2019; Paramasivam & Venkatramanan, 2019). Neither of the highlighted papers show any research interested in geospatial technology for human mediated conservancies, hence the need to asses' disturbance in such areas using geospatial technology.

A study done in the tropics addressed land cover change in the context of global environmental change (Worlanyo & Jiangfeng, 2021; Zerbe, 2023). There has been an abrupt and continuous change in the regional and global climate variables such as cloud cover, precipitation, temperature, drought among others, in the past decade (O'Brien, 2012). But the question is how does the ongoing global changes affect the Earth's ecosystems, biodiversity, land cover changes and vice versa? (Worlanyo & Jiangfeng, 2021; Zerbe, 2023). Land cover changes are local and site specific, yet their collective impact is one of the most important facets of global environmental change. Since the local ecosystems are linked to prevailing climatic conditions, any change in climate is expected to have a greater impact of change in the ecosystems (Worlanyo & Jiangfeng, 2021; Zerbe, 2023). On the other hand, a change in the local or regional ecosystems can cause variations in the climatic condition, particularly with their role as carbon dioxide sink or their effect on greenhouse gasses (Brauch, 2009; Lambin et al., 2001; O'Brien, 2012). It is also ascertained that, humans are more and more regarded as dominant force behind global environmental change (Brauch, 2009; Lambin et al., 2001; O'Brien, 2012). Human use of the environment has affected almost 40% of the net primary production of the Earth, and changes in these may alter ecosystem service locally and globally (Comberti, Thornton, De Echeverria, & Patterson, 2015).

Disturbance occurs when there is a change in conditions which interferes with the normal functioning of a biological system (Johns & Skorupa, 1987). A 'disturbed habitat' can be defined as an ecological concept which indicate a temporal change in the conditions of the environment, which has pronounced changes in the ecosystem (Scott et al., 2014; Seltmann et al., 2017). Disturbances are classified into two, human caused or natural. Disturbances which are anthropogenic related include cultivation, weeding, land clearing, digging, mining, burning among others. Natural disturbances include natural fires, lightning strikes and fires; temperature changes storms, strong winds among others (De Chazal & Rounsevell, 2009; Jewitt et al., 2015; Kamdem et al., 2012; Kunedzimwe, Muposhi, & Taru, 2022). The relationships that exist between the changes in the environment and health is well known (Kamdem et al., 2012). This has been documented by several scientific studies conducted in the past for both animal species and humans and vegetation, although little is known on the extent of habitat damage and the associated consequences in a mining landscape (Dobson et al., 2006; Kamdem et al., 2012; Mantyka-Pringle et al., 2015; N. Michelutti, McCleary, Douglas, & Smol, 2013; Nagendra et al., 2013; Young, 2013).

Habitat disturbance is associated with mass extinction of a variety of species, although the potential magnitude of the destruction is not very clear (Seltmann et al., 2017). Present studies have focused on estimating and predicting global extinction rates and on quantifying effects at local and regional scales (Françoso et al., 2015). This research directly assesses the extent of habitat diversity disturbance in a human mediated landscape. The natural habitats sector is also the means of livelihood for the majority of the people close by. It contributes a lot to human ecology as well. Most development programs today pay little attention to habitats because it is not perceived as a viable engine of growth (Michelutti, Montagna, & Antonialli-Jr, 2013; Young, 2013). Additionally, it is noted that little attention has been paid on the extent of disturbance of these habitats and the effect they have to the biota.

The use of geo-technology can help quantify and describe the extent of habitat disturbance (matrix, fragments, and corridors) and their spatial distribution, minimizing the uncertainties of the habitat disturbance (Convertino & Valverde Jr, 2013). The combination of various geo-technologies can be used to build very crucial systems which are currently being applied in the determination of priority areas for ecosystem conservation and restoration (Convertino & Valverde Jr, 2013). The use of geo-technology is also important in the diagnosing of the sites which have a minimum resilience but high restoration potential, thus maintaining ecological processes and services as well as favoring biodiversity increase. Upon this background the technology will facilitate the implementation of restoration projects, increase environmental gains and decreasing costs and potentiating the regeneration of the natural environment. As of today, few studies have been done in the study area pertaining the geo-technological approaches in the assessment of habitat disturbance (Pöhlker et al., 2019; Skaloš et al., 2011). This study aims at assessing the extent of disturbance in a human mediated environment using geo-technology and the following problem statement and objectives were a focus of this research.

1.2 Problem Statement

There is habitat fragmentation/disturbance and changes in land cover in the conservancies where mining and other activities are being undertaken hence, the need to use a geospatial assessment for an in-depth analysis and understanding. Mining and other activities within the protected areas have diminishing effects on the habitat diversity. Species are coming into direct contact with human beings, and this is now having adverse effects on the human fraternity in that some of the diseases which were found within the original natural habitats are now transferred into human beings causing diseases. For instance, the outbreak of the recent Covid 19 pandemic is said to have emerged from habitat disturbance (Lone & Ahmad, 2020). As humans alter the environment through habitat fragmentation, the microbes that live within will spill over into human communities leading to disease outbreaks. In Zimbabwe the mining industry has become a major threat to biodiversity as people clear land for different mining activities. This has caused the extinction of some endangered species as well as keystone species within the ecosystem. There is need to develop robust and comprehensive systems approach which is geospatial technology based in order to properly restore the ecosystem within the mining sector. This systems approach is a vital input in building mining resource monitoring and management strategies. This study aims at providing tools and insights for improved understanding of vulnerability patterns of diversity of habitats in a mining environment through the use of geospatial technology. The study will help the society in that it will give a comprehensive assessment of the potential threats on livelihoods, health and assets during the mining operations. Ecologically the study will also help in the precise management of specific ecosystems under threat. Scientifically the study will help in the development of a geo-technological system which will help for proper assessment of disturbance within a mining/human mediated landscape.

1.3 Objectives

1.3.1 Main Objective of the study

The aim of this study is to assess habitat disturbance and land cover changes in a human mediated environment using geospatial insights in Midlands Black Rhino Conservancy, Zimbabwe.

1.3.2 Specific Objectives

(i) To determine spatio-temporal landscape information in a disturbed conservancy.
(ii) To predict the patterns of habitat diversity and land cover change using GIS and Remote Sensing.
(iii) Assess and quantify the level of habitat disturbance using patch metrics
(iv) To characterize vegetation productivity in a protected area in relationship to environmental change.

1.4 Study/Research Questions

Having considered the specific objectives under the main aim of assessing the impact of habitat disturbance and land cover change in a human mediated environment the following research questions would follow.

(i) How can geospatial technology be used to generate spatio-temporal landscape information in a disturbed protected area?
(ii) How can GIS and Remote Sensing help in the prediction of the patterns of habitat diversity and land cover change?
(iii) What are the relationships that exist between the nature of fragmentation processes and the magnitude of disturbance in the protected area landscape?
(iv) Is there any relationship that exist between vegetation productivity environmental change?

1.5 Hypothesis

(i) H1: Geospatial technology can be used to generate spatio-temporal landscape information in a disturbed protected area.
(ii) H1: Geospatial techniques are used to understand the state of habitats (patterns and extent of disturbance)
(iii) H1: A relationships exist between the nature of fragmentation processes and the magnitude of disturbance in the protected area landscape
(iv) H1: Vegetation productivity in a conservancy can be characterized in relationship to environmental change

1.6 Study assumptions

The research assumed that:

(i) Landscape information in a disturbed protected area vary across space and time.
(ii) The prediction of patterns of habitat diversity and land cover change can be done easily using GIS and Remote sensing.
(iii) There is a relationship that exist between the nature of fragmentation processes and the magnitude of disturbance in the protected area landscape.
(iv) Environmental change can be a main factor that determine vegetation productivity.

1.7 Significance of the study

Most of the researchers have been limited to empirical methods in assessing the extent of habitat loss due to disturbance such as mining and agriculture (Yunxuan Liu et al., 2022; Yan et al., 2022). The research adds to the existing literature on researches that have gone into the assessment of habitat loss focusing more on understanding the state of habitats in a human mediated environment**.** The geographical technology helps to gather location information and provides us with data that can give a deeper understanding of a whole host of issues. This is done through correlating an object's position with its spatial position (Coetzee, Bansal, & Chirwa, 2020; Dangermond & Goodchild, 2020). Data which is spatially referenced can help to answer questions, predictions, analysis and decision making. The in-depth understanding of habitats in disturbed areas need urgent attention, since it enables conservation planners to develop spatially explicit decision support tools that link populations with habitats for effective conservation planning, implementation, and evaluation at landscape scales (Stiver et al., 2015). There is empowerment of decision makers that happen when a shift from local to landscape conservation occur. This will also help to maximize the likelihood of achieving conservation by implementing site-scale actions within priority landscapes.

There is need to develop a sound and comprehensive systems approach which is geospatial technology based in order to properly restore the ecosystem within the mining sector. This systems approach is a vital input in building mining resource monitoring and management strategies. There is limited information provided by land managers pertaining the ecological nature of an area prior or even during the implementation of a project.

The study will help the society in that, it will give a comprehensive assessment of the potential threats on livelihoods, health and assets during the mining operations. Ecologically the study will also help in the precise management of specific ecosystems under threat. Scientifically the study will help in the development of a geo-technological system which will help for proper assessment of disturbance within a mining landscape.

This study should generate new knowledge by providing an in-depth understanding of the habitats in a disturbed environment and provide geospatial technological insights that can in future empower environmental planners to make subtle and robust decisions on adopting the best procedure of habitat damage assessment strategies. Additionally, this study should empower policy makers to be able to propose a system that effectively disseminate disturbance resilient options which can be easily adopted by project implementers. Information generated from this study seeks to educate society on various opportunities surrounding the proper management of habitats since it plays a very important role in safeguarding the ecosystems goods and services offered by conservancies. The information is very important as there has been a notable decline in the services offered by conservancies due to anthropogenic activities such as mining and agriculture.

Furthermore, the results from this study contribute to law enforcement plans to be put in place in managing, improving, and monitoring of resources in conservation areas. The study contributes to the sustainable management of habitats that are vulnerable to human disturbance in Midlands Black Rhino conservancy and other similar areas within the savannah biome. More so, the results of this study help in contributing to sustainable management of habitat diversity hence reducing biodiversity loss.

The terrestrial diversity of habitats within an ecosystem is expected to be mainly affected by the changes in land use and land cover (Krauss et al., 2010). The activities of human beings such as mining and its resultant loss of biota have raised concern among conservationists (Souza et al., 2015). A lot of damage has been done on habitats in mining areas that are found in Mashonaland West Province of Zimbabwe. The mining activities in these areas have changed the diversity of habitats, land use potential and even the aesthetic value of the landscape. Therefore it is very crucial for spatial planning policies to restore the damage to the ecosystems and open up new land use possibilities (Johnson, Evans, Montgomery, & Chenery, 2022).

1.8 Scope/ Delimitation

The study focused on the use of geospatial knowledge in the monitoring of changes within the protected area conservancy over a forty-year period (from 1980 to 2020). The study was carried within the Midlands Black Rhino Conservancy which is a protected area with mining activities.

1.8 Limitations of the study

The research used remotely sensed data which was acquired on the same month (May). Spatial variations in land use changes, sun angle, altitude, cloud cover and their shadows contribute to additional processing even though the magnitude might be very small. The use of radar imagery to overcome the cloud problem is recommended since radar can penetrate cloud and shadow.

1.9 Definition of key terms

The defined words below are the key terms of this study because they have featured more frequently in the write up. Various sections of literature review in this document have helped much in giving an in-depth explanation of these key terms.

- Geospatial technology- the use of scientific methods, geographic information systems techniques and remote sensing in the monitoring and assessment of natural resources.
- Land use- this refers to the monitoring, management and modification of the natural environment into built environment such as settlements and semi-natural habitats such as arable fields, pastures, and managed woods.

- Land cover- Land cover is the physical material at the surface of Earth. Land covers include grass, asphalt, trees, bare ground, water.

- ❖ Disturbance- the interruption of a settled and peaceful condition.

1.10 Outline of Thesis

The compilation of this project was done in the conventional format. The mentioned format is made up of six chapters. This particular episode /chapter provides a general overview of the study. The chapter begins with the study background followed by the problem statement, objectives, study questions, statement of hypothesis, rationale / significance of the study and assumptions. Limitations, delimitations of the study, definition of terms and description of the study area, form party of this chapter.

Chapter 2 presents the literature review related to the study, through a subtle systematic review. There are also highlights of important research gaps from literature related to this study. The literature review provided initial insights into the research area that guided the manner in which the research was conducted and communicated to the audience at the end. A review of literature is an account of what has been published on a topic by accredited scholars and researchers (Choga &Njaya 2011).

Chapter 3 provides the outline of the research design under which data for this study was collected and analyzed. It highlights the description of the study areas as well as the methods that were used their justification for the use and, their application in the study. Details of the data analysis and subsequent statistical analysis is also outlined in this chapter. Analysis as well as presentation of research findings which answer the research questions guiding this study.

Chapter 4 presents, outlines and give a description of the research findings for the study. This chapter present and future land cover changes of the Midlands Rhino Conservancy which is a protected area with mining activities. The chapter also presented changes in vegetation productivity with respect to the global environmental change using NDVI as a measure in estimating the health and productivity of vegetation.

Chapter 5 details the discussions of the results from the study. The changes that have occurred in the Midlands Black Rhino conservancy as well as the future prediction of the state of the conservancy are discussed. Then the spatiotemporal variation in land use patches were also discussed as well as the land occupied by the land use patches. The chapter also discussed the reasons behind the changes in land use as well as vegetation productivity over time.

Chapter 6 is an outline of the conclusions made from the research findings. Their highlights, the recommendations on the scientific, societal, and conservation take home points from the study. There are recommendations to different groups of people and these included climate change scientists, ecologists, policy makers, miners, conservationists as well as future researchers. The last part of the chapter summarizes the organizational nature of the whole thesis from the first chapter up to the last (Figure1:1).

The outline for the thesis is also given in form of a diagram on figure 1.1 below.

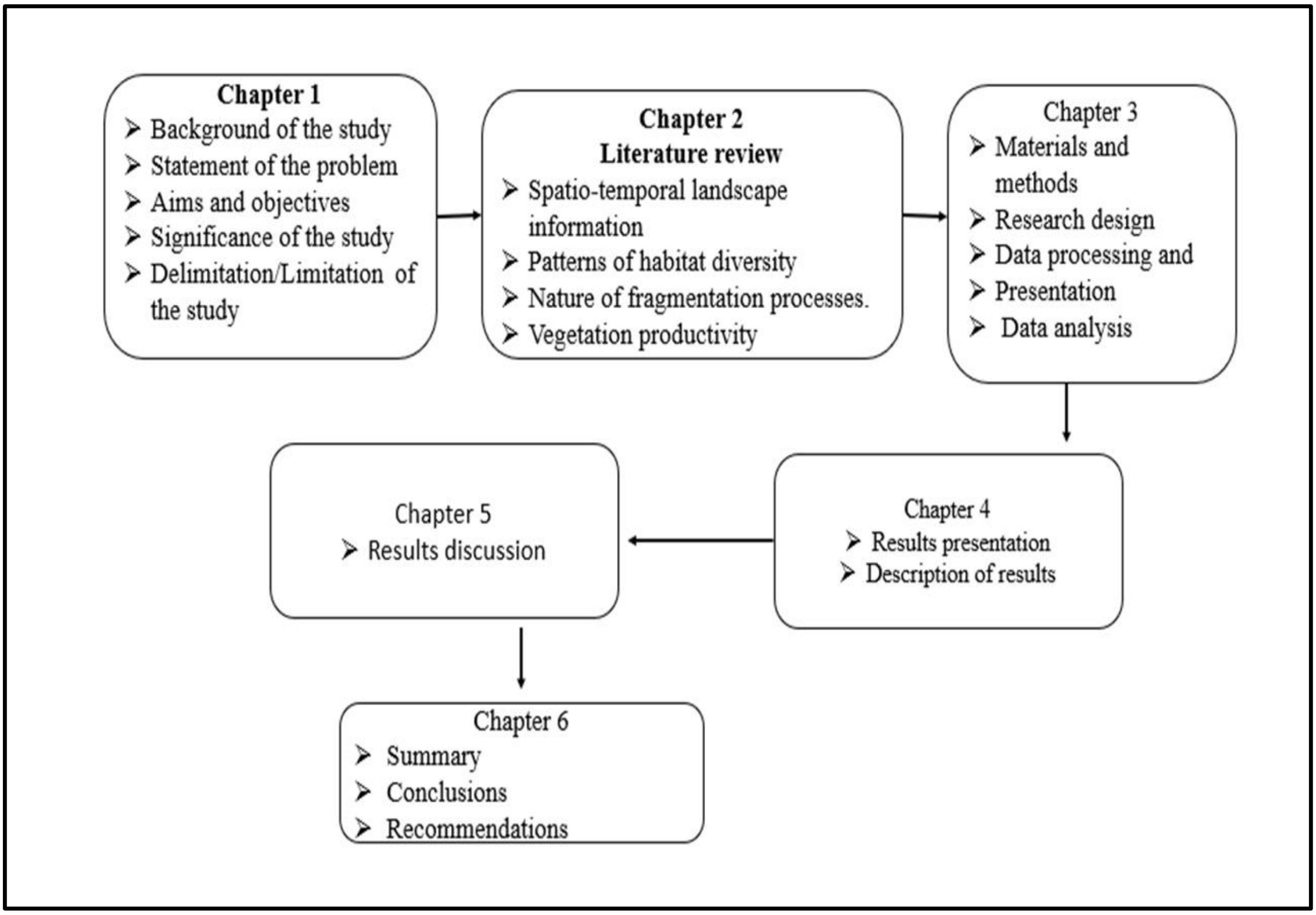

Figure 1.1: The outline of the thesis

1.11 Chapter summary

The chapter introduced the main aim or purpose of the study. It also discussed the problem in question. the rationale of the study, research specific objectives, and study questions which highlighted the research gaps found in literature as well as scientific and societal significance the research. The delimitation and limitation of the study were also discussed. The background information highlighted the major anthropogenic activities which are resulting in disturbed ecosystems which in turn are resulting in biodiversity loss within the conservancies.

CHAPTER 2

LITERATURE REVIEW

***Parts of this chapter are published as**: Kunedzimwe Francisca, Muposhi Victor K, Taru Philip (2022), Spatio-Temporal Analysis of Trends on Habitat Disturbance Between 1986 And 2021 In Protected Areas of, Zimbabwe. Journal of Earth and Environmental Science Research. SRC/JEESR-203. DOI: doi.org/10.47363/JEESR/2022(4)170.*

2.1 Introduction

This chapter provides an overview of recent studies using geospatial techniques (thus Remote Sensing (RS) and Geographic Information Systems (GIS) to assess the extent of mining disturbance on plant habitats in protected areas of Zimbabwe. Through a systematic review, literature hotspot analysis as well as a trend analysis at regional specific level together with statistical tests helped to come up with an overview of the past studies which were done on habitat disturbance in protected areas of Zimbabwe over a forty year period (Kunedzimwe et al., 2022)

Human activities such as deforestation and the resultant loss of natural habitats is one of the most causes of decline in habitat diversity in terrestrial ecosystems across the globe (Crausbay et al., 2017). According to FAO the rate of deforestation is continuing at an alarming high rate in many countries (Caravaggio, 2020). This is mainly emanating from different human activities such as mining, agriculture, urbanization among others. These mentioned factors ultimately contribute more to habitat fragmentation. These processes reduce and fragment habitats into patches. The extent of disturbance, coupled with the composition and structure of the original and remaining habitat and their physical characteristics are expected to influence the populations and faunal composition of diversity of habitats in different ways (Boldy et al., 2021, Larondelle 2012, Chave 2004, Hubbel 2001).

One would expect that species restricted to fragmented sites to disappear in the short, medium, or long term (Hibbitts et al., 2013). This depends on the nature and degree of disturbance and characteristics of the species. At present habitat conservation is based on specific habitats and specific species but there is need of a comprehensive geo-technological system essential to integrating strategies into larger landscape scale (dynamic and within interconnected habitats) through which habitat conservation can be facilitated in the perspective of global environmental change (Melbourne-Thomas, Constable, Wotherspoon, & Raymond, 2013).

Many studies were done on habitat loss and mining in protected areas but have missed the geo-technological systems approach to the management of ecosystems that surrounds the mining landscape. Most of the studies are review studies on the use of GIS in biodiversity conservation, for instance reviewing the use of remote sensing and GIS techniques for mapping, monitoring and modelling lichens and their habitats (Prasad et al., 2020). Some studies have done studies on species-level distribution maps along with structural information on dominance, canopy diameters and age–class distribution using GIS (Remya, Ramachandran, & Jayakumar, 2015; Zlinszky et al., 2015). Several examples were provided of accurately identifying plant species based on the high spatial resolution imagery (Gillespie et al., 2012). Recent studies have reported that the spectral bands of the wavelength region 2 ranging from 400 to 1,040 nm are suitable for discriminating tree species (Prasad et al., 2020). Another research assessed the accuracy of LANDSAT-based large-scale sea grass mapping against patterns detectable with very high-resolution IKONOS images (Wabnitz, Andréfouët, Torres-Pulliza, Müller-Karger, & Kramer, 2008). Other studies have looked at detecting the effect of disturbance on habitat diversity and land cover change in a post-mining area using GIS (Antwi, Krawczynski, & Wiegleb, 2008). No studies have focused on assessing disturbance in a mining environment through the use of a geo-technological systems approach.

Although high spatial resolution satellite remote sensing is a very useful source of data, researchers have rightfully pointed out that it is the most potentially powerful yet underutilized source for tropical research on biodiversity and stimulating discussion on its possible applications should be the first step in promoting a more extensive use of such data (Nagendra & Rocchini, 2008).

The scale of human influence is driving the earth system towards a new unstable state which is characterized by extreme climate dynamics and biodiversity loss (Pickett & Cadenasso, 1995). This is explained by the new geological epoch in which the earth has entered-the Anthropocene. Literature suggests that human activities (primarily agriculture, urbanization and mining) create dynamic complex coupled landscape signatures which alter processes regulating the stability and resilience of the earth`s system from which humans depend on, (interactions among the atmosphere, land/biosphere, and ocean) (Vitousek and Fletcher 2008). The world`s main source of income and wealth is mineral extraction and continued extraction of these minerals is expected to be among the prominent drivers of global environmental change (McLaren 2012, Pathirana et al. 2014). The reason behind this is, mining transforms landscape with marked impacts on the natural ecosystems, since it replaces natural land surfaces with artificial surfaces for instance, asphalt surfaces that alter ecological processes, such as nutrient fluxes (Pathirana et al. 2014). Although mining areas occupy <5% of the Global land surface area, its impacts on the natural ecology span over large spatial extents and even beyond the mining boundaries (Richards and Hoxey 1993, Ritter’s et al. 2000). Consequently, assessing the spatial extent of disturbance in mining environments is an emergent trans-disciplinary scientific question for conservationists and natural resource managers (Saunders et al. 1991).

The advent of mining as a main economic activity for many countries has resulted in the adverse consequences on the environment especially the ecological habitats (Amankwa 2003, Richards and Hoxey 1993). These mines use some of the available resources to meet their needs, for example trees for timber and even for fuel, road construction and water for washing their machines (Murwendo et al 2011). Such activities have diminishing effects on the habitat diversity (Mberengwa 2010, Murwendo et al. 2021). Species are coming into direct contact with human beings, and this is now having adverse effects on the human fraternity in that some of the diseases which were found within the original natural habitats are now transferred into human beings causing diseases. For instance, the outbreak of the recent Covid 19 pandemic is said to have emerged from habitat disturbance (Ahmad et al. 2020). As humans alter the environment through habitat fragmentation, the microbes that live within will spill over into human communities leading to disease outbreaks. In Zimbabwe the mining industry has become a major threat to biodiversity as people clear land for different mining activities (Zwane et al. 2006). This has resulted in the extinction of some endangered species as well as key species within the ecosystem (Spiegel 2009).

One challenge for natural resource managers is the maintenance of near natural ecosystem function in mining landscapes. The proposed solution to that challenge lies in understanding the extent of disturbance and landscape conditions which can make the ecological processes persist in mining areas (Maponga and Ngorima 2003). Consequently, understanding and predicting the extent of habitat disturbance in a mining environment is very imperative (Kennedy et al. 2015). In comparison to natural forested and agricultural landscapes, mining landscapes consist of mosaics of heterogeneous landscape elements varying widely in both structural and functional characteristics in very close proximity and are often juxtaposed (Zwane et al. 2006, Maponga and Ngorima 2003). Attempts to assess the complex-coupled spatiotemporal changes of habitat disturbance pre-dates the 1960s. Since then, in Zimbabwe the interdisciplinary studies have processed theoretical perspectives to explain or predict the extent of habitat disturbance.

Given the recent attention on mining and its impacts on the environment, it is very imperative to have a constant synthesis on growing literature**.** The review of literature is of paramount importance since it helps us to identify hot topics (mostly pursued topics) and cold topics (receiving less attention) as well as to identify the direction of future research. This part of research is a documentation of empirical literature on the use of geospatial information for habitat disturbance assessment in the field of mining. To date the comprehensive review of literature assessing habitat disturbance using geospatial technology is minimal.

Herein the study adopted a systematic review process after other researchers to quantify trends in habitat assessment in mining environment using geospatial technology between 1986 and 2021 in different spatial environment journals (Roberts et al. 2007). The core aim of this chapter is to systematically review literature on habitat disturbance assessment using geospatial technology from 1986-2021. The first objective is to identify literature hotspots for key terms used in the use environment and biodiversity literature for 1986– 2020. The second objective is to quantify trends in habitat loss in spatial literature in terms of study approaches and methods, and geographic region of study. This also contributes towards evidence for policy makers to make informed decisions on the best strategies and restoration measures for the habitats located in mining environments within the semi -arid savannah ecosystems.

2.2 Literature review methods and synthesis

The review was guided by the analytical framework (figure 2:1) which emanated from the Unified theory of biodiversity and biogeography, which aims to provide a theoretical framework for explaining biodiversity patterns across all spatial and temporal scales (Chave 2004, Hubbel 2001). This neutral theory also assumes classically (i) that biotic communities are essentially governed by random population drift (thus, demographic stochastic hypothesis), (ii) that all individuals irrespective of species share the same per capita birth, death, migration and speciation rates (neutral hypothesis) and (iii) that the number of individuals in the system is constant through time (zero-sum hypothesis) (Chave 2004). Additionally, several studies have shown that mining has adverse consequences on the environment for instance, direct impact on ecosystems and hence provision of goods and services from the same (Boldy et al. 2021, Larondelle and Haase 2012, Maponga and Ngorima 2003, Xiao et al. 2018, Yanda et al. 2010).

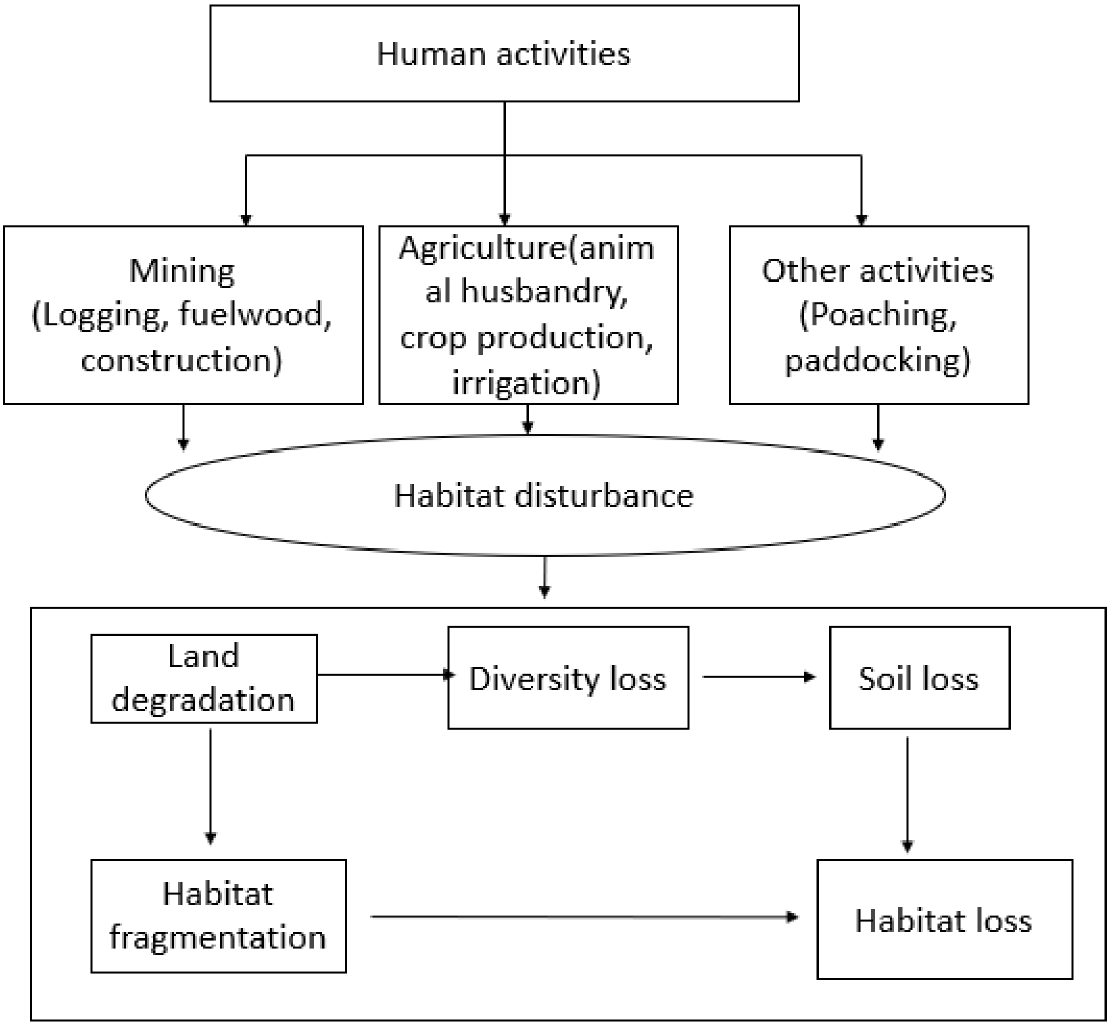

Figure 2.1: Analytical framework for habitat disturbance assessment

2.3 Journal selection and identification

In order to identify journals on the assessment of habitat disturbance using geospatial technology, the biodiversity and environmental section of the Institute for Scientific Information Journal Citation Reports was used to filter the leading journals, basing on impact factor sorting. All journals on environment which stated that they publish original research in time and space were included from the databases searched. Book chapters, journal articles, books, academic theses and reports were all included in the search. Electronic databases including Web of science, Sci-Hub, Scorpus, Dimensions, Sage Elsevier Science Direct, PubMed, Scopus, Plosone and Google Scholar among others were searched for potential studies published in English between 1986 and 2021 reporting on Geospatial information advances on habitat disturbance in a mining environment (Chuvieco 2020).

Statistics on the number of publications per continent per year were drawn from different databases to produce a spatial analysis map showing the changes in time and space in the distribution of publications in the field of study. Some of the potentially relevant journals were excluded, because they were non English. In this study a choice of journals was expected to influence the results, but the journals used for this study provided a widely read and authentic studies which are specific to the theme of habitat disturbance and geospatial technology.

2.3.1 Collection and Categorization of data on habitat assessment literature

The systematic review approach was adopted from the recommendation by some robust scholars. (Munn et al. 2018, Roberts et al. 2007). The approach is a rigorous and transparent methodology which enables a detailed exploration, critical evaluation, and interpretation of available evidence that is relevant to a particular subject based on a sample of original studies (Khan et al. 2001, Roberts et al. 2007). Credits behind the systematic reviews are the capacity in the limitation of bias and random error in quantitatively synthesizing independently conducted studies(Gates 2002, Mulrow 1994). The "traditional narrative review method" is mostly used by reviewers (Muderere et al. 2018). The "traditional narrative review method" quantitatively synthesize published results based on the subjective judgment as well as experience of the author(s) lacking clear methodological transparency, which is a main source of bias. Systematic reviews are both replicable and repeatable. This paper used a method based on electronic searches. The year 1986 in this study is regarded as the base year which was used for this research because it is the year when most of the journals began publishing online. The inclusion of a publication in this study was based on text search of listed keywords of titles and abstracts using the following search words: Geographic information systems and conservation, habitat disturbance, mining and conservation, satellite imagery, spatial analysis. Specifically, a repetitive year on year filter was run using the search function in the online repositories of each database by filling in the key words. Query language was used facilitated by Boolean operators such as OR, AND, NOT among others and the following is one of the examples used, *(GeographicInformationSystemANDconservation)AND(LIMIT-TO(AFFILCOUNTRY,"United States"))AND(LIMIT-TO(PUBYEAR,2021 PUBYEAR,1986))).* From the larger pool 5,869 articles were included from the filtered search on geospatial information and habitat disturbance in the journals published from 1986-2021. Data for a specific region was also collected and some were analyzed in Vos Viewer to come up with a text connection map.

The creation of a text file comprising of 358659 words, including titles abstract and keywords of all the 5869 open access articles on the theme of geospatial assessment for habitat disturbance was created. Text data were cleaned at the same time eliminating publication details such as author name(s), publication dates, publication year, journal names, volume, page numbers. Each journal article was then examined using the following criteria a) spatial/non spatial and b) geographic region. After meeting each criterion, the article was given a score of 1.0 otherwise 0.0. Then the sums of the scores were used to infer trends in the literatures against time. All the data were cleaned, captured/recorded and processed in a Microsoft excel spread sheet for further analysis in R software.

2.2.3 Synthesis of literature

2.2.3.1 Temporal geographical distribution of habitat disturbance and geospatial systems studies

The observation was that 5,869 out of 39,678 published papers from the extracted journals investigated habitat disturbance using geospatial technology between 1986 and 2020. Most of the 5,869 were conducted in Asia (40.0%,2348 articles), followed by America (27%,1585 articles) and South America, (17.0%,997 articles). The rest of the region had few published articles with Europe, (8.0%,470articles), Africa (5.3%,311 articles) and Australia (4.6%,270 articles) as clearly illustrated in figure2.

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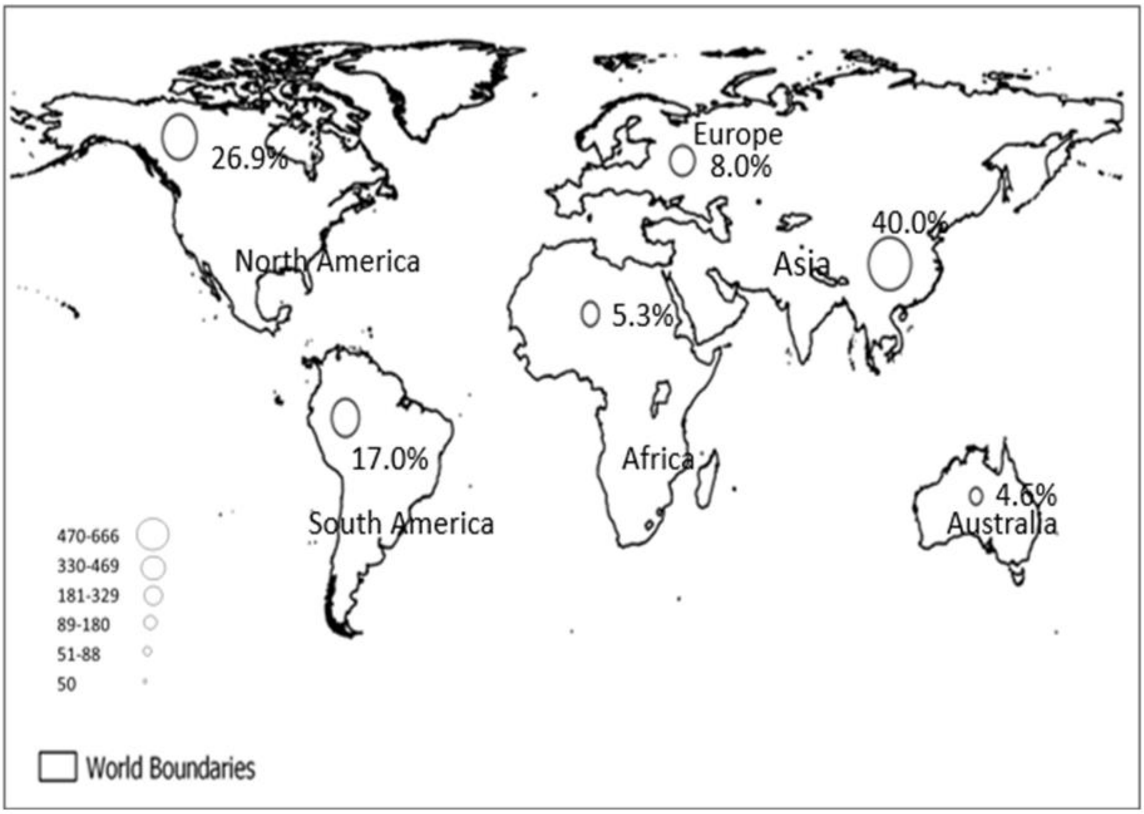

Figure 2.2: Spatiotemporal distribution of the foci on habitat disturbance and geospatial articles found using a search of ‘habitat disturbance’ AND ‘biodiversity’ OR ‘geospatial information’ AND ‘conservation’ spanning between 1986 and 2021.

Another observation is illustrated on figure 2.2, where there is a diagrammatic representation of trends of articles published between 1986 and 2021. Asia has the largest number of articles published but from 1986 to 1990 it is showing a delay in online publication. North America is a little bit advanced in terms of technology because its online publication started from way before 1986, the same applies to Europe, South America and Africa.

2.2.3.2 Regional Trends of habitat disturbance between 1986 and 2021.

For spatially weighted regional trend determination, spatial overlay analysis in Quantum GIS 3.18 was done with the aim to assess the spatial distribution of the themes of geospatial information and habitat disturbance across the globe for the 5,869 articles. The shapefile on the frequencies of themes was created and integrated through the spatial join function with the world map. To visualize the trends in the regions, line graphs were created in R software for each region against time between 1986 and 2021.

A non-parametric Mann Kendall test was run in R software in order to statistically assess if there is a monotonic upward or downward trend of the publication data from 1986 to 2021. This is a rank non-parametric test developed by Mann and Kendall (Kendall 1975, Mann 1945). In this test, the null (H0) and alternative hypotheses (H1) are equal to the non-existence and existence of a trend in the time series of the observational data, respectively. Man Kendall was used to run the predictive statistical test in order to observe the monotonic trend behavior in the publications for each region including Zimbabwe for the period of study.
A monotonic upward (downward) trend means that the variable consistently increases (decreases) through time, but the trend may or may not be linear (Gilbert 1987, Kendall 1975, Mann 1945). The results for Man Kendall test run in R, are found in table 2:1.

Table 2.2: Mann Kendall test for the global regions including Zimbabwe

Region	z	p-value	s	tau
North America	-4.93	0.0008	348	0.59
Asia	-7.31	0.0002	513	0.88
South America	-6.76	0.0001	476	0.81
Europe	-5.73	0.0009	493	0.69
Africa	-6.77	0.0001	464	0.84
Australia	-4.30	0.0002	404	0.69
Zimbabwe	1.97	0.048	117	0.27

Man Kendal results show that there is a monotonic trend over the years for European continent with m 0.0008, 0.0002,0.0001,0.0009,0.00016, Northern America, Asia, Southern America, Africa and Australia respectively (Table 2.2). Zimbabwe has a p-value of 0.048 which is less than 0.05 significance level. This shows that there is a monotonic trend in the publications that were done in Zimbabwe for the period study thus between 1986 and 2020, hence the null hypotheses that there is no trend in the publications that were done in Zimbabwe is rejected. This helps much in strengthening the gap in knowledge for Zimbabwe. There is a pattern which is exponential for the regions, but at country level there tends to suffer a lot of criticism. Zimbabwe was computed among the regions as a study area, and the results are reflecting that more needs to be desired.

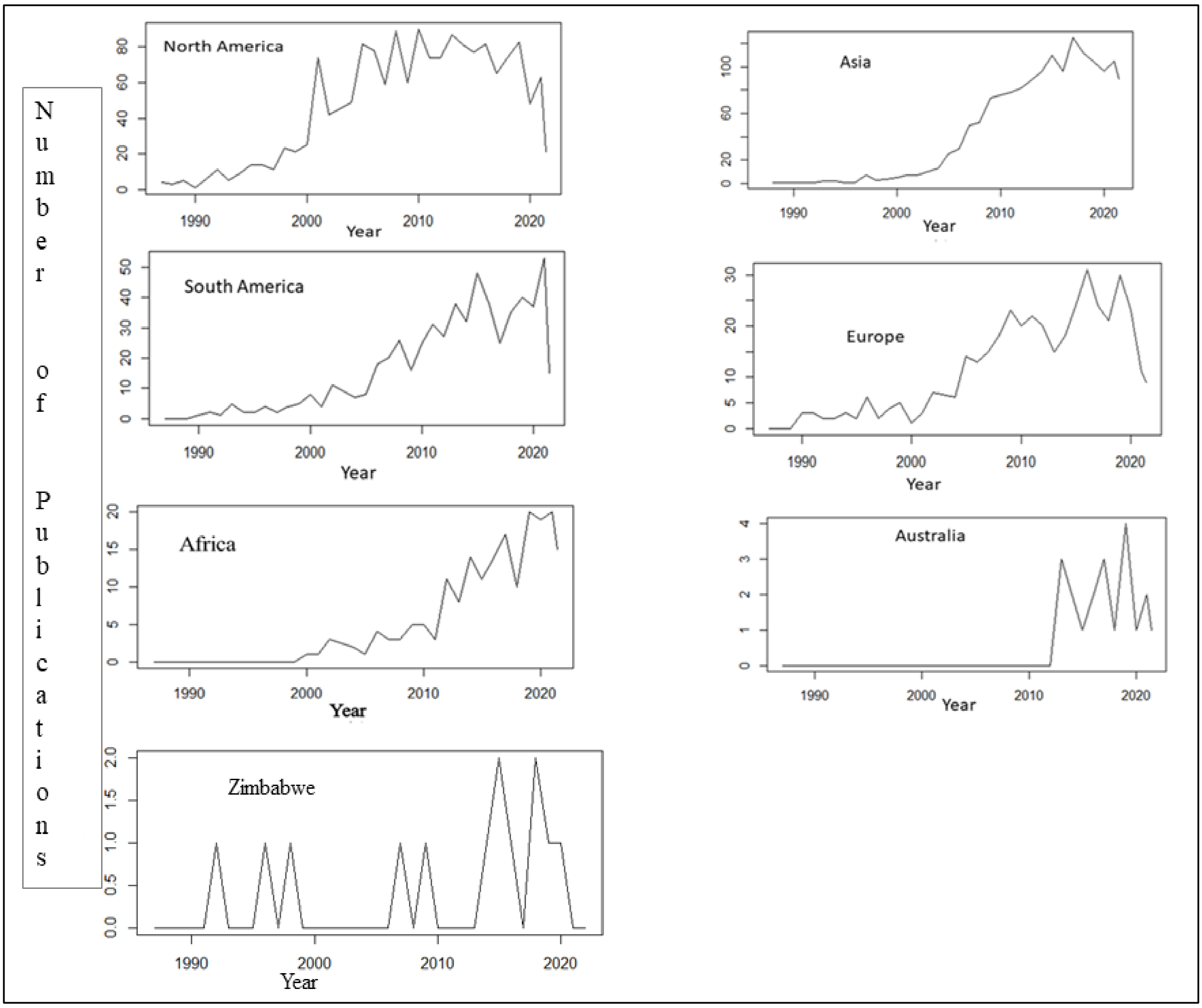

Figure 2.3: Trend analysis of literature at a global scale for a period between 1986 and 2021

From the analysis above, there is a relatively exponential growth rate in the publication of scientific articles on the theme of geospatial technology and habitat disturbance in a mining environment. For instance, in 1986, the studies constituted 0.11% of scientific articles on theme of Geospatial technology, habitat disturbance and mining in 1990 they were 0.27%, 2.03 in 2000, 4.83 in 2010 and 5.44 in 2020. This is consistent with previous results reviews which observed in some other fields like urban landscape ecology where there was an increase in the number of studies that applied the concepts and techniques of the ecology of landscape in disturbed areas (Francis et al. 2021, Wheeler and Neale 2013). This reflects the filling of an important gap in spatial ecosystems such as the need to advance in geospatial technology. The findings on the geographical distribution of studies were also consistent with some other studies although they are not well connected to the main focus of this study. Under the focus of this study little has been done so far and more attention is desired (Turner and Lambert 2005).

2.2.3.3 Networks of word clouds with heat signatures based on frequency of key words

The observation was that most of the articles connections range from 0 to -1 using standard deviation, showing how the search words were deviating from the mean. From the field of study, the observation was the range from -0.5 to 5 and that is the category where most of the search words on geospatial information and habitat disturbance fall in. (figure 2:4). This is also well described by the heat map on figure 2:5. These results concur with some other studies that did systematic review analysis using the networks of word clouds with heat signatures and they found out that there is less frequency on the search words that are specific to the focus of their study (Muderere et al., 2018).

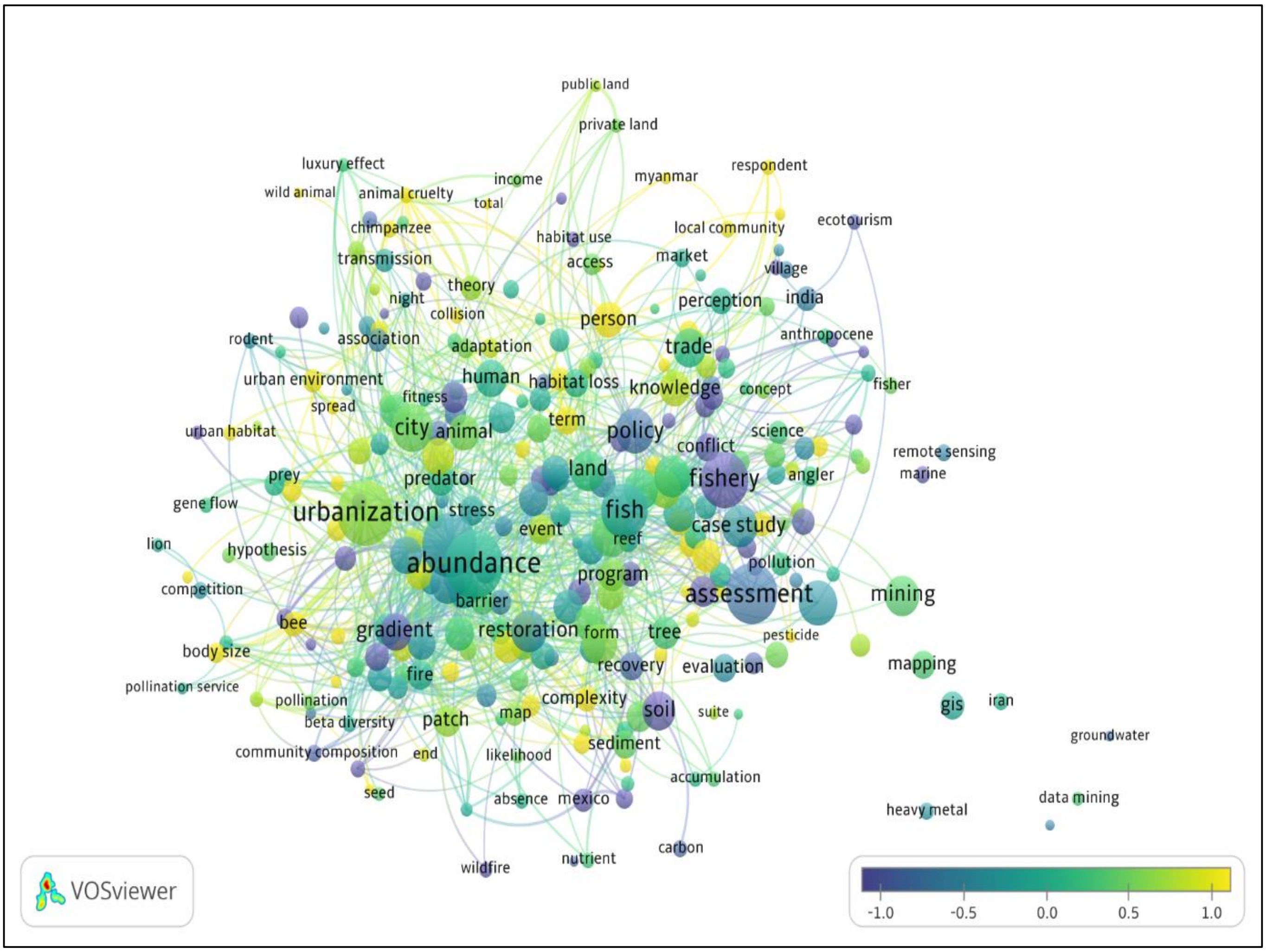

Figure 2.4: Co-occurrence networks of word clouds with heat signatures based on frequency of key words

2.2.3.3 Literature hotspot analysis based on frequency of key words

Literature hotspot analysis was done based on the text file with 358,659 words filtered from the 5,869 articles through the use of VOS viewer (*http://www.vosviewer.com*). VOS viewer is a machine learning open software tool for constructing and visualizing bibliometric and text networks maps which are scientific in nature (*Van Eck N and L. 2009*). It also offers text mining functionality which was used to construct and visualize co-occurrence networks of word clouds with heat signatures based on frequency of key words (*Van Eck N and L. 2009*). VOS viewer supports the novel mapping of citation data extracted from Web of Science, Scopus, Dimensions and PubMed among other databases

The observation was that most of the articles ‘connections range from 0 to -1 using standard deviation, showing how the search words were deviating from the mean (Figue 2.1). From the field of study, the observation was the range from -0.5 to 5 and that is the category where most of the search words on geospatial information and habitat disturbance fall in. (figure 4). This is also well described by the heat map on figure 6. These results concur with some other studies that did systematic review analysis using the networks of word clouds with heat signatures and they found out that there is less frequency on the search words that are specific to the focus of their study (Muderere et al 2018).

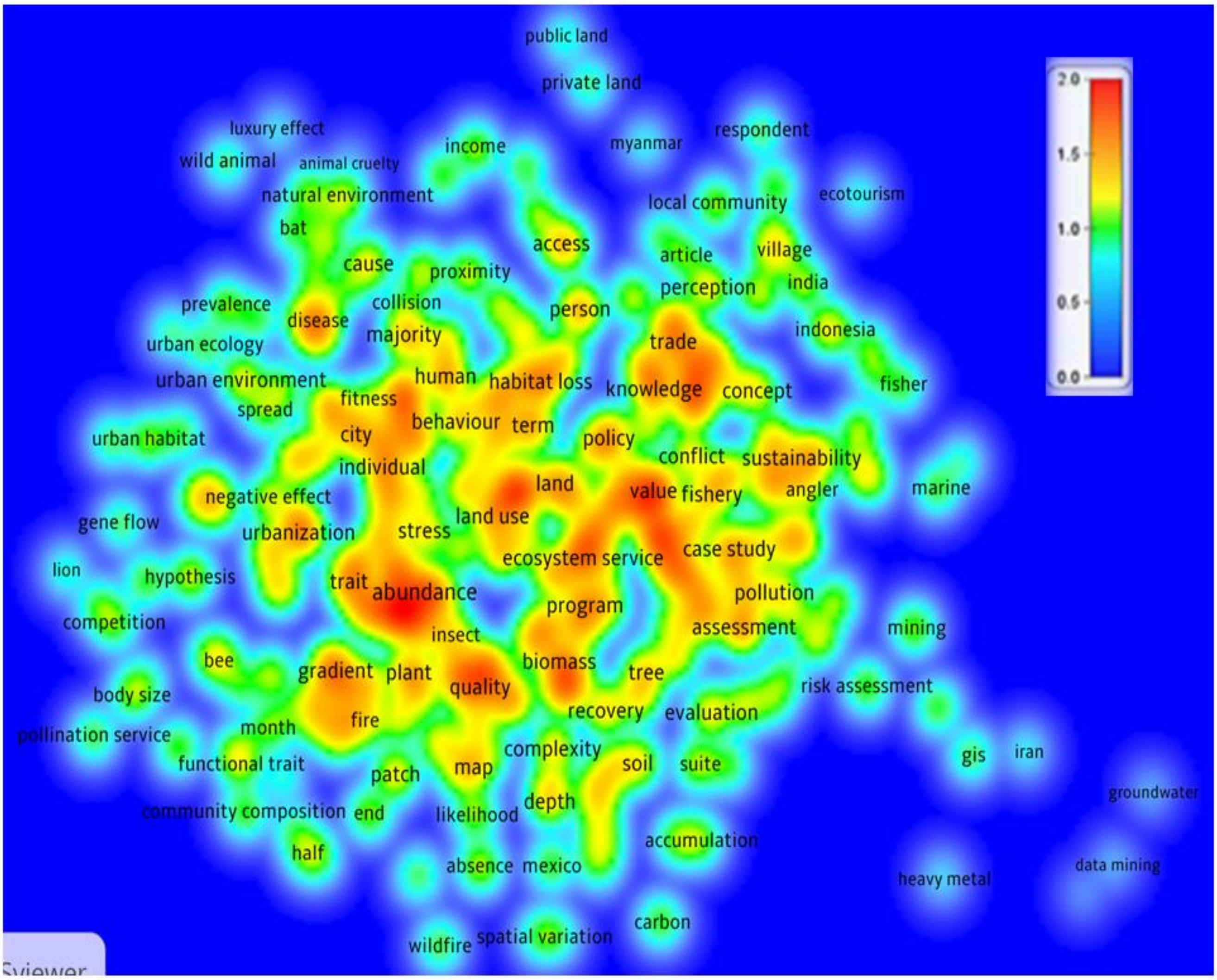

Figure 2:5: Heat map with frequency of key terms

Heat map (figure 2:5) shows frequency of key terms based on a text corpus of all the titles, keywords, and abstracts of articles of the geospatial information and habitat disturbance journals between 1986 and 2020 on a scale of 0 to 2 where 0 represents low frequency and 2 represents high frequency. Another observation was that, a total of 3944 non-Geographic Information Systems (GIS) and or Remote Sensing (RS) based studies and a total of 1925 were Geographic Information Systems (GIS) and or Remote Sensing (RS) based studies (figure 2.6)

2.1.3.3 Approaches and Methods in Geospatial technology and habitat disturbance in a human mediated environment

Two major approaches were observed thus, geospatial based studies and the Non spatial based approaches. There is a growing number of studies who are not integrating GIS and habitat disturbance studies in mining environments, and this indicates a limited but growing attention on the spatial aspect on habitat disturbance over the study period. This finding tally well with some other reviews on landscape ecology that found out that most of the studies of ecology have rarely used Geo technological approaches. On the other hand, it can be noted that while there is a small proportion of GIS based research, there cannot be a conclusion that the Application of GIS in habitat assessment in mining environments is limited. Some of the studies may have deliberately failed to mention GIS terms yet they did some GIS based mapping. While GIS can be regarded as an important tool for assessing habitats in mining environments, but it is not the only approach. Some other approaches such as experimental approach which does not requires GIS or complex spatial analysis.

Remote sensing is the art and science of acquiring information about some property of an object, area or phenomena which is not in physical contact with the objects or area under investigation (Ejigu 2016, Janssen et al. 2005, Mironga 2004). On the other hand, GIS is computerized software that stores, retrieves, manipulates, analyses and displays geographically referenced data sets, which can be used for different applications (Kanga et al. 2014, Kangas et al. 2018, Mironga 2004, Roy and Ravan 1996). There are two basic types of data that can be managed by GIS and these are known as geospatial data that defines the position /location of a feature or object on the ground and attribute data that describe the characteristics of these features. GIS has an analytical ability which can result in the generation of new information as patterns and spatial relationships are revealed (Milla et al 2005). Remote sensing data are being used to manage various types of natural resources and monitoring the dynamics of land-use/land-cover, which is a basic pre-requisite for planning and implementing various developmental activities (Murthy et al. 2003).

GIS and remote sensing provide land cover information and landscape characterization statistics on the assessment of habitat disturbance in a mining landscape (Milla et al., 2005). Intermediate disturbance enhances diversity although the species will be vulnerable to change (White 1979). This was well confirmed at a study undertaken in Schlabendorf which confirmed the explicit disturbance and fragmentation due to land cover changes are related to processes with strong relationships that affect habitat diversity in a mining environment (Odum 1985). Mining operations generate range of ecological and environmental impacts that can be measured spatially using geographic information system and remote sensing methods (Larson et al., 2004). A study done on the Spatial evaluation of land-use dynamics in gold mining area using remote sensing and GIS technology revealed that areas with low index values are susceptible to the impact of mining and other anthropogenic activities, whereas high-index areas connote little or no impact (Salem et al. 2003). Another study also reflected that a strong linear relationship (r^2>0.86) was found between NDVI and MNDVI (Modified Normalized Difference Vegetation Index)

The combination of various geo-technologies can be used to build very crucial systems which are currently being applied in the determination of priority areas for ecosystem conservation and restoration (Kohnen et al. 2001). The use of geo-technology is also important in the diagnosing of the sites which have a minimum resilience but high restoration potential, thus maintaining ecological processes and services as well as favoring biodiversity increase (Larson et al., 2004). Upon this background the technology will facilitate the implementation of restoration projects, increase environmental gains and decreasing costs and potentiating the regeneration of the natural environment. As of today, nothing has been done in Midlands Black Rhino Conservancy, Zimbabwe, pertaining the geo-technological approaches in the assessment of habitat disturbance. It is clear (figure 2.6) that GIS is a tool which is yet to gain a ground and people must use it to move away from the empirical methods of biodiversity and conservation management in mining environments.

Geo-technological tools are very important for the assessment of Net Primary production. Normalized Difference Vegetation Index (NDVI) is used for tracking the history of any place's vegetation dynamics (Goetz and Prince 1999). NDVI is derived from reflectance data registered by 'National Ocean and Atmospheric Administration and Advanced Very High Resolution Radiometer (NOAA AVHRR), which act as a surrogate measure of NPP (Wang, Ni, and Tenhunen 2005, Waring et al. 1998). NDVI can also be used to parametrizes models that may also accurately reflect actual changes in NPP and as well as quantifying its absolute amount (Reeves 2001). Net Primary Production represents the net flow of carbon to plants from the atmosphere and defines a balance between gross photosynthesis and autotrophic respiration (Field et al. 1995, Gower et al. 1999, Maisongrande et al. 1995). Upon this background, it is of paramount importance to apply geo-technological tools for assessment of primary productivity for the better management of ecosystems in mining environments.

Literature have suggested that advancements in geospatial approaches have opened the possibilities for understanding the spatial pattern of landscapes and the associated ecosystem patterns (Muderere et al., 2018). Some of the scholars have asserted that Geospatial technology have made it possible for researchers to analyze patterns and coexistence thereby strengthening the methodological rigor of studies (Legendre et al. 2002). The final assertion would be, Geo-technological based assessment of habitat disturbance in mining literature would be beneficial if there is the incorporation of geospatial analysis in its approaches (Legendre et al. 2002). Figure 2:6 shows number of articles found each year on Habitat disturbance and geospatial information found using the search ‘Remote sensing’ AND ‘Geographic information System’ between 1986 and 2020.

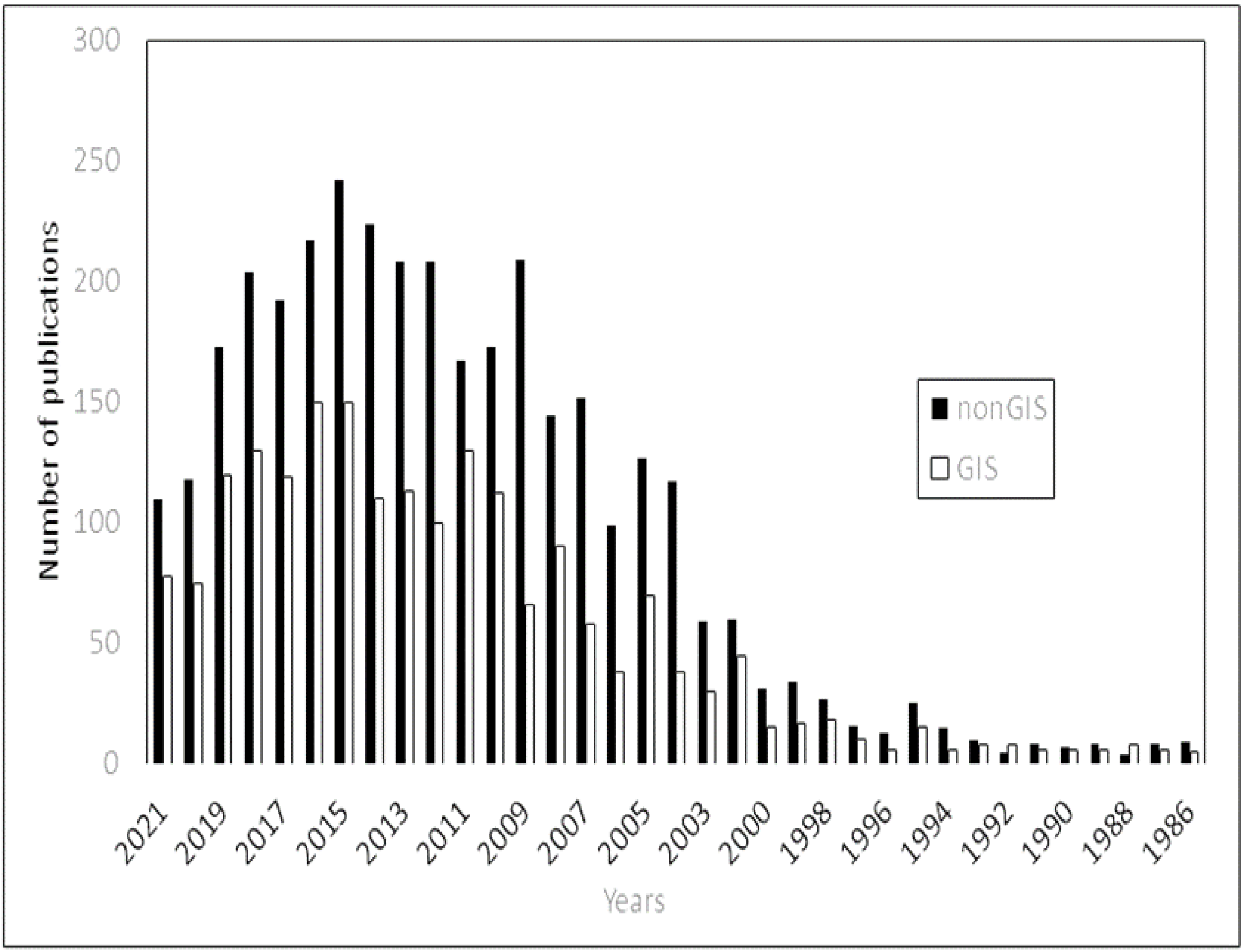

Figure 2.6: Trends of spatial and non-spatial articles from 1986 to 2020

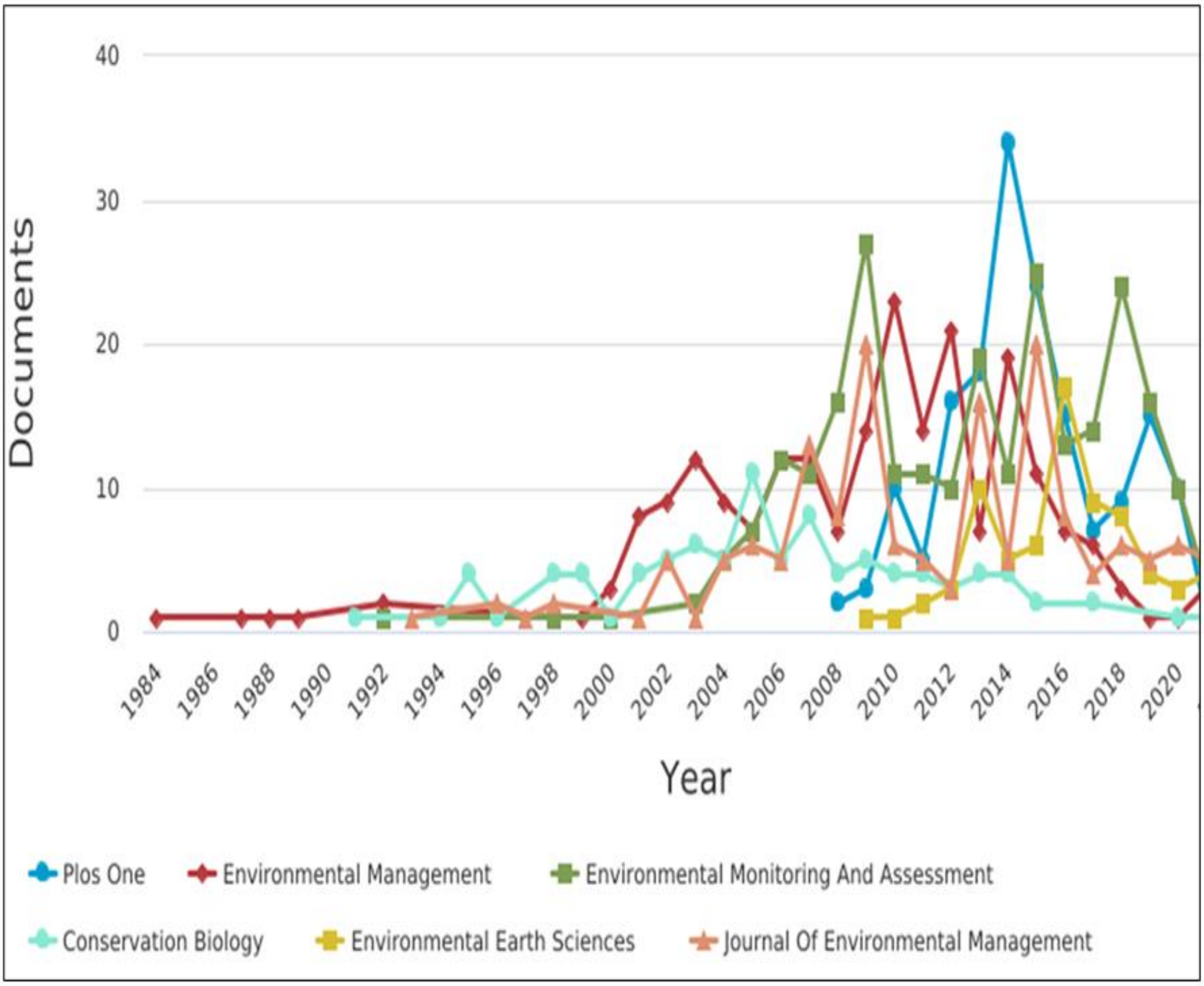

Figure 2.7: Journals with documents counts of up to ten sources by Elsevier in Scorpus. (source: Elsevier platform 2021)

The above is a line graph showing the counts of documents published in the area of study for the period of study. Journal of environmental management and environmental management journal are leading journals when it comes to publications in the area of study since they have been publishing for long as compared to Plos one and conservation biology.

2.3 Habitat disturbance

Habitat disturbance occurs when there is a change in conditions which interferes with the normal functioning of a biological system (Johns and Skorupa 1987). A 'disturbed habitat' is an ecological concept which indicate a temporal change in the conditions of the environment, which has pronounced changes in the ecosystem (Seltmann et al. 2017, Young et al. 2013). Disturbances are classified into two, human caused or natural. Disturbances which are anthropogenic related include cultivation, weeding, land clearing, digging, mining, burning among others. Natural disturbances include natural fires, lightning strikes and fires; temperature changes storms, strong winds among others (De Chazal and Rounsevell 2009, Jewitt et al. 2015, Kamdem et al. 2012). The relationships that exist between the changes in the environment and health is well known (Jewwitt et al., 2015). This has been documented by several scientific studies conducted in the past for both animal species and humans and vegetation, although little is known on the extent of habitat damage and the associated consequences in a mining landscape (Dobson et al. 2006, Mantyka-Pringle et al. 2015, Michelutti, Montagna, and Antonialli-Jr 2013, Nagendra, Reyers, and Lavorel 2013, Young et al. 2013, Jewitt et al., 2015). A study conducted in Matabeleland South Province, Zimbabwe on assessing the efficiency of mining frameworks and highlights on how institutions affect the management of other natural resources/ecosystem goods and services found that formal institutions have become a major catalyst in converting common property into an open access regime that is susceptible to the Tragedy of the Commons. The study also showed that the reigning status quo had negative effects on other rangeland-inclined ecosystem services and compromised the ability to effectively manage them (Dube et al. 2020).

Habitat disturbance is defined as the breaking up of a habitat, ecosystem or land cover types into smaller portions (Ramírez et al., 2013) which are called habitat patches. Habitat fragmentation is a major factor in the loss of biodiversity globally (Marvier et al., 2004).the two most significant effects of habitat fragmentation are a decrease in population size as well as reduction in species diversity (Huxel and Hastings, 1999). Disturbance regimes can be measured by using different indices, thus degree of fragmentation, fractal dimension, contagion, juxtaposition, evenness and patchiness(Withers and Meentemeyer, 1999). Scholars have suggested four general types of fragmentation indices that describe spatial pattern in habitat maps (Hargis et al., 1998). They are patch or habitat area, frequency distribution of patch size, measure of patch shape and length of edge between different habitat types. A decrease in the area of habitat patches decreases the survival probability of the populations in these patches. When the areas of habitat patches are reduced, there is increasing vulnerability of the conditions in the patches to external influences (Hobbs et al., 1993).

2.4 Mineral production as a driver to habitat loss and fragmentation

Mineral production has adverse environmental impacts which lead to challenges on sustainable development(Yang et al., 2018). The clearing of vegetation for mining and land occupation should be seriously considered since it is associated with ecological and biodiversity degradation (Murguía et al., 2016). Mineral production as an anthropogenic factor can transform the ecological system, therefore because of this; there is need for the development of a geo-technological system for biodiversity assessment to facilitate restoration of the damaged ecosystem.

The mining environment is characterized by mosaics of patches which are found in different stages although the effects of disturbance vary due to connectivity of these patches (Castilla et al., 2009). Differences in size, structure, contents, and history of patch mosaics characterize spatially heterogeneous areas which are defined as landscapes. There is need for an integrated spatio-temporal examination of disturbed biodiversity for proper management of the ecological landscapes.

Mining has a massive influence on the natural environment in Africa (Blum et al. 2015, Bolnick and Doebeli 2003). The effects of mining on habitats are in two ways, thus direct and indirect. Direct impacts occur within the immediate confines of the mining enterprise (Kamdem et al. 2012). Indirect effects are a consequence of external infrastructure, pollution among others. Mining activities can lead to the destruction of environmental habitats in the surrounding areas (Pourret et al. 2016). Clearing of land is the first process where the land above the mine is cleared of all obstructions in order to allow free space for the activity and it's clear that most mines are willing to destroy the entire forest to get access to mineral wealth (Bernhardt-Römermann et al. 2015). The process of clearing land yields several effects to the environment and among them are, all living creatures including births, crawling small animals, insects among others and all that depend on trees and plants for food or shelter lose their homes or starve to death. Any remaining survivors are forced to relocate and find a new dwelling (Pourret et al. 2016). The indiscriminate cutting down of tree can significantly affect the plants that rely on them for shade from the scotching effects of the harsh sun. Upon this background there is need to effectively assess the extent of habitat disturbance in a mining environment using geospatial technology.

2.5 Land cover change and biodiversity

There are a wide range of factors that drive loss in biodiversity and these vary among biomes (Mantyka-Pringle et al., 2015). Among the different drivers one of the main threat to biodiversity is change in land use and land cover of the whole system which result in the severe stress of vegetation, this can also be regarded a fragmentation. At a landscape level fragmentation, considers connectivity, ecotones presence and corridors as major factors. Fragmentation occurs due to many anthropogenic factors such as mining agriculture construction among others which all modify the greater part of the natural ecosystem.

Land cover change result in the isolation of species and increases the vulnerability of patches to disturbances (Françoso et al., 2015). Habitat disturbance by humans mainly result in the conversion of habitats from one type to the other and modification of conditions within specific habitats (Kamdem et al., 2012, Mantyka-Pringle et al., 2015, Nagendra et al., 2013). The houses of biological resources are natural ecosystems, but excessive uncontrolled human activities are rapidly depleting them. There is need for a development of a systematic way which will help in the proper assessment of habitat loss in a human mediated environment.

2.6 Spatial heterogeneity

It is well known that spatial heterogeneity is a natural phenomenon, the anthropogenic activities change the natural landscape by altering the abundance and spatial pattern of a habitat. The mining landscapes are more heterogeneous than the naturally occurring landscapes due to mine dumps (Hirons, 2011). The degree of spatial heterogeneity has a direct relationship with the total amount of habitat edge (Antwi et al., 2008). A complex relationship exists between disturbance and the heterogeneity of a landscape and this depends on the underlying environmental factors. The landscape disturbance may decrease or increase landscape heterogeneity whereas heterogeneity may inhibit or enhance spread of disturbance (Nagendra et al., 2013).

The purpose of this research is to undergo a geo-technological approach for the assessment of habitat disturbance and land cover change in a mining landscape, and specifically focusing on the assessment of disturbance on habitat diversity, predicting patterns of habitat diversity using GIS and remotely sensed data and to use geospatial technology to assess primary production.

2.7 Spatio-temporal landscape information in a disturbed environment.

GIS and remote sensing have been used as a strong tool for the surveying of natural resources and for better understanding of the process in which the natural systems operate. The patterns and distribution of vegetation and some other environmental phenomena can be accurately interpreted through satellite images (Vihervaara et al., 2017). Geospatial technology has tremendous potential for gathering large amounts of ground information about the environment (Dickson & Kapos, 2012).

Monitoring of land cover change using geospatial technology has been categorized as one of the main important component in current strategies for managing biodiversity dynamics and environmental change. There is wide use of remote sensing data in the provision of LULC information for environmental conservation (Naikoo et al., 2019; Naikoo, Islam, Mallick, & Rahman, 2022; Naikoo, Rihan, & Ishtiaque, 2020) .

A combination of GIS and remote sensing (Elagouz, Abou-Shleel, Belal, & El-Mohandes, 2020; Koko, Yue, Abubakar, Hamed, & Alabsi, 2020) detects and control land use/cover change in a way which is easier and faster than the traditional methods of monitoring land use/cover change . This study focused on spatio temporal assessment of the dynamics that occur in a protected area landscape where there is a combination of wildlife activities, agriculture and mining. Understanding these changes in a protected area setup has potential to improve land use planning and avert environmental challenges including biodiversity loss and species extinction. Information of land use /land cover is required for a wide range of planning purposes(Elagouz et al. 2020, Koko et al. 2020).

Land use planning was understood and still is a social process that aims at a sustainable land use and balance of interests in protected areas and some other territories (Naikoo et al. 2020).

The environmental condition of Midlands Black Rhino conservancy was very health before the advent of mining and agricultural activities. The protected area was endowed with vast wetlands, rich forest scenic beauty diversity of wildlife among others, hence the main motivating driver to carrying out this research.

Geospatial technology (GIS and Remote Sensing) have proved to be a very important tool in the ecology of the landscapes as well as in the mapping of disturbance zones in the ecosystem, quantifying the impacts on biodiversity as well as detecting change of land use/land cover in time and space (Wolters & Steel, 2020). To understand the cause and effect of disturbance on habitats there is need of a spatio-temporal assessment of land cover change (Tang, Fu, Wang, & Zhang, 2020). Previous studies have proved that the biodiversity of the terrestrial ecosystems is expected to be mainly affected by anthropogenic changes within the next century (Ge et al., 2019). Wolters and Steel (2020) also came up with research that helped much in addressing the issue of land cover /land use change within the context of global environment. For the past decades the research addressed a drastic and continuous change in the regional and climate variables such as temperature, rainfall, cloud cover among others (Yang et al., 2018). Upon this background the problem still remains on how the on-going changes affect the global ecosystems, biodiversity, landscape and cover changes.

The collective impact of land cover changes is regarded as the most important aspect of global environmental change despite the local and site-specific nature of the changes. Another researcher ascertained that; human beings are the key players regarding the dominant force behind global environmental change (Hackmann, Moser, & St. Clair, 2014). The research went on to address that the use of land by human beings has effects which amounts to 40% of net primary production globally and locally and this alters ecosystem services on terrestrial ecosystems (Hackmann et al., 2014). Midlands Black Rhino conservancy is a protected area in Zimbabwe where there is extensive mining of chrome which has been practiced for over a decade. In a disturbed environment like that, landscape patterns have a tendency of fluctuating widely over time in response to the interplay between disturbance and natural regeneration leading to change in biodiversity. The extensive mining of chrome in the protected area is changing the environment, land use potential and the aesthetic value of the landscape. There is damage over a large area due to mining although farming is another factor. Therefore, it is of great importance to do a spatial assessment of land cover changes in the area so as to address the extent of damage by these anthropogenic activities. Most of the studies which were done on mining focused on the post mining environments outside protected areas as well as in urban areas, so there in need to assess the damage caused by mining activities during the activities other than after the damage.

The spatio-temporal advantage offered by the technology specifically remote sensing images helps in environmental monitoring through the integration of spatially heterogeneous entities into measurable formats by quantifying spectral response at a specific scale over a specific time frame. Remote sensing has potential of extracting maximum information of an area in image format which can be effectively interpreted and this is accomplished through the differential reflection properties (Vihervaara et al., 2017). Images derived from remote sensing have the ability to provide critical information on a quite number of things, but this study focuses on damage assessment of the habitats in a mining landscape

Of particular importance to habitat disturbance is the need for a geo-technological framework/ system that can help in the assessment of habitat disturbance at various scales in an anthropogenic affected environment. The spatial analysis and modelling capabilities of GIS is of crucial importance in modelling habitats and, analysing gap in biodiversity and assessing degree of biodiversity conservation and planning (LaManna et al., 2017). Land fragmentation has have caused loss in habitat diversity and the corridors for their easy movement and migration. Patch characterisation is important to find out the relationship between diversity loss and some other parameters.

GIS is a powerful set of computer based tools which store retrieve manipulate analyses and display spatial data from the real world (Lü et al., 2019). It has one of its most powerful ability to examine spatially referenced objects over time. GIS has been found to be powerful tool for modelling purposes (Skidmore, 2017). The relationship that exists between processes and landscapes are spatial patterns that can be analyzed by a GIS. Of importance to this research is the development of a GIS system that can handle ecological landscape data in a hierarchical form. There are two main ecological roles of a GIS, and these are, it has a capability of locating features in space, associate them with their attributes for the development of new relationships between environmental features and associations between landscapes. Secondly, it effectively communicates diverse of information. GIS capability of modelling and spatial analysis make it useful in modelling habitats and conservation planning (Goodchild, 1994; Hinton, 1996). GIS is a very important computer based tool which helps in the assessment of habitat disturbance; the extent of spatial distribution of several species with the aim to determine biodiversity hotspots; past and present maps for monitoring land cover and land use changes. GIS helps with the provision of possibilities to extrapolate observations, for example, mapping and defining the potential habitat of a given species as well as comparing it with the locations where, it has been locally observed. GIS improves remote sensing information extraction capabilities, and it provides parameters for ecosystem modelling (Osborne, Alonso, & Bryant, 2001). The geospatial technology's potential in mapping zones of disturbance in natural ecosystem and the quantification of its implications on biodiversity have been proven and this has also been ascertained through the use of satellite imagery and high-resolution scanning data (Skidmore, 2017).

2.9 Land use land cover Change detection.

Land use and land cover are terms which are often used interchangeably, but they have different meanings. Land cover is defined as the surface ground cover such as vegetation, urban infrastructure, water, bare soil among others. Land cover is also defined as anything that occupy the ground, for instance, vegetation or man-made constructions. Bare rock, ice, water gravel, sand among other similar surfaces they all can be count as land cover. In other words, land cover can refer to the surface cover on the ground and the use of land normally depends on the type of cover of that particular land (Tang et al., 2020). Land cover identification helps in establishing baseline information for activities like thematic mapping and change detection analysis.

Another definition of land use is the purpose the land serves, for example, recreation, wildlife habitat, or agriculture. Some scholars define it as a series of operations undertaken on land by human beings mainly for gaining the services provided by the land (Naikoo et al. 2020. Furthermore land use can also be defined as the purpose saved by specific land (not the specific cover of the land), for instance agriculture, habitats, recreation among others (Knoke, Gosling, & Paul, 2020). If the two terms are used together with the phrase Land Use / Land Cover (LULC) generally refers to the categorization or classification of human activities and natural elements on the landscape within a specific time frame based on established scientific and statistical methods of analysis of appropriate source materials (Knoke et al., 2020).

It is very important to study land use and land cover because the images produced (LULC maps) play a significant and prime role in planning, management and monitoring programs at local, regional and national levels (Knoke et al., 2020). Furthermore, LULC information helps with the provision of better understanding of how land can be utilized, it also plays a very crucial role in the formation of policies and programs required for development planning. To ensure sustainable development, it is very important and necessary to monitor the ongoing process on land use/land cover pattern over a specific period of time. The changes that happen in poor ecosystem and the environment can be well understood through studying LULC maps. The provision and availability of information about land Use/Land Cover of the study unit allows researchers to can make informed decisions as well as policies and launch programs to save the environment.

With the advancements in remote sensing, monitoring networks, and geographic information systems (GIS), the availability of spatial data is rapidly increasing (Singh, Serbin, McNeil, Kingdon, & Townsend, 2015). The geospatial information includes not only maps and locations of land use and land cover (LULC), but also multiple attributes of data, such as socioeconomic data from some other sources. Improvements in the use and accessibility of multi-temporal, satellite-derived environmental data or other thematic raster data have contributed to the growing use in environmental modelling (A. Singh et al., 2015; Tewabe & Fentahun, 2020). LULC maps are known for their ability to provide information on natural resource management, baseline mapping for GIS input, legal boundaries for tax and property evaluation among others. LULC mapping is not possible without the help of other geospatial datasets (Tewabe & Fentahun, 2020). LULC mapping has been widely used to detect changes over time in management areas and varying spatial ranges (Rwanga & Ndambuki, 2017). This study is going to add knowledge in the LULC knowledge pool specifically on the understanding of the patterns and the extent of habitat disturbance in a human mediated environment. This is going to be achieved through the use of GIS and remote sensing technology.

Change detection is a process that measures how the attribute of a particular area have changed over time (between two or more-time periods) (Elagouz et al., 2020; Gandhi, Parthiban, Thummalu, & Christy, 2015). In summary of the explained concepts, change detection can also be identified as the process of identifying state of an environmental phenomenon through observing it at different time periods. It involves comparing satellites imagery taken at different times. It has been widely used for the assessment of natural disasters like cyclones, impact of earthquakes, land use land cover shifts among others over time (Gandhi et al., 2015; Hegazy & Kaloop, 2015).

2.10 Net Primary Productivity(NPP)

Net primary production is an indicator of carbon sequestration by terrestrial ecosystems (Imhoff et al., 2004). It is defined as the rate at which vegetation fixes CO_2 from the atmosphere (Gross Primary Production, GPP) minus the rate at which vegetation returns CO_2 to the atmosphere through respiration (DeLucia et al., 1999). It also represents the net carbon(C) input from the atmosphere into the vegetation for various political and historical reasons, vegetation data for mining landscapes in Zimbabwe is very difficult to access despite its obvious importance to the global system (Prince & Goward, 1995). This research used remote sensing and GIS for the estimation of NPP for the different patch mosaics that are found within the vicinity of three different mining areas.

Globally, NDVI has been used for the identification and interpretation of a a range of phenology metrics that describe periodic plant life-cycle events and how these are influenced by seasonal and inter-annual variations in climate and habitat (Lei, Ren, & Bian, 2016). The rate of change in NDVI may indicate speed of increase or decrease of photosynthesis (Seltmann et al., 2017). These metrics are influenced by several characteristics of the vegetation. One of the most important in remote sensing is the leaf area index (LAI) which refers to the projected area of leaves per unit of ground area (Fang, Baret, Plummer, & Schaepman-Strub, 2019).

Potential for the use of normalized difference vegetation index (NDVI) as a proxy for land productivity (one of the indicators of the state of land degradation) is based on numerous and rigorous studies that have identified a strong relationship between NDVI and NPP (Prince & Goward, 1995; Sala et al., 2000; Seltmann et al., 2017). Remotely sensed data products which are derived from the measurements from satellites come in several bands of the electromagnetic spectrum. Indices that are used to determine vegetation condition and other related indices, use bands in the visible and infrared wavelengths for instance NDVI. When using satellite-derived products, it is important to consider sensor and image characteristics such as: image size, region of the earth from which images are acquired, spatial resolution, number of bands and wavelengths detected, spectral characteristics of the bands concerned, frequency of image acquisition, date of origin of the sensor (Nischitha, Ahmed, Varikoden, & Revadekar, 2014). A very important consideration to put in mind when using satellite-derived products is the time of acquisition of such the data (time of the day, or season in question). Such temporal differences may give rise to alterations such as shadows (depending on the time of the day) or phonological differences (depending on the season) that may affect the quality of the data (Nischitha et al., 2014).

Through the observation of wavelength spectrum of sunlight reflected by plants (i.e. visible and near infrared light), a researcher is able to determine the density of green in a particular patch of land. The green coloring matter in plant, (chlorophyll), strongly absorbs visible light for the synthesis of its food at a wavelength of 0.4 to 0.7 mm. on the other hand, the plant leaf cell structure reflects near-infrared at a wavelength of 0.7 to 1.1 mm. If vegetation in a particular land patch reflects radiations in such a way that a significant level of radiation is reflected in the near-infrared wavelength (0.7 to 1.1 mm) than the visible light at 0.4 to 0.7 mm, then the vegetation is said to be dense vegetation such as forest. On the other hand, if the difference in absorption intensity of visible and near infrared is not high, the vegetation is sparse and not health.

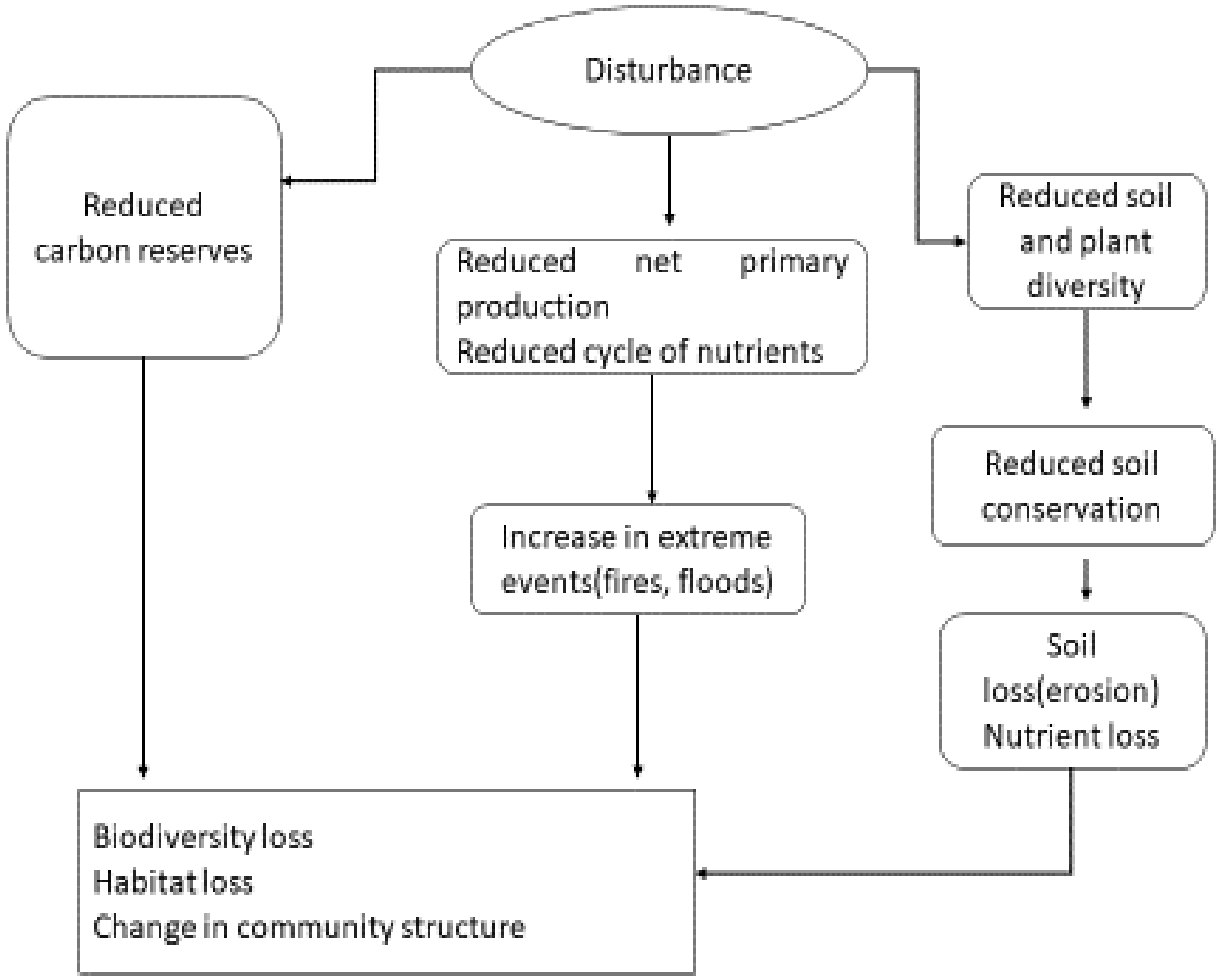

Figure2: 8 Conceptual framework showing effects of disturbance on vegetation.

The above conceptual framework helps well in understanding the procedures which lead to vegetation loss and low productivity. It is the disturbance that affect the ecosystem in any terrestrial or aquatic environment. Once vegetation, landscape as well as the soil is disturbed then low productivity follow. Disturbance can be in form of soil loss, overharvesting, clearing of trees, tilling of land among others. This reduces the amount of carbon stocks within the ecosystems hence leading to poor productivity, (thus biodiversity and habitat loss). This is the case with the Midlands Black Rhino Conservancy.

2.11 Estimating disturbance using landscape metrics

The changes in the landscape state in a protected area as a result of human activities such as mining, agriculture and logging can be detected by the landscape metrics values depicting land cover characteristics such as diversity and land cover change. The ecological changes within the changing ecosystem can be subtly presented using computed landscape metrics. A 'patch' is defined as each individual occurrence of a particular land cover type in the landscape. A 'class' is the occurrence of a specific type of land cover in a landscape (Bourne & Graves, 2001). There is an active connection between landscape metrics and the changing ecological environment within the biota. In order to compute landscape metrics. This study made use of remotely sensed images which were acquired from satellite imagery. Various rigorous studies have undergone research on different algorithms and mathematical formulations on landscape metrics mostly through the use of artificial raster data and or coarse grain satellite information (Hargis, Bissonette, & David, 1998).

There is a detailed and comprehensive choice of landscape information offered by patch analysts' plugin at patch, class and landscape levels. Patch analysist extension helps much in the calculation of spatial statistics on raster and vector files using Arc/Infor grids. Land cover maps extracted from satellite imagery or aerial photograph are used for computing landscape metrics. The mathematical formulation of landscape metrics has been intensively researched, mostly using artificial raster data or coarse-grain satellite information (Hargis et al., 1998).

There is a comprehensive choice of landscape metrics offered by patch analyst at the patch, class, and landscape levels. It calculates spatial statistics on both polygon files (vector format such as shape files) and raster files (e.g. Arc/Info grids) (Didham, 2010). It provides several basic landscape metrics depending on the format of the input map, vector or raster. Raster grid provides more comprehensive metrics as compared to vector grids. In spatial analysis of the landscape indices of shape, richness and diversity help much and they also provide additional information of the spatial distribution of land cover in a specific landscape. There is profound as well as rapid changes that occurred in protected areas which are suffering from anthropogenic activities such as mining and agriculture (Wang, Blanchet, & Koper, 2014). Protected areas are vast areas suitable for research focusing on the assessment of change detection of spatio-temporal patterns. A study done in the tropics examined the behaviour of landscape metrics through the generation of patches using GIS software controlling size shape and disturbance patches (Antwi et al., 2008). Table below is a representation of metrics used in this study.

Table 2.2: Landscape metrics used for the study

Landscape Metric	Indicators	Description	Range
Habitat Richness/ Number of Patches Fragmentation(NP)	Number of Patches NP	It is a measure of the extent of subdivision or fragmentation of the habitat type NP = 1 if there is a single patch	NP ≥ 1, without limit
Edge Density ED		It measures habitat length in a landscape. ED = 0 when the entire landscape and border, if present, consists of the corresponding patch type	ED ≥ 0, without limit
Patch /Habitat Size	Mean patch size	The range in MPS is limited by the grain and extent of the image and the minimum patch size in the same manner as patch area	MPS > 0, without limit
Mean patch index		measures the average patch shape or perimeter-to-area ratio.	

		MSI = 1 when all patches of the corresponding patch type are circular (vector). It increases without limit as the patch shapes become more irregular.	
Evenness Habitat Heterogeneity	Shannon Evenness Index (SEI)	It measures distribution of area among patch types SEI = 0 when the landscape contains only 1 patch (i.e., no diversity) and approaches 0 as the distribution of area among the different patch types becomes increasingly uneven. SEI = 1 when distribution of area among patch types is perfectly even (i.e., proportional abundances are the same).	0 ≤ SEI ≤ 1
Habitat Diversity	Shannon's Diversity Index	measures diversity in community ecology SDI = 0 when the landscape contains only 1 patch (i.e., no diversity). SDI increases as the number of different patch types (patch richness, PR) increases.	SDI ≥ 0, without limit
Evenness Habitat Heterogeneity	Shannon's Evenness Index	measures distribution of area among patch types SEI = 0 when the landscape contains only 1 patch (i.e., no diversity) and approaches 0 as the distribution of area among the different patch types becomes increasingly uneven. SEI = 1 when distribution of area among	0 ≤ SEI ≤ 1

		patch types is perfectly even (i.e., proportional abundances are the same).	

2.12 Framework for assessing habitat disturbance in a protected area using geo technological tools.

The protected areas of Zimbabwe and in the countries that are located in the sub-Saharan of Africa as a whole have been extensively affected and impaired by very extensive anthropogenic activities. Globally, many commitments were done by different countries in a bid to restore the damages attributed by human activities but not specific to protected areas. A national commitment to restore the gulf was done through an assessment of framework and associated indicators to try and characterize the health and sustainability of an ecosystem having the scale and complexity of the Gulf in Mexico (M. C. Harwell & Jackson, 2021). Below is a very good example of one of the frameworks which was developed among others.

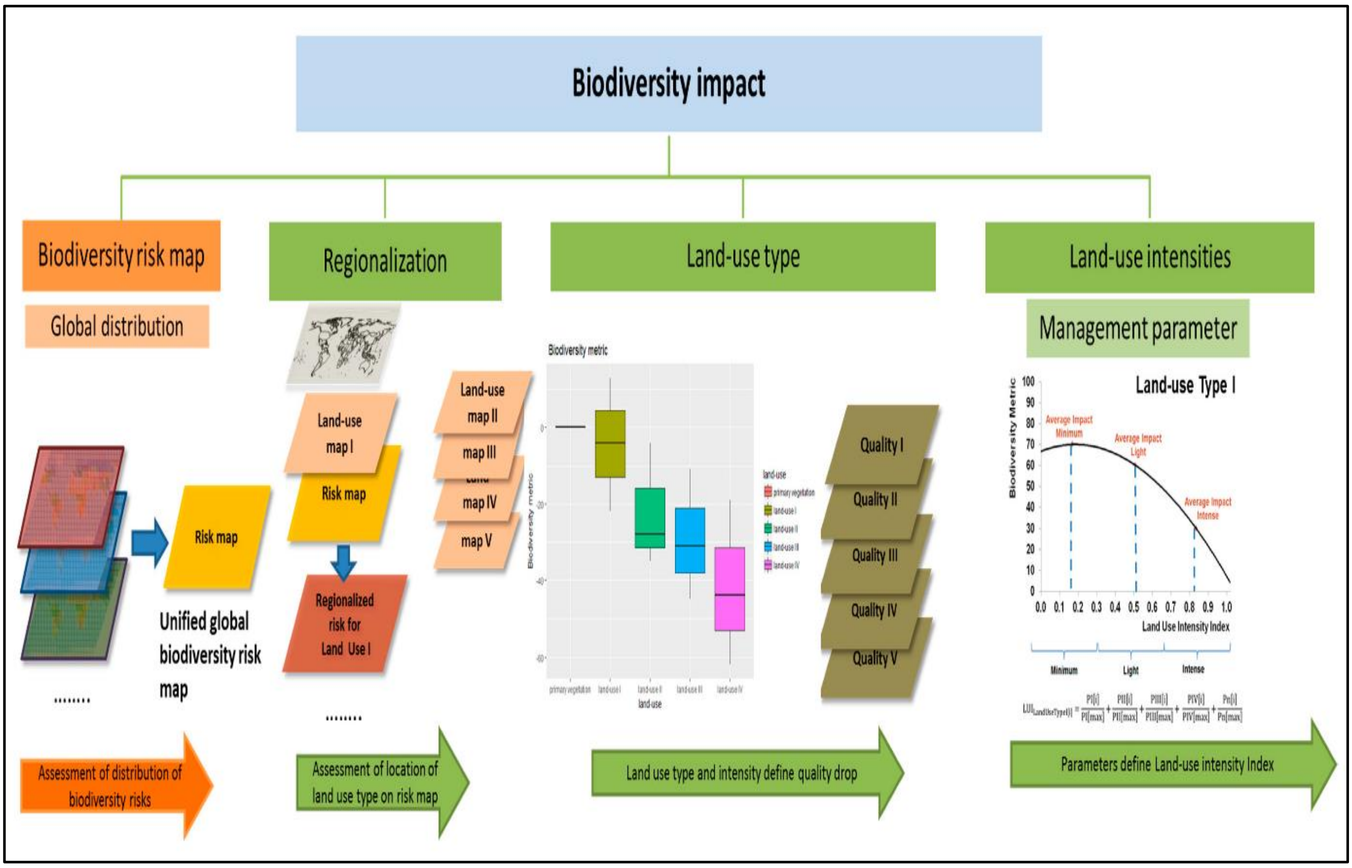

Figure 2.9: Framework for the impact of biodiversity at regional level. (source: Harwell et al 2019)

There is also another study which was done on the assessment of freshwater systems in lakes and the researchers came up with a framework which can help to assess habitat loss and ecological integrity in fresh water systems in Minnesota lakes where they present a Conceptual model of fish habitat in lakes with associated properties and disturbance drivers (Jacobson, Cross, Dustin, & Duval, 2016).

Protected areas around the world are facing extensive threats from different ecological stressors (Carpenter, Aldridge, & Boyce, 2010). There is habitat loss, species diversity loss, invasive species invasion, human disturbance and climate change which are threatening the integrity of protected areas around the globe (Dudgeon et al., 2006). The conservation of protected areas is of very paramount importance for sustenance of species populations and habitats. Wildlife in protected areas are important in that they help to boost the economic status of the country through trophy hunting. Trophy hunting has a potential of creating incentives for conserving habitat and ecosystems (Njerekai & Mabika, 2016). In most e developing countries, trophy hunting provides means of income, employment, and community development (Arnett & Southwick, 2015). African tourism has generated above 200 million revenues per annum (Odeku & Rudolf, 2019). The charged cost for 21-day lion hunt is approximately around US$ 20,000 to US$ 70,000, which is a huge amount which has a potential of increasing the GDP of any country involved (Lindsey, Balme, Booth, & Midlane, 2012). There is need of an effective geo technological based framework which will help to support different management strategies for protected areas.

2.13 Conclusion

The chapter revealed important gaps in literature as discussed above. The theme of habitat disturbance and geospatial technologies has limited citations which highlight it as an emergent theme in literature. Despite the limited number of citations, the available citations from the highlighted leading spatial journals showed that there shall be an exponential increase in publishing in the long run at regional level. There is a significant trend in the publications pertaining thematic concerns at global level as well as local as signified by the publication trends in Zimbabwe.

CHAPTER 3

MATERIALS AND METHODS

3.0 Introduction

This chapter describes the research methodology, delimitation of the study, the sampling design, data collection, data analysis, validity and reliability of the survey. The chapter also provides the background of the study area, the physical and socio-economic characteristics of the study area. The chapter also provides the design and sampling approaches as well as data collection methods used in a bid to achieve objectives. The chapter provides justification for using different tools methods as well as the approaches to analyzing the different types of data collected in the study. The different methods used depend on the scope, type, purpose and focus of the research topic as well as the specific context in which such research is undertaken. The researcher's belief about the world (ontology) and always knowing the world (epistemology) is also linked to the type of method employed (Winchester, 2000). This study was therefore developed to understand the utility of geospatial technological tools in the assessment of habitat disturbance in the Midlands Black Rhino Conservancy which is a conservancy.

3.1 Study Site

Midlands Black Rhino Conservancy (MBRC) was formed in 1987 to move the Black Rhino from the Zimbabwean boarder lying areas (Zambezi valley) which were being slaughtered by mainly cross border poachers. The idea was to make it difficult for the poacher to get to the animals. The area originally set up for this purpose was 63000ha which consisted of farmland and forestland.

MBRC is lying between 18 ° 58, 31 ° S and 030 ° 06, 62 ° E bounded by Munyati River and Mvuma-Kwekwe road on the north and south respectively (Figure 3.1). The midlands Black Rhino Conservancy lies in the third region of the agro ecological region of Zimbabwe's agro-ecological region 3 which is categorized under the semi-intensive farming region that receives a high total annual rainfall of between 650- 900 mm. The region is well characterized by mid-season dry spells and high temperatures in summer season with annual average minimum and maximum of 11.9 and 27.5^{o}C respectively, and an annual average of 21.1^{o}C (Makaure & Makaka, 2013). The area where the conservancy is located is suitable for drought-tolerant crops, livestock and semi-intensive agriculture.

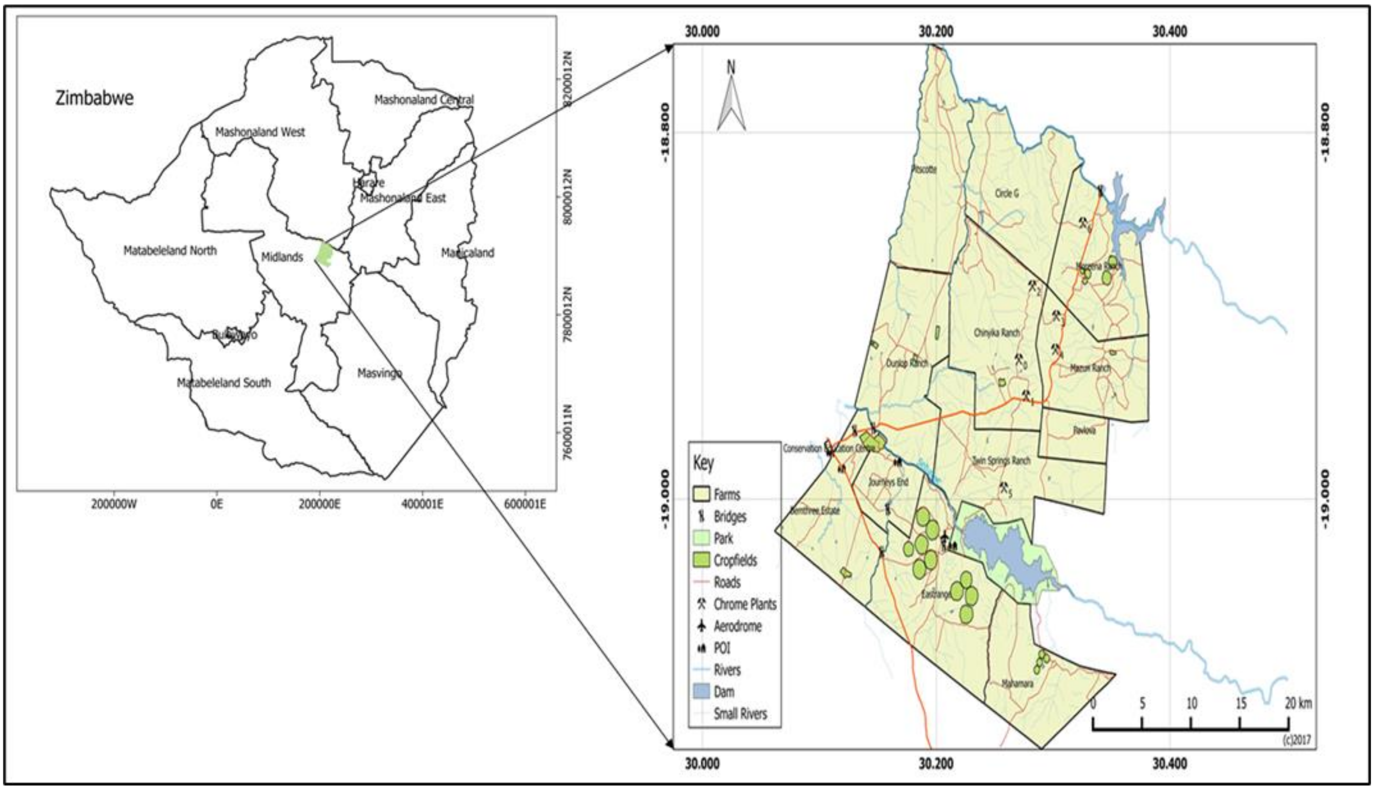

Figure 3. 1: Study area, Midlands Black Rhino Conservancy Zimbabwe.

The midlands Black Rhino Conservancy typically receives about 87 millimetres of precipitation and has 95.53 rainy days (26.17% of the time) annually. The wet season is always and mostly cloudy as compared to the dry season which is mostly dry and clear. The area is relatively warm all year round. There is a variation of temperature in the study area over a period of a year cycle. The hot season lasts for two and half months, from September 12 to November 27, with an average daily high temperature. The hottest month of the year is November, with an average high of 84°F and low of 65°F.The cool season lasts for 2.1 months, from May 31 to August 1, with an average daily high temperature below 74°F. The coldest month of the year in the study area is July, with an average low of 49°F and high of 72°F.The drier season lasts 7.7 months, from March 17 to November 7. The month with the fewest wet days is July, with an average of 0.1 days with at least 0.04 inches of precipitation. The rainy period of the year lasts for 6.6 months, from October 7 to April 27, with a sliding 31-day rainfall of at least 0.5 inches. The month with the most rain is December, with an average rainfall of 5.4 inches (Kundhlande, 2018; Makaure & Makaka, 2013)

The topography of place contains only modest variations in elevation, with a maximum elevation change of 210 feet and an average elevation above sea level of 3,984 feet. Within 10 miles contains only modest variations in elevation (797 feet). Within 50 miles contains significant variations in elevation (2,057 feet) (Chibanda, 2019).

Within the midst of the park lies the Sebakwe dam which is one of the largest inland dams in Zimbabwe. The dam lies on the eastern side of the Great Dyke among the Msasa woodlands within the Midlands Black Rhino conservancy. On the northern side of the dam lies a park where wildlife is being conserved. The Sebakwe river feeds into the Sebakwe dam and like the Ngezi River, the Sebakwe River flows to the west and has forced a narrow defile through the Great Dyke. Initially built as a small dam, an enlargement project was undertaken in 1981 with the main wall including the spillway being lengthened from 225 metres to 305 metres and the maximum height of the dam was raised to 47.2 metres. This dramatically increased the size of the lake and the maximum depth of the water increased to 39.4 metres and the surface area of the water body became 2,600 hectares making it one of the largest inland dams in Zimbabwe (Kundhlande, 2018).

3.2 Methodological framework

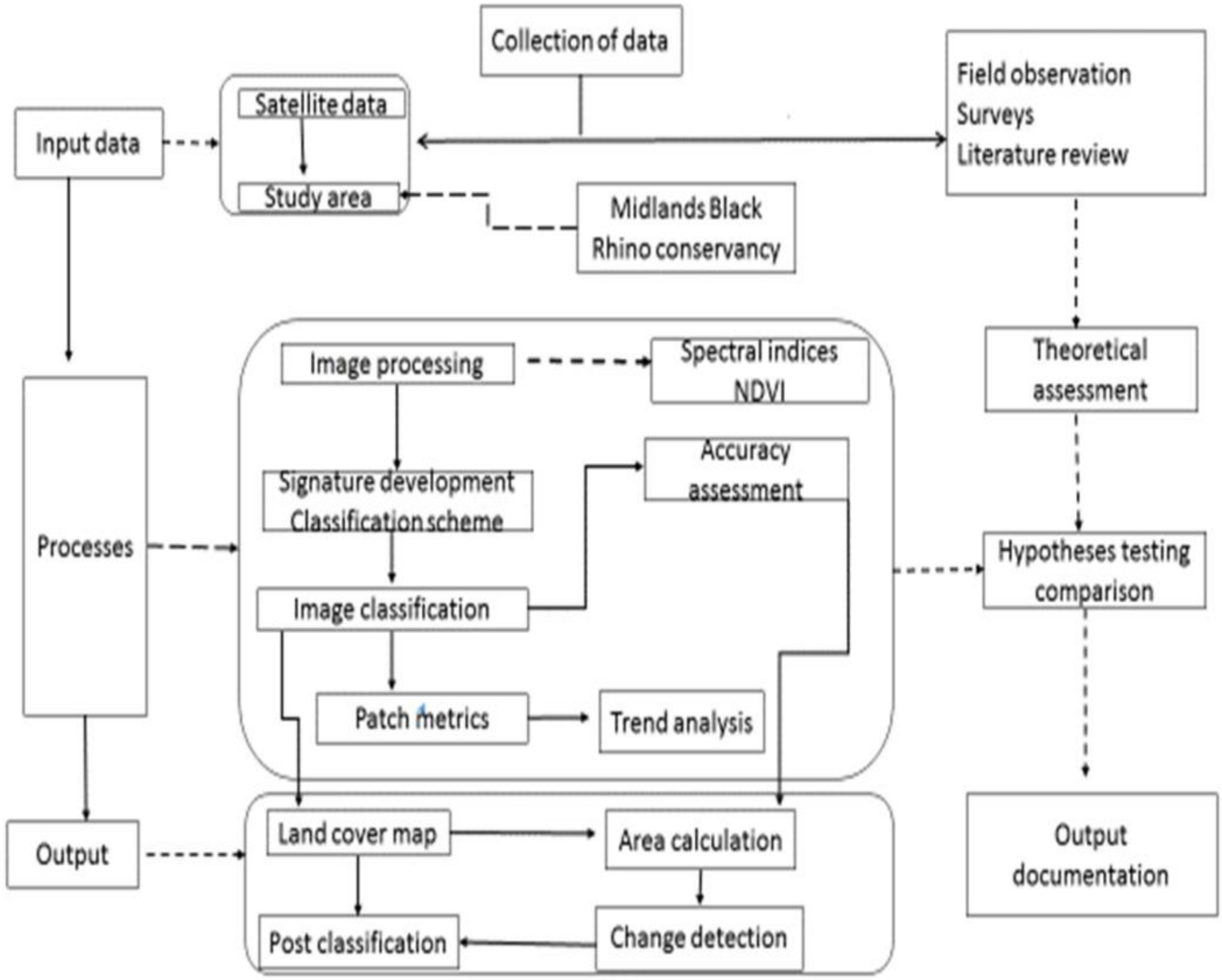

Figure 3. 2: Methodological Framework Used (Source: created by the author)

3.3 Primary Data collection

3.3.1 Field Data Collection and Measurements.

To acquire training samples, for ground truthing purposes simple random sampling design was used. A portable handheld Global Positioning System (GPS Garmin GPS 12) device was used for the collection of field sampling data points. The data was collected using the Universal Transverse Marketer (UTM) coordinate system (Zone 36S projection). Georeferencing was based on the WGS 1984 UTM. This was to conform to already georeferenced satellite images.

Simple random sampling (SRS) is the simplest form of probability sampling, where a series of random locations or samples are selected from a population of possible locations without constraint. SRS offers simple prescriptive calculations for the mean response at those locations (or for those samples) and thus straightforward statistical inferences. There is also flexibility to easily increase or decrease the sample size if required.

On the downside, SRS designs tend to yield clustered sampling units, implying that some parts of the population are represented more heavily (due to chance) than others. In other words, there is no assurance of spatial balance or regularity.

There is always an inhibitory effect on vegetation productivity or the accumulation of biomass in the landscape. This is mainly caused by the direct removal of plants and the destruction of stable ecosystems. Disturbance has direct effect on habitat diversity within a specific ecosystem (Antwi et al., 2008; Comberti et al., 2015). This is because disturbance is patchy and patches formed are characterized by varying size, shape, dispersion and internal heterogeneity. There is need to answer the question on the actual causes of disturbance. Is it the anthropogenic causes, natural causes or combination of the two? But it is mostly known that the activities of human beings’ catalyses’ the land cover changes since they are dynamic and the changes are more rapid as compared to natural processes which are rainfall dynamics and patterns as well as temperature variability (climate change which is one of the most factors which affect change in a landscape) (Alizadeh & Hitchmough, 2019).

3.4 Secondary data collection

3.4.1 Image acquisition and pre-processing

Firstly, the available Landsat 3, Landsat 5, Landsat 7 and Landsat 8 images for 1980 to 2020 were collected of the resolutions shown on table 3.1. The 30m resolution from Landsat is preferred because it is readily available and for free to the users unlike high quality spatial resolution images from sensors such as sentinel 2 among others which are very expensive and are not readily available for everyone (Li et al., 2020). Landsat data was also chosen because the images dates back to 1976 other than other sensors which are of high spatial quality but were launched recently. The images were collected based on the scene quality as well as the phenology thus based on minimum cloud cover as well as better plant or vegetation cover. Landsat images were calibrated/ processed and projected to Universal transverse Mercator (UTM) using the World Geodetic Datum (WGS 84 zone 36S) (Alhedyan, 2021; Li et al., 2020). The pre-processing of data was done through image mosaicking, radiation calibration, atmospheric corrections, image enhancement analysis of the data (Alhedyan, 2021).

Table 3.1: Image acquisition information

Sensor	Year	Date Acquired	Path/Row	Spatial Resolution	Cloud Cover(%)
Landsat 3	1980	15/05/1980	170/73	38x38m	0.22
Landsat 5	1990	10/05/1990	170/73	30x30m	0.5
Landsat 7	2000	06/05/2000	170/73	30x30m	0.00
Landsat 7	2010	25/05/2010	170/73	30x30m	0.02
Landsat 8	2020	17/05/2020	170/73	30x30m	0.00

The remotely sensed data was processed and projected to Universal transverse Mercator (UTM) using the World Geodetic Datum (WGS 84 zone 36). All the data were resampled to 30m resolution through the use of the cubic convolution interpolation approach which is a new technique used for resampling of discrete data (Alhedyan 2021, Li et al. 2017). Cubic convolution interpolation function converges uniformly to the function being interpolated as the sampling increment approaches zero. With the appropriate boundary conditions and constraints on the interpolation kernel, it can be shown that the order of accuracy of the cubic convolution method is between that of linear interpolation and that of cubic splines.

The pre-processing of data was done through image mosaicking, radiation calibration, atmospheric corrections, image enhancement before the classification of the images using ILWIS (The Integrated Land and Water Information System) and ENVI tool (Image Processing and Analysis Software Solution) (Keys 1981). In order to obtain high quality satellite images, data fusion can also be done through the use of STF (Spatio-temporal data fusion) method which is a method used for fusing satellite images from two sensors, with sensor one having high frequency but coarse spatial resolution such as MODIS and AVHRR, and sensor two having very high spatial resolution but lower frequency such as Landsat and Sentinel-2) (Li et al. 2017).

3.4.2 Land cover classification and accuracy assessment

For the mapping of habitat disturbance, the research borrowed some of the procedures from the terrestrial habitat classification schemes which provides a common language through which data can be stored and gathered (Jung et al., 2020). This study made use of supervised classification technique. This is defined as a machine learning technique where, the method "learns" from the training sample or dataset by iteratively making predictions on the data and adjusting for the correct answer (Takano & Alaghband, 2019). While supervised learning models tend to be more accurate than unsupervised learning models, they require upfront human intervention to label the data appropriately. This type of classification is characterized by its use of labelled datasets. These datasets are designed to train or "supervise" algorithms into classifying data or predicting outcomes accurately (Fan, Zhang, Wang, Huang, & Li, 2021).

Through the use of labelled inputs and outputs, the model can measure its accuracy and learn over time. Using this method, the training samples were selected and the images were classified based on the chosen samples. Training samples are important because they help in determining the specific class each pixel inherits in the overall image. After the selection of the training samples, the signature file was generated. The signature file is that which holds all the training sample data that collected up to this point. It's a way to save samples for to work on at a later time. After the creation of the signature file the maximum likelihood classification algorithm was run and the classification outputs were displayed. The research used Landsat satellite images from 1980 to 2020 to identify habitat types. The images were classified through the use of the supervised classification method in Arc GIS 10.8. The patch analyst extension in Arcmap was used to display information on diversity change, fragmentation and indication of disturbance through displaying landscape characteristic of the area.

The study used a series of five decadal images from 1980, 1990, 2000, 2010 and 2020, to do a trend analysis to check on the patterns of habitats over the 40-year period. This helps to reflect the changes that may have occurred over time in a changing environment. Classification was done in Arcmap and then change detection in Terraset/Idirisi and the final map layouts was done in QGIS.

In order to assess the accuracy of the classified images for the period of study, validation data based on ground truthing was set ground trothed data was collected using stratified purposive random sampling where the conservancy was divided into two parts, the northern and the southern section and then six points for each classification category were collected. The validation data was comparable to the measures derived from the remotely sensed images. The procedure followed the random generation of 250 points that were uniformly distributed across each cover map which were later cross checked with the reference data. The overall accuracy of greater than 85 % was accepted suitable for this study. Kappa coefficient and the overall accuracy assessments reports are shown on table 3.2 below.

Table 3. 2: The accuracy assessment for land use land cover change for the year 1980 -2020

Year	1980	1990	2000	2010	2020
Overall accuracy (%)	95.28	92.3	94.84	93.57	90.47
Kappa coefficient	0.89	0.88	0.85	0.90	0.86

High resolution images were used as reference images from google earth and visual interpretation was done using Landsat images as the reference images. The overall accuracy is higher than 92% which is followed by the kappa coefficients higher than 85%. Hence an important requirement for this research.

3.4.3 Land use and land cover change prediction

Cellular automata_ Markov (CA-Markov) in IDRISI (under Terrset 2020) was used to predict the land use land cover information in Midlands Black Rhino conservancy. The model has a potential to accurately simulate the dynamics in land cover in time and space through a combination of its ability to do chain prediction long time series and can precisely help in simulation of land use land cover change in time and space (Silva, Giannotti, & de Almeida, 2020; Singh, 2003). This model is a stochastic model mainly used for the modelling of land use land cover change (Gandhi et al., 2015). Theoretically, the use of Cellular Automata-Markov model for prediction means that the simulated period is equal to the inter-annual interval between the base and the end images used for the prediction (Alhedyan, 2021; Lei et al., 2016; Yanxia Liu, Huang, Qiu, & Fan, 2013). The model helps to describe the land use change over time as well as predicting the future trends in land cover change (Goetz, 2009). Cellular Automata has an advantage as a model in that it is simple and easy. It has an ability to perform spatial dynamics, and time explicitly and it can be considered as analytical engine of GIS. Raster GIS with map algebra can be integrated with enhanced capabilities (Cihlar, 2000; Goetz, 2009) .

Cellular Automata Markov model the different parameters and follow specific steps in predicting land use land cover change. It uses data format the technique of conversion and reclassification to obtain fixed land use types, the state probability matrix and the transfer, area matrix was obtained as well as transition image were all set. This research used a 5*5 filter which is a matrix space composed of 5*5 cells around each central cell. Following this, this research used Kappa coefficient as an error matrix in assessing the accuracies of prediction according to the actual images (Pöhlker et al., 2019; Poornima & Chinthaparthi; Zidan, 2015). This research is mainly focused on detecting and predicting land use land cover change and CA Markov is very useful in that it has high prediction abilities other than any other software. The base land use image of 2020 is used as the starting point for change simulation.

For the mapping of habitat diversity, the research borrowed some of the procedures from the terrestrial habitat classification schemes developed, especially the color codes (Brooks et al., 2019; Jung et al., 2020). It provides a common language through which data can be stored and gathered. For the images the research will use Landsat TM band which were pan sharpened or fused before the habitat classification is done. The study uses a series of five decadal images from 1969, of disturbance habitats 1979,1989,1999,2019, to do a trend analysis to check on the patterns of habitats over a 40-year period.

The data analyses were done in a GIS using Arcmap or Illwis and for object-based classification e-cognition was used. This was also done to find the error matrix. The confusion matrix was found by crossing the two different types of classifications and find the error which determined the extent of disturbance which a habitat has undergone. The study measured the area of the patch sizes for all the years from the conservancy and determine the extent of disturbance in terms of size, structure and connectivity.

3.4.4 Predicting patterns of habitat disturbance in a mining landscape

To determine the rates of habitat disturbance, a time series analysis was conducted using Idris GIS software using 5 different land cover maps for the entire period of study (1980, 1990, 2000, 2010 and 2010). Land cover maps were produced from a supervised classification technique of Landsat TM satellite imagery (Ullah, Ahmad, et al., 2019; Ullah, Tahir, et al., 2019). Training sample was used to identify water, crop fields and houses. The same algorithm was applied to all the images. The images were pan sharpened first and fused as well as resampled to have a finer resolution of the maps (Xie, Zhang, & Xue, 2019). The maps were used to calculate the area under each land cover type and to measure the rate of habitat disturbance.

3.4. 5 Assessment of vegetation productivity (primary production)

Images were acquired from the Landsat satellite sensor (Landsat 3,5,7 and 8 at 30x30m resolution except for Landsat 3 which was 38x38m spatial resolution). The images were collected based on the scene quality as well as the phenology thus based on minimum cloud cover as well as better plant or vegetation cover. Landsat images were calibrated, processed and projected to Universal transverse Mercator(UTM) using the World Geodetic Datum (WGS 84 zone 36S). Resampling was done to 30m resolution using cubic convolution interpolation method which is a technique used for resampling of discrete data (Alhedyan, 2021; Li et al., 2020). The pre-processing of data was done through image mosaicking, radiation calibration, atmospheric corrections, image enhancement analysis of the data.

3.4.6 Climate data acquisition

Climate data, primarily rainfall and temperature was acquired from the Climate Change Knowledge Portal (CCKP) (https://climateknowledgeportal.worldbank.org). The portal provides an online tool for access to a comprehensive country and global specific data related to climate variability and development. The portal provides high level information for specific countries including Zimbabwe. The data was downloaded as an excel file with mean monthly temperatures and rainfall for the forty-year period (1980-2020). The data was then filtered, sorted and exported to SPSS for further analysis.

3.5 Analysis of data

3.5.1 Trend analysis of classified parameters over the years

The study used a non-parametric method which is a mathematical way of analysis used in statistical hypothesis testing. The non-parametric test do not make assumptions about the frequency distribution of variables ready for evaluation (Kaur & Kumar, 2015). Non parametric type of experiment comprise of techniques that do not depend on data pertaining any distribution but rather, it is used on skewed data (Hussain & Mahmud, 2019; Mann, 1945). Several number of parameters and characteristics are not pre-defined and are very flexible, hence the name, distribution free models. Non parametric tests are normally used when data does not follow a normal distribution and are usually on an ordinal level of measurement. This research chose a non-parametric test because they can be easily understood, the assumption of distribution is not required and it is applicable to all types of data, although some researches have concluded that they are less efficient as compared to parametric tests (Rood, Foster, Hillman, Luek, & Zanewich, 2016). Non parametric tests are used when parametric tests have shown to be unsatisfactory, and when the data available is not scale related (Rood et al., 2016).

3.5.2 Mann-Kendal trend test

Trend analysis is known to be one of the most important measurements in studying time series data is trend analysis. This type of test incorporates both parametric and non-parametric tests but the two have different requirements as explained earlier. This research made use of the Mann–Kendall trend test (in R studio) which is a widely used a non-parametric test in the detection of significant trends in time series (Kendall, 1975; Mann, 1945). The MK Trend Test is used to analyse time series data to check on monotonic upward or downward trends (consistently decreasing or increasing trends). The test does not require the data to be normally distributed but rather have no element of autocorrelation. This type of test can be used in place of a parametric linear regression analysis, which can be used to test if the slope of the estimated linear regression line is different from zero. The regression analysis requires that the residuals from the fitted regression line be normally distributed; an assumption not required by the MK test, that is, the MK test is a non-parametric (distribution-free) test. This method has two known advantages of using it, firstly, it is a non-parametric test and does not require the data to be normally distributed. Secondly, the test has low sensitivity to abrupt breaks due to inhomogeneous time series. The data values are evaluated as an ordered time series. Each data value is compared to all subsequent data values.

The MK test factor in the hypotheses theory, with the null hypotheses being the absence of trend and the alternative being that having a trend. When the P value is < 0.05 its tells that there is a (monotonic)trend and if P value is >0.05, it tells no monotonic trend, away from monotonic trend. For time series $X_{1 \ldots,}\, x_{n.}$ The MK Test uses the following statistic:

$$S = \sum_{i=1}^{n-1} \sum_{j=k+1}^{n} sign\left(x_j - x_i\right)$$

Where:

Sign(x_j-x_k)=1 if $x_j-x_k > 0$

Sign(x_j-x_k)=0 if $x_j-x_k = 0$

Sign(x_j-x_k)= -1 if $x_j-x_k < 0$

A very high positive value of S is an indicator of an increasing trend, and a very low negative value indicates a decreasing trend. Rather, it is necessary to compute the probability associated with S and the sample size, n, to statistically quantify the significance of the trend.

The variance for MK Test of *S* is given by

$$var = \frac{1}{18}\left[n(n-1)(2n+5) - \sum_t f_t(f_t-1)(2f_t+5)\right]$$

where *t* varies over the set of tied ranks and f_t is the number of times (i.e. frequency) that the rank *t* appears.

MK Test uses the following test statistic:

$$z = \begin{cases} (S-1)/se, & S > 0 \\ 0, & S = 0 \\ (S+1)/se, & S < 0 \end{cases}$$

where *se* = the square root of *var*. If there is no monotonic trend (the null hypothesis).

The trend is said to be decreasing if Z is negative and the computed probability is greater than the level of significance. The trend is said to be increasing if Z is positive and the computed probability is less than the level of significance. If the computed probability is less than the level of significance, there is no trend (Alhaji, Yusuf, Edet, Oche, & Agbo, 2018).

For these tests, the null hypothesis H_0 is that there is no trend in the series. The three alternative hypotheses are that there is a negative, non-null, or positive trend. The Mann-Kendall tests are based on the calculation of Kendall's tau measure of association between two samples, which is itself based on the ranks with the samples. The computations assume that the observations are independent.

To assess the trend patterns in Midlands Black Rhino Conservancy, historic NDVI data was computed from 1980 to 2020. Mann Kendall Test was used to compute time series variation in R software. Graphs were plotted using R software with the aim to study the variations in these parameters (Alhaji et al., 2018).

3.4.1 Assessment of plant productivity

Based on spectral signatures, the earliest estimates of plant parameter (primary productivity) is normalized vegetation index (NDVI). NDVI is regarded as a vegetation index which is very reliable for detecting plant biomass accumulation within different habitats (Duncan, 2012). NDVI is also regarded as a very reliable indicator of surface disturbance (Parida, Sparsha, Bar, Pandey, & Kumar, 2023). Various field studies have applied and used NDVI for, monitoring of crop productivity, land cover classification and stress detection on crops (Murwendo, Murwira, & Masocha, 2021). High NDVI value determine health and dense vegetation while low NDVI values indicate sparse or unhealthy vegetation. Remotely sensed images were obtained from Landsat TM and Landsat legacy as well as Landsat 8 of the years 1980, 1990, 2000, 2010, and 2020 (theses were acquired during peak vegetation periods). They were masked in Arc Map environment. The masked layer contains amongst other bands, the Landsat band 4 or band 3 as well as Landsat legacy, Landsat 8 bands used were 5 and 4. The extracted bands were imported into Arc GIS environment where the raster calculator from spatial analyst extension aided the computation of net NDVI values. Thus, NDVI was calculated using the near infrared (TM band 4, red band 3) using the following formula:
NDVI = (NIR – R)/(NIR+R)

(Where NDVI is Normalized vegetation index, NIR is the Near Infra-Red band and R is the red band)

With the LANDSAT TM images, band 3 (red) was subtracted from band 4 (near infrared). The resulting layer was multiplied by 100. Band 4 (near infrared) was added to band 3 (red).

The (band 4 – band 3) was divided by (band 4(band 5 for Landsat 8) + band 3(band 4 for Landsat 8)) and the resulting layer was saved. The net NDVI values for each map year were estimated from the attribute tables.

The NDVI output layer now has values ranging from –1 to +1. Higher NDVI values represent a more active growth and primary production. NDVI values below 0 represent vegetation free surface to less active vegetation growth. NDVI is regarded as a dimensionless vegetation index which provides precise quantitative measure that indicates vegetation density in an ecosystem and is directly related to. photosynthetic activity and provides indirect measure of ecosystem health (Jensen, Bourgeron, Everett, & Goodman, 1996).

It should be noted that, though NDVI is a good measurable indicator, good measurements are best collected in summer and rainy seasons. Figure below shows healthy or dense vegetation that absorbs most visible light and reflects most near-infrared light radiations. Unhealthy vegetation, desert and sparse reflect more visible but less near infrared.

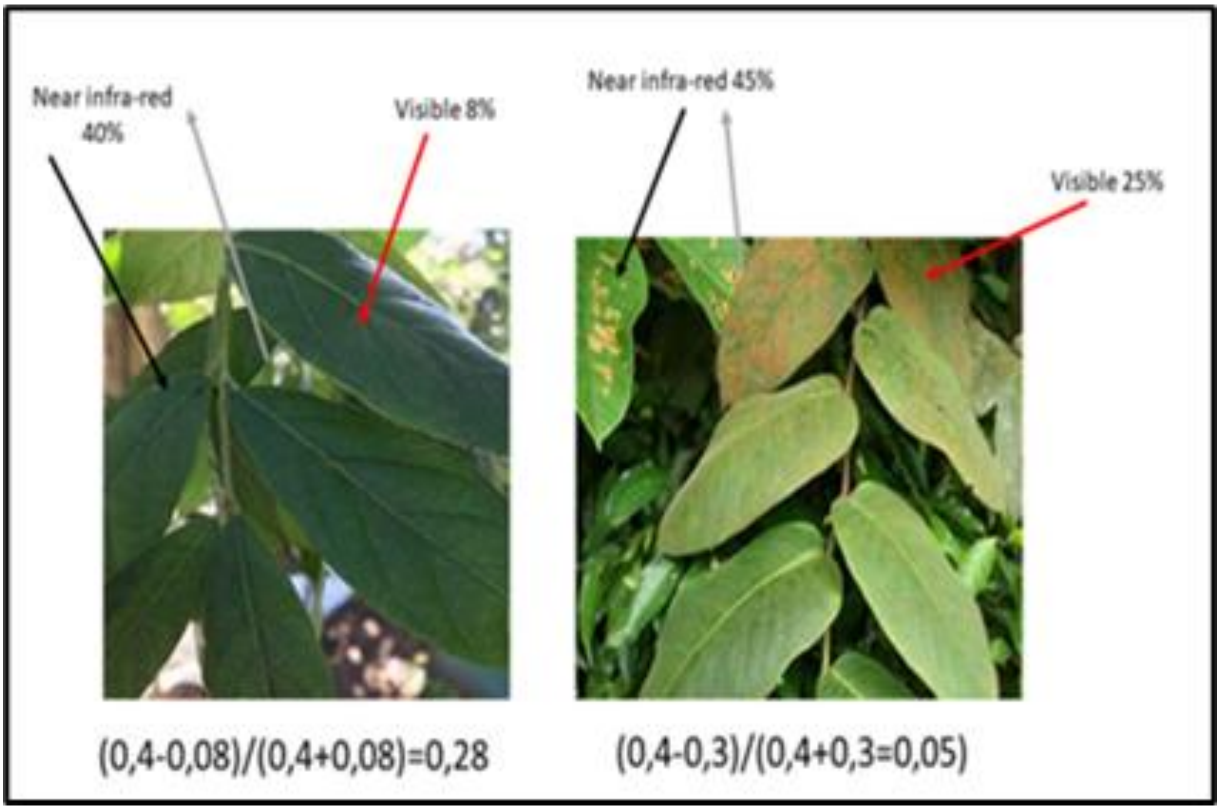

Figure 3. 3: Visible Light and Near-Infrared absorption by healthy and unhealthy Vegetation.

Through the observation of wavelength spectrum of sunlight reflected by plants (i.e. visible and near infrared light), a researcher was able to determine the density of green in a particular patch of land (Duncan 2012). The green coloring matter in plant, (chlorophyll), strongly absorbs visible light for the synthesis of its food at a wavelength of 0.4 to 0.7 mm. On the other hand, the plant leaf cell structure reflects near-infrared at a wavelength of 0.7 to 1.1 mm. If vegetation in a particular land patch reflects radiations in such a way that a significant level of radiation is reflected in the near-infrared wavelength (0.7 to 1.1 mm) than the visible light at 0.4 to 0.7 mm, then the vegetation is said to be dense vegetation such as forest. On the other hand, if the difference in absorption intensity of visible and near infrared is not high, the vegetation is sparse and not health. The NDVI attribute table was extracted from the map and exported as a CSV to excel workbook for sorting and cleaning. The data was then transformed and exported to SPSS for analysis. NDVI was plotted against the years for correlation analysis using polynomial regression analysis.

3.4.3 Response of NDVI to climate variables

To determine the linear association between NDVI observed over time in response to rainfall and Mean temperature, regression analysis was done in SPSS. The value range of analysis has a value between -1 and 1. Where: -1 indicates a perfectly negative linear relation between two variables: 0 indicates no linear relation between two variables and 1 indicates a perfectly positive linear relation between two variables. In this research we computed a linear relationship between the predictor and response variable by using simple linear regression. Generally, in order to assess the relationship between the two variables when having a dataset with one predictor and one responsive variable simple linear regression is normally used (Ostertagová, 2012).

Nonetheless, simple linear regression (SLR) assumes that there is an existence of a linear relationship between the predictor and response variable(Guisan, Edwards Jr, & Hastie, 2002). When written in mathematical notation, SLR assumes that the relationship takes the following form:

$Y = \beta_0 + \beta_1 X$

Contrarily in real practice, the relationship between the two variables can actually be nonlinear and the attempt to use linear regression can result in a poorly fit model (Ostertagová 2012). There is a way to account for a nonlinear relationship between the predictor and response variable, thus using polynomial regression**,** which takes the form:

$Y = \beta_0 + \beta_1 X + \beta_2 X^2$

3.4.4 Landscape metrics

This study adopted spatial statistics description of landscape metrics, where area and perimeter fields and values were added to the attribute table using the command 'Add Area/Perimeter' tab (Turner et al., 2003). To generate result in desirable units, the map units were set from the view properties dialog box. Every patch in the dataset had a unique record in the attribute table and boundaries of adjacent patches that belong to the same themes were dissolved. The core area theme was generated to do an analysis of interior of patches. The spatial analysis dialog box was used to generate landscape metrics and the appropriate theme and analysis level were selected.

3.4.5 Quantification of habitat disturbance using patch metrics

The landscape data to detect changes in diversity of habitat was carried out using remotely sensed imagery (LANDSAT ETM/TM) at a 10-year decadal period from 1980 to 2020. Land-over maps were acquired from satellite imagery. The land cover maps were divided into 5 minimum vegetation classes or land cover types depending on the dominant vegetation types in the area. The landscape pattern was calculated, and this was accomplished through the quantification of land cover structure, how it changes over time as well as the associated diversity of change. This was accomplished using statistical metrics (area density, size and diversity metrics will be used) which describe the composition of a landscape (Keane, Parsons, & Hessburg, 2002). Land cover statistics was calculated for each map year and the computing of landscape metrics were done using Patch Analyst for the entire landscape level (Guisan et al., 2002; Justeau-Allaire, Ibanez, Vieilledent, Lorca, & Birnbaum, 2023).

The study also conducted a patch analysis and this helped in giving a better understanding on how the landscape functions. The dimensions were established and estimates of areas, shape and frequency over a specified landscape analyzed. The measurement of the degree of regularity of proximity, dispersion and contagion helped to do an analysis of the spatial arrangement of a patch with other patches and all this was accomplished through the neighborhood concept (Of much help in the relative measurement of size and isolation of patches) (Guisan et al., 2002; Justeau-Allaire et al., 2023).

Patch metrics also regarded as the variability of statistical measures is a quantifiable standard indicator of biodiversity (Antwi and Wiegleb, 2008). The research made use of topology analysis from the vector environment and cell by cell from a raster data model all for spatial analysis. The vector data was used for the analysis of area and perimeter. The same resolution was kept with the aim to do a comparable spatial coordinate system. The land cover structure and the associated diversity over time was quantified using patch metrics. To accomplish this, area, patch density size edge and shape have been greatly used.

CHAPTER 4

RESULTS

4.0 Introduction

The basis of this chapter was characterized by the main thematic concerns of this study which was to assess habitat disturbance in a human mediated environment in the Midlands Black Rhino conservancy. This chapter present an outline of the results followed by a description of key findings for each study objective. The results presented on this chapter are on spatio-temporal landscape information in a disturbed protected area, patterns of habitat diversity and land cover change, extent of habitat disturbance using patch metrics and vegetation productivity in a protected area in relationship to environmental change.

4.1 Spatio-temporal landscape information in a disturbed protected area

4.1.1 Land use land cover change detection

From the results, the dominant land cover in 1980 was forest followed by vegetation then water, agricultural land and built-up. Bare land area decreased from 1980 to 1990 and most of the bare areas were occupied by vegetation in 1990. Land under cultivation (Agriculture) increased from 20% to 50% between 1980 and 2020 (Table 4.1). The area covered by water has been slightly increasing over the years as well. Built-up has the least area of them all which is increasing insignificantly throughout the study period. Forest land is decreasing over the years but in a monotonic way with 60%, 67%, 29%, 40% and 23 for the years respectively (1980, 1990, 2000, 2010 and 2020). Bare land has been increasing as for the years with 40%,31%,61%,48% and 51% from 1980 to 2020 respectively (Table 4.1).

Table 4.1: Land use/land cover change from 1980 to 2020, Midlands Black Rhino Conservancy

	1980		1990		2000		2010		2020	
Class	Area(Ha)	%	Area(Ha)	%	Area(Ha)	%	Area(Ha)	%	Area(Ha)	%
Water	300	0,5	500	0,84	1000	1,87	3000	5,02	5000	8
Forest	35107	60	40224	67	15560	29	23865	40	13799	23
Bare land	23712	40	18533	31	35873	67	28654	48	30314	51
Agriculture	415	0,7	426	0,71	1000	2	4202	7	10676	18
Built-up	20	0,03	30	0,05	35	0,07	40	0,07	50	0,08

The above is also representation of a transition from 2000 to 2010 in Midlands Black Rhino Conservancy which is a protected area where mining and agriculture is a business. The dominant land cover in 2000 is bare land followed by shrinking patches of vegetation. Maybe the reason behind that is the drought which occurred in 1999/2000 season which left most parts of the conservancy bare (Figure 4.1). The land cover changed in 2010 with most of the bare parts found on rocks along the mountain range. The rest of the conservancy is covered with vegetation and the lake has increased with 5%. This is because of the better 2009/2010 season which saw increased amount of rainfall in the country and the region of study. The bare areas away from the mountain range where there are few rocks describe the presence of mining areas. The agricultural plots have slightly increased and some of the areas that were agricultural areas in 2000 have turned to bare land (Figure 4.1).

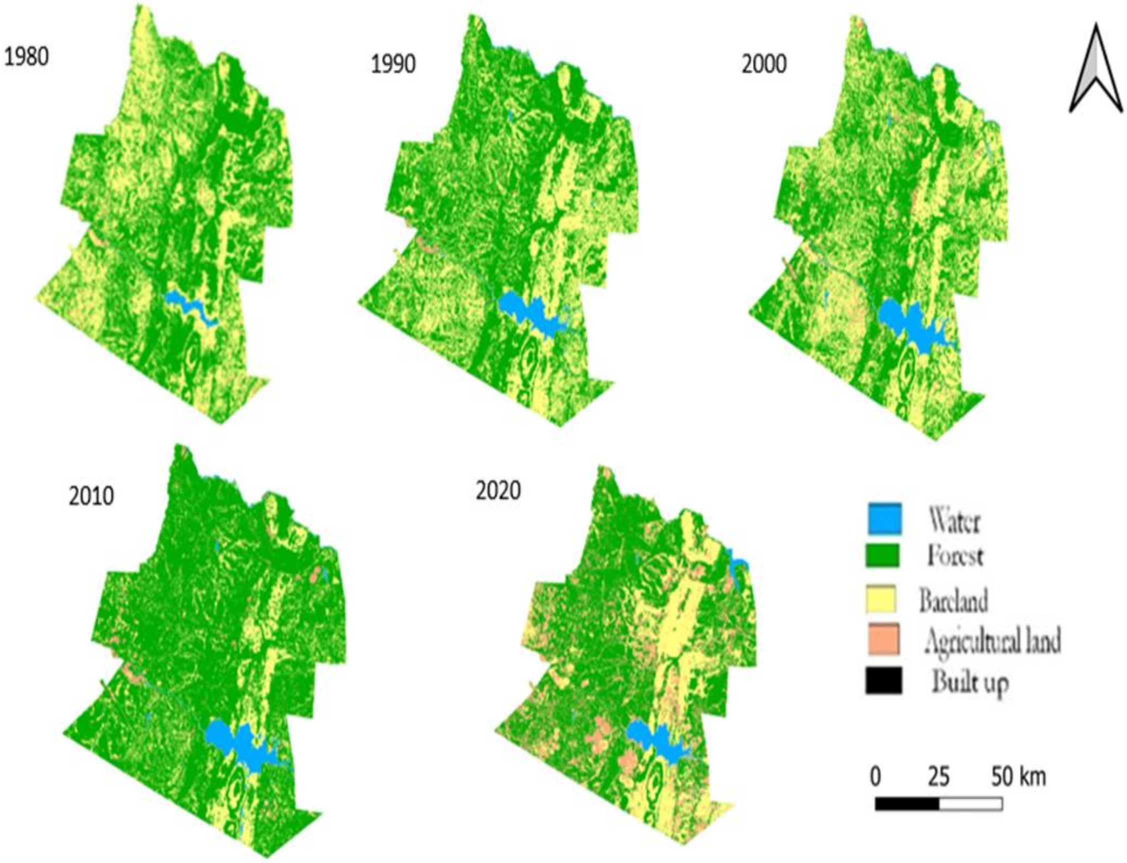

Figure 4. 1: Land use/land cover change maps from 1980 to 2020

For the period under investigation (1980 – 2020), forests patches in the conservancy, show a decreasing trend over time (Figure 4.2). The vegetation is changing over time because of factors such as farming and mining. Bare land is increasing as illustrated on the line graph followed by a remarkable increase in agriculture.

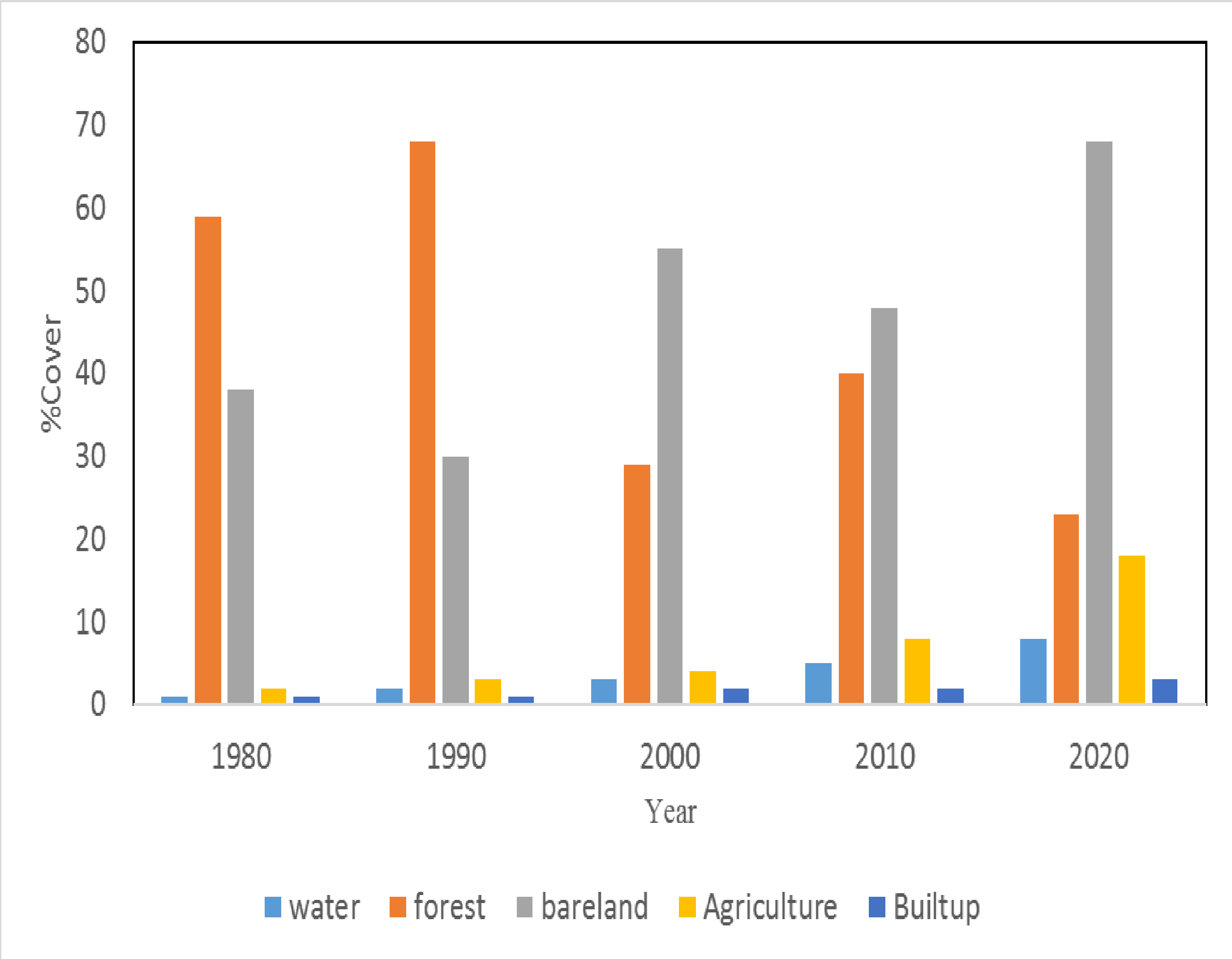

Figure 4. 2: Percentage of and use land cover change for the period 1980 - 2020.

4.1.2 Trend analysis of land cover change

Trend analysis of vegetation productivity in Midlands Black Rhino Conservancy was done using a forty-year vegetation productivity data from 1980 to 2020. Mann-Kendall was used to determine the trend (figure 4.3) which show the NDVI for the study period.

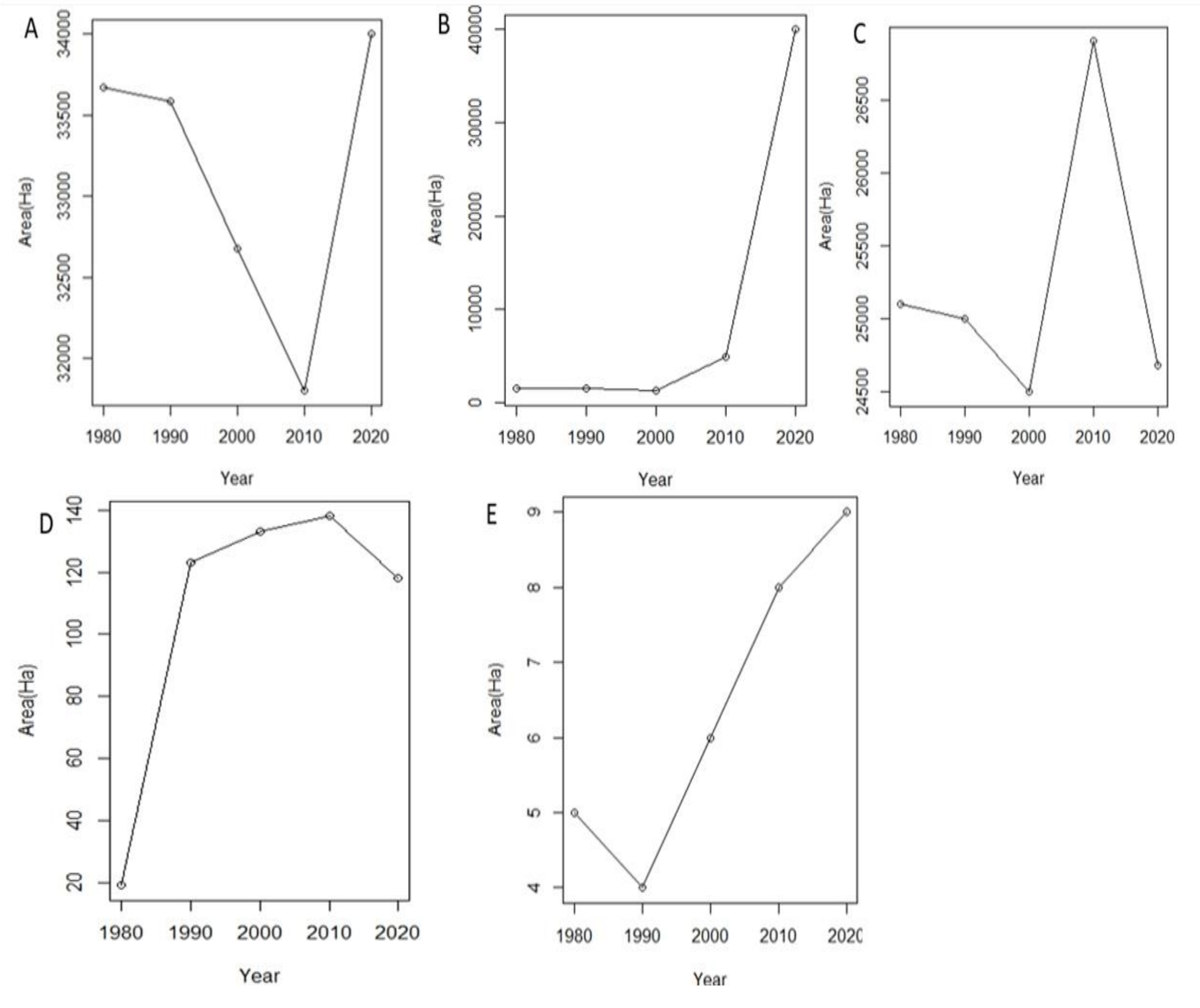

Figure 4. 3: Trend analysis of land use land cover classes from 1980 to 2020

(A is Bare and Mining Agriculture, B is Agriculture, C is Forest D is Water, E is Built-up,)

The results on figure 4.3 (A) show a generally increasing trend from 1980 to 2020 of bare and mining area. There is a gentle increase in the area from 1980 to 1990. The year 2000 saw a decline in bare and mining activities up until 2010 which marks the minimum level in the decline in mining related activities. There is a very sharp and abrupt increase in the bare and mining activities from 2010 to 2020as shown on the graph (Figure 4.3 (A)).

From figure 4.3(B), the results show the presence of a constant increasing trend from 1980 to 2020 for agricultural areas within the conservancy. There is a constant decrease between 1980 and 1990 in area occupied by the agricultural land. The graph abruptly changes taking constant increasing shape between the year 2000 and 2010 then saw a sharp increase in 2020.

For forest cover (figure 4.3 C), the results show a highly fluctuating trend from 1980 to 2020 for forested area within the conservancy. There is a fluctuating trend over the years as signified by the graph. There is a sharp increase in the area covered by forest in 2010. This explains the application of sustainable forest management strategies in the conservancy that saw a remarkable increase in forest area. Then the year 2020 saw a decline in forest cover in the conservancy maybe because of the introduction of more anthropogenic activities within the park following a dry season as well.

The results above show a generally increasing trend from 1980 to 2020 of surface water (Figure 4.3D) bodies. These results are projecting a sharp increase in the area covered by water from 1980 to 1990. The graph shows a negative change between 2010 and 2020 in area occupied by water though it is insignificant.

There is generally an increasing trend in the area occupied by built-up over the years. There is a decreasing trend in the area occupied by built-up between 1980 and 1990. From 2000 across to 2020 the area occupied by built-up changes sharply up until the year 2020 as shown on the graph (Figure 4.3F).

4.1.3 Trend test

Table 4.2: Mann Kendal Test for Land use land cover classes

Land cover Class	z	p-value	s	tau
Water	0.73	0.462	4	0.4
Forest	-0.02	0.806	2	-0.2
Agriculture	1.22	0.221	8	0.6
Built-up	1.7	0.09	8	0.8
Bare and mining	2.20	0.03	10	1

The p-value for Mann Kendall test for water for the period from 1980 to 2020 was 0.462. Following the MK test hypothesis theory with the null hypothesis being having no trend and the alternative being having a trend. 0.462 is greater than 0.05, (not less than <0.05). This result depicts that there is no monotonic trend for the period of study, hence the null hypotheses that there is no trend in area covered by water for the years is true therefore it is accepted and the alternative hypotheses that there is a monotonic trend in the area covered by water is rejected.

Factoring in the hypotheses theory, with the null hypotheses being, having no trend and the alternative being that having a trend. The P value for forest cover for the period of study from 1980 to 2020 was 0.806 which is greater than 0.05. This tells no monotonic trend, away from the monotonic trend. With these results the null hypotheses that there is no a monotonic trend in the changes in area covered by forest for the period of study is accepted and alternative hypotheses that there is a monotonic trend in forest cover for the years is rejected.

The Mk trend test for Agriculture which is one of the land cover classes was found to be 0.221 which is greater than 0.05 level of significance. With these results the null hypotheses that there is a monotonic trend in the area covered by agricultural areas for the period 1980 to 2020 is accepted. The alternative hypotheses that there is a monotonic trend in the area covered by agricultural areas for the period of study is rejected.

The area covered by built-up had shown no significant relationship with time. Following the MK test which factor in the hypotheses theory with the null hypotheses being having no trend and the alternative hypotheses being the opposite of null hypotheses. The P-value for Built-up land cover class is 0.09 which is greater than 0.05 significance level. The null hypotheses are accepted following these results and the alternative hypotheses that there is a monotonic trend in area covered by Built-up area is rejected.

The area covered by Bare and Mining areas show a monotonic trend following the hypotheses theory that there is no monotonic trend for the null hypotheses and there is a monotonic trend saved by the alternative hypotheses. The p-value for the MK test run was 0.03 which is less than 0.05 level of significance. This test saves as an acceptance of the null hypotheses that there is no trend in the area covered by Bare and mining area. The alternative hypotheses that there is a trend in the area covered by Bare is rejected.

4.1.4 Predicting Land use land cover change

There is a significant change indicated by the simulated results in Midlands Rhino Conservancy. The vegetation cover has decreased from 35107 ha in 1980 to 10397 ha projected for 2030. Bare land is increasing in a rapid way from 23712 ha in 1980 to 40567 ha in 2030.The area covered by water is expected to increase slightly by 5.4 % in the year 2030 as shown below (Table 4:3).

Table 4.3: Projected Land use/land cover change

	1980		1990		2000		2010		2020		Projected2030	
Class	Area(ha)	%	Area(ha)	%	Area(ha)	%	Area(ha)	%	Area(ha)	%	Area(ha)	%
Water	300	0.5	500	0.84	1000	1.87	3000	5.02	5000	8	3670	5.4

Forest	35107	60	40224	67	15560	29	23865	40	13799	23	10397	15
Bareland	23712	40	18533	31	35873	67	28654	48	30314	51	40567	59
Agriculture	415	0.7	426	0.71	1000	2	4202	7	10676	18	13788	20
Built-up	20	0.03	30	0.05	35	0.07	40	0.07	50	0.08	57	0.08

The results of the simulation and prediction done in Idrisi indicate an expected increase in bare land and a decrease in forest land as well as an increase in agricultural land. Given the condition that the factors that affect change such as climatic events, political interventions among others have not changed over the years they are likely to affect the predicted outcome of Land use/land cover change in the area. The validity of the simulation using a multiple base resolution statistical algorithm which measure the agreement and disagreement between the images was done using the Kappa statistics with accuracy exceeding 90% (table 1.1). Kappa statistics measures the association or agreement that exists among the images (Fathizad et al. 2015, Lu et al. 2019, Razavi 2014). The predicted maps for Midlands Black Rhino conservancy were produced based on the Land use/land cover maps of 1980-2020, and the later year was used for validation and comparison. There is a high agreement between the predicted 2020 map and the actual map as shown on figure 4.4, hence revealing that CA-Markov is one of the proper models for future land use/land cover prediction.

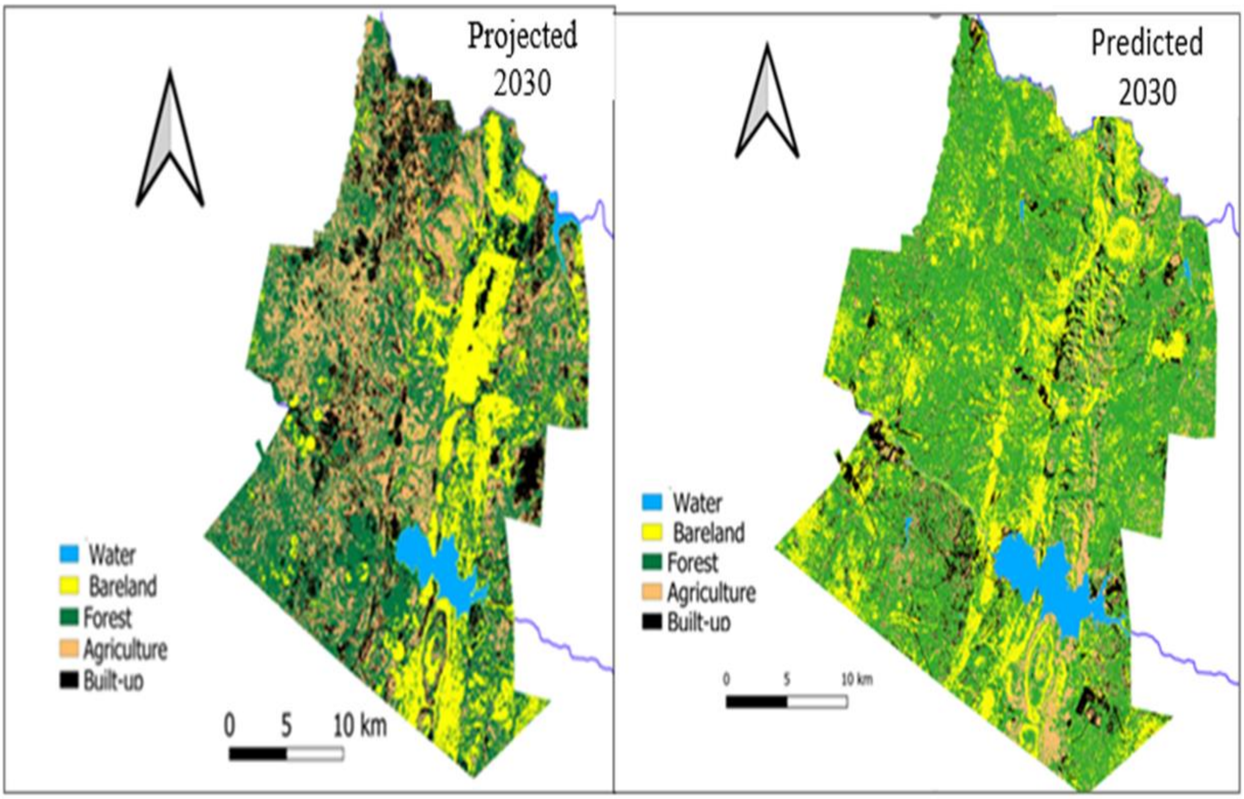

Figure 4. 4: Projected and predicted maps for 2030

4.2 Determining Vegetation Productivity

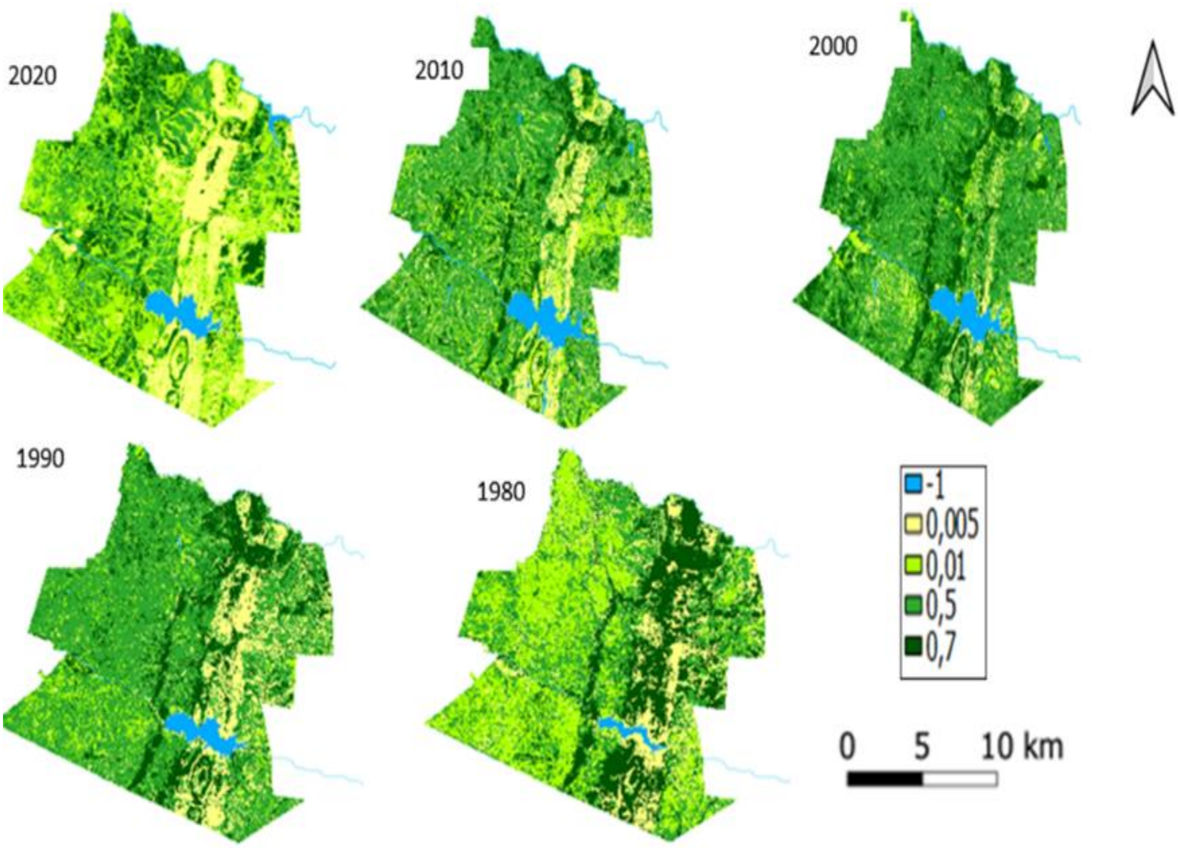

Figure 4. 5: NDVI maps from 1980 to 2020

The NDVI results are showing a range between -1 to 0,7. The year 1980 is signified by low average NDVI which range from -1 to 0,01 which is an indication of very low productivity for the year. The year 2000 is characterized by very high NDVI values which range from 0,5 to 0,7. In 2010 within the same protected area as the place saw a remarkable decrease in vegetation productivity. The decrease was signified by a fall in the NDVI values which were ranging from -1 to 0,5. The year 2020 is another year which has low productivity despite good seasons that have occurred from over a ten-year period from 2010

4.2.1Trend analysis of NDVI over time

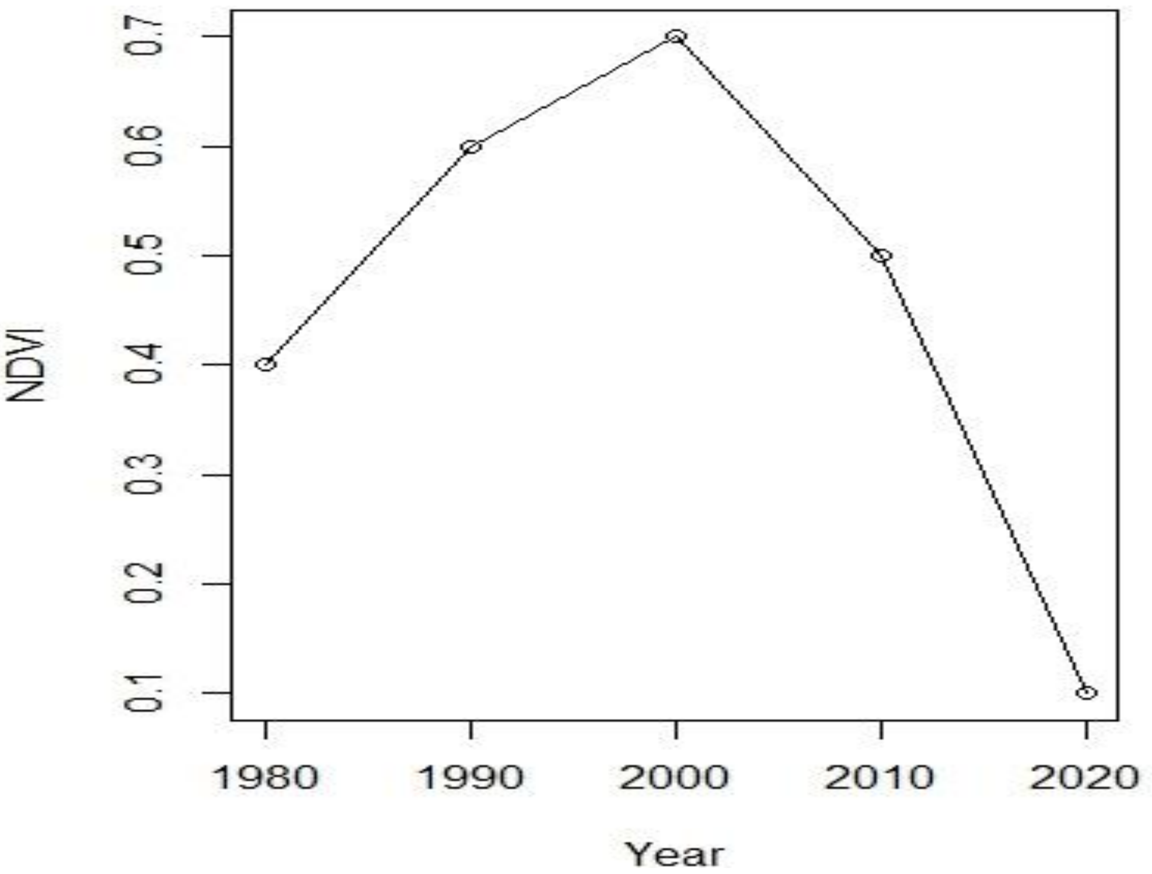

Figure 4. 6: NDVI trend analysis from 1980 to 2020

Basically there is an increasing trend from 1980 to 2000 in NDVI. These results are projecting a sharp to gentle increase in the NDVI over the projected years.

There is a sharp decrease in NDVI from the year 2000 to 2020 as shown on the diagram above. The decrease in NDVI indicate a decline in vegetation and ecosystem productivity over the years as projected on the graph (figure 4.10). There is a significant trend coming out over a 15-year period from 1980 to 2000 and from 2000 to 2020 as shown by the NDVI graphs for the years.

4.2.2 NDVI behavior in relationship to climate over the years

The results indicate the relationships among different climate variables in space, thus between rainfall and NDVI, temperature and NDVI as well as the spatiotemporal graphical presentation of rainfall and temperature changes over the years.

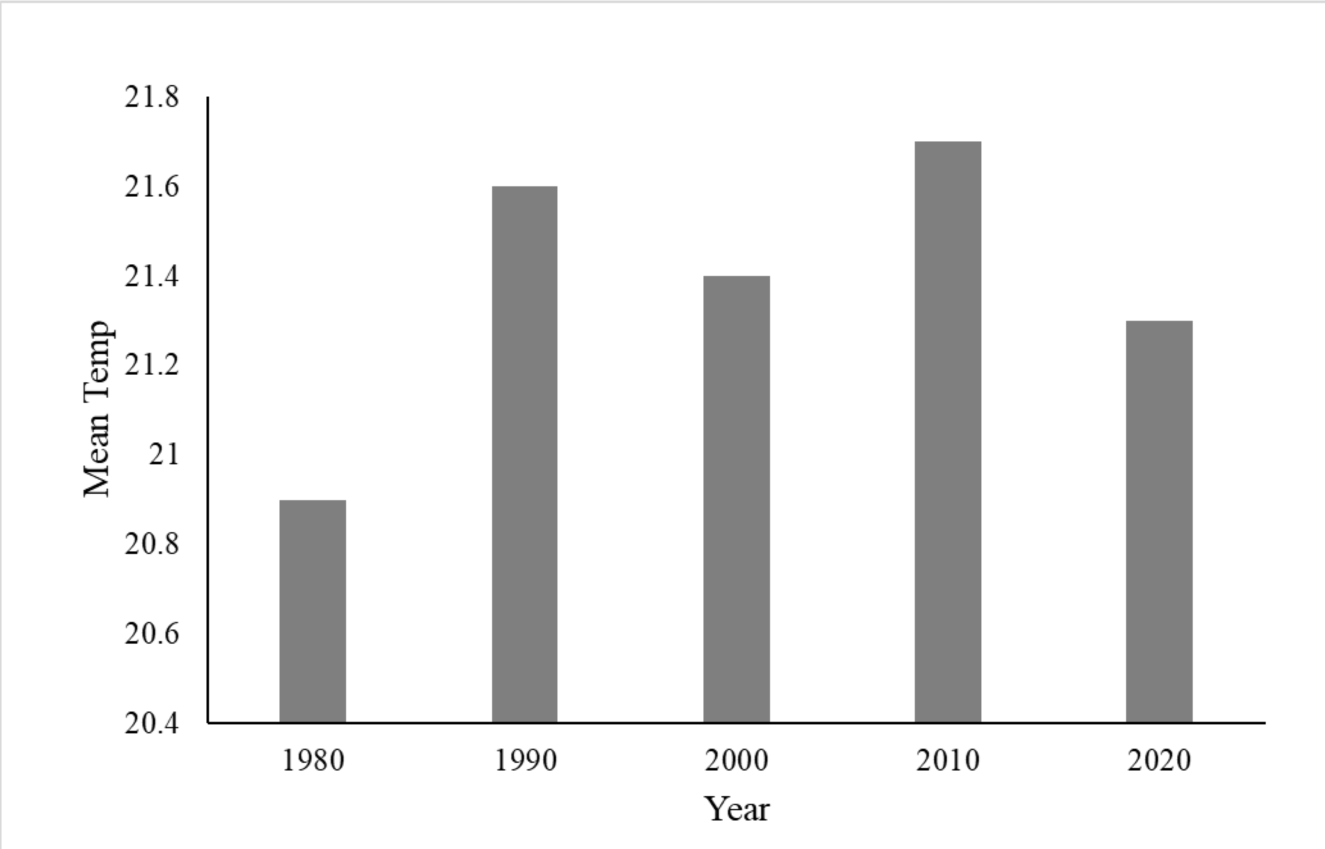

Figure 4. 7: Temporal changes in mean temperature over the years

The results on figure 4.7 are showing the behavior of mean temperature over the years. Mean temperature was low in 1980 followed by 2020 then 2000. The highest year that had the highest mean temperature was 2010 followed by 1990. Generally, there are fluctuations in the mean temperature over the years.

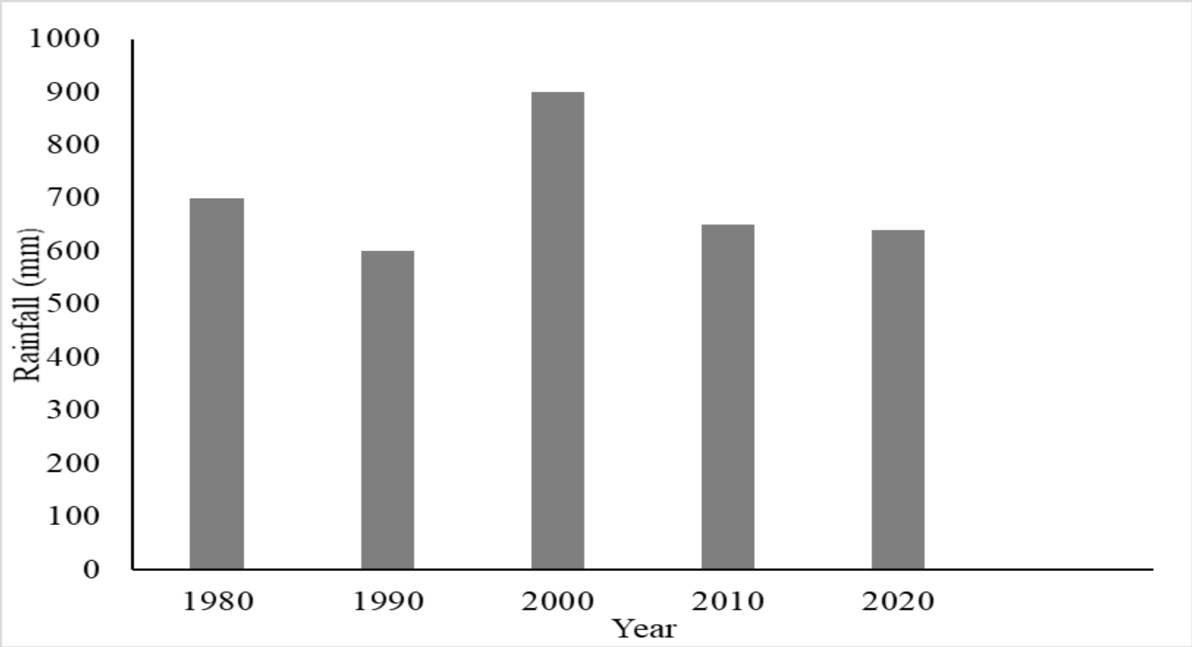

Figure 4. 8: Temporal changes in mean rainfall over the years

There are changes in rainfall pattern from 1980 to 2020 (figure 4.8). The year 2000 has the highest rainfall record followed by 1980, 2010,2020 and lastly 1990. Generally, there is a constant change in rainfall pattern over the years

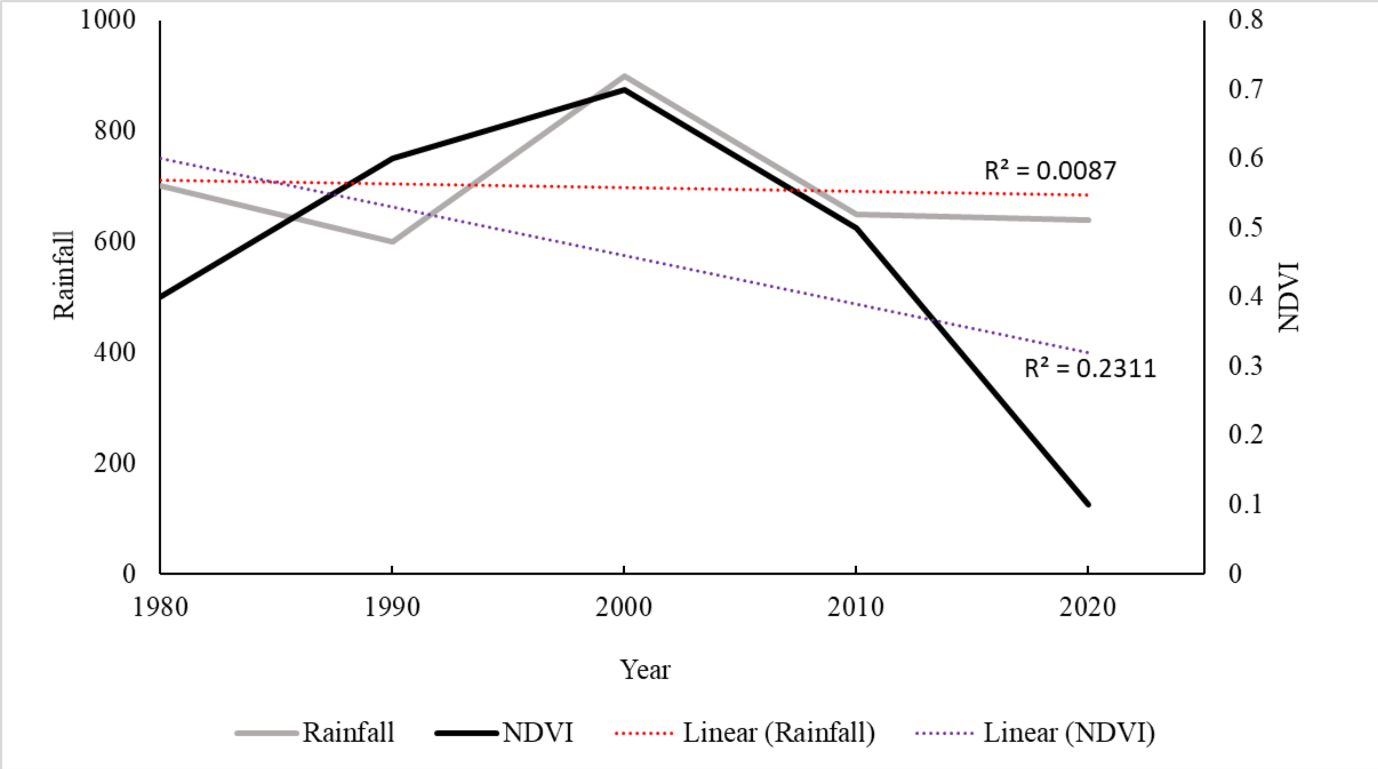

Figure 4. 9: Response of NDVI to mean rainfall changes over time

The results displayed (Figure 4.9) are showing the influence of rainfall on the observed NDVI trends. Rainfall was fluctuating over the study period and an R^2 of 0.008 suggest a very weak positive linear relationship between rainfall and NDVI over the years. Generally, there is a decreasing trend in NDVI in response to rainfall over the years signified by R^2 of 0.23, which suggest a weak positive decreasing trend in observed NDVI.

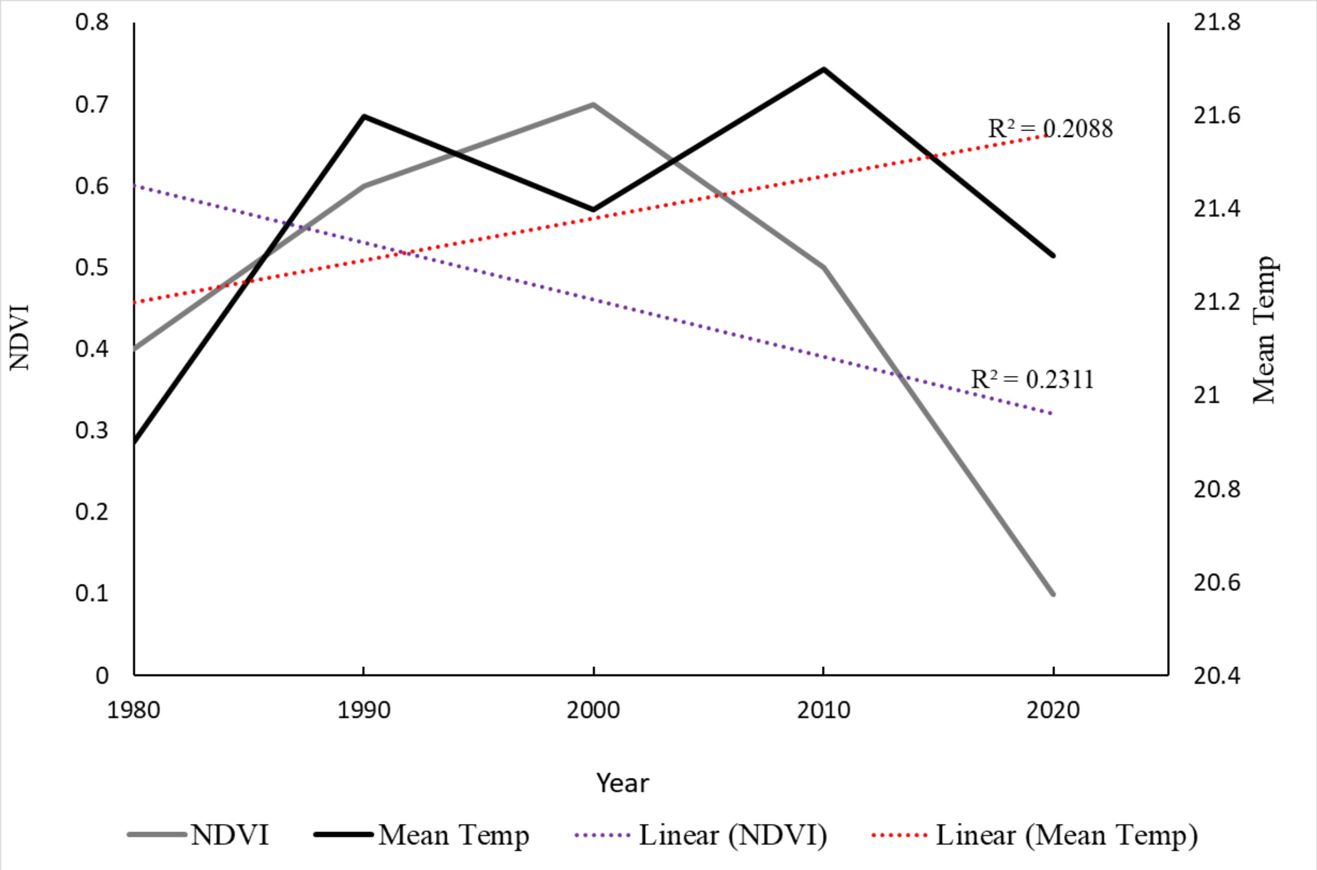

Figure 4. 10: Response of NDVI to change in mean temperature over time

The behavior of Mean temperature has an effect on observed NDVI trend over the years. Mean Temperature was fluctuating in an increasing trend throughout the study period. The relationship between NDVI and Mean temperature is very weak as suggested by the R coefficient of 0.3. The regression line for NDVI is decreasing which is an indication of a very weak relation between the two variables (4.10).

4.3 Estimating disturbance using landscape metrics

4.3.1 Patch area metrics

Table 4.4: Landscape patch metrics output

Year	NUMP	MPS(ha)	ED(m/ha)	MSI	SDI	SEI
1980	120	19	100	1.9	1.7	0.69
1990	90	23	90	2.3	2	1.58
2000	275	10	155	1	2.5	2
2010	180	13	120	1.3	1.5	0.55
2020	369	6	310	0.6	2.2	1.45

The quantification of disturbance using patch metric analysis is a very subtle way of determining disturbance in a protected area. The mean patch size within the study area seem to be decreasing over time with 1980 having19 ha, 1990 with 23 being the year with the highest mean patch size and 2020 has the least area on the mean patch size. The number of patches generally have been increasing within the conservancy with the year 1990 seeing the least number of patches within all classified sectors.

Landscape patch size indicates the grain of a landscape. From the results presented, the mean patch size is generally decreasing with the highest mean patch values found in 1980, 1990 and 2010. 2020 is highly patched as well as the year 2000 and have the least mean patch size values. The trend of the mean patch size in the Midlands black rhino conservancy, the area is becoming more fragmented in space and time. Generally, the fragmentation is increasing in the area as shown below. The low values of mean patch size represent high fragmentation and vice versa.

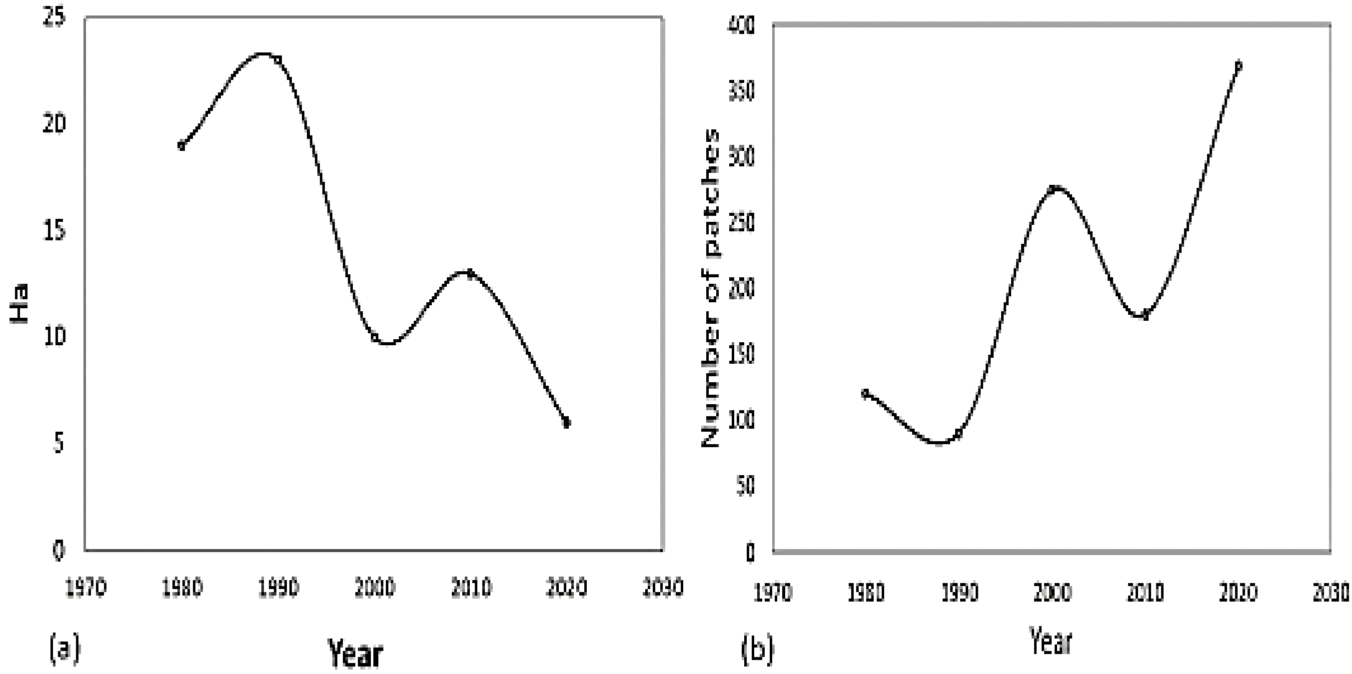

Figure 4. 11: Mean patch size(a) and number of patches (b)

The first segment of the period of study has the least number of patches ranging from 130 to 200 from 1980 to mid-1998 (figure 4.11(b)). The number of patches tend to increase with time from 1990 to 2020 and they range from 200 to 330. Generally, there is an increasing trend in the number of patches throughout the study period with the least number of patches in 1990 under this index.

The number of patches is inversely proportional to the mean patch size. As the number of patches increases the mean patch size decreases (figure 4:11a). The year 1980 has less number of patches but the year 1990 has lesser. There is an increasing trend in the number of patches as indicated by the graph (figure 4:11b). The year 2020 has the largest number of patches as compared to other years.

4.3.2 Edge Density Metrics

There is an insignificant sharp decrease in edge density between 1980 and 1990, the metric increases over time from1990 to 2010. The highest edge density value was recorded in 1980 followed by 2010 with 320/ha and 150/ha respectively. Hence there is a considerable decrease in edge density for the entire study period.

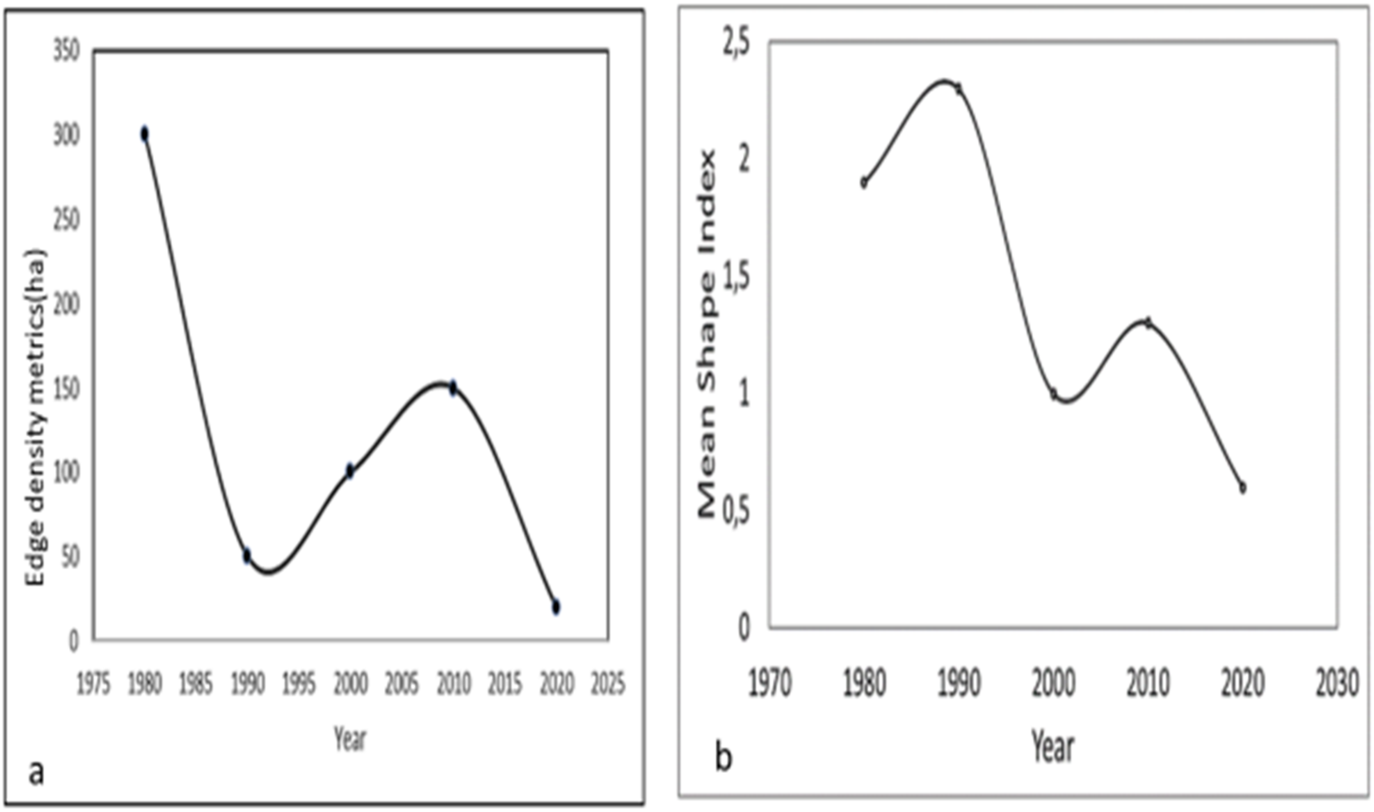

Figure 4. 12: Edge density metrics(a), and mean shape Index(b)

The edge density metrics(a) was way above zero(300ha) in 1980 and it decreases sharply to 1990 (figure4.12(a)). The density metrics increases sharply from 1995 to 2010. The density metrics decreases again up until 2020 which reflects a fluctuating trend throughout the study period. The shape metrics denotes the shape of the patch and is when all patches are polygons either circles or squares. This explains the complexity of the shapes in space. The index decreases, (figure4.12(b)) are an indication of simpler shape. There is more complexity in habitat patches in the study area from 1980 to 2000 with higher level of complexity. From then onwards there are simpler with higher level of simplicity.

4.3.4 Diversity Metrics

The results of are showing the two main popular measures of diversity in community ecology Shannon Diversity index (SDI) and Shannon Evenness index(SEI). The lowest SDI is found in 1980 and 2010 with the indexes of 1,7 and 1,5 respectively. The highest indexes are found in 2000 and 2020 with the values of 2,5 and 2,2 respectively. Generally, there is a fluctuating trend in habitat diversity within the conservancy over the years.

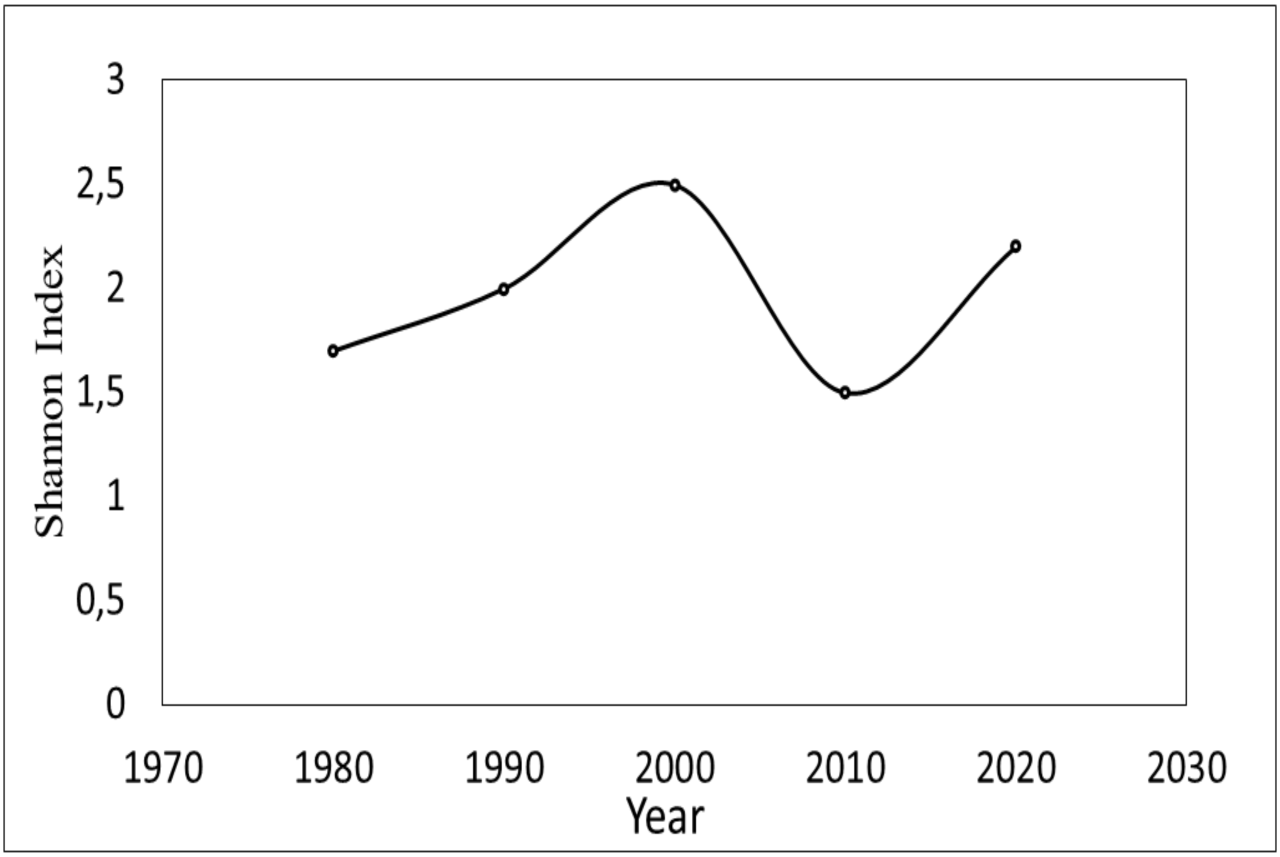

Figure 4. 13: Shannon diversity Index

4.4 Spatio- temporal distribution of patches per classification category

The images below are a representation of the general distribution of patches per classification category in space and time. The first set of maps is showing the distribution of agricultural patches within the Midlands Black Rhino conservancy. The second set of maps are showing bare areas, followed by vegetation then water.

4.4.1 Agricultural patches

The maps (Figure 4.14) are showing the general distribution of agricultural patches in the midlands black rhino conservancy over the study period. The year 1980 is signified by sparsely distributed patches of agricultural activities and more are concentrated on the edges of the conservancy. There are some that are concentrated along the riverbanks for instance the main left characterized by the linear pattern of these agricultural activities.

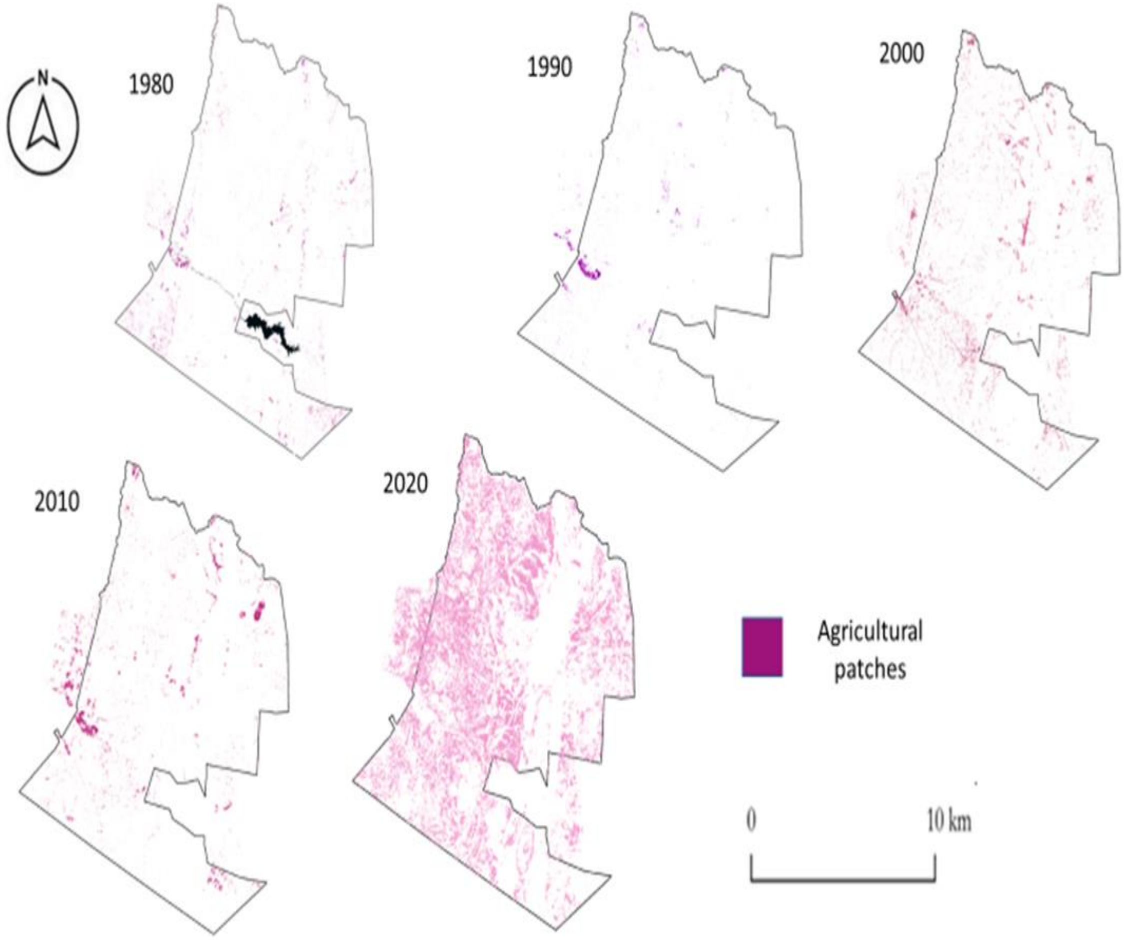

Figure 4. 14: Distribution of agricultural patches in time and space

The year 1990 has less agricultural patches as compared to 1980, with most of the patches being concentrated on the south west corner of the conservancy and a sparse distribution at the centre. The changes in agricultural activities between 1980 and 1990 shows that maybe the rules and regulations of the park were now being put into effect. There is a remarkable increase in the number of patches in the year 2000, and these are evenly distributed over the map. There are more patches on the south western part of the park and along the surface water reservoirs for the year 2000. The year 2010, there is a decline in the number of patches within the conservancy, with the south western corner having more patches concentrated on one main corner as indicated on the map. The year 2020 has a very sharp increase in the number of patches as compared to any other year, with the greater part of north and north western part of the map having more patches as compared to any other part of the map as shown on the image.

4.4.2 Bare patches

The areas covered by bare from 1980 to 2020 seem to be increasing as shown in the results. The year 1980 has barer patches as compared to 1990. The year 1990 has less number of bare patches as compared to the year 1980. The eastern side of the lack is highly patched as compared to the rest of the image. The year 2000 is highly bare patched as compared to the year 1980 and 1990.

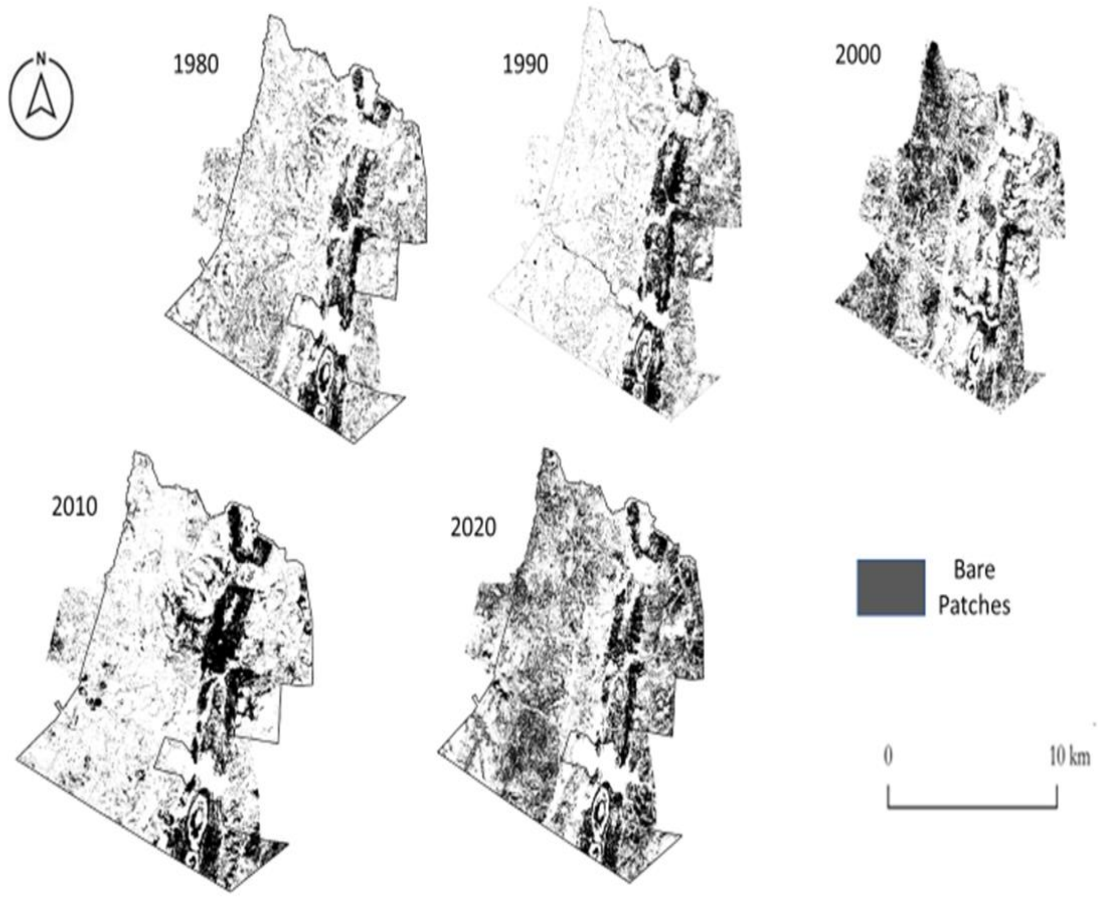

Figure 4. 15: Distribution of bare patches in time and space

The north western, south western and south eastern part of the 2000 image is highly patched, is characterized by the highest number of patches as compared to 2010. The year 2010 has less bare patches as compared to the year 2000. The year 2020 is highly patched with the greater part on the eastern side and western side being highly bare patched. The central part of all the images going towards the east are highly patched.

4.4.3 Vegetation patches

From the images, the year 1980 has a fewer number of patches as compared to 1990. The south-western part of the 1980 map has more gaps and less vegetation patches as compared to the south-western part on the 1990 image.

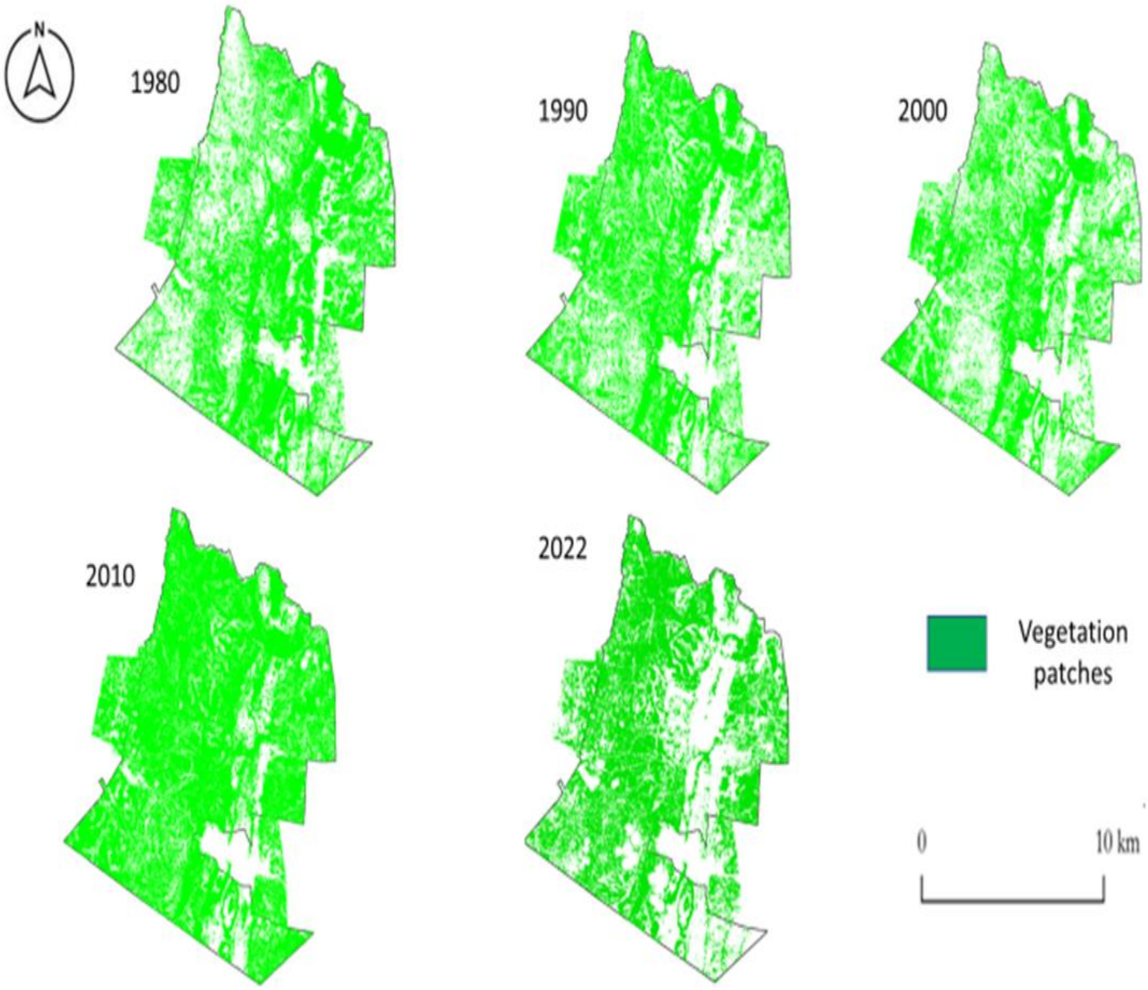

Figure 4. 16: Distribution of vegetation patches in time and space

The year 2000 is highly patched as compared to the year 2010 only the south-eastern corner of the 2010 image is highly patched. The year 2020 is highly patched as compared to any other image on the map. The central part of the park has lots of vegetation patches from the northern part to the southern part. The central part of the images with the great dyke has more vegetation patches as compared to some other parts of the images.

4.4.4 Water patches

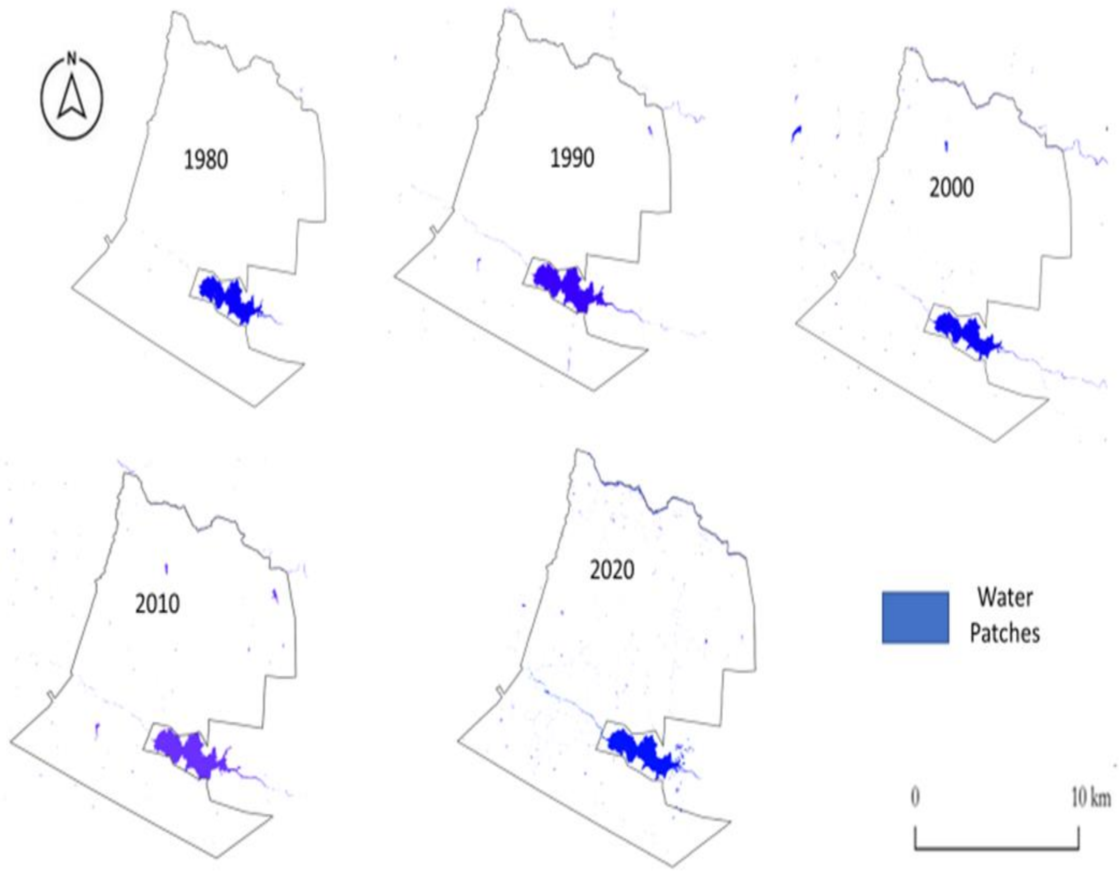

Figure 4. 17: Distribution of water patches in time and space

The year 1980 is being characterized by the lowest number of patches of water followed by the year 1990. The patches of water are much more concentrated on the southern part of the image with closer to the dam as shown on the image. The year 1990 has sparsely distributed patches below the dam and on the north-eastern corner of the image. The year 2000 has a smaller number of water patches as compared to the year 2010. There are more patches on the entire eastern side of the year 2000 image which are sparsely distributed. The year 2010 show an increase in the number of patches as compared to the year 2000 with the entire image having more patches of water which are sparsely distributed. The year 2020 has the highest number of water patches, and these are evenly distributed throughout the image as shown. Generally, there the number of water patches has been increasing significantly over time within the conservancy.

CHAPTER 5
DISCUSSION

5.0 Introduction

This particular chapter is a discussion on the research findings based on the obtained results described in Chapter 4. The discussion focused on spatio-temporal changes on landscape information in a human mediated environment, predicting the patterns of habitat diversity and land cover change, quantification of the level of habitat disturbance as well as the characterization of vegetation productivity in relationship to environmental change.

5.1 Spatio-temporal landscape information in a disturbed area

5.1.1 The detection of Land use land cover change

The shrinking of the land covers in the Midlands Black Rhino conservancy especially forest and vegetated areas, as well as the increase in the areas of some land covers such as bare and agriculture, was accompanied by the interaction of different land covers types and this has resulted in increased disturbance in the protected area. The greater part of the forested areas is likely to be affected in future because of the increase in the area being undertaken by different anthropogenic activities in the park. In order to maintain the reasonable areas of forested areas in the protected area there is need for human intervention. Proposing of the working policies to help reduce the negative impacts of human activities within the park is an alternative and it will help to curb continued increase in the areas occupied by bare land, agriculture and some other land covers within the protected area. These finding concur with a research which was done in Nigeria where the results of the negative land cover change mainly forest cover was as a result of human intervention although the study area was not a protected area (Koko et al., 2020).

The reasons behind the positive change in water cover throughout the study period is because of the time which was given to the park to regenerate after independence and 1980 drought. During the liberation war the conservancies were also at risk and under much disturbance since they were the hiding places for the war fighters. These results concur with the findings of a research which was conducted in China in 2013 where the study saw a decline in forest land and an increase in bare land because of seasonal variability (Ran et al., 2013). There was also a decline which saw the forested area over the study period. This is attributed to the anthropogenic factors as well as climate change which is topical in the biodiversity management sector. This has drastic effects on the flora and fauna since it disturbs the terrestrial habitats within the park. This can even affect the future status of the conservancy which is well explained by the negative future predictions made in this study on the drastic decrease in vegetation as well as increase in the number of patches on different classes on the landscape(section4.4). Climate change and anthropogenic activities such as mining and agriculture in the protected areas seem to have contributed much to the changes that have occurred in the park. These results concur with the study which was done in Germany on detecting disturbance in a post mining environment, where the findings of the research show a strong relationship between habitat disturbance and anthropogenic factors such as mining, agriculture and construction although the study area was not a protected area (Antwi et al 2008). There is also a research which was done on the effects of mining on biodiversity, the results reflected that there is a strong relationship between mining and biodiversity loss and increased anthropogenic activities can further affect biodiversity (Fernandes, Fernandes, Ferreira, Cortes, & Pacheco, 2018; Ross et al., 2021).

The increase in bare land in the conservancy is a clear sign that the change in time is affecting the conservancy. Increasing anthropogenic activities within the conservancy(logging, farming, mining and building) are also factors which have contributed much to the changes in the conservancy, and this has also been increased by the changes in the climate which has affected the entire world as a whole (global climate change) (Fernandes et al., 2018; Ross et al., 2021). Maybe the reason behind increase in bare land area in 2000 was the drought which occurred in 1999/2000 season which left most parts of the conservancy bare. The land cover changed in 2010 with most of the bare parts found on rocks along the mountain range. In 2010, the rest of the conservancy was covered with vegetation and the lake has increased with 5%. This is because of the better 2009/2010 season which saw increased amount of rainfall in the country and the region of study. These results concur well with the study which was done in Shimla

Netherlands in 2003 which saw the decrease in area of vegetation patches and an increase in bare land in the study area due to occurrence of droughts (Razavi 2014). There is a remarkable increase in bare land between 1990 and 2000. 67% of the land cover in 2000 is bare land, maybe because of the drought which occurred during the 1999/2000 season. The hazard increased the bare land cover and the conservancy saw an increase in agricultural land and the few patches of forest. There is an abrupt transition in land use land cover change from 2000 to 2010. There is a 40% vegetation cover in 2010 maybe because the area received a lot of rainfall during the 2009/2010 season and since the study area is a protected area the regeneration of vegetation is much quicker even if it had experience of drought in the past season. The bare areas outside the mountain range again explains the existence of abandoned farming areas as well as mining areas in the conservancy. There is also remarkable transition from 2010 to 2020 in land use land cover change (figure 4:1 and figure 4:2) The transition saw an increase in the area covered by agricultural land covering at least 18% of the area. There is also an increase in the area covered by bare land outside the mountain range which marks the presence of mining areas in the conservancy. Vegetation is mainly in patches and has decreased in cover throughout the conservancy. Some of the areas close to the water storages such as rivers and dams have been cleared for agricultural purposes and it shows from the map that its mostly irrigation since the farms are close to the water storages.

5.1.2 Quantification of land cover changes over time

The results of man Kendall trend analysis to show trends in land use classes over time, reveal the absence of a monotonic trend between on water over time within the conservancy. An increasing trend explains the increase in the number of surface water surface storages artificially constructed to cater for the wildlife within the conservancy as well as better sustainable water harvesting techniques for the benefit of the conservancy. From 1990 through to 2020 there is a constant increase affected partially by the year 2020 which saw a dry rainfall season which contributed a lot to the displayed change (figure4.12). The statistical value (p-value) of 0.462 on the (table 4.2) indicates the absence of a monotonic trend over the years.

Midlands Black Rhino conservancy has experienced significant forest loss due to land cover changes which occurred between 1980 and 2020. The major drivers of forest degradation were anthropogenic development mostly mining and agriculture, opening of new crop fields and infrastructure development in the conservancy. The accelerated deforestation rates in the conservancy are due to quest for mining and agriculture by the citizens of Zimbabwe. This saw a large influx of new small-scale farmers occupying the conservancy, and in the process clearing large areas of forests for different farm-related activities amongst crop farming and settlement. Forests have been lost persistently throughout the study period. This is a negative feedback since the country is working towards reducing carbon emission following the sustainable development goal (SDG) number13 and 15. SDG number 13 calls for climate action and combat global warming and number 15 emphasizes life on earth where we should sustainably manage forests, combat desertification, halt and reverse land degradation as well as halt biodiversity loss (Tan et al., 2022). The results of a study which was done on the analysis of SGDs 15 states that Forest cover fell from 31.9 per cent of total land area in 2000 to 31.2 per cent in 2020, a net loss of almost 100 million hectares (Erin, Bamigboye, & Oyewo, 2022).

The responsible authorities of the Midlands Black Rhino conservancy try to enforce the conservancy regulations according to the Zimparks wildlife conservancy but because of poverty as well as political instability in the country, some of the regulations cannot stand for long. The regulation by the ministry of mines which state that no law surpasses the law of ministry of mines, is the one which is being taken advantage of by the people of Zimbabwe and this has caused them to indiscriminately change the conservancy in a negative way. Because of this, people continue to clear the forested areas within the conservancy. These results concur with a study which was done in China on Land-use change in Changli County where the author predicted the spatio- temporal evolution in habitat quality. The results revealed that anthropogenic activities have severe impacts on the vegetation of any area that man can think of (Azizi, Ghosta, & Ahmadpour, 2020). Habitats within the midlands black Rhino conservancy have been severely changed due to anthropogenic activities in the park and this need to be addressed as soon as possible so as to reduce further human encroachment as well as allow natural restoration to occur.

There is also remarkable transition from 2010 to 2020 in land use land cover change (table 4.1). The transition saw an increase in the area covered by agricultural land covering at least 18% of the area. There is also an increase in the area covered by bare land outside the mountain range which marks the presence of mining areas in the conservancy. Vegetation is mainly in patches and has decreased in cover throughout the conservancy. Some of the areas close to the water storages such as rivers and dams have been cleared for agricultural purposes and it shows from the map that its mostly irrigation since the farms are close to the water storages. This explains the increase in human activities in the park such as heavy logging and extensive land clearing to pave way for mining activities as well as road construction. This also implies that there is poor land management in the park that saw a decline in forest cover and an increase in bare land cover.

The positive changes in agriculture within the conservancy explains well the human encroachment within the park. This is well explained by the changes that are taking place within the conservancy where a lot of population pressure outside the park has seen multitudes seeking land to do agriculture in the park. Man Kendall analysis revealed the absence of monotonic trend (p-value of 0.221) in agricultural activities over the years (table 4.2). There is a constant increase in the area occupied by agriculture. This explains the increase in the number of people who are coming to inhabit in the conservancy. The presence of water provided by Sebakwe river and dam as well as arable land for agriculture and presence of minerals are the main provisional services that are attracting people into the conservancy.

5.2 Predicting patterns of future land cover land use changes

Simulation and prediction of the future land cover which was done in Terrset (Idirisi) indicate an increase in bare land, decrease in forest land as well as an increase in agricultural land and water. This might be as a result of the simulation model in Markov. Under normal circumstances, where the factors that affect change such as climatic events (rainfall and temperature), political interventions among others have not changed over the years they are likely to affect the predicted outcome of Land use/land cover change in the area. The Markov model uses the contiguity rule which suggest that a pixel near to an environmental phenomenon is likely to be classified under the same (neighborhood analysis). The validity of the simulation using a multiple base resolution statistical algorithm, measure the agreement and disagreement between the images (Fathizad, Rostami, & Faramarzi, 2015; Yanxia Liu et al., 2013). Basing on the

Kappa statistics with accuracy exceeding 90%(table 3.3), the predicted maps for Midlands Black Rhino Conservancy were produced based on the land use/land cover maps of 1980-2020, and the later year was used for validation and comparison. There is a high agreement between the predicted 2020 map and the actual map as shown on figure 4.8, hence revealing that CA-Markov is one of the proper models for future land use/land cover prediction.

These results concur with the predictions and projected maps that were done in a research on Land use land cover change in Ningxia North China, where the findings of the research were proving Markov to be the most appropriate model for Land use land cover change (Gidado et al., 2019). The land cover of bare land has been increasing, forest cover decreasing, agricultural land increasing as well as water in the future projected land use land cover for the year 2030 (figure 4.8). Increased population and expanding mining activities may be the main reasons behind the increase in bare land and agricultural activities in the conservancy. The decrease in forest or vegetation cover maybe attributed by expanding residential area as well as need for agricultural expansion (figure 4.8).

5.3 Determining Vegetation Productivity

The NDVI results show modelled representation of the vegetation productivity within the protected area. There are fluctuating changes in vegetation productivity as indicated by the results throughout the study period (figure 4:9). The changes maybe because the year 1980 was characterized by a dry season from 1979/1980 season, and since it was also soon after war, not much conservation was being done in the area and the regulations of a protected area were not into effect because of political unrest which was seen in the previous years in the country.
There is a remarkable positive change in productivity from 1980 to 1990 as shown by the maps (figure4:9). The NDVI value ranges for the year 1990 are 0,01 to 0,7. This indicate a very healthy vegetation within the protected area. Maybe this can be explained well by the changes on regulations that also occurred within the conservancy. Real conservation had started and the owners were now abiding to the conservation rules alongside the support from ZimParks. The year also saw a series of good rain seasons from 1980 to 1990 with the exception of 1982 which

saw an extensive drought which acted a little bit as a drawback to the natural productivity within the conservancy.

The year 2000 was characterized by very high NDVI values which range from 0,5 to 0,7. This is a very positive development which has occurred in the conservancy, and it helps to link well the increasing trend in productivity within the protected area. The year has high productivity as signified by high NDVI values because it also saw a series of good consecutive rain seasons accompanied by good and proper conservation laws which the conservationists are abiding with. There was less intrusion from outside into the conservancy as well.

A controversy occurred in 2010 within the same protected area as the place saw a remarkable decrease in vegetation productivity. The decrease was signified by a fall in the NDVI values which were ranging from -1 to 0,5. This is a very negative change which had severe effects on the ecosystems within the conservancy. The reasons behind a sharp decline were attributed to seasonal changes, human intervention as well as changes in ownership and breach of conservancy regulations. The year saw increasing human intrusion within the conservancy coming with different intentions., mining, agriculture, and logging. These activities catalyzed the decrease in productivity which saw a decline from 2000 to 2010 through to 2020. The year 2020 is another year which has low productivity despite good seasons that have occurred from over a ten-year period from 2010. The year 2020 was pathetic because there are no signs that the vegetation might regenerate again in the next 20 years. There is a lot of human intervention that has occurred within the conservancy, some engaging in crop farming and mining disturbing the natural ecosystem within the conservancy.

5.3.1 NDVI behavior in relationship to climate over the years

The climate status of the conservancy shows signs of changes, for instance, temperature is gradually increasing over time (Figure 4.12). These results concur well with the study which was done in China in 2012 on the relationship between NDVI and temperature from 2004 to 2008. The results on behavior of temperature over time suggest that there is an increasing positive trend of temperature over the years (Dubey, Ranjan, Misra, Wanjari, & Vishwakarma, 2022). This also explains well that it is not only human or anthropogenic factors that are resulting in changes within the conservancy, but climate change is also a factor (Dubey et al., 2022).

The relationships between rainfall and time was showing that rainfall is generally decreasing over time and if it's to increase then it does so slightly. These results concur with the results of a study which was done in India on analyzing temporal responses of NDVI to rainfall. From this study Among climatic factors, rainfall robustly influences both spatial and temporal outline of NDVI. Linear regression was used for analyzing the statistical relationship among NDVI and rainfall and their trend (Kundu, Denis, Patel, & Dutta, 2018).
A strong relationship between NDVI and rainfall suggest that vegetation productivity is highly affected by rainfall as shown on the graph(figure4.14). This study concurs with a study which was done in India where the results of correlation between NDVI and rainfall for the sites revealed consistent increasing NDVI with increasing trend of rainfall. The research investigated the weak positive relationships (r^2= 0.499) between vegetation dynamics and average rainfall (r^2= 0.023) from 1998 to 2013 (Kundu et al. 2018) . The positive and negative changes on the relationships that exists between NDVI and temperature strongly explain the effect of anthropogenic activities in the protected area. This study also concur to a research which was done on mapping of Temporal Variation of Drought using Geospatial Techniques, where the report showed a temporal variation in vegetation in space (Paralikar & Patil, 2022). There are some other studies which were also done on relationships between NDVI and climate which concur with this study (Cui et al., 2022; Huang, Tang, Hupy, Wang, & Shao, 2021).

5.4 Estimating disturbance using landscape metrics

Patch metrics analysis assumes the edge density to be characterized as 0 when there is no edge in the landscape. The number of patches correspond inversely in a proportional way to the mean patch size (McGarigal, Tagil, & Cushman, 2009). Where we have more patches the mean patch size is always small, and the edge density will be high and the species density index tend to be high as well. The decrease in the mean patch size as reflected by the results suggest that their conservancy is highly fragmented and anthropogenic activities are affecting the diversity within the protected area. This study concurs to a study which was done in South Sudan on the assessment and prediction of land-use/land-cover change around Blue Nile and White Nile due to flood hazards in Khartoum based on geospatial analysis .The results indicated that floods are among the factors which also cause a change in the patch sizes of land cover if they occur over time just like climate change and some other anthropogenic activities such as logging and mining (McGarigal et al., 2009).

The protected areas of Zimbabwe and in the countries that are located in the sub Saharan of Africa have been significantly altered and impaired by very extensive anthropogenic activities (Kupika, Gandiwa, Kativu, & Nhamo, 2017; Wang et al., 2014). Globally, many commitments were done by different countries in a bid to restore the damages attributed by human activities but not specific to protected areas. For example, a national commitment to restore the gulf was done through an assessment of framework and associated indicators to try and characterize the health and sustainability of an ecosystem having the scale and complexity of the Gulf in Mexico (Harwell et al., 2019).

5.4.1 Patch area metrics (Mean patch size, number of patches, size and edge density)

The increasing trend in the mean patch size throughout the study period indicates a highly fluctuation trend with the year 2020 having the least mean patch size (table 4.3.). This shows that the sizes of patches are decreasing with time which is a proof of severe habitat fragmentation due to human intrusion into the protected area. The main reasons for the human intrusion being farming, mining, among others. Fragmentation at this point means the segmentation of parts of habitats into smaller patches and large patches tend to be much more complex as compared to smaller patches. A decrease in the size of a patch is highly related to high fragmentation and less species diversity within a specific area. If the area is highly fragmented, then the ecosystem services that were being offered by that particular place will be disturbed and the general interactions within the biotic and abiotic environment will be negatively altered (Rhodes, Angerer, Fox, & McAlister, 2021). The results of this research indicate high patchiness, but the patches are decreasing in size which indicate a decreasing species richness over time. These results inversely concur with a study which was done in Ghana where a post mining area was showing high degree of patchiness on rehabilitated areas which was an indication of high species diversity (Antwi ae al 2009). The study which was done in Ghana help much to explain the reasons behind the increasing number of patches with decreasing patch area size. The high patch edges have more opportunities for organisms. The transformation in the landscape in the study area has resulted in relatively low niche or habitat opportunities in 2020. Decreased edge density help or facilitates disturbance in a habitat.

It is generally known that the number of patches is directly related to habitat richness (the higher the number of patches, the higher habitat richness). The year 1990 and 1980 are less rich in terms of diversity as compared to the year 2000 and 2020. The area of study is a little bit richer in diversity in the year 2020 and 2000 since they are characterized by highest number of patches.

According to the fragmentation hypothesis, High degree fragmentation due to
decreased mean patch size, increased number of patches and edge effect according to the fragmentation hypothesis (contrary to the mosaic hypothesis) might lead to reduced species richness in the area (Saunders 1991). There is always an increase in the vulnerability of the patches to external forces if the areas of habitat patches are reduced (Forman 1995). Upon this background, the year 2020 had its habitats affected by external influences and these will eventually negatively affect species in those fragmented habitats. Small patches often have high species richness, but they contain only common edge species, hence susceptible to external forces which may lead to their extinction.

5.4.3 Diversity metrics (Shannon diversity index)

The reduction in the Shannon diversity index is an indication of the unevenness of habitat patch types within the conservancy. The Shannon diversity index was generally high throughout the study period ranging between 1,7 to 2,5 throughout the study period. There was a constant increase in diversity between 1980 and 2000. This conforms well to the intermediate disturbance hypothesis which predicts that intermediate disturbance leads to the high diversity (Johst and Huth, 2005).

Since the study area is a conservancy, maybe despite all the disturbance factors mentioned before, the regeneration occurs faster as compared to any other place outside the conservancy. Then from 2000 to 2010 there is a decrease in diversity within the conservancy maybe because of extensive anthropogenic as well as the general global climate change which act in a negative way to change the state of the conservancy. Severe disturbance, or even a prolonged absence of disturbance generally has depressing effect on biodiversity, but intermediate disturbance seems to enhance diversity in a system (Pickett and White, 1985).

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5.5 Spatio- temporal distribution of patches per classification category

5.5.1 Agricultural patches

The year 1980 has more patches than 1990, maybe because it was soon after war and the 1978/79 drought had catalyzed the movement of people from their permanent residents moving into the conservancy in search of better ecosystem services provisions such as water for irrigation purposes and wildlife for family consumption. There are more patches on the south western part of the park and along the surface water reservoirs for the year 2000. Maybe these were as a result of 1999/2000 drought which was followed by heavy cyclones. For instance, cyclone Eline which washed away many people's houses and homes around the area of Kwekwe. So most of the victims moved into the conservancy to seek better places to live as well as to do agriculture rerf.hbvwiofuvjofv

The year 2010 saw a decline in the number of patches within the conservancy. The abrupt change saw the greater part of the conservancy regenerating from the effects of agriculture which was done in 2000. The parks and wildlife regulations were being effected into the park and most of the people were evacuated from the park since they did not have the license and right to encroach into the conservancy, and only those who had the right to stay like the conservationists were allowed to stay.

The year 2020 saw a very sharp increase in the number of patches as compared to any other year. This entails the massive encroachment that is happening within the conservancy with many coming in to do commercial agriculture where they would cultivate wheat and maize for livelihood and commercial purposes. These farmers are getting water from the rivers which are in the conservancy like Sebakwe and some other tributaries. This is reflecting that in the long run wildlife is going to be affected and we will be left with nothing because of increased poaching and indiscriminate killing of animals in the protected area.

5.5.2 Bare patches

The reason behind the increasing trend in the number of bare patches in the protected area is because of different but culminating factors. There is high and intensive encroachment into the protected area from outsiders. The main reason for them coming being mining and agriculture. This has very great impacts on the habitats within the conservancy. Sooner than later, the conservancy will suffer from the high effects of disturbance caused by human encroachment. The diversity of species will be affected as well as the general functioning of the ecosystems. The other reason behind the high number of bare patches at the center going towards the east of all the images is because the area is made up mainly an extensive rock which is part of the great dyke which provides minerals for those who engage in mining activities within the park.

5.5.3 Vegetation patches

Generally, there is an increasing trend in the number of patches within the conservancy over the period of study. This maybe because of changes that are happening within the conservancy due to anthropogenic activities such as mining and agriculture. People cut trees and clear the land as they prepare for their activities and this has increased the number of patches within the park. There are less patches in the year 1980 because park encroachment was limited due to the governing parks regulations which were being observed and there was also sound conservation which was introduced. There is a constant and abrupt increase in the number of patches from 1980 to 2020 as shown on the images above. The main reason for the increase in the number of patches maybe because of uncontrolled human intrusion into the protected area. If this continues like this in the next five years, there will be mores patches. High number of patches has a high impact on species population as well as diversity. High number of patches means more fragmentation of habitats hence disturbance effects will arise and affect the species diversity and evenness within the park since their habitats would have been fragmented as well.

5.5.4 Water patches

The number of water patches within the conservancy does not correspond to the rainfall pattern of the place, so rainfall pattern cannot be an explanation behind the increase in the number of patches within the conservancy. The patches have increased for all the years, maybe because of different anthropogenic activities within the park. There are many open pits which are being created by the miners and these with time accumulate water and store it over a long period of time. These water surface storages/dumps can be well viewed on a remotely sensed image, hence the increase in the number of water patches within the conservancy. Despite the increase being attributed by climate change. Some of the patches of water are coming from the discharges from the chrome processing industry where they discharge their effluent into open pits into the environment. Some of the residents within the park are harvesting rain water hence increasing the number of water patches within the conservancy.

5.6 Summary

Tools used for the assessment and protection of protected areas are different from tools used for restoration and an effective framework must correctly identify appropriate management for specific protected areas. Habitat quality assessment in the Midlands protected area was done and surrogate measures and analysis were done representing important a tools for analysis. Therefore, we used surrogate GIS measures of habitat quality to assess habitat quality and anthropogenic habitat disturbance. Classification was done and patch analysis as well to detect the extent of disturbance in a protected area using geo technological ways which are going to be presented by the following framework.

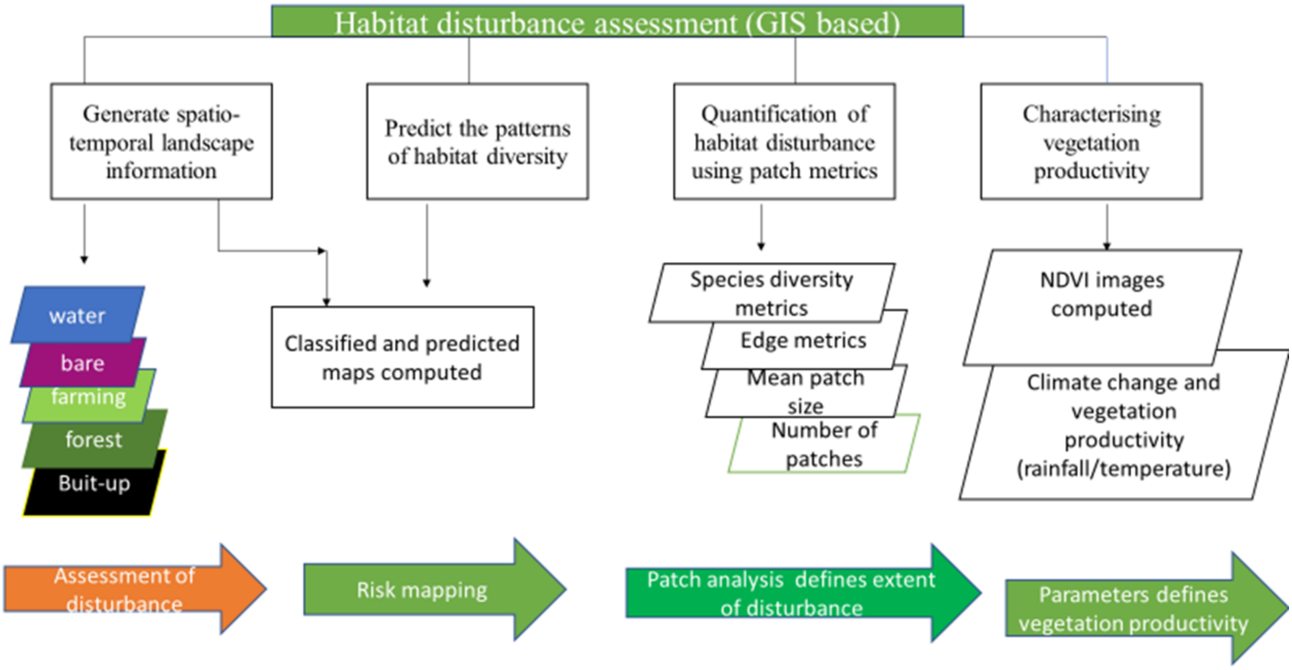

Figure 5. 1 Geospatial frame work for the integration of land cover change and environmental processes (source: created by the author)

The above is acting as an overall tool which anyone can use to assess the disturbance in a human mediated environment where the main activities are mining and agriculture.

CHAPTER 6
CONCLUSION AND RECOMMENDATIONS

6.0 Introduction

This chapter provides conclusions and recommendations from the research based on the objectives of the study. The conclusions presented here act as important points to consider after the end of the research journey. The concluding statement is providing the reader with important information for decision making. The recommendations provided help in encouraging the readers to apply the findings through the innovative knowledge offered by this research in the management of human mediated ecosystems.

6.1 Conclusion

The Midlands Black Rhino conservancy has experienced significant forest loss due to land cover changes which occurred between 1980 and 2020. The major drivers of forest degradation where anthropogenic development mostly mining, agriculture opening of new crop fields and infrastructure development in the conservancy. The accelerated deforestation rates in the conservancy quest for mining and agriculture by the citizens of Zimbabwe. This saw a large influx of new small-scale farmers occupying the conservancy, and in the process clearing large areas of forests for different farm-related activities amongst crop farming and settlement. Forests have been lost persistently throughout the study period. This is a negative feedback since the country is working towards reducing carbon emission. Forest management through REDD+ programs is one way Zimbabwe can reduce atmospheric carbon through carbon sequestration by vegetation. Forests in the Midlands Black Rhino Conservancy are facing a risk of clearance if the current socio-economic development activities are not harmonized with the country's climate change mitigation policies particularly policies to reduce carbon emission and forests conservation. The study recommends the harmonization of the socio-economic development activities in the protected area with the national policies and legislations that are aiming to reduce carbon emissions.

This research examines the scientific basis for the use of remotely sensed data, particularly NDVI, in productivity assessments at different scales and for a range of applications within a protected area conservancy. It draws on evidence primarily from the scientific peer-reviewed literature as well as a wide range of investigations, but not limited to non-journal sources. Research in vegetation productivity based on satellite remote sensing currently makes use of wide variety of datasets of different geographical scales, spatial, spectral and temporal resolutions. The availability of free data of continuous land surface observations from medium to coarse spatial resolution satellite sensors is of paramount importance for the support of a range of ecosystem models and environmental applications. At the global level however, a few of these datasets stand out. NDVI continues to be valid for measuring and reporting on some of the key strategic objectives of productivity and has the appropriate qualities for use as an indicator for a number of indices.

The theme of habitat disturbance and geospatial technologies has limited citations which highlight it as an emergent theme in literature. Despite the limited number of citations, the available citations from the highlighted leading spatial journals showed that there shall be an exponential increase in publishing in the long run at regional level. Considering the current trends in mining and its impacts on the habitats, there is need to improve the focus on its spatial literature. The conclusion is that spatial temporal habitat disturbance is receiving very limited but growing focus. Another important point noted was that most of the research did not integrate geospatial approaches in their studies. Hence the conclusion that habitat disturbance studies in protected areas could benefit from considering GIS approaches. Landscape scale areas are the most frequently studied spatial extents, like the patch size of a habitat. There is need for multiple spatial scales to allow for comparison of findings across scales. There is also need for longer temporal scales studies that span decades to observe and account for lags in ecosystems responses to patterns of ecosystems regeneration. Similarly, majority of studies were done over short time spans, so there is need for multiple spatial scales to allow for comparison of findings across scales. Built up areas and forest fragments are the most studied ecosystems and fewer studies are on grassland, freshwater, wetland, wasteland, and austral ecosystems. Hence, there is need for research to focus on cross ecosystem studies and the neglected ecosystems. Studies that will focus on these ecologically vulnerable areas would help in providing crucial insights for the conservation of biodiversity. The trends highlighted are an important representation of very important gaps in knowledge that need to be addressed through the funding of research and cross regional collaborations.

6.2 Recommendations

This research has shown that generally most crucial land use land cover categories are changing in the Midlands Black Rhino conservancy throughout the study period and these comprise of forest cover decreasing, increase in bare land, increase in agricultural activities, as well as water. The reasons behind this are anthropogenic activities as well as the general global climate change which is hitting the world at a very uncontrollable rate. It is therefore recommended that;

The protected area responsible authorities (Zimparks, Zinwa and Midlands Back Rhino Conservancy) should conduct workshops and awareness campaigns at village, ward and district level to the communal people on the significance of vegetation cover and forests to wildlife. Starting from the grassroots level, such campaigns should be directed on conservation agriculture to maintain fertility and reduce erosion, as well as forests conservation. This will reduce field degradation, abandonment, fallowing and encroachment into marginal lands. The result is a continuous increase in vegetation cover.

Secondly, clearing of forests should be minimized. This should be done through the use of traditional management authorities such as chiefs and kraal heads counsel officers and government authorities. Land allocation for agriculture purposes should be done in authorization from these local authorities. Such grassroots management strategy might help in continuous increase in vegetation cover at the same time reducing the risk of global warming.

Lastly there should be tree planting, land reclamation and gully filling so as to maintain densely vegetated areas as well as upgrading bare areas. This should be done by the local people since they are the beneficiaries of high density vegetation cover in the form of reduced risk of global warming.

There is need to revise the ministry of mines law which is not surpassed by any other law. Any Zimbabwean is allowed to mine anywhere they want as long as they have an approved license from the ministry of mines. This law is the one which is affecting the Midlands Black Rhino Conservancy at present. People are clearing land within the midst of the conservancy in a bid to do mining and some are even ending up doing agriculture. All these anthropogenic activities should be halted before the whole conservancy is turned into a historical site.

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APPENDICES

Appendix I: Publications

1. **Kunedzimwe Francisca, Muposhi Victor K, Taru Philip (2022) Spatio-Temporal Analysis of Trends on Habitat Disturbance Between 1986 And 2021 In Protected Areas Of, Zimbabwe. *Journal of Earth and Environmental Science Research*. SRC/JEESR-203. DOI: doi.org/10.47363/JEESR/2022(4)170**

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Spatio-Temporal Analysis of Trends on Habitat Disturbance Between 1986 And 2021 In Protected Areas of, Zimbabwe

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ABSTRACT
The main aim of this research is to analyse spatio- temporal trends on habitat disturbance between 1986 and 2021 in protected areas of, Zimbabwe with a focus on anthropogenic activities such as mining which are leading to biodiversity loss, habitat and ecosystem services disturbances. This paper provides an overview of recent studies using Remote Sensing (RS and Geographic Information Systems (GIS) techniques to assess the extent of mining disturbance on plant habitats in protected areas of Zimbabwe. Through a systematic review, literature hotspot analysis was done as well as a trend analysis at regional specific level together with statistical tests in order to come up with an overview of the past studies which were done on habitat disturbance in protected areas of Zimbabwe over a thirty-five-year period. The paper highlights the complex nature of the impacts of mining as well as discuss spatial research methods, data sources and limitations. The results indicated an exponential growth of scientific literature on human-environment interactions in the mining environments at regional scale and a non- monotonic trend at country level. This has prompted a need to synthesize literature to guide future research. Conclusively there is limited research done on habitat disturbance in protected mining environments, hence the need for advanced geospatial scientific studies in the future on spatio-temporal analysis of trends on habitat disturbance.

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Introduction
The scale of human influence is driving the earth system towards

mines use some of the available resources to meet their needs, for example trees for timber and even for fuel, road construction and water for washing their machines. Such activities have diminishing effects on the habitat diversity [9,10]. Species are coming into direct contact with human beings and this is now having adverse

2. **Kunedzimwe Francisca, Taru Philip, Goronga Ashton (2023) Detecting land-use land cover changes in a protected area conservancy using geospatial technology.** ***International Journal of Science and Technology Research Archive, 2023 04(01), 182–191Article DOI: https://doi.org/10.53771/ijstra.2023.4.1.0014***

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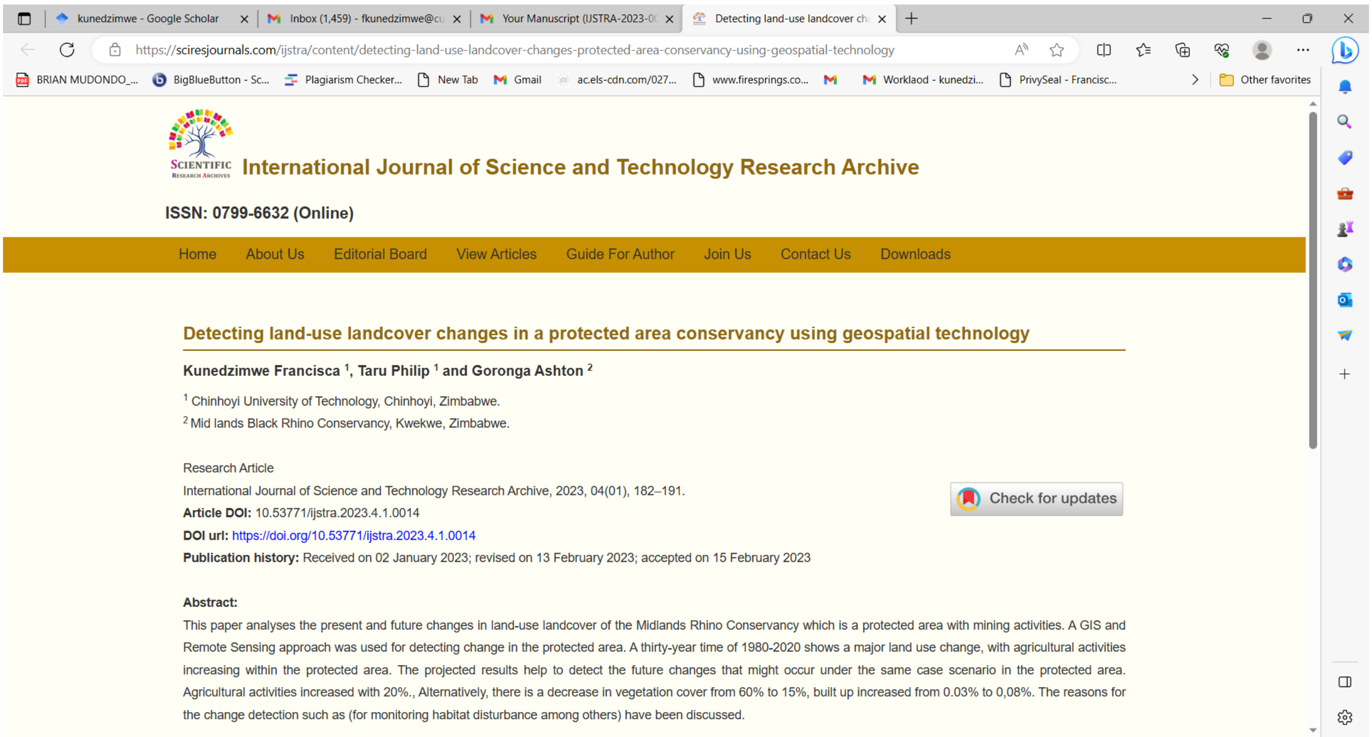

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Detecting land-use landcover changes in a protected area conservancy using geospatial technology

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Abstract:

This paper analyses the present and future changes in land-use landcover of the Midlands Rhino Conservancy which is a protected area with mining activities. A GIS and Remote Sensing approach was used for detecting change in the protected area. A thirty-year time of 1980-2020 shows a major land use change, with agricultural activities increasing within the protected area. The projected results help to detect the future changes that might occur under the same case scenario in the protected area. Agricultural activities increased with 20%., Alternatively, there is a decrease in vegetation cover from 60% to 15%, built up increased from 0.03% to 0,08%. The reasons for the change detection such as (for monitoring habitat disturbance among others) have been discussed.

Appendix II: Permit letter

MIDLANDS BLACK RHINO CONSERVANCY TRUST
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15 October 2020

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To whom it may concern

RE: PERMISSION TO CONDUCT RESEARCH AT MIDLANDS RHINO CONSERVANCY FOR COMPLETION OF DOCTOR OF PHILOSOPHY DEGREE.

This is to certify that Kunedzimwe Francisca is given permission to conduct research in the Midlands Black Conservancy for the following period (15 October 2020 to 30 August 2023) subject to the following:
"If the study is purely on GIS and Remote sensing and does not require any wildlife animal handling as suggested by your proposal."
"Results from this study shall not be published without consent from the Ecologist"

She will be working closely with the Chief Conservancy Ecologist, throughout the study.

Yours sincerely

Ashton Goronga
(Chief Conservancy Ecologist)

turnitin

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AUTHOR

francisca kunedzimwe

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