Impacts of Spatio-Temporal Variability in Forest Landscape Metrics on Soil Quality, Erosion Severity and Patch Morphology in the Copperbelt Province of Zambia

By

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DEDICATION

I dedicate this research work to God for the unconditional loving-kindness, tender mercies, great compassion, and strength showered upon me during the study period. To my father, Mr. Harrison Mwape Malunga, and my mother, Ms. Elizabeth Mumba, for the support they have rendered and to my wife, Monica Kazolwe for enduring my absence. Further to my family as an inspirational to prove that all things are possible when we trust in God.

DECLARATION

I, Mwelwa Mwape Malunga, student number u14444497 hereby declare that this thesis, titled “Impacts of Spatio-Temporal Variability in Forest Landscape Metrics on Soil Quality, Erosion Severity and Patch Morphology in the Copperbelt Province of Zambia” is submitted in accordance with the requirements for the degree of Doctor of Philosophy (Ph.D.) in Forest Science at the University of Pretoria and is the result of my work. This thesis has not previously been submitted by me for any degree at any other institution of higher learning. All sources cited or quoted in this thesis are indicated and acknowledged with a comprehensive list of references.

Signature:

Date: 30th August 2021

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TABLE OF CONTENTS

DEDICATION I

DECLARATION II

ACKNOWLEDGEMENTS III

SUMMARY IX

LIST OF FIGURES XIV

LIST OF TABLES XVII

LIST OF APPENDICES XVIII

LIST OF ACRONYMS AND ABBREVIATIONS XIX

CHAPTER 1: GENERAL INTRODUCTION 1

1.1 INTRODUCTION 1

1.1.1 Land use land cover and drivers of change in Miombo woodlands 1

1.1.2 Forest management and economic policies in Zambia 2

1.1.3 Soils of Miombo woodlands 4

1.1.4 Landscape metrics, fragmentation and the impact on soil quality 6

1.1.5 Morphological / shape characteristics for spatial planning 8

1.1.6 Problem statement and rationale of the study 8

1.1.7 Research objectives 10

1.1.8 The conceptual framework 11

1.1.9 Thesis structure 14

1.2 REFERENCES 17

CHAPTER 2: LAND USE INDUCED LAND COVER CHANGES AND FUTURE SCENARIOS IN EXTENT OF MIOMBO WOODLAND AND DAMBO ECOSYSTEMS IN THE COPPERBELT PROVINCE OF ZAMBIA 27

2.1 INTRODUCTION 28

2.2 METHODS 31

2.2.1 Study area *31*

2.2.2 Image acquisition and pre-processing *32*

2.2.3 Field data collection on land use activities *33*

2.2.4 Data analysis-land cover classification *33*

2.2.5 Classification accuracy assessment...*34*

2.2.6 Change detection *34*

2.2.7 Prediction of land use land cover change into the future (2050)...................................*35*

2.2.8 Land use induced land cover changes in Woodlands and Dambos *36*

2.3 RESULTS..37

2.3.1 Land use land cover change between 1984 and 2016..*37*

2.3.2 Land use land cover change and statistics for predicted 2050 ....*39*

2.3.3 Change in the extent of Miombo woodlands and Dambos...*41*

2.4 DISCUSSION..45

2.4.1 Land use land cover change between 1984 – 2016 and prediction to 2050 ....*45*

2.4.2 Implications..*47*

2.4.3 Study limitations..*48*

2.5 CONCLUSION 49

2.5 REFERENCES 51

CHAPTER 3: EXTENT OF FRAGMENTATION AND THE IMPACT OF FOREST FRACTAL GEOMETRY ON SELECTED SOIL PARAMETERS IN MIOMBO WOODLANDS OF ZAMBIA'S' COPPERBELT REGION...63

3.1 INTRODUCTION..64

3.2 MATERIALS AND METHODS 66

3.2.1 Study area..*66*

3.2.2 Image acquisition and pre-processing 67
3.2.3 Field data on land use activities and soil samples 68
3.2.4 Data analysis 68
3.3 RESULTS 74
3.3.1 Landscape and class level metrics 74
3.3.2 Forest fragmentation 78
3.3.3 Quantities / Concentrations of soil chemical parameters 79
3.4 DISCUSSION 83
3.4.1 Landscape and forest fragmentation between 1984 and 2019 83
3.4.2 Impact of forest fractal dimension on the level of soil chemical parameters 84
3.4.3 Implication 86
3.5 CONCLUSION 87
3.6 REFERENCES 88
CHAPTER 4: EXTENT OF SOIL LOSS AND THE IMPACT OF FRACTAL GEOMETRY OF TWO COMPETING LAND USES (CROPLAND AND FORESTLAND) ON EROSION SEVERITY IN THE MIOMBO ECOSYSTEM OF THE COPPERBELT ZAMBIA 99
4.1 INTRODUCTION 100
4.2 METHODS 103
4.2.1 Study area 103
4.2.2 Data collection 105
4.2.3 Data analysis 106
4.3 RESULTS 114
4.3.1 Results on erosion factors 114
4.3.2 Changes in the extent of soil Loss and erosion severity between 1984 and 2019 116
4.3.3 Effect of fractal geometry of croplands and forestlands on soil loss 119

4.4 DISCUSSION 121

4.4.1 Factors of soil loss *121*

4.4.2 Extent of soil loss and erosion severity between 1984 and 2019 .... *122*

4.4.3 Impact of fractal geometry on soil loss in persistent Cropland and Forestlands *124*

4.5 CONCLUSION 127

4.6 REFERENCES 128

CHAPTER 5: MODELLING THE PATTERN AND MORPHOLOGICAL CHARACTERISTICS OF FOREST AND CROPLAND PATCHES FOR USE AS INDICATORS IN SPATIAL PLANNING 141

5.1 INTRODUCTION 142

5.2 MATERIALS AND METHODS 144

5.2.1 Study area *144*

5.2.2 Image acquisition and pre-processing *146*

5.2.3 Data analysis *146*

5.3 RESULTS 151

5.3.1 Morphological spatial pattern of patches *151*

5.3.2 Description of shape in FRAC-1 and 2 between Forestlands and Croplands *152*

5.3.3 Description of shape in FRAC-1 and 2 within Forestlands and Croplands *153*

5.4 DISCUSSION 158

5.4.1 Morphological spatial pattern analysis *158*

5.4.2 Description of the shape of Cropland and Forest patches *160*

5.5 CONCLUSION 162

5.6 REFERENCES 163

CHAPTER 6: SYNTHESIS OF THE IMPACT OF LANDSCAPE METRICS ON SOIL PARAMETERS, SOIL LOSS, EROSION SEVERITY AND PATCH MORPHOLOGY 169

6.1 BACKGROUND 169

6.2 INTRODUCTION..169

6.3 REFLECTING ON THE CONCEPTUAL FRAMEWORK..171

6.4 ASSESSMENT OF THE MATERIALS AND METHODS USED IN THE STUDY 172

6.5 LINKING MAJOR FINDINGS AND THEIR IMPLICATIONS IN MANAGEMENT STRATEGIES.........173

6.6 POLICY DIRECTION 178

6.7 RECOMMENDATIONS 179

6.8 CONSIDERATION FOR FUTURE STUDIES 180

6.9 REFERENCES...182

APPENDICES 187

SUMMARY

Studies focusing on the impact of forest and cropland fractal geometry (FRAC) on soil loss, erosion severity and patch morphology are rare and the gap is particularly large in the Miombo ecosystem leaving substantial uncertainty. Most studies have concentrated on land use land cover change (LULCC) and yet significant variations in soil properties have been shown by this study to be influenced by the geometric pattern of landscapes such as Forestlands. This means that soil nutrients, soil loss and erosion severity can be managed / manipulated by designing / adjusting the geometry and morphological characteristics of patches which presents a new cost effective and environmentally friendly approach to ecosystem management. Therefore, the link between LULCC and the intensity of fragmentation, soil loss and erosion severity is important. These findings are especially critical in highly heterogeneous landscapes such as the Miombo woodlands.

This study was carried out in the Copperbelt Province of Zambia. This predominantly mining province has undergone massive LULCC which has resulted in decline in the extent of natural ecosystems such as Forestlands / woodlands and Dambos leading to an increase in fragmentation. High rates of forest degradation and fragmentation have negatively affected the climate, soil properties, fauna and flora. The loss of forest cover also entails loss of plants and biodiversity that anchor the soil and protect it from soil nutrient loss. With increased soil erosion, agricultural production is expected to decline which may compel farmers to increase the use of expensive inorganic fertilizers or clear more forest in a bid to raise yields. This trend is impacting on global food security at the time when human population is increasing. It is therefore critical to quantify the past, present and future impacts of LULCC, forest fragmentation dynamics on soil quality, loss and erosion severity and the morphological characteristics of landscapes / patches for effective land use planning. However, this field of

science has also remained largely unexplored in forestry and soil science leading to inadequate information necessary to trigger effective mitigation action resulting in negative effects on ecosystem function.

This study aimed to quantify the impacts of spatio-temporal variability of LULCC, landscape metrics on soil quality, loss and erosion severity and on morphological / shape characteristics of patches. This was done by assessing the LULCC from 1984 and predicting the same to 2050, evaluating the impact of the Fractal Dimension (FRAC) on selected soil parameters, assessing the impact of FRAC on soil loss and erosion severity and modelling the morphological and shape descriptors of landscape / patches for use as indicators in spatial planning for sustainable management of forest and soils.

The first study analysed the LULCC between 1984 and 2016, and projected to 2050 because the pattern of Miombo woodland conversion to other land uses and the attendant impacts on vital Miombo ecosystems such as Dambos is not well understood. Land use land cover (LU/LC) maps were produced through supervised image classification in ArcGIS 10.3 and ENVI 4.7 and used as input in subsequent studies (Chapter 3-5). The effects of LULCC on the extent of Miombo woodlands and Dambos was determined by intersecting layers of Croplands, Settlements, Plantations, Grasslands and Barelands on Woodland and Dambo pixels. Prediction of future LULCC was done using the land change modeller (LCM) in TerrSet. Woodlands and Dambos were predicted to decrease by 26.4% and 2.0%, respectively, by 2050. Conversion to Cropland was the highest contributor to the loss of Woodlands and Dambos accounting for more than 54% of the total loss. Expansion of Croplands caused a decline in Woodlands and Dambos. Therefore, it was recommended that sustainable agriculture practices that do not rely upon land expansion should be adopted.

The second study quantified the extent of fragmentation and the impact of FRAC on some soil parameters using LU/LC of the Copperbelt Province of Zambia from the first study. The LU/LC were processed into persistent forest and croplands (1984 to 2019). FRAC and other landscape metrics were computed in FRAGSTATS 4.2. The impact of FRAC on soil nutrients was assessed in the persistent forest layer (1984 to 2019) which was divided into FRAC-1 (Areas of Frac index ≤1.25 with simple shapes of patches) and FRAC-2 (areas of Frac index > 1.25 to 1.5, with more open, complex shaped patches); in sandy and loamy soil. The persistent layers were used in order to ensure that the only factor causing the variation in soil properties was the forest / cropland geometric pattern. Soil samples were collected for analysis of soil texture, pH, phosphorus (P), nitrogen (N), ammonium-nitrogen (NH_4-N), nitrate-nitrogen (NO_3-N), carbon (C) and potassium (K) concentrations. In areas with simple shapes of patches (FRAC-1), N, NH_4-N, NO_3-N, C and K concentrations were higher compared to areas with complex shaped patches (FRAC-2) in loamy soils. Forest geometric pattern affected the levels of soil parameters, therefore, incorporating fragmentation analysis in forest and soil conservation is recommended.

The third study compared the extent of soil loss and determined the impact of FRAC of persistent Forests and Croplands (1984-2019) on erosion severity in sandy and loamy soils. The Revised Universal Soil Loss Equation (RUSLE) was applied in ArcGIS 10.3. The area covered by the Low Erosion Severity class (<5 t.ha^{-1}yr^{-1}) reduced by a net change of 15.05% while the Moderate Erosion Severity (5 – 12 t.ha^{-1}yr^{-1}) and High Severity class (>12 t.ha^{-1}yr^{-1}) classes increased between 1984 and 2019. The mean soil loss (MSL) varied according to differences in the geometric pattern and soil textural classes. Areas with simple shaped patches had higher MSL by 10.2% and 18% in Croplands and Forestlands, respectively, than in areas with complex shaped patches in loamy soils. Overall, the MSL in Croplands was 95% higher than in Forestlands considering all fixed factors. Cropland and Forestland geometric pattern affected soil loss and erosion severity, therefore, it is suggested that fragmentation analysis should be incorporated into land use planning for sustainable agriculture, soil, and forest management.

The fourth study modelled the morphological spatial pattern and shape characteristics of persistent Forest and Cropland areas (1984 to 2019). Morphological Spatial Pattern Analysis (MSPA) used GUIDOS 3.0 to compute the Cores, Islets, Loops, Bridges, Perforations, Edges, Branches and Contortion while shape descriptors (Roundness, Circularity, Convexity, Elongation, Width and Length, Number of Holes and Directionality) were computed in ImageJ1.53 software. The study found that forestlands recorded the highest number of Core areas while Croplands had the highest amount of Islets with over 63% in both FRAC metrics. The implication of the MSPA results is that landscape connectivity is reduced by a decline in Core areas in the forest class, which blocks the migration of species, affects ecosystem integrity, nutrient flows and impacts on the provision of ecosystem services.

Forest areas (FRAC-1 and FRAC-2) had lower average values of Elongation and Convexity index than Croplands. Forest areas also recorded higher Contortion index than Croplands suggesting more complex patch shapes in natural landscapes. We identified the dimensional characteristics of FRAC areas for easy application in landscape design and restoration programmes. For instance, FRAC-1 forest areas would be restored by ensuring an average patch length and width of 800 m x 588 m respectively; with a maximum contortion index of 188 while for FRAC-2 Forestlands, the mean length and width would be about 28,818 m x 20,169 m with contortion index of over 2,000 corners. This indicates high shape complexity in FRAC 2 areas. This study concluded that the spatial and temporal morphology of natural

landscapes (Forestlands) differed significantly with human induced land uses (Croplands) with implications on ecological connectivity and the provision of ecosystem services in general. It is recommended that strategies like land zoning, practicing safe and climate smart agriculture, effective enforcement of laws and policies, strengthening institutions and developing mechanisms for prescribing forest/vegetation geometry patterns should be implemented.

The overall conclusion of the study was that the geometric pattern of Forestlands had significant impact on soil quality, loss and erosion severity. This means that soil quality, loss and erosion severity can be managed by manipulating the geometric and morphological characteristics of patches / landscapes which presents a new approach to ecosystem management. Years of uncoordinated and uncontrolled land use activities will reduce the area of persistent forests and if the situation is not addressed, significant amounts of topsoil / nutrients and vegetation would be lost. The loss of nutrients will lead to a decline in agricultural production which will affect the already unstable food security situation in the area. Therefore, there is urgent need to incorporate FRAC analysis in land use planning.

LIST OF FIGURES

Figure 1. 1. Study conceptual framework 13

Figure 2. 1 . Panel chart A and B showing trends in land use land cover from 1984 to 2050; panel A (high value classes >200,000ha to 2,500,000ha) and panel B (low value classes >0 to 90,000ha) 41

Figure 2. 2. Land cover and change map of the-Copperbelt province (a) presents the initial land cover map of 1984 (b) shows the change map between 1984 and 2016 (c) shows the land cover map of 2016 (d) shows the predicted land cover map of 2050. 43

Figure 2. 3. State of Woodlands and Dambos in the Copperbelt province (a) presents the initial state of Woodlands in 1984 (b) shows the Woodlands converted to Cropland by 2016 (c) shows the initial state of Dambos in 1984 (d) shows the Dambos converted to cropland 44

Figure 3. 1. The Location of the Copperbelt province, Zambia with sampling sites indicated by * 67

Figure 3. 2. Land use land cover categories showing persistent forest of the Copperbelt province from 1984 to 2019 71

Figure 3. 3. Soil textural classes of the Copperbelt province derived from particle size analysis 74

Figure 3. 4. Landscape fragmentation of the Copperbelt province a) Number of Patches (NP), b) Patch Density (PD), c) Largest Patch Index (LPI), d) Shannon Diversity Index (SHDI) 76

Figure 3. 5. Forestland metrics in the Copperbelt Province a) Total Area (CA), b) Number of patches (NP) c) Percent of Landscape (PLAND), and d) Largest patch Index (LPI) 78

Figure 3. 6. Distribution of fractal dimension of the persistent forest (1984-2019) of the Copperbelt province 79

Figure 3. 7. Mean quantities/concentrations of soil chemical parameters in loamy and sandy soils of FRAC-1 and FRAC-2 metric areas a) Carbon (C); b) Nitrogen (N), c) NH_4-N (Ammonium Nitrogen), d) NO_3-N (Nitrate Nitrogen), K (Potassium), P (Phosphorus) and pH....81

Figure 4. 1. The Location of the Copperbelt province, Zambia 104

Figure 4. 2. Flow chat for computing the slope length and slope steepness factor 109

Figure 4. 3. Persistent areas between 1984 – 2019 in the Copperbelt province (a) Persistent Forestland; (b) Persistent Cropland....113

Figure 4. 4. Factors used in soil loss modelling a) Rainfall erosivity, b) Soil Erodability, c) Slope Length and Slope Steepness, d) Cover and Management-1984, e) Cover and Management Factor-2019 f) Support Practice -1984 g) Support Practice Factor-2019....115

Figure 4. 5. Extent of erosion severity in the Copperbelt province (a) Erosion severity in 1984; (b) Change map of erosion severity between 1984 and 2019 (c) Extent of erosion severity in 2019....117

Figure 4. 6. Variations in mean soil loss in FRAC-1 and 2 areas and soil textural categories in persistent (a) Forestlands (b) Croplands 120

Figure 5. 1. The Location of the Copperbelt Province, Zambia, Southern Africa....145

Figure 5 2. Categories of forest and Cropland areas assessed; a) FRAC-1 Forestlands, b) FRAC-2 Forestlands, c) FRAC-1 Croplands, d) FRAC-2 Croplands....148

Figure 5 3. Distribution of MSPA parameters in persistent Forestlands and Croplands a)FRAC-1 Forestland, b) FRAC-2 Forestland, c) FRAC-1 Cropland, d) FRAC-2 Cropland 154

Figure 5 4. Intensity of MSPA parameters in persistent Forest and Cropland classes 155

Figure 5 5. Distribution of contortion parameters in persistent Forestlands and Croplands a) FRAC-1 Forestland, b) FRAC-2 Forestland, c) FRAC-1 Cropland, d) FRAC-2 Cropland..156

Figure 5 6. Intensity of shape descriptors in persistent FRAC categories a) Convexity, Roundness, Circularity Elongation, b) Directionality c) Average length and Width of patches 157

Figure 5. 7. A Snapshot of FRAC2 Forest patches outlined in Imagej for computation of shape descriptors, b) An illustration of shape descriptor index adapted from (Bogan et al. 2010) 161

LIST OF TABLES

Table 2. 1. Overall transitions matrix for land use land cover change (per cent in brackets) in the Copperbelt province, Zambia between 1984 and 2016......................................38

Table 2. 2. Transitions matrix for land use land cover change (per cent in brackets) of the Copperbelt province between 1984 and 2050..40

Table 2. 3. Extent of Woodlands and Dambos converted to degrading land use type for the period 1984 to 2016 and 1984 to 2050 in the Copperbelt province.........................42

Table 3. 1. List of indices applied in the study 71

Table 3. 2. Reclassification of standard soil textural classes into soil categories.......................73

Table 3. 3. Class metrics for the Copperbelt province from 1984 to 2019................................77

Table 3. 4. Reconstructed table of test between-subject effects results of ANOVA 82

Table 4. 1. Cover management factor (C_{mt}) and support practice factor (P_{sp})..........................111

Table 4. 2. Reconstructed table of the change in the area of erosion severity classes between 1984 and 2019. 118

Table 4. 3. Difference in mean soil loss between Cropland and Forestland in FRAC-1 and FRAC-2 metric areas in sandy and loamy soils 119

Table 4. 4. Tests of between-subjects effects-Croplands..120

Table 4. 5. Tests of between-subjects effects-Forestlands..121

Table 5. 1. Description of indices applied in the study..150

LIST OF APPENDICES

Appendix A 1: Land use land cover maps from 1984, 2016, 2050 187

Appendix A 2: Summary of training, validation data and overall accuracy for the various years between 1984 and 2019..189

Appendix A 3: Accuracy of driver variables used in transition potential modeling in the Copperbelt province, Zambia...197

Appendix B 1: Land use land cover for 2019 198

Appendix B 2: Validation / Confusion matrix for 2019 199

Appendix C 1: Data collection tools / sheets 200

Appendix D 1: Shape descriptors for FRAC-1 and 2 Forest and Croplands 205

Appendix E 1: Cross validation of ordinary kriging for interpolating soil parameters 206

LIST OF ACRONYMS AND ABBREVIATIONS

7NDP	:	Seventh National Development Plan
A	:	Mean Annual Soil Loss
ANN	:	Artificial Neural Networks
ANOVA	:	Analysis of Variance
ASE	:	Average Standard Error
C	:	Carbon
C_{mt}	:	Cover and management
CEC	:	Cation Exchange Capacity
CSO	:	Central Statistics Office
CTF_x	:	The Class Total for the final year of class x
DEM	:	Digital Elevation Model
DN	:	Digital Number
DRC	:	Democratic Republic of Congo
EMA	:	Environmental Management Act
ENVI	:	Environment for Visualising Images
ERFAC	:	Alternative Soil Erodibility Factor
EROS	:	Earth Resources Observation and Science
ESRI	:	Environmental Systems Research Institute
ETM	:	Enhanced Thematic Mapper
FAO	:	Food and Agriculture Organisation
FISP	:	Farmer Input Support Programme
FRAC	:	Fractal Dimension
FSP	:	Fertiliser Support Program
GIS	:	Geographic Information Systems

GPS	:	Global Positioning System
GRZ	:	Government of the Republic of Zambia
GUIDOS	:	Graphical User Interface for the Detection of Objects and Shapes
G_x	:	Gain in area for class x
ICF	:	Inner City Fund
ILUA	:	Integrated Land Use Assessment
ILWIS	:	Integrated Land and Water Information System
IPCC	:	Intergovernmental Panel on Climate Change
ITCZ	:	Inter Tropical Convergence Zone
K	:	Potassium
K_{er}	:	Soil erodibility
LCM	:	Land Change Modeller
LM	:	Landscape Metrics
LPI	:	Largest Patch Index
LS	:	Slope length and Slope steepness
LU/LC	:	Land Use Land Cover
LULCC	:	Land Use Land Cover Change
L_x	:	Loss in area (class change)
MAL	:	Ministry of Agriculture and Livestock
MCA	:	Markov Chain Analysis
ME	:	Mean Error of Prediction
MENR	:	Ministry of Environment and Natural Resources
MLP	:	Multi-layer Perceptron
MLPNN	:	Multi-layer Perceptron Neural Network
MSE	:	Mean Standardized Error

MSL : Mean Soil Loss

MSPA : Morphological Spatial Pattern Analysis

MWDSEP : Ministry of Water Development, Sanitation and Environmental Protection

N : Nitrogen

NAP : National Agriculture Policy

NBSAP2 : Second National Biodiversity Strategy and Action Plan

NCCRS : National Climate Change Response Strategy

NEP : National Energy Policy

NH_4-N : Ammonium-nitrogen

NO_3-N : Nitrate-nitrogen

NOAA : National Oceanic and Atmospheric Administration

NP : Number of Patches

NPCC : National Policy on Climate Change

NPE : National Policy on Environment

NQC_x : Net Quantity Change for class x

NRCS : Natural Resources Conservation Service

P : Phosphorus

P_{sp} : Support practices

PA : Patch Area

Pa : Pixel Area

PD : Patch Density

PFAP : Provincial Forestry Action Programme

PH : Power of Hydrogen

PLAND : Percent of Landscape

Pr	:	Annual average rainfall
Pv	:	Pixel Value
P_x	:	Area of unchanged pixels for class x between the initial and final year
R	:	Rainfall runoff-erosivity
RATSA	:	Road Transport and Safety Agency
RMSE	:	Root-Mean-Square Error
RMSSE	:	Root-Mean-Square Standardized Error
ROI	:	Region of Interest
sA	:	Percentage change in erosion severity class
SAP	:	Structural Adjustment Program
SASSCAL	:	Southern African Science Service Centre on Climate Change Adaptive Land-use
sF	:	Erosion severity for Final year
sG_x	:	Gain in area for erosion severity of class x
SHDI	:	Shanon Diversity Index
sI	:	erosion severity in the Initial year
sK	:	Magnitude of change in erosion severity between Initial year and Final year
sL_x	:	Loss in area of erosion severity
SPSS	:	Statistical Package for Social Sciences
sP_x	:	Area of unchanged pixels for erosion severity class x
sS_x	:	Swap between final and Initial year for erosion severity x
sTC_x	:	Total change in area between initial and final year for erosion severity class x
S_x	:	Swap in LU/LC classes

Ta : Total Study Area

TC_x : Total Change in area between the final year and initial year for class x.

TEB : Total Exchangeable Bases

TM : Thematic Mapper

TSL : Total Soil Loss

USDA : United States Department of Agriculture

USGS : United States Geological Survey

USLE : Universal Soil Loss Equation

UTM : Universal Transverse Mercator

WARMA : Water Resources Management Authority

WGS : World Geodetic System

ZAFFICO : Zambia Forestry and Forest Industries Corporation

ZEMA : Zambia Environment Management Agency

ZFAP : Zambia Forestry Action Programme

ZSA : Zambia Statistics Agency

CHAPTER 1: General introduction

1.1 Introduction

1.1.1 Land use land cover and drivers of change in Miombo woodlands

Tropical forests cover about 2 billion ha (13%) of the world's land area (FAO 2015, Gumbo et al. 2018) and account for an estimated 25% of carbon in the terrestrial biosphere (Bonan 2008). The loss of tropical forests and other natural landscapes such as Dambos due to land use land cover change (LULCC) is therefore a major concern because it causes global CO_2 fluctuation (Bonan 2008, Pongratz et al. 2014). Nested within the tropical forests are Miombo woodlands that are dominated by *Isoberlinia, Julbernadia* and *Brachystegia* tree species (Backéus et al. 2006, Dewees et al. 2010) and covers approximately 10 countries including Angola, Zimbabwe, Zambia, Mozambique, Tanzania and most of the southern part of the Democratic Republic of Congo (Campbell et al. 2008). This ecosystem occupies approximately 2.7 million km^2 (Ribeiro et al. 2015) and holds about 43% of the world's tropical dry forests (Kalaba et al. 2012) with about 8,500 species of higher plants. Of this quantity, 54% are endemic to the region (Chirwa et al. 2008, Dziba et al. 2020, Mittermeier et al. 2003). The Miombo ecosystem has important ecological functions; because they maintain soil fertility, regulate climate by maintaining carbon stocks, modify the hydrological cycle, control soil erosion and support livelihoods of more than 100 million people within and outside the region (Chidumayo and Gumbo 2010, Jew et al. 2016, Ryan et al. 2016).

Despite the ecosystem services and benefits provided by the Miombo woodland, approximately 13 million ha of forests are cleared every year (Keenan et al. 2015, Sloan and Sayer 2015). The ecosystem is threatened by drivers of deforestation that include population increase, construction, charcoal production, firewood collection, increase in agricultural activities, settlements, illegal exploitation of timber, mining, and forest fires (Dam 2017, Handavu et al.

2019, Mzuza et al. 2019, Shackleton 2015). It is therefore important that the resulting land cover changes are determined at periodic intervals (Brink and Eva 2009). Additional underlying drivers of deforestation in Zambia include: rising electricity tariffs, unreliable electricity supply, high price of electric cooking stoves, and lack of reliable and affordable alternative energy sources (Moombe et al. 2020, Mwitwa and Makano 2012, Tembo et al. 2015). Over 50% of the world population is currently living in urban areas with an expected increase to 60% by the year 2030 (Ahmed et al. 2013). This trend is expected to lead to an increase in the amount of forests being harvested or cleared for other land uses causing changes in the structure of the landscape.

1.1.2 Forest management and economic policies in Zambia

Structural changes to the Zambian economy, such as the shift from nationalization to privatization in the 1990s contributed to the increased encroachment of forest reserves especially in mining dominated regions such as the Copperbelt Province. This was because of massive job losses resulting from privatization and structural adjustment programs (SAP) during this period (Mulungushi 2007). Most of the retrenched workers turned to the forest areas for agricultural land, firewood and other forest products. It is therefore important to understand the interdependencies between land use land cover (LU/LC) and livelihoods (Gondwe et al. 2020, Kamwi et al. 2017, Munthali et al. 2019). The high level of deforestation compelled the Zambian Government, through the then Ministry of Environment and Natural Resources (MENR) in 1994 to institute the Zambia Forestry Action Programme (ZFAP) and the Provincial Forestry Action Programme (PFAP) (between 1995 and 1998) (GRZ 1998). These programmes were aimed at mitigating deforestation by providing a viable policy and legal framework to attract investments, creating responsive corporate/public enterprises, redefining forest land ownership and attracting viable commitments from a variety of stakeholders to tree growing, protection and utilization of forest products (GRZ 1998). This led to the formulation of the 1998 Forest Policy and Act number 7 of 1999. However, the Act was not put to action (Kokwe 2007). One of the reasons why the Act was not put to action was that it did not address cost and benefit mechanisms for communities.

Until 2015, forestry management in Zambia was based on the Forest Act No. 39 of 1973. This Act is widely blamed for failures in the forest management sector due to its centralised approach and exclusion of local communities from the planning and managing of forest resources (Malunga 2009, Tembo et al. 2015). However, in 2015, Act No. 39 was repealed and replaced by Act No. 4 of 2015. This new Forest Act provides for the establishment and declaration of National Forests, Local Forests, joint forest management areas, botanical reserves, private forests and community forests. It also provides for the participation of local communities, local authorities, traditional institutions, non-governmental organisations and other stakeholders in sustainable forest management. In addition, the Act calls for the establishment of the Forest Development Fund and provides for the implementation of international environmental agreements (GRZ 2015).

In summary, Zambia has made progress in developing an enabling policy, legal frameworks and plans in addressing natural resources conservation and climate change. These include the Vision 2030 – adopted by GRZ in 2006, Seventh National Development Plan of 2017 (7NDP), Second National Biodiversity Strategy and Action Plan of 2015 (NBSAP2) , National Policy on Environment, 2007 (NPE), National Policy on Climate Change, 2017 (NPCC) (GRZ 2017). In addition, the National Climate Change Response Strategy 2012 (NCCRS), Forest Act of 2015 (GRZ 2015), .National Agriculture Policy 2016 (NAP), Environmental Management Act 2011 (EMA), National Energy Policy 2008 (NEP) are in place (GRZ 2017).

Institutions responsible for the management of natural resources and the environment include the ministries of Green Economy and Environment, Agriculture, Water Development and Sanitation, Lands and Natural Resources, Energy, and Local Government and Rural Development and Home Affairs; Other departments/agencies instrumental include the Planning Department of the Ministry of Finance, Department of National Parks and Wildlife, Zambia Environment Management Agency (ZEMA), Water Resources Management Authority (WARMA), the Zambia Forestry and Forest Industries Corporation (ZAFFICO), Climate Change and Natural Resource Management and the Forest Department.

Notable policy gaps or failures include: unsustainable consumption of forest products; agriculture expansion; land use change; unsustainable utilisation of natural resources, mining & infrastructure development; wildfires; and poor governance. According to Mwitwa et al. (2018), there are no guidelines provided in the Environmental Management Act to ensure that the money raised from Carbon tax through the Road Transport and Safety Agency (RATSA) is used for the intended purpose. These funds go into a central account and some of the money may be used for non-carbon sequestration activities. Generally, the management of natural resources and environment is done in a fragmented approach which is no longer viable. Therefore a more holistic approach to management is required (Mwitwa et al. 2018).

1.1.3 Soils of Miombo woodlands

Soil is an important resource vital for enhancing biodiversity, regulating climate, carbon sequestration, filtering contaminants, providing nutrients and producing food (Panagos et al. 2020). The dominant soils in the higher rainfall zones of the Miombo ecosystem are classified as Haplorthox and Haplustox according to the United States Department of Agriculture (USDA) taxonomy with the FAO soil classification equivalents given in parenthesis (Orthic, Rhodic and Xanthic Ferralsols respectively); Paleustults and Palexerults (Ferric Acrisols) (Campbell 1996). Haploxeralfs (Ferric Luvisols), Tropudalfs and Paleustults (Eutric Nitosols), and Paleudults and Tropudults (Dystric Nitosols) occur over basic rocks. The dominant soils in the lower rainfall zones are Ustropepts (Ferralic and Chromic Cambisols), Paleustalfs and Rhodoxeralfs (Chromic Luvisols), and Plinthustalfs (Plinthic Luvisols) (Araki 1993, Campbell 1996).

The combination of the crystalline nature of many of the rocks, low relief, moist climate, and warm temperatures has produced highly weathered soils that are often more than 3 m deep on the plateau. Shallow, stony soils are common along escarpments and inselbergs. Loamy sand, sandy loam and sandy clay loam textures predominate in both the top and subsoils. The amount of clay often increases substantially with depth. Soils of Miombo woodlands are typically nutrient-poor, acidic, have low cation exchange capacities (CEC), and are low in nitrogen (N), exchangeable cations (total exchangeable bases: TEB) and extractable phosphorus (P) (Araki 1993, Campbell 1996). Organic matter levels are generally low, except under densely wooded vegetation. The generally low CEC values of Miombo woodland soils therefore reflect a combination of low organic matter levels and predominantly low activity clays. The soils are generally freely drained although drainage can be restricted locally by shallow depth, low relief, clay subsoils or indurated laterite (Araki 1993, Campbell 1996).

Soils are constantly degraded because of population growth, economic development, and climate change (Montanarella et al. 2016). Globally, more than 1 billion hectares of land are affected by water or wind erosion (Lal 2003). Thus, soil erosion is widely recognized as a serious environmental problem (Osei and Kabwe 2018, Sanchez and Swaminathan 2005). Soil erosion by water (the focus of this study) is defined as the wearing away of the earth's surface by the force of water and gravity, and the process involves soil particle dislodgement, entrainment, transport, and deposition (Gao et al. 2020, McCool and Williams 2008). Soil erosion dominates on areas with scanty vegetative cover and on agricultural lands (Ravi et al. 2010). The erosion of top soil costs billions of dollars worldwide and has caused the displacement of people who end up as environmental refugees each year. According to the GSP (2017), 75 billion tonnes of soil are eroded every year from arable lands worldwide, which equates to an estimated US $400 billion per year in financial loss (Borrelli et al. 2017, Sartori et al. 2019). Erosion is a threat to soil functions (FAO and ITPS 2015, Montanarella et al. 2016), risking food security, water quality and climate change mitigation. The decline in forests caused by anthropogenic activities leads to the removal of plants that anchor the soil and protect from nutrient loss. Soil erosion assessments therefore serve as a scientific base for soil conservation and watershed management (Patil 2018). Therefore, the link between, LULCC and the intensity of fragmentation, soil loss and erosion severity is important.

1.1.4 Landscape metrics, fragmentation and the impact on soil quality

The configuration and composition of landscape elements in an ecosystem play an important role for maintenance of ecological functionality and biological diversity (Echeverría et al. 2007, Forman and Godron 1986, McGarigal 2015). Fragmentation describes landscape-level process in which a large intact parcel of land is progressively divided into smaller, geometrically altered and isolated patches (Carranza et al. 2014, Fahrig 2003, Forman and Godron 1986) altering the fractal geometry. Human and biophysical factors affect ecosystem function (Jew et al. 2016). The changes in landscape elements and pattern is influenced mainly by the type of natural resources, accessibility and demographic processes. These factors vary worldwide leading to great differences between landscapes in terms of the distribution, extent and pattern of LU/LC such as settlements, forests, agricultural land, grasslands and others (Cho et al. 2013, Frost et al. 2007, Malunga et al. 2021). For instance, urbanization affects the structure and function of earth’s ecosystems through the transformation of the natural landscape, alteration of biophysical processes and habitat, and modification of major biogeochemical cycles (Alberti 2010, Kaye et al. 2006). Evidence shows that the amount of Forestland converted to agriculture use every year in Africa is approximately 310,000 ha leading to fragmentation (Achard et al. 2002, FAO 2020). Human activities can disturb the structural integrity of a landscape and are expected to reduce, or in some cases facilitate ecological flows (Kacholi 2013). These activities significantly affect the shape, size and configuration of patches across the landscape matrix. The increasing number of fragments and the isolation of forest habitats have been cited as reason for the decline of fauna and flora populations (Haddad et al. 2015).

In fractal geometry analysis, and landscape metrics (LM) in general, remote sensing and Geographic Information Systems (GIS) provides LU/LC maps; which is the first step of fragmentation analysis (Achard and Hansen 2012, Stehman 2012). Fractal geometry has been used to quantify the size / shape relationship of vegetation patches (Franklin and Forman 1987, Krummel et al. 1987, Loehle 1983, Mandelbrot 1982, Medina et al. 2012, O'neill et al. 1988, Zhang et al. 2007). Spatial pattern metrics such as FRAC among numerous other metrics, allow researchers to quantify size/shape relationship of vegetation patches (Franklin and Forman 1987, Krummel et al. 1987, Loehle 1983, Mandelbrot 1982, Medina et al. 2012, O'neill et al. 1988, Zhang et al. 2007). Fractal theories have been employed in studying soil characteristics (Karami et al. 2017, Li et al. 2016, Miloš and Bensa 2017, Oleschko et al. 2008, Tuffour 2015, Yu et al. 2015, Zhang et al. 2013). Wang et al. (2007), Wang et al. (2010) also concluded that fractal parameters provided potential indicators of soil quality and are capable of characterizing spatial and temporal differences in different land-use patterns. Nevertheless, studies focusing on the impact of forest and cropland fractal geometry on soil loss are rare and the gap is particularly large in the Miombo ecosystem leaving substantial uncertainty.

1.1.5 Morphological / shape characteristics for spatial planning

Ecological processes are influenced by landscape pattern shaped by the morphology of patches that may exist in different ecosystems. At landscape level, morphological metrics/indices can be applied to provide indicators in monitoring of global, and regional biological and ecological changes (Ostapowicz et al. 2008). Morphometry is the quantitative analysis of form, a concept that encompasses size and shape of entities. Shape is all the geometrical information that remains when location, scale and rotational effects are filtered out from an object (Dryden and Mardia 2016). The morphology of a landscape /patch has a direct influence on ecosystem services and functions such as on the movement of water, physical and chemical properties of soil, vegetation cover and distribution (Dujardin 2017). The morphology further influences humans through shaping and reshaping of the landscape in which social and cultural entities are established. While natural landscapes are influenced by a combination of forms shaped by climate, water, land and vegetation through time, cultural landscapes are designated by anthropogenic activities such as settlements, agriculture, transport networks and industries (Camarretta et al. 2018, Dujardin 2017, Moghaddam 2018). Therefore, estimating and understanding these morphometric changes can provide essential ecological information for policy-making in the protection of the species diversity, forest resource conservation and management (Camarretta et al. 2018, Ferrara et al. 2016, Rabalais et al. 2010).

1.1.6 Problem statement and rationale of the study

The potential to use fractal dimension / geometric pattern of landscapes such as Forestlands to manage the impacts of LULCC on soil nutrients, soil loss and erosion severity has not been explored widely. LU/LC activities lead to LULCC which influences the geometry (FRAC) of the landscape that cause land exposure and potential degradation. Such environmental impacts are widespread especially in recent years when extensive LULCC has occurred in many regions of the world leading to extreme precipitation events such as droughts, intense rainfall and floods, that have increased in magnitude and frequency and this has further accelerated soil erosion that impacts on soil properties. The loss of forest cover further leads to the removal of plants that hold the soil and protect from nutrient loss. As soil erosion continue to increase, agricultural yields will reduce and this will compel people to apply expensive inorganic fertilizers or clear even more forest. This trend is impacting on global food security at the time when human population is increasing (Pokhrel et al. 2018, Rosenstock et al. 2019).

High rates of forest degradation and fragmentation negatively affect soil properties, fauna and flora including climate. For instance, most parts of the world are warming up due to climate change, which has been partly associated with large scale conversion of forests and other natural ecosystems to human induced ones such as Settlements and Croplands. A warming trend has been recorded globally with surface temperatures increasing by over half a degree Celsius in most parts of Africa (Rosenstock et al. 2019). Eroded soil is carried in rivers downstream further causing damage to hydroelectricity and irrigation facilities (Pokhrel et al. 2018). Siltation of rivers also increases the intensity of floods. The increased sediments have negative effect on marine organisms such as coral reefs and further affect mangrove forests and the fishing industry. The erosion of top soils costs billions of dollars worldwide and has caused displacement of people as environmental refugees each year.

It is however not clear how varying patterns of forest/woodland fragmentation such as size, connectivity and FRAC of patches vary or affect soil properties, soil loss and erosion severity.

Most studies have concentrated on land use land cover change (LULCC) and yet significant variations in soil properties and erosion severity may be influenced by the geometric pattern of landscapes such as Forestlands. Therefore, it is important to quantify the trends (past, present and future) in the impacts of LULCC, forest fragmentation dynamics on soil parameters, loss and erosion severity and the morphological characteristics of patches in order to achieve effective spatial planning. In order to ensure that the only factor causing the variation in soil properties was the forest / cropland geometric pattern, the persistent layers from 1984 to 2019 of the two LU/LC were used in the computation of FRAC. Consequently, the lack of morphological indicators for spatial planning and limitations in the application of landscape metrics in forest management has led to unfavourable land uses that have negative effects on ecosystem functions.

1.1.7 Research objectives

To evaluate the impacts of spatial temporal variations in forest fragmentation on soil quality, loss and erosion severity and to model morphological spatial decision support indicators for mitigation through effective spatial planning.

Objective 1- Evaluate the impact of LULCC on woodlands and Dambos from 1984 to 2016, and predict up to 2050

Research questions were:

1.1: What is the extent of LU/LC from 1984 to 2016 and the predicted changes to 2050?

1.2: What are the impacts of human induced land uses on Forestlands and Dambos?

Objective 2: To quantify the spatial variability of soil chemical properties attributed to changes in fractal dimension (FRAC)

Research questions were:

2.1: What is the extent of fragmentation in the Copperbelt Province Miombo forest from 1984 to 2019?

2.2: What is the impact of FRAC on soil properties?

Objective 3: To quantify the extent of soil loss and the impact of FRAC on erosion severity

Research questions were:

3.1: What is the extent of soil loss and erosion severity in the Copperbelt Province Miombo forest and cropland?

3.2: What is the impact of FRAC on soil loss and erosion severity?

Objective 4: To identify and quantify the morphological spatial pattern and shape characteristics of Forestland and Cropland patches for use as indicators in spatial planning

Research questions were:

4.1: What are the morphological spatial patterns and shape characteristics of Forestland and Croplands?

4.2: Are there significant differences in morphological / shape characteristics between Forestland and Croplands in the same FRAC Category?

1.1.8 The conceptual framework

This study evaluated the variations in forest fragmentation, patch / landscape geometric pattern that have influence on soil parameters, extent of soil loss and erosion severity and on the morphological/shape characteristics of patches. It is hypothesized that, for a given LU/LC, the geometric pattern of patches/landscape has influence on the maintenance of soil quality and ecosystem function. Therefore, this means that with the current increase in degradation of natural ecosystems, changes in the structure and geometry of the landscapes have occurred leading to alterations in soil properties, biodiversity and changes in climate variables such as LST, rainfall and albedo. The situation is blamed on drivers of LULCC that include urbanization, agriculture, timber, population growth and fuel wood (Figure 1. 1). Theoretically, forests influence climate through biological, chemical and physical processes. Differences in LST, albedo and soil properties are therefore bound to occur with varying extents of LU/LC and the state of forest fragmentation over time.

In theory, land surface albedo is an important indicator that determines the energy budget and change in micrometeorological conditions such as the temperature, aridity and humidity of the land (Ismael 2015). It is affected by the change in vegetation, LST and soil moisture. Increased albedo implies increased net radiative loss. Studies have shown that increasing land surface albedo implies a degradation of land quality (Silva et al. 2020). The percentage of light reflected from the ground increases if the cover decreases and will decrease if the cover increases thus albedo is an indicator of the state of LU/LC including the state of soil erosion which can be quantified using remote sensing.

Therefore, at the centre of influencing the state of LU/LC in a terrestrial ecosystem is the state of vegetation, soil and anthropogenic factors. The succession of vegetation is often accompanied by changes in soil properties. This is the reason why clearing of forests also entails the removal of plants that anchor the soil and protect nutrients from loss. The soil-vegetation feedback loop is critical in determining vegetation succession and condition of soil and influences LU/LC and microclimate across the landscape.

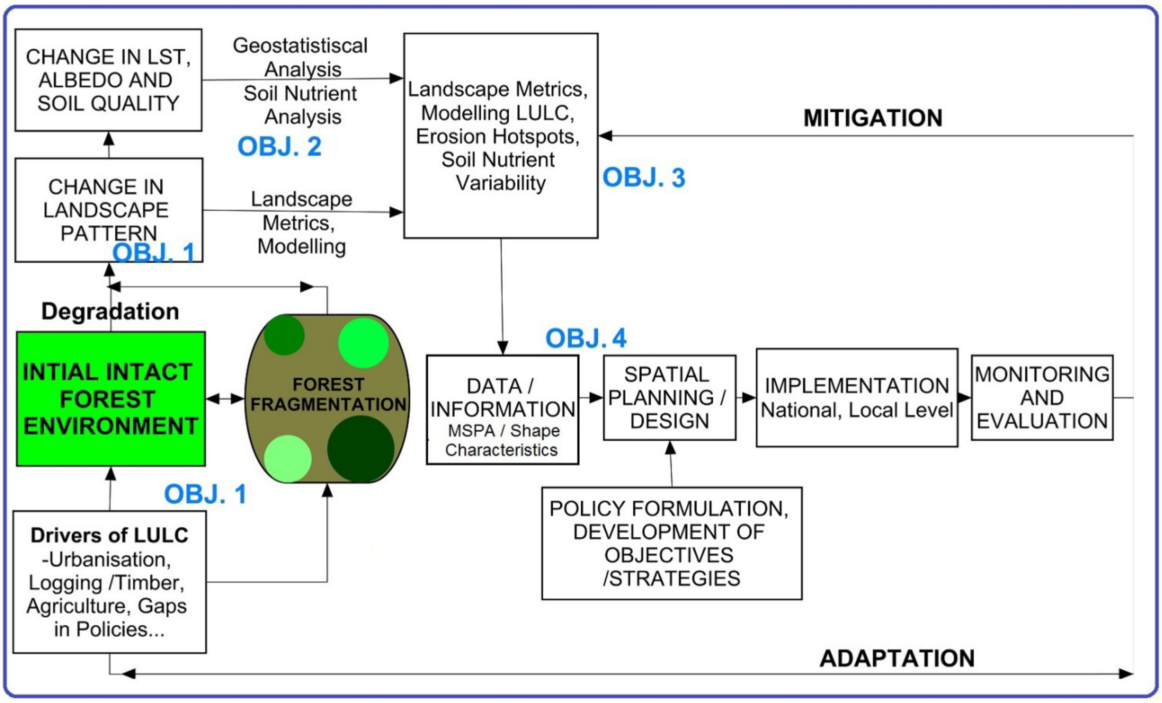

Figure 1. 1. Study conceptual framework
Note: MSPA: Morphological Spatial Analysis of patches, LST: Land Surface Temperature

Landscape ecology has further provided a strong conceptual and theoretical basis for understanding landscape function, structure, and change (Forman and Godron 1986, O'Neill et al. 1997). Therefore, methodology that describes landscape pattern and soil nutrients quantitatively are required and yet forest management is dominated by the use of non-spatial methods void of landscape metrics. Spatial methods are necessary in order to generate up to date information through GIS and remote sensing techniques that incorporate geo-statistical analysis, landscape metrics, modelling and social aspects in developing a spatial forest planning framework for sustainable management of forests and soils. It is therefore important to model the resulting morphological characteristics of landscapes /patches that would be applied as indicators in spatial planning to ensure sustainability.

1.1.9 Thesis structure

This thesis is made up of six chapters. In Chapter 1, the overview of the research and a description of LULCC/ Forest cover changes, related drivers, extent of landscape fragmentation and its impacts on soil parameters, and the influence of FRAC on soil loss and erosion severity are presented. Further, the chapter presents the MSPA and shape characteristics of Forestlands and Croplands in Miombo woodlands of the Copperbelt province. The chapter also presents the study problem statement and rationale, aim, specific objectives, research questions, and the conceptual framework. In Chapters 2 to 5, studies related to specific objectives 1-4 have been presented in a manuscript / journal article format. Each chapter has its introduction, methodology, results, discussion, and conclusion. The synthesis is presented in Chapter 6 which links results, implications and recommendations of objectives presented in Chapters 2 to 5.

The second chapter addresses the first objective, which focussed on "*Land-use induced land cover changes and future scenarios in extent of Miombo woodland and Dambo ecosystems in the Copperbelt province of Zambia*".

The third chapter addresses the second objective, which focussed on "*Extent of fragmentation and the impact of forest fractal geometry on selected soil parameters in Miombo woodlands of Zambia's' Copperbelt region*".

The fourth chapter addresses the third objective, which focussed on "*Extent of Soil Loss and the Impact of Fractal Geometry of two Competing Land Uses (Cropland and Forestland) on Erosion Severity in the Miombo Ecosystem of the Copperbelt Zambia*"

Chapter 5 addressed the fourth and the final specific objective which focused on "*Modelling the Pattern and Morphological Characteristics of Forests and Cropland patches for use as indicators in Spatial Planning*"

Chapter 6 is the synthesis, which has linked the results of the four chapters (specific objectives one to four). The results of the study are presented with reference to the conceptual framework, drawing conclusions and recommendations to understand the overall LULCC/forest, extent of landscape fragmentation (FRAC) and its impacts on soil parameters, soil loss and erosion severity and the morphological / shape characteristics of forests and croplands in Miombo woodlands of the Copperbelt province.

For the publications, this thesis contains one article that has been published (Chapter 2, specific objective 1). Manuscripts in Chapters 3-5 have been submitted to the Journals for peer-review. The titles are as follows:

Chapter 2 (specific objective 1) - *Land-use induced land cover changes and future scenarios in extent of Miombo woodland and Dambo ecosystems in the Copperbelt province of Zambia*" African *Journal of Ecology,* DOI: 10.1111/aje.12921

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Chapter 3 (specific objective 2) - *Extent of fragmentation and the impact of forest fractal geometry on selected soil parameters in Miombo woodlands of Zambia's' Copperbelt region*

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Chapter 4 (specific objective 3) –*Extent of Soil Loss and the Impact of Fractal Geometry of two Competing Land Uses (Cropland and Forestland) on Erosion Severity in the Miombo Ecosystem of the Copperbelt Zambia (Submitted).*

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Chapter 5 (specific objective 4) - *Modelling the Pattern and Morphological Characteristics of Forests and Cropland patches for use as indicators in Spatial Planning*.

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CHAPTER 2: Land use induced land cover changes and future scenarios in extent of Miombo woodland and Dambo ecosystems in the Copperbelt province of Zambia

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Abstract

The pattern of Miombo woodland conversion to other land uses and the attendant impacts on vital Miombo ecosystems such as Dambos is not well understood. Using the Copperbelt province of Zambia as a case study, we assessed the spatio-temporal patterns of Miombo woodland and Dambo conversion to other land uses between 1984 and 2016; and predicted the changes to 2050. The effects of land use land cover change (LULCC) on the extent of Miombo woodlands and Dambos was determined by intersecting layers of Croplands, Settlements, Plantations, Grasslands and Barelands on Woodland and Dambo pixels. Prediction of future LULCC was done using the land change modeller (LCM) in TerrSet. It was observed that in the period between 1984 and 2016, Woodlands decreased by 17.9% while Dambos increased by 4.9%. The two classes were predicted to lose 26.4% and 2.0%, respectively, by 2050. Conversion to Cropland was the highest contributor to Woodland loss, accounting for 57.5% of total loss by 2016, and projected to reach 67.6% by 2050. Similarly, establishment of Cropland was shown to result into 53.5% (2016) and 58.9% (2050) of loss of Dambos. Expansion of Croplands caused a decline in Woodlands and Dambos. Therefore, the expansion of croplands should be controlled while efficient agricultural techniques should be implemented.

KEYWORDS: **Land use, copperbelt, dambo, miombo woodland, modelling, forestland, cropland**

2.1 Introduction

Tropical forests cover about 2 billion ha (13%) of the world's land area (FAO 2015, Gumbo et al. 2018) and account for an estimated 25% of carbon in the terrestrial biosphere (Bonan 2008). The loss of tropical forests due to land use land cover change (LULCC) is therefore a major concern because it causes global CO_2 fluctuation (Bonan 2008, Pongratz et al. 2014). Nested within the tropical forests are Miombo woodlands that are dominated by *Isoberlinia, Julbernadia* and *Brachystegia* tree species (Backéus et al. 2006, Dewees et al. 2010). This ecosystem covers approximately 2.7 million km^2 in 10 countries of central and southern Africa (Ribeiro et al. 2015). These woodlands hold about 43% of the world's tropical dry forests (Kalaba et al. 2012, Mittermeier et al. 2003) with about 8,500 species of higher plants of which 54% are endemic (Chirwa et al. 2008, Mittermeier et al. 2003). The Miombo ecosystem has important ecological functions; because they maintain soil fertility, regulate climate by maintaining carbon stocks, modify the hydrological cycle, control soil erosion and support livelihoods of more than 100 million people within and outside the region (Chidumayo and Gumbo 2010, Jew et al. 2016, Ryan et al. 2016). Conservative estimates of the benefits (derived from forest and non-forest products) provided by the Miombo woodland range from US$7 to US$11 million per year (Mbanze et al. 2019, Ryan et al. 2016). Despite the benefits provided by the Miombo woodland, approximately 13 million ha of forests are cleared every year (Keenan et al. 2015, Sloan and Sayer 2015). The ecosystem is threatened by land clearance for settlements, agriculture, logging, firewood collection, charcoal production and tobacco curing (Dam 2017, Handavu et al. 2019, Mzuza et al. 2019, Shackleton 2015).

The extent of wetlands globally is projected to be at least 6% of the Earth's surface (Finlayson and D'Cruz 2005). Africa contains in excess of 131 million ha of these wetlands

(McCartney et al. 2011). Interspersed within the Miombo ecosystem are wetlands which appear as broad, grassy wet depressions also known as Dambos, that cover between 10% - 40% of the landscape (Whitlow 1990, Zolho 2005). Dambos are vital habitats for specialised flora and fauna and they contribute to the livelihoods of the local communities (Mbanze et al. 2019). According to von der Heyden and New (2003), the functionality of Miombo woodlands depends on Dambos, because of their ability to capture rainfall and groundwater. Within the hydrological cycle, Dambos store water, thereby mitigating extreme events like floods and droughts (Schlaffer et al. 2016). They also play a vital role in biogeochemical cycles, acting both as sources and sinks of carbon and nitrogen emissions (Schlaffer et al. 2016). Nevertheless, wetlands are also vulnerable to climate change and land-use conversion activities (Junk et al. 2013, Seki et al. 2018) such as extensive agriculture, over grazing, gulley erosion and fires (Matiza 1994, Wood et al. 2013).

It is widely reported that anthropogenic activities may result in the drying up of Dambos, streams and rivers (Mabeza and Mawere 2012, Nyamadzawo et al. 2014). A number of studies have reported on the influence of Dambos on downstream flow regime despite contradictions and lack of consensus on the issue (McCartney et al. 1998, von der Heyden and New 2003). Research on the effect of anthropogenic activities and extent of Dambos are scarce and have been reported in Malawi (Chidanti-Malunga 2011, Mloza-Banda 2005), Zambia (Kuntashula et al. 2006, Shimada 1994), Zimbabwe (Bell 1987, Bell and Roberts 1991, Berka et al. 2001, Scoones and Cousins 1991), Kenya and Tanzania (Franke et al. 2009, Mwita 2013) and in Mozambique (Mbanze et al. 2019). Globally, few studies have highlighted the role of wetlands and the impacts of LULCC such as in the Himalayas (Alam et al. 2011) and in Beijing, Hanshiqiao wetland, (Zhang et al. 2011). Gaps still exist in terms of the extent and current state of Dambos in Africa (Rebelo et al. 2010). The choice to study

Dambos in Miombo woodlands was motivated by their potential role in providing life support for a number of terrestrial and aquatic species (Fynn et al. 2015, Matayaya et al. 2017) and economic benefits through agriculture from the fertile land (Kotze 2011, Ryan et al. 2016, Whitlow 1990). Dambos are among the most threatened habitats in the world (Kotze 2011, Mbanze et al. 2019).

Understanding the elements and processes generating LU/LC in terms of interactive environmental and social subsystems requires land systems theory (Rounsevell et al. 2012). However, such theories remain elusive (Zhou et al. 2019). According to Steffen et al. (2018), land system approaches have previously emphasized the application of the integrated social-ecological systems (SESs), for understanding LULCC. However, human-environmental research fields, such as resilience (Biggs et al. 2015), sustainable landscapes (Wu 2013) and land systems (Verburg et al. 2013), have emerged from those previously focused on either the environmental or social subsystems. According to Roy and Turner (2019), approaches focused on the environmental subsystem, tend to treat anthropogenic activities such as land use, as disturbances to ecosystem functioning, with minimal interactions within the social subsystem. Resilience approaches on the other hand emanate from ecosystems research (Meerow et al. 2016) and calls for SES integration and adaptation in terms of general systems attributes, rather than, LU/LC outcomes. To a large extent, theories, and explanations addressing land dynamics do not fully integrate both the social and environmental dimensions of the SES but tend to focus on one subsystem. Among these research approaches however, land system science seeks to improve the observation, monitoring, understanding, modelling, and sustainability of land systems and their change (Robinson et al. 2018, Verburg et al. 2015).

The main aim of the study was to investigate the effect of LULCC on the extent of Miombo woodlands and Dambos and predict the changes to 2050. We have used the Copperbelt province of Zambia as a case study. LULCC in the province has significant impact on the environment and livelihoods of people particularly in mining dominated areas of the Miombo eco-region. No LULCC and modelling study information was available in the province, suggesting that information on the current and future extent, rate of resource utilisation, gains, losses and impacts are unknown. The relative contribution of human induced land uses (Cropland, Settlements, Barelands, Grasslands and Plantations) to the loss of Woodlands and Dambos have not been assessed. Investigations into wide temporal and spatial scale for changes in Dambos are also not available prompting this study to assess 32 years (1984 to 2016) of LULCC. LULCC determined using remote sensing and modelling techniques would play a vital role in assessing, planning, and monitoring changes in the Woodlands and Dambos.

2.2 Methods

2.2.1 Study area

This study was conducted on the Copperbelt province of Zambia. The Copperbelt is one of Zambia's ten provinces covering 31,328 km² (3.1328 million ha); 4.2% of the total area of the country. The name Copperbelt is derived from the copper mining activities associated with the area. The province lies between latitude S12° to S13° 50'and longitude E27° to E29° (ACCC 2010) and is bounded by Central (in the south), North-Western provinces (to the west) and the Democratic Republic of the Congo (to the north and east). The province lies on the eastern central African plateau that is characterised by a gently undulating plateau of between 1,200m and 1,455m above sea level. The Kafue River flows in the southward direction through the province forming Dambos along the River and its numerous tributaries.

The Copperbelt province was chosen because of its high population density (63.0 persons per square kilometre) that has increased pressure on natural resources as an alternative source of livelihood thereby impacting on the environment of the area (CSO 2014). According to CSO (2014), the population of the province was 1,972,317 (15.2% of Zambia's total population) with about 81% and 19% living in urban and rural areas respectively. Land use in the province are influenced by livelihood activities that are based on agriculture, forestry and mining. The unemployment rate of the province is over 22% (CSO 2014).

2.2.2 Image acquisition and pre-processing

The study area falls within Landsat path/row: 172/69, 172/68, 173/69, and 173/68. Landsat images covering the period 1984 to 2016 were obtained from the United States Geological Survey (USGS) website (ESRI 2016). These images were assessed at the following intervals: Landsat 5-TM images for 1984, 1989 and 1999; Landsat 7-ETM for 2004, and 2009 and Landsat 8 images for 2016. Landsat images were used in land cover classification, change detection, prediction of LULCC into the future (2050) and planning some field data collection on land use activities. The images were geometrically corrected and projected to the Universal Transverse Mercator zone 35s coordinate system and the World Geodetic System (WGS) 84 datum. This was essential in change detection because it ensured alignment of images of different years so that corresponding elements of the same ground area appear in the same place thereby increasing accuracy (NOAA 2005). Radiometric correction and normalization of the images was done in order to ensure that the changes in pixel values from various images reflect actual changes on the surface (Du et al. 2002). ArcGIS 10.3 (ESRI 2015) and ENVI 4.7 (Solutions 2018) software were employed in the analysis process using both raster and vector data.

2.2.3 Field data collection on land use activities

One hundred and fifty (150) random sample sites amounting to a total sample area of 45,151ha (out of 3,138,589ha total study area) were generated for ground truthing the LU/LC giving a sampling intersity of 1.44%. Ground truth data was collected between October and December 2016. Data on land use types, fauna and flora, land use activities such as agriculture, settlements, charcoal production, firewood collection and fires were recorded during ground truthing. The data collected from observations were supplemented by desk research on published literature.

2.2.4 Data analysis-land cover classification

Supervised image classification using the maximum likelihood classification method was applied (ESRI 2012). Training site data were selected in easily identifiable areas of classes such as water; indigenous and plantation forest; and non-forest areas such as bare soil and built-up areas, using a GPS receiver and Google Earth. Representative sites were visited and their locations recorded with a GPS unit as ground truth points in order to match the land use class with the digital number (DN) in each band (Millard and Richardson 2015). Classes adapted from IPCC (2003) and Münch et al. (2017) were applied and are described as follows: Dambo (depressions with grasses and seasonal water); Woodland/Forestland (land of >0.5 ha with trees ≥5m and a canopy ≥10%); Settlement (urban, industrial land covers with buildings and roads); Bareland (barren land, bare soil and rock outcrops); Grassland (grasses, shrubs, pasture or herbaceous rangeland); Cropland (agricultural land with standing or harvested crops including livestock); Water (water bodies such as ponds, lakes, rivers, streams and canals); and Plantation (felled or standing trees of pine, eucalyptus and other exotic tree species).

2.2.5 Classification accuracy assessment

For accuracy assessment, 150 sample points were evenly distributed to each category of the LU/LC by the class area ratio using the stratified random sampling method. Each sample point location representing a class was located using the GPS receiver. The validation of features collected on the ground was crossed with each of the classified maps to create an error matrix (confusion matrix) according to Olofsson et al. (2013). The overall accuracy was computed through kappa statistic by dividing the correctly classified points by the total number of points multiplied by 100% using ENVI 4.7 software (Appendix A2, A3). An overall accuracy of 85% was acceptable in the study (Kamusoko and Aniya 2007).

2.2.6 Change detection

LULCC detection used the “Postclassification” function in ENVI 4.7. The classified images were compared using cross-tabulation in determining the changes between the initial year (1984) and the final year (2016/2050) in a transition matrix. The magnitude and percentage of changes were calculated using the formula:

$$K = F - \mathrm{I} \qquad (1)$$

$$\mathrm{A} = \frac{(F-I)}{\mathrm{I}} X \; 100 \qquad (2)$$

Where K = magnitude of changes between the initial year and the final year in hectares; A = percentage of changes; F= the final year, and I = the initial year (Mahmud and Achide 2012). Additional change detection statistics as outlined in (Aldwaik and Pontius Jr. 2012) and (Pontius Jr. 2019) where adapted into the methods using the following formulae:

$$\mathrm{L_X} = \mathrm{CT}F_{\mathrm{x}} - \mathrm{P_x} \qquad (3)$$

$$\mathrm{G_X} = \mathrm{CT}I_{\mathrm{x}} - \mathrm{P_x} \qquad (4)$$

$$\mathrm{NQC_X} = \mathrm{G_x} - \mathrm{L_x} \qquad (5)$$

$$S_X = (G_X + L_x) - NQC_x \quad (6)$$

$$TC_X = S_x + NQC_x \quad (7)$$

Where L_x= the loss in area (class change) for class x; CTF_x = the class total for the final year of class x; P_x =the area of unchanged pixels for class x between the initial and final year; G_x= the gain in area for class x; CTI_x= the class total of the initial year for class x; NQC_x (image difference) = the Net Quantity Change for class x; S_x = the swap in LU/LC classes; TC_x= the total change in area between the final year and initial year for class x.

2.2.7 Prediction of land use land cover change into the future (2050)

Prediction of LULCC analysis was done through the land change modeller (LCM) for ecological sustainability available in TerrSet. The Multi-layer Perceptron (MLP) and Markov chain analysis (MCA) method were applied for prediction to the year 2050. The MLP was chosen because it is one of the most commonly used Artificial Neural Networks (ANN) that gives accurate predictions (Ahmed and Ahmed 2012, Eastman 2012, Mishra et al. 2014). The Markov chain projection was performed by creating a matrix to estimate the area of each LU/LC class for future dates and the quantity of change for each transition. The probability of each transition was computed in order to assess the change potential (Eastman 2009, Mas et al. 2014). Finally, transition potential modelling, prediction and validation were done. The transition potential maps for each sub-model were produced based on dynamic and static variables, LU/LC transitions, with the help of the Multi-layer perceptron neural network (MLPNN). The transition probability matrix was calculated for the time period of 1984–2016 for the prediction of LU/LC map of 2050. To carry out validation, the predicted LU/LC map of 2016 was compared with the observed LU/LC map of 2016 using kappa index statistics (Aburas et al. 2016, Kamusoko et al. 2009, Wang et al. 2012).

2.2.8 Land use induced land cover changes in Woodlands and Dambos

To determine the contribution of each degrading LU/LC class on the extent of Miombo woodlands and Dambos, values for each class were extracted from transition matrix derived from LULCC analysis. In this study, Croplands, Bareland, Settlements, Plantations and Grasslands were considered as degrading LU/LC to Woodlands and Dambos because they are human induced and have been shown to impact on naturally occurring land cover (Gondwe et al. 2020, Malunga 2009). To create Boolean maps for the area of Woodlands and Dambos converted by each degrading LU/LC, mask layers were created through the "Band Threshold to ROI" and the "Subset Data via ROIs" in ENVI. The "AND" function in the Raster calculator of ArcGIS was applied in order to intersect the Woodland and Dambo class layers to each degrading LU/LC layers.

To test the contribution of each degrading LU/LC type to Woodland and Dambo loss, multiple regression analysis was applied using Microsoft Excel 2016 set at 95% confidence level through the "Data Anlysis" function. The area of Woodlands and Dambos of 1984 and 2016 were the dependant variables while the areas of the degrading LU/LC (Croplands, Settlements, Grasslands, Barelands and Plantations) were the independent variables. The determination coefficient (R^2) was used in evaluating the multiple regression model. All variables retaining p values >0.05 where considerd to have insignifcant influence on the area of Woodlands and Dambos while those retaining p values <0.05 were taken to have significant effect.

2.3 Results

2.3.1 Land use land cover change between 1984 and 2016

Classified images for all the years under review yielded robust and reliable results with 87.04% as the lowest user and producer accuracy (Appendix A1, A2, A3). Model performance results indicated an overall accuracy of 90.57% and kappa statistic of 0.89. Table 2.1 provides the transition matrix for the initial year (1984) and final year (2016). The bold diagonal values indicate areas that did not change (Persistence). Woodland was the largest class in 1984 (64.9% of the landscape), followed by Dambos (12.5%). Grasslands covered 11.08% and Croplands were within 6.43% of the landscape. Settlements, Barelands, Water and Plantations each fell below 2.5% in landscape coverage. Land cover changes show that Woodlands gained 8.14%, and lost 26.05% to give NQC of -17.91%. Croplands gained 15.93% but lost 4%; Dambos gained 13.16%, lost 8.3% giving NQC of 4.9%; Grasslands gained 9.59% against a loss of 8.97% giving NQC of -1.50%.

Table 2. 1. Overall transitions matrix for land use land cover change (per cent in brackets) in the Copperbelt province, Zambia between 1984 and 2016

	2016-Area in ha									
	Dambo	**Woodland**	**Settlement**	**Bareland**	**Grassland**	**Cropland**	**Water**	**Plantation**	**Area in 1984**	**Loss**
Dambo	**131,837.94**	111,730.77	4,329.09	733.32	55,748.16	72,030.51	12,710.25	1,765.35	392,280.75	260,442.81
	(4.20)	(3.56)	(0.14)	(0.02)	(1.78)	(2.29)	(0.40)	(0.06)	(12.50)	(8.30)
Woodland	247,892.85	**1,217,998.62**	13,686.57	2,600.10	197,821.89	310,781.43	17,368.02	15,939.36	2,035,694.25	817,664.40
	(7.90)	**(38.81)**	(0.44)	(0.08)	(6.30)	(9.90)	(0.55)	(0.51)	(64.86)	(26.05)
Settlement	4,422.06	4,075.11	**15,026.67**	1,114.38	3,938.13	8,115.93	648.09	243.18	37,624.95	22,598.28
	(0.14)	(0.13)	**(0.48)**	(0.04)	(0.13)	(0.26)	(0.02)	(0.01)	(1.20)	(0.72)
Bareland	1,131.03	730.8	1,890.63	**4,803.93**	1,093.77	2,462.49	506.79	19.17	12,649.86	7,845.93
	(0.04)	(0.02)	(0.06)	**(0.15)**	(0.03)	(0.08)	(0.02)	(0.00)	(0.40)	(0.25)
Grassland	89,848.53	72,393.84	10,999.53	2,731.14	**66,476.07**	94,126.86	7,738.65	2,679.03	347,898.15	281,422.08
	(2.86)	(2.31)	(0.35)	(0.09)	**(2.12)**	(3.00)	(0.25)	(0.09)	(11.08)	(8.97)
Cropland	32,727.69	39,912.39	14,326.74	1,523.16	32,598.54	**76,879.80**	2,273.67	995.76	201,837.51	124,957.71
	(1.04)	(1.27)	(0.46)	(0.05)	(1.04)	**(2.45)**	(0.07)	(0.03)	(6.43)	(3.98)
Water	30,249.81	12,189.33	324.27	791.19	6,026.67	6,887.16	**6,816.78**	483.39	64,147.50	57,329.19
	(0.96)	(0.39)	(0.01)	(0.03)	(0.19)	(0.22)	**(0.22)**	(0.02)	(2.04)	(1.83)
Plantation	3,619.98	6,258.24	292.5	35.64	2,577.24	3,418.11	382.86	**29,734.29**	46,471.77	16,737.48
	(0.12	(0.20)	(0.01)	(0.00)	(0.08)	(0.11)	(0.01)	**(0.95)**	(1.48)	(0.53)
Area in 2016	544,867.47	1,473,405.75	60,991.47	14,349.96	367,444.80	577,004.94	48,644.82	51,879.96	3,138,589.17	
	(17.36)	(46.94)	(1.94)	(0.46)	(11.71)	(18.38)	(1.55)	(1.65)	(100)	
Total Gain	413,029.53	255,407.13	45,964.80	9,546.03	300,968.73	500,125.14	41,828.04	22,145.67		
	(13.16)	(8.14)	(1.46)	(0.30)	(9.59)	(15.93)	(1.33)	(0.71)		
Total Change	(21.46)	(34.19)	(2.18)	(0.55)	(20.67)	(19.92)	(3.16)	(1.24)		
Swap	(16.6)	(52.10)	(1.44)	(0.50)	(22.17)	(7.96)	(3.65)	(1.07)		
Net Quantity Change	(4.86)	(-17.91)	(0.74)	(0.05)	(-1.50)	(11.95)	(-0.49)	(0.17)		

Note: Transition matrix with initial year (1984) in rows and final year (2016) in columns; –NQC indicate Loss, +NQC indicate Gain. Bold diagonal values indicate areas that did not change (Persistence)

2.3.2 Land use land cover change and statistics for predicted 2050

Table 2.2 shows the transition matrix for the change between 1984 and 2050. The area expected to remain unchanged in this period is 1,314,486.99 ha. Woodlands would lose 32.89% and gain 6.49%; Croplands would lose 3.47%, gain 30.53%; Water would loss 1.84%, gain 1.56%; Dambos would lose 9.84%, gain 7.76% giving NQC of -2.0%; Settlements loss would be 0.72%, gain 2.11%; Bareland would lose 0.25%, gain 0.30%; Plantations loss would be 0.53%, gain 0.71% and Grasslands would lose 8.58% and gain 11.08% . Woodlands and Croplands would undergo the highest NQC with -26.40% and 24.1 respectively. Trends in LULCC are shown in Figure 2.1 (Appendix A1).

Table 2. 2. Transitions matrix for land use land cover change (per cent in brackets) of the Copperbelt province between 1984 and 2050

	2050-Area in ha									
	Dambo	**Woodland**	**Cropland**	**Water**	**Settlement**	**Bareland**	**Plantation**	**Grassland**	**Area in 1984**	**Loss**
Dambo	**83,301.12**	93,264.48	119,148.48	13,502.16	7,381.08	733.32	1,766.52	73,183.68	392,280.84	308,979.72
	(2.65)	(2.97)	(3.80)	(0.43)	(0.24)	(0.02)	(0.06)	(2.33)	(12.50)	(9.84)
Woodland	144,225.18	**1,003,300.11**	585,630.09	22,070.25	26,873.28	2,600.28	15,957.27	235,037.79	2,035,694.16	1,032,394.05
	(4.60)	**(31.97)**	(18.66)	(0.70)	(0.86)	(0.08)	(0.51)	(7.49)	(64.86)	(32.89)
Cropland	17,597.16	32,405.04	**92,955.78**	2,965.14	15,452.73	1,523.16	995.76	37,942.74	201,837.51	108,881.73
	(0.56)	(1.03)	**(2.96)**	(0.09)	(0.49)	(0.05)	(0.03)	(1.21)	(6.43)	(3.47)
Water	20,965.50	10,744.83	14,380.92	**6,552.81**	811.53	791.19	483.39	9,417.33	64,147.50	57,594.69
	(0.67)	(0.34)	(0.46)	**(0.21)**	(0.03)	(0.03)	(0.02)	(0.30)	(2.04)	(1.84)
Settlement	2,433.69	3,276.90	10,012.41	733.5	**15,149.34**	1,114.29	243.27	4,661.55	37,624.95	22,475.61
	(0.08)	(0.10)	(0.32)	(0.02)	**(0.48)**	(0.04)	(0.01)	(0.15)	(1.20)	(0.72)
Bareland	736.47	564.03	2,911.86	457.65	1,918.80	**4,803.93**	19.17	1,237.95	12,649.86	7,845.93
	(0.02)	(0.02)	(0.09)	(0.01)	(0.06)	**(0.15)**	(0.00)	(0.04)	(0.40)	(0.25)
Plantation	2,047.59	4,933.26	5,689.53	485.55	364.86	35.73	**29,773.71**	3,141.54	46,471.77	16,698.06
	(0.07)	(0.16)	(0.18)	(0.02)	(0.01)	(0.00)	**(0.95)**	(0.10)	(1.48)	(0.53)
Grassland	55,666.62	58,534.29	127,566.36	8,674.20	13,396.23	2,731.14	2,679.12	**78,650.19**	347,898.15	269,247.96
	(1.77)	(1.86)	(4.06)	(0.28)	(0.43)	(0.09)	(0.09)	**(2.51)**	(11.08)	(8.58)
Area in 2050	326,973.33	1,207,023.21	958,295.43	55,441.26	81,347.85	14,333.04	51,918.21	443,272.77	3,138,589.17	
	(10.42)	(38.46)	(30.53)	(1.77)	(2.59)	(0.46)	(1.65)	(14.12)	(100)	
Total Gain	243,672.21	203,723.10	865,339.65	48,888.45	66,198.51	9,529.11	22,144.50	364,622.58		
	(7.76)	(6.49)	(27.57)	(1.56)	(2.11)	(0.30)	(0.71)	(11.62)		
Total Change	(17.61)	(39.39)	(31.04)	(3.39)	(2.83)	(0.55)	(1.24)	(20.20)		
Swap	(19.69)	(65.79)	(6.94)	(3.67)	(1.43)	(0.50)	(1.06)	(17.16)		
Net Quantity Change	(-2.08)	(-26.40)	(24.10)	(-0.28)	(1.39)	(0.05)	(0.17)	(3.04)		

Note: 1984 is in rows, predicted 2050 in the columns with area in hectares and %; –NQC indicate Loss, +NQC indicate Gain. Bold diagonal values indicate areas that did not change (Persistence)

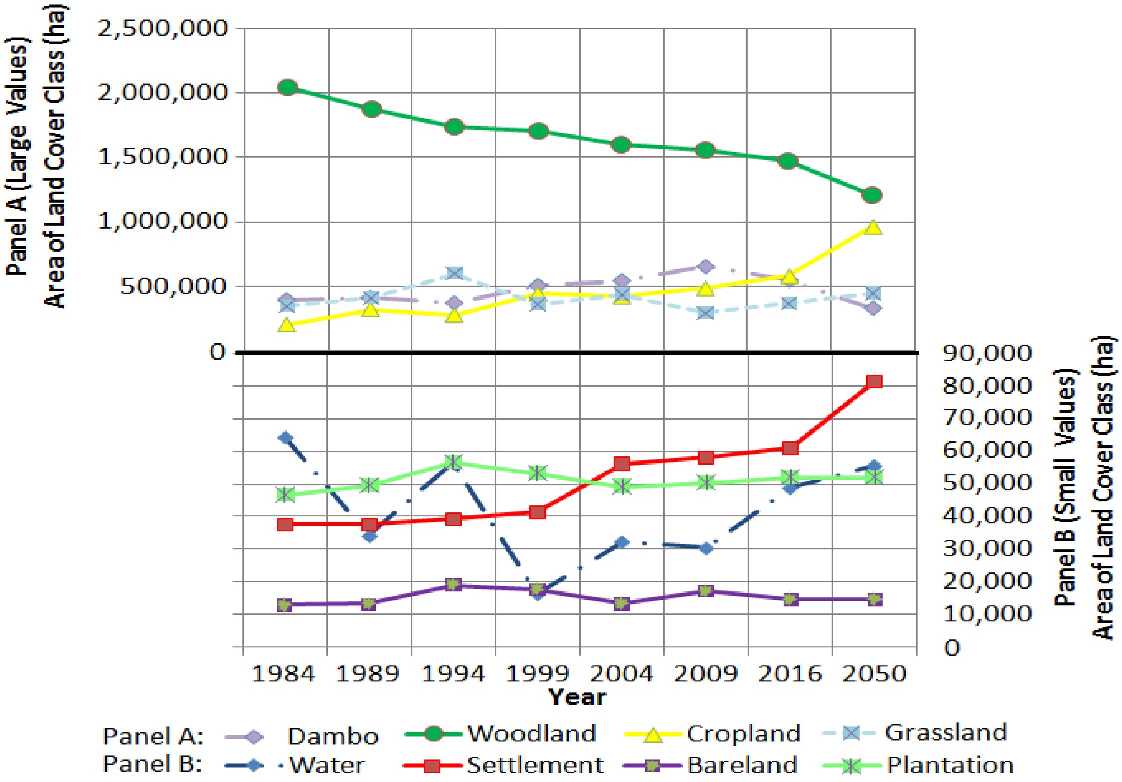

Figure 2. 1 . Panel chart A and B showing trends in land use land cover from 1984 to 2050; panel A (high value classes >200,000ha to 2,500,000ha) and panel B (low value classes >0 to 90,000ha)

2.3.3 Change in the extent of Miombo woodlands and Dambos

Table 2.3 shows that in the period between 1984 and 2016, Woodlands lost 17.9% while Dambos gained 4.9% of the total area and are projected to lose 26.4% and 2.0% by 2050 respectively. Expansion of Croplands was responsible for major loss in Woodlands with over 310,768.50 ha (57.5% of total area lost) between 1984 and 2016 and projected to lose 585,623.20 ha (67.6% of total area) by 2050. The contribution of Cropland and Grasslands to forest loss was significant with p=0.023 and p=0.038 (at 95% confidence level), respectively. Woodlands are predicted to cover 38.46% of the Copperbelt province in 2050 (Figure 2.2). Expansion of Croplands accounted for the highest loss in Dambos with 72,030.51 ha (53.5% of total area lost) and is projected to lose 119,148.50 ha by 2050 (Figure 2.3). Dambos will decline from 12.5% in 1984 to 10.42% in 2050.

Table 2. 3. Extent of Woodlands and Dambos converted to degrading land use type for the period 1984 to 2016 and 1984 to 2050 in the Copperbelt province

	Area of Woodlands Converted by Degrading Land Use				**Area of Dambos Converted by Degrading Land Use**			
	(1984 to 2016)		**(1984 to 2050)**		**(1984 to 2016)**		**(1984 to 2050)**	
Degrading LULC	**Forest Converted (Ha)**	**(%)**	**Forest Converted (Ha)**	**%**	**Dambos Converted (Ha)**	**%**	**Dambos Converted (Ha)**	**%**
Cropland	310,768.50^{a}	57.5	585,623.20	67.6	72,030.51	53.5	119,148.50	58.9
Grassland	197,813.30^{b}	36.6	235,031. 90	27.1	55,748.16	41.4	73,183.68	36.2
Settlement	13,686.12	2.5	26,873.10	3.1	4,329.09	3.2	7,381.08	3.7
Plantation	15,939.18	2.9	15,957.09	1.8	1,765.35	1.3	1,766.52	0.9
Bareland	2,600.10	0.5	2,600.28	0.3	733.14	0.5	733.32	0.4
Total Area Converted to degrading Land use	540,807.20	**27%**	866,085.57	**43%**	134,606.25	**34%**	202,213.1	**52%**
Rate of conversion to degrading land use / Annum (Ha / Year)	-16,900.23		-13,122.51		-4,206.45		-3,063.83	

Note: Areas with superscript letters $^{(ab)}$ show statistically significant contribution to conversion of woodlands to degrading land use ($p<0.05$)

Note: The contribution of all degrading LU/LC to Dambo loss are statically insignificant ($p<0.05$)^{1}

Regression Statistics, Woodland Conversion:
Adjusted R^{2}=99.9; Significance F=0.0160

	Standard Error	*t Stat*	*P-value*
Intercept	130100.40	12.2472	0.0519
Cropland	0.0553	-27.6226	0.0230
Grassland	0.0634	-16.6198	0.0383
Plantation	2.4712	9.7207	0.0653
Settlement	1.0081	1.3272	0.4111
Bareland	0.9744	-13.9435	0.0456

Regression Statistics, Dambo Conversion:
Adjusted R^{2}=57.71, ; Significance F=0.4389

Standard Error	*t Stat*	*P-value*
1814315.68	0.5281	0.6907
0.7721	0.3939	0.7611
0.8843	-0.3593	0.7804
34.4618	-0.3724	0.7731
14.0572	0.1351	0.9145
13.5890	0.6591	0.6290

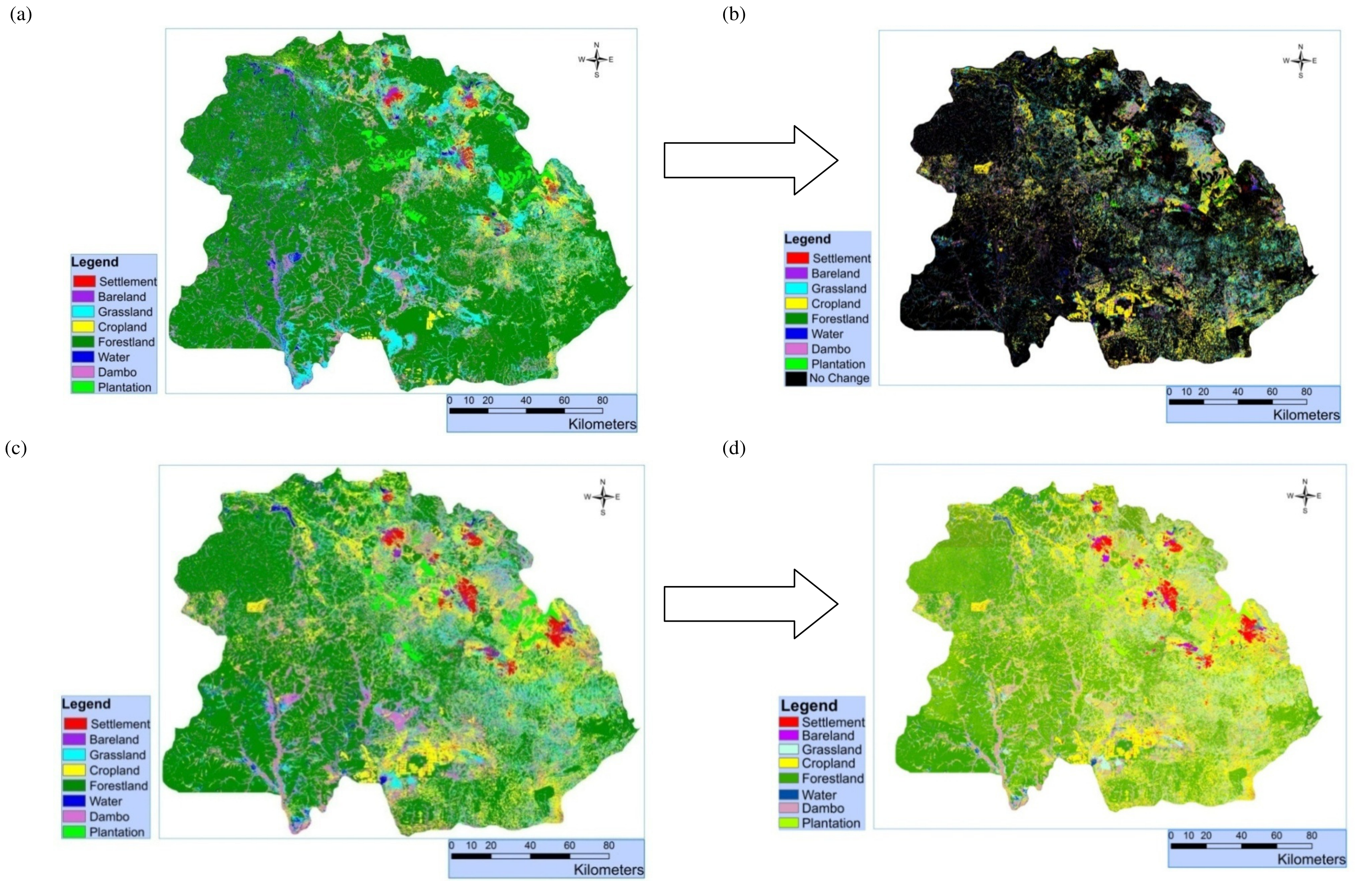

Figure 2. 2. Land cover and change map of the-Copperbelt province (a) presents the initial land cover map of 1984 (b) shows the change map between 1984 and 2016 (c) shows the land cover map of 2016 (d) shows the predicted land cover map of 2050.

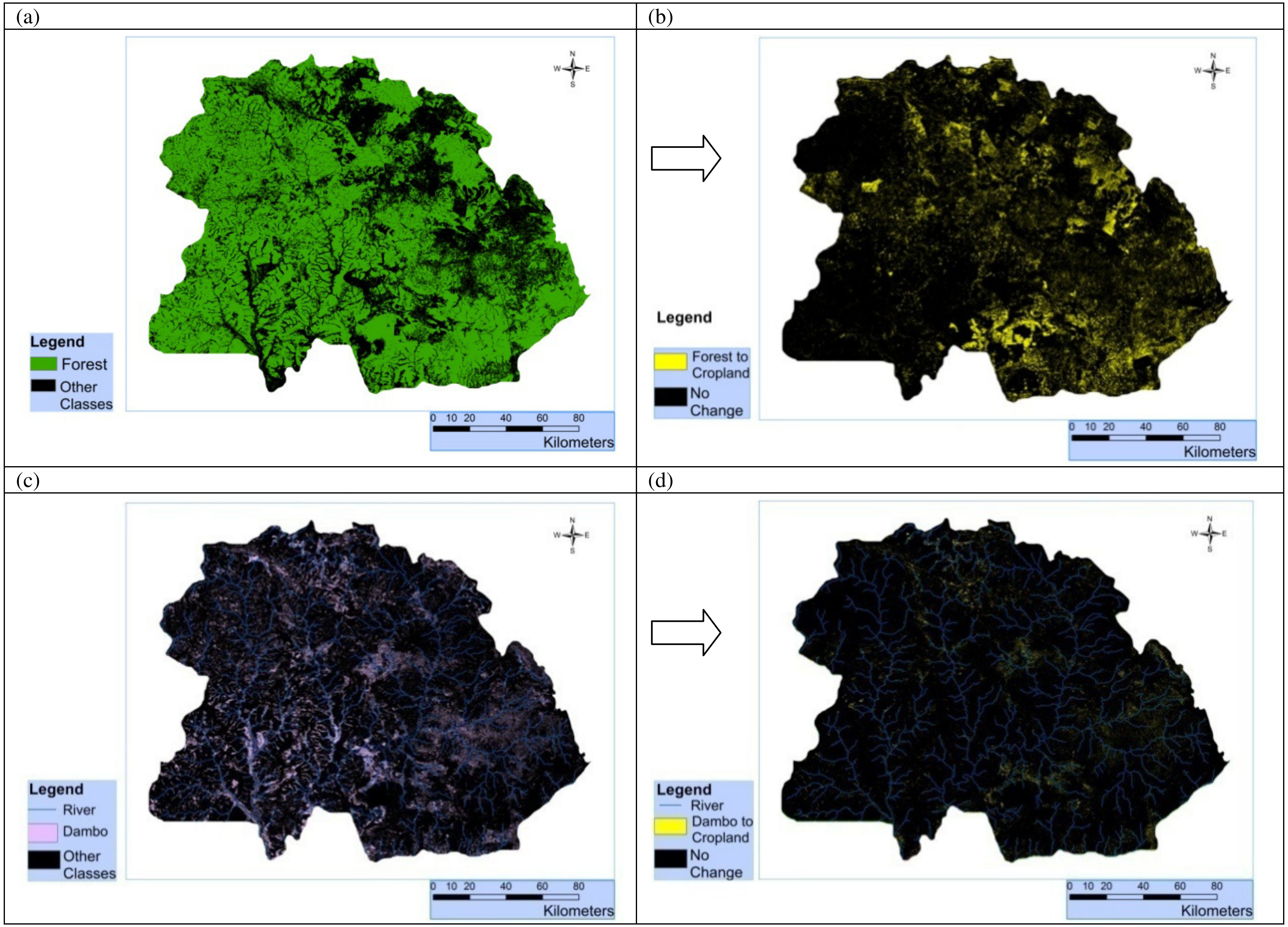

Figure 2. 3. State of Woodlands and Dambos in the Copperbelt province (a) presents the initial state of Woodlands in 1984 (b) shows the Woodlands converted to Cropland by 2016 (c) shows the initial state of Dambos in 1984 (d) shows the Dambos converted to cropland

2.4 Discussion

2.4.1 Land use land cover change between 1984 – 2016 and prediction to 2050

Woodland was the most dominant land cover class in 1984 covering 64.9% of the landscape despite declining to 46.9% in 2016 (Table 2.1) and projected to 38.5% in 2050 (Tables 2.2). The high initial area of forests in 1984 was logical because 90% of the Coppebelt province landscape was originally Miombo woodland (GRZ 1998). The results have shown that the establishment of Croplands accounted for between 57% and 68% of Woodland loss (Tables 2.3). However, Chirwa et al. (2017) found that agriculture was responsible for 80% of forest loss in Africa while (Mwitwa et al. 2018) reported a higher figure of 90% in Zambia. The reason for the difference could be attributed to the assessment methods. In this study, the assessment was based on the number of actual Dambo and Woodland pixels converted to Cropland while other studies have used social economic data and this may have led to over estimating the results.

These findings are supported by the observation that people preferred to clear primary forests to take advantage of fertile soils using the slash and burn system (Gondwe et al. 2020). According to Mulungushi (2007), the drive towards agriculture in the province was further triggered by high poverty levels arising from macroeconomic policies such as economic liberalisation, privatisation and the Structural Adjustment Program (SAP) initiated in the 90s. Some of the established Croplands in earlier years were abandoned (due to shifting cultivation) leading to an increase in Grasslands, Settlements, Barelands and in some areas regenerating forests as indicated by Swap and NQC values (Table 2.1, 2.2). The impact of agriculture on other land uses increased over time especially with the introduction of the Fertiliser Support Program (FSP) in 2002 (now called Farmer Input Support Programme; FISP) (Funsani et al. 2016, MAL 2013). The increase in the number of beneficiaries to the FISP over the years suggest that more land was needed for anthropogenic activities, hence the recorded increase in the area of Croplands from 4% in 1984 to 18.4% in 2016 (Table 2.1) and is predicted to further increase to 30.5% by 2050 (Tables 2.2). These results agree with the national trend in agricultural land area for Zambia reported by World Bank (2020) showing an increase from 26% in 1961 to 32% in 2016. Clay (2013), Hosonuma et al. (2012), Ogg (2016), Ricker-Gilbert et al. (2013), World Bank (2012) also observed that rapid loss of forest resources occurred in Nigeria, Ethiopia, Kenya, Zambia, Malawi, Tanzania, and Ghana where the cost of fertilizer, water, or credit for farmers have been heavily subsidised.

As land became scarcer, people began to use existing crop fields for longer periods of time leading to the construction of permanent structures for accommodation. This suggests that the structures would eventually increase with growing population leading to the recorded increase in the area of Settlements, Grasslands and Barelands (Figure 2.1). According to CSO (2014), the population of the Copperbelt province rose from 2,143,413 in 2011, to 2,362,207 in 2015, and projected to 3,823,642 people in 2035. An increase in population, coupled with poor economic conditions, high poverty levels, high electricity tariffs, contributed to the rising pressure on forest resources further inducing LULCC.

Dambos on the other hand had shown similar trends with woodlands attributing the highest loss to Croplands followed by Grassland and Settlement expansion (Figure 2.2, Table 2.3). The interaction between woodland cover and Dambos was worth noting. It was found that a decline in Forest cover led to an increase in the area of Dambos in 1999, 2004, 2009 and 2016 (Figure 2.1). Part of the reason for the increase is that, Dambos are found interspaced within Miombo woodlands (Malmer and Nyberg 2008, Mbanze et al. 2019, Whitlow 1990, Zolho 2005). This suggests that clearing of Forestland / riparian forests meant that more Dambos and water bodies became visible to the LU/LC classifier

(Figure 2.3). The fluctuations in the loss and gain in the area of Dambos also suggest that there was constant clearing and use of land for agriculture followed by periods of abandonment that led to recovery as observed in Swap and NQC values in tables 2.1 and 2.2. These results show that Dambos are especially targeted by people because they present moist and fertile soil conditions that can support crops and animals during drought periods thereby serving as safety net for livelihoods (Kotze 2011, Lupankwa et al. 2000, Ryan et al. 2016, Whitlow 1990). The trend is hypothesised to have reduced the area of Dambos from 12.5% in 1984, 17.36% in 2016, to 10.42% in 2050 (Table 2.1, 2.2). Results of this study are consistent with regional and global trends as reported in Malawi by Gondwe et al. (2020), Alam et al. (2011) in the Himalayas; Zhang et al. (2011) in Beijing; Franke et al. (2009) and Mwita (2013) in Tanzania. The results have shown that -NQC were recorded for Woodlands and Dambos while +NQC were recorded in Plantations, Settlements, Grasslands, Croplands and Bareland further confirming that the latter five are degrading land uses.

2.4.2 Implications

Miombo woodlands and its Dambos play an important ecological and socio-economic role at provincial, national and global scale. However, the ecosystem is declining at an alarming rate indicating that policies, laws and institutions responsible for their management are not effective (GRZ 2018). The decline in woodlands will have devastating consequences on Miombo woodlands and Dambos, climate and the people. This is because LULCC affect the hydrology of a watershed by altering the rainfall, evaporation and runoff balance (Nyirongo 2009). According to Mumeka (1986), and Nyirongo (2009), stream flow and erosion increases while infiltration reduces with an increase in deforestation. Therefore, disturbances induced by LULCC will have wider impact on the Kafue river basin subsequently affecting countries like Mozambique, Angola, Namibia, Botswana, Zimbabwe and Malawi and other regions that depend on the catchment area. Similar findings were reported by Malmer and Nyberg (2008) and Mwita (2013). Hydrological characteristics are altered when land use is changed to croplands because trees are able to transpire more water than agricultural crops meaning that more rain that would have been intercepted by canopies is lost through evapotranspiration (Nyirongo 2009).

According to Acreman and Holden (2013), Dambos have been shown to influence the hydrological cycle by decreasing or increasing a particular component of the cycle such as transpiration, runoff and infiltration. Dambos are natural sponges absorbing water during the wet season and slowly releasing the water to streams during the dry season thereby controlling floods and maintaining dry season river flows (Balek and Perry 1973). Therefore, the disturbances recorded in Dambos will affect the ability to effectively provide these ecosystem services. Nevertheless, the rapid recovery of woodlands and Dambos in abandoned areas observed in the study provides the motivation to conserve deforested areas for restoration purposes. This view is also shared by Geldenhuys (2010), Gonçalves et al. (2017), Syampungani et al. (2017) who reported that the resilience and stable characteristics of the Miombo ecosystem present opportunities to initiate recovery programmes. The use of Dambos for agriculture also indicates a potential that should be optimised to offer both economic and ecological benefits for the nation. The findings underscore that improvement in land system science theory requires accurate monitoring, understanding and modelling for sustainable land management.

2.4.3 Study limitations

Findings of this study could have been affected by lack of consistent cloud free multitemporal Landsat data from the same season for some years and scenes under review. This would have affected identification of features during classification and subsequently cover change analysis. Furthermore, misclassification arising from similarity in classes such as Dambos and Grasslands also caused difficulties in visual interpretation and the classification process. Nevertheless, the LU/LC classification accuracy results were above 87%. According to Kamusoko and Aniya (2007), LU/LC accuracires of above 85% are considered reliable. In modelling to 2050, the availability and choice of socio-economic and biophysical data used as factors and constraints was challenging. This may have created some uncertainty in predicting LULCC to 2050 and could have further affected the precision of the model. Similar challenges were pointed out by Aburas et al. (2016) and Amthor et al. (2001) who reported that these limitations also affected testing and validation of models. Despite the limitation, modelling accuracy results in this study indicated strong association between the predicted map and the observed map because according to Zheng et al. (2015), kappa values >0.8 show strong association or agreement.

2.5 Conclusion

The study concluded that extensive LULCC had occurred in the Copperbelt province between 1984 and 2016 and the trend was predicted to continue to 2050. The study showed that over time, Miombo woodlands and Dambos have been decreasing in extent as indicated by the – NQC, thereby loss of their benefits. Settlements, Barelands, Plantation, Grasslands and Croplands showed +NQC indicating an increase in proportion with devastating effects. Cropping accounts for more than half of the total area lost and the current trajectory suggests it will get worse if nothing is done. We can conclude from the study that adoption of economic policies such as FISP and SAP led to loss of natural resources such as forests and Dambos as these were used as safety-nets or coping strategy for the livelihoods of communities. Overall, the loss of the Woodlands and Dambos would have a devastating impact on the quality of the ecosystem that supports endangered fauna and flora in the region. It is therefore recommended that interventions to curb the loss should be put in place through strategies like land zoning of Woodlands and Dambos in order to balance between economic and ecological benefits. Safe agricultural practices and the enforcement / sensitisation of land and water use laws and policies are vital. Institutions should be strengthened in order to enhance coordination and optimisation of resources for effective management.

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CHAPTER 3: Extent of fragmentation and the impact of forest fractal geometry on selected soil parameters in Miombo woodlands of Zambia's' Copperbelt region

Abstract

A rapid rise in the exploitation of forest resources is leading to more fragmentation and loss of soil nutrients in developing countries. Yet, the impact of forest fractal geometry on soil properties is not well understood globally. The objective of this study was to determine the extent of fragmentation and the impact of fractal dimension (FRAC) on some soil chemical parameters. Land cover maps of the Copperbelt Province of Zambia (1984 to 2019) were produced by supervised classification and used in fragmentation analysis. Soil samples were collected for analysis of pH, phosphorus (P), nitrogen (N), ammonium-nitrogen (NH_4-N), nitrate-nitrogen (NO_3-N), carbon (C) and potassium (K) concentrations, and soil texture. At landscape scale, fragmentation increased by more than 8.6% between 1984 and 2019. The PLAND for Croplands increased by more than 18% (1984 to 2019). Where the FRAC was lower (≤1.25), N, NH_4-N, NO_3-N, C and K concentrations were statically higher compared to the >1.25 FRAC metric. Forest geometric pattern affected the levels of soil chemicals, therefore, incorporating fragmentation analysis in forest and soil conservation is recommended.

KEYWORDS: **landscape metrics, miombo, forest geometry, fractal dimension, fragmentation, soil parameters**

3.1 Introduction

Fractal theory has been applied in assessing shape complexities of various environmental phenomena that exhibit self-similar, extensive, and scale invariant characteristics (Katz and Thompson 1985, Mandelbrot 1982, Perfect 1997). According to Li et al. (2013), the impact of forest ecosystems on soil properties can be explained by the interactive soil-vegetation feedback system. In this system, soil provides essential nutrients for vegetation growth, and this in turn influences soil formation and modification. However, land use and land cover changes (LULCC) are occurring globally at unprecedented rates causing alterations to the geometric pattern of forest ecosystems (Fahey and Puettmann 2008, Lambin and Geist 2008, Ye and Comeau 2009).

The global coverage of forests is over 4 billion ha, making up 31% of the worlds land surface area. Tropical forests make up about 13% of the earth (FAO 2015, Gumbo et al. 2018b). Miombo woodlands are part of tropical forests found in southern and central Africa. They are dominated by *Isoberlinia, Julbernardia* and *Brachystegia* tree species (Backéus et al. 2006, Dewees et al. 2010). The Miombo ecosystem covers over 2.7 million km^2, or, 10% of the African landmass (Malmer and Nyberg 2008, Ribeiro et al. 2015, Syampungani et al. 2020). The Miombo ecosystem sequesters carbon, controls flooding; moderates climate conditions, filters pollutants, maintains biodiversity, protects soils from erosion, and provides food (Alberti 2010, Gökyer 2013, Shackleton and Gumbo 2010). The ecosystem supports the economic livelihood of millions of people (Campbell et al. 2007, Gumbo et al. 2018b, Ryan et al. 2016). Despite the benefits provided by the Miombo, the ecosystem is affected by anthropogenic activities such as rising population, construction, charcoal production, firewood collection, increasing agricultural activities, settlements, illegal exploitation of timber, mining and forest fires that have led to LULCC and forest fragmentation (Syampungani et al. 2020, Tembo et al. 2015, Vinya et al. 2011). Conversion to agriculture is the highest contributor to forest loss with 310,000 ha lost to cropland every year in Africa (Achard et al. 2002). The rate of forest fragmentation worldwide calls for urgent action to assess the effectiveness of current natural resources management techniques (Gamfeldt et al. 2013, Gómez-Sanz et al. 2014).

In fractal geometry analysis, remote sensing and Geographic Information Systems (GIS) provides land use land cover (LU/LC) maps; which is the first step of fragmentation analysis (Achard and Hansen 2012, Stehman 2012). Spatial pattern metrics such as fractal dimension (FRAC) among numerous other metrics, allow researchers to quantify size/shape relationship of vegetation patches (Gustafson 1998, He et al. 2000, McGarigal and Marks 1995, Milne 1992, O'neill et al. 1988, Turner 1989). Fractal geometry has been used to quantify the size / shape relationship of vegetation patches (Franklin and Forman 1987, Krummel et al. 1987, Mandelbrot 1982, Medina et al. 2012, O'neill et al. 1988, Zhang et al. 2007). Franklin and Forman (1987) concluded that measures based on FRAC as a basis for locating and designing timber harvesting can lessen ecological impacts while Turner et al. (1989) reported that FRAC can help explain the spread of disturbances such as fires or insect damage. FRAC has also been applied in habitat suitability related studies (Cushman et al. 2010, Dibble and Thomaz 2009, Fahrig 2003, Forman and Godron 1986). Fractal theories have been employed in studying soil characteristics (Karami et al. 2017, Li et al. 2016, Miloš and Bensa 2017, Tuffour 2015, Yu et al. 2015, Zhang et al. 2013). For instance, Wang et al. (2008) found that the, fractal dimensions of soil particle size distribution were influenced by land use and management practices. Wang et al. (2007) also reported that fractal parameters provided potential indicators of soil quality and are capable of characterizing spatial and temporal differences in different land-use patterns. Gao et al. (2014) revealed that vegetation restoration had positive effects on soil recovery with improvements on soil water availability, clay, silt and nutrient content. Nevertheless, studies focusing on the impact of forest fractal geometry on soil chemical and physical properties are rare and the gap is particularly large in the Miombo ecosystem.

The objectives of the study were to: i) quantify the extent of forest fragmentation in the Copperbelt province; and ii) determine the impact of forest fractal dimension on the concentrations of selected soil chemical parameters in different soil textural classes. The study is based on the hypothesis that significant spatial variations in soil properties are influenced by the geometric pattern of forest cover. We used the Copperbelt province as a case study because this predominantly mining region has undergone massive changes since the privatisation and structural adjustment programme of the 1990s and yet information on LULCC and forest fragmentation; and their impacts on soil chemical properties are absent. We assessed the period between 1984 and 2016 and then 2019 to coincide with the repeal of Forest Act No. 7 of 1999 of Zambia on which the management of forest resources was based until 2015 when the current Act (No. 4 of 2015) was enacted. This trend in lack of information on soils properties has potential to impact on regional and global food security and climate.

3.2 Materials and methods

3.2.1 Study area

This study was conducted on the Copperbelt Province of Zambia (Figure 3.1). The Copperbelt is one of Zambia's ten provinces covering 31,328 km² (3.1328 million ha); 4.2% of the total area of the country. The Province lies between latitudes S12° to S13° 50'and longitudes E27° to E29° (ACCC 2010). It is on the eastern central African plateau that is characterised by a gently undulating plateau of between 1,200 m and 1,455 m above sea level. The soils in the Copperbelt Province comprise of red lateritic soils with sandy topsoil overlying more loamy clayey subsoil. The total annual average rainfall is approximately 1,300 mm, with the majority falling during the summer months of November to April.

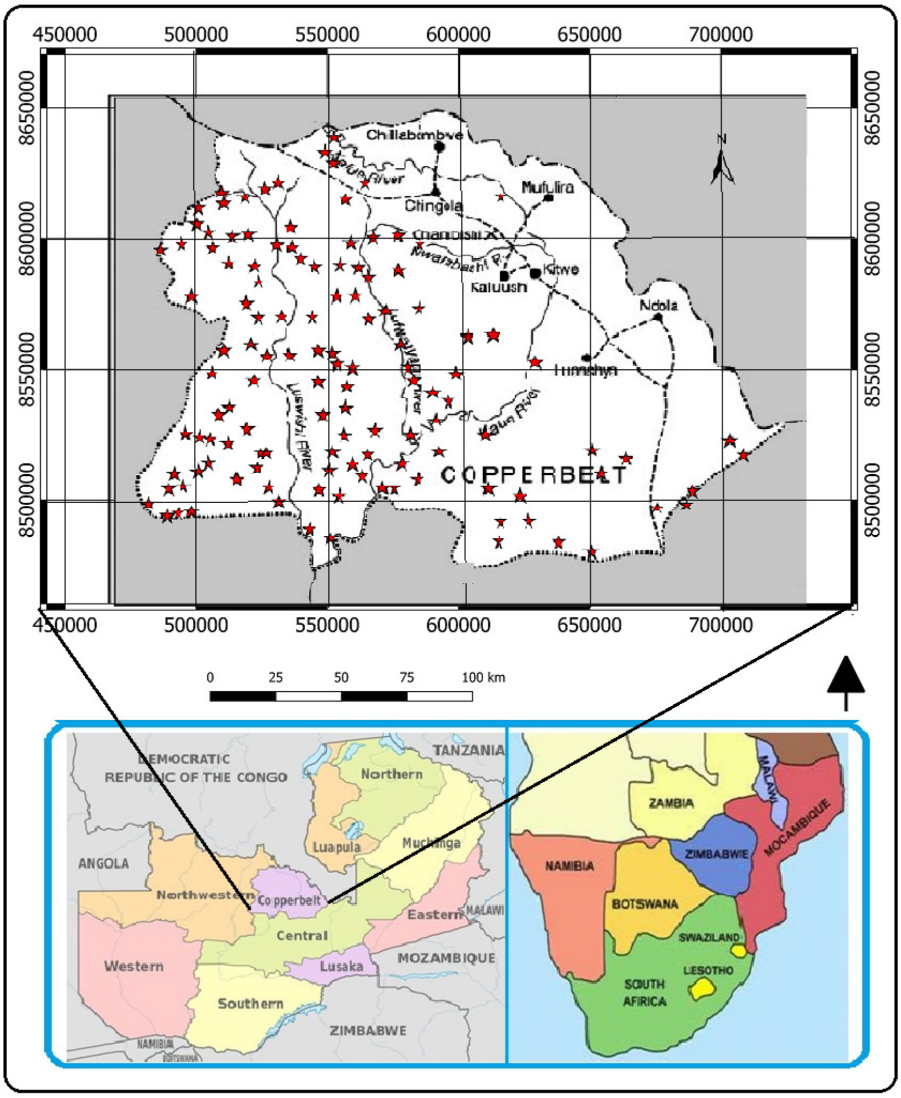

Figure 3. 1. The Location of the Copperbelt province, Zambia with sampling sites indicated by *

3.2.2 Image acquisition and pre-processing

Landsat images covering path/row: 172/69, 172/70, 173/69, and 173/68 from 1984 to 2016 were obtained from the United States Geological Survey (USGS) website (ESRI 2016) and used for preparation of maps used in fragmentation analysis. These images were assessed at five year intervals based on Landsat 5-TM images for 1984, 1989 and 1999; Landsat 7-ETM for 2004, and 2009 and Landsat 8 images for 2016 and 2019. Landsat images were used in land cover classification, fragmentation analysis and planning for collection of soil samples. The images were geometrically corrected and projected to the Universal Transverse Mercator zone 35s coordinate system and the World Geodetic System (WGS) 84 datum. Radiometric correction and normalization of the images was done in order to ensure that the changes in pixel values from various images reflect actual changes on the surface (Du et al. 2002). ArcGIS 10.3 and ENVI 4.7 software were employed in the analysis process using both raster and vector data.

3.2.3 Field data on land use activities and soil samples

One hundred and twenty-six (126) random sample points were generated across the Coperbelt Province using the “Create Random Points” tool in ArcGIS 10.3, for ground truthing the LU/LC and collection of soil samples. The 126 sample points were used in subsequent kriging interpolation of soil parameters. This is because according to Mulla and McBratney (2002), kriging yields robust results when the data to be interpolated have a well-developed spatial structure, and are sampled at more than 70-80 points. At the centre of each plot, one composite soil sample was obtained from 0 cm and 20 cm depth, collected using a 5 cm diameter soil auger. Soil sample locations were marked using Global Positioning System (GPS) unit by recording the latitude and the longitude. Additional data recorded at the sample point included the following: the patch type, its state and cause, LU/LC, and landforms present.

3.2.4 Data analysis

3.2.4.1 Land cover classification

Supervised image classification using the maximum likelihood classification method was applied (ESRI 2012). Training site data were selected in easily identifiable areas of classes such as water; indigenous and plantation forest; and non-forest areas such as bare soil and built-up areas, using a GPS receiver and Google Earth. Representative sites were visited and their locations recorded with a GPS unit as ground truth points in order to match the land use class with the digital number (DN) in each band (Millard and Richardson 2015). Classes adapted from IPCC (2003) and Münch et al. (2017) were applied and are described as follows: Dambo (depressions with grasses and seasonal water); Forestland/Woodland (land of >0.5 ha with trees ≥5m and a canopy ≥10%); Settlement (urban, industrial land covers with buildings and roads); Bareland (barren land, bare soil and rock outcrops); Grassland (grasses, shrubs, pasture or herbaceous rangeland); Cropland (agricultural land with standing or harvested crops including livestock); Water (water bodies such as ponds, lakes, rivers, streams and canals); and Plantation (felled or standing trees of pine, eucalyptus and other exotic tree species). The land cover classes were merged into three categories; Persistent Forest, Disturbed Forest and Non Forests. Persistent forests included all forest areas (pixels) that never changed from 1984 to 2019 created by intersecting all Forestland pixels for all years under review using the "And "Boolean operation in ArcGIS. None Forests included areas that had never been forested, that is, all Cropland, Water, Dambos, Settlements and Barelands. Disturbed forests were areas that had transitioned to forestland at any one time instant under review. The Persistent category was created in order to isolate the influence of other human activities so that the only factor contributing to the variation in soil chemical nutrients was the spatial configuration of forests.

3.2.4.2 Classification accuracy assessment

For accuracy assessment, 126 sample points were evenly distributed to each category of the LU/LC by the class area ratio using the stratified random sampling method. Each sample point location representing a class, was located using the GPS receiver. The validation of features collected on the ground was crossed with each of the classified maps to create an error matrix (confusion matrix) according to Olofsson et al. (2013). The overall accuracy was computed through kappa statistic by dividing the correctly classified points by the total number of points multiplied by 100% using ENVI

4.7 software (Appendix A1, B2). An overall accuracy of 85% was acceptable in the study (Kamusoko and Aniya 2007).

3.2.4.3 Quantifying landscape pattern and indices

Landscape indices were computed from LU/LC maps produced in ArcGIS 10.3 and ENVI 4.7 using FRAGSTATS 4.2 application. The indices were computed at three spatial levels: patch, class, and landscape (McGarigal and Marks 1995). In this study, 7 landscape metrics (Table 3.1) were selected because of their widespread use, well-documented effectiveness (Qindong et al. 2018) and relevance to the study objectives. To determine the relationship between fragmentation and the quantities of soil chemical parameters, fractal dimension (FRAC) metric was applied in the persistent forest area (Figure 3.2). All images were resampled to 250 m grain scale because according to Tian et al. (2019) this scale provided more accurate results. The fractal dimension was divided into two categories; FRAC-1 ($\geq$ 1 to 1.25) and FRAC-2 (>1.25 to 1.5) metrics indicating high and low degrees of shape/pattern complexities, respectively. FRAC values were used as fixed factors in ANOVA. The advantage of fractal analysis is that it can be applied to spatial features over a wide variety of scales (Mandelbrot 1982).

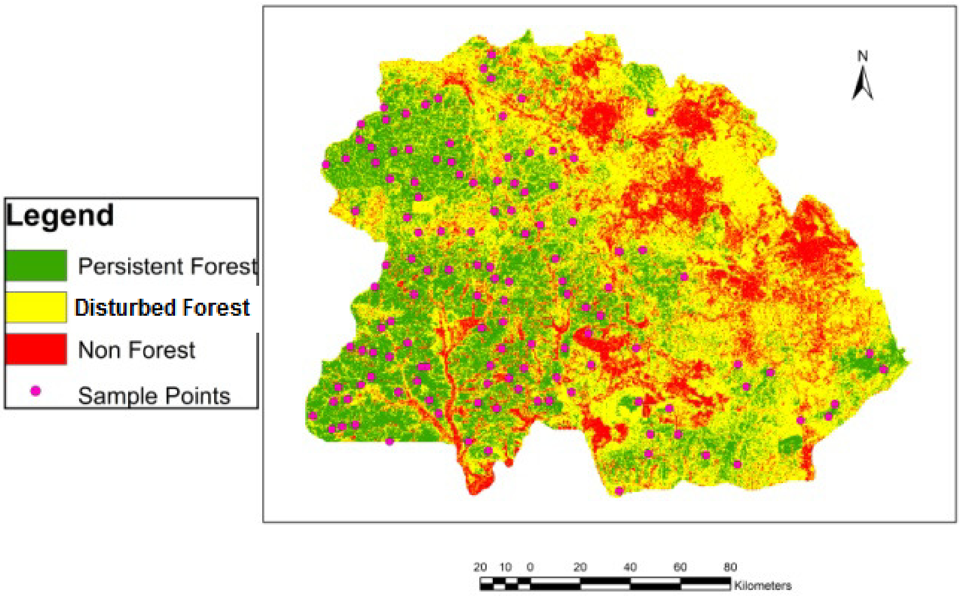

Figure 3. 2. Land use land cover categories showing persistent forest of the Copperbelt province from 1984 to 2019

Table 3. 1. List of indices applied in the study

	Metric	Description
1.	Fractal Dimension Index (FRAC)	Equals 2 times the logarithm of patch perimeter (m) divided by the logarithm of patch area (m^2); the perimeter is adjusted to correct for the raster bias in perimeter. FRAC approaches 1 for shapes with very simple perimeters such as squares, and approaches 2 for shapes with highly convoluted, plane-filling perimeters
2.	Number of Patches (N.P)	Equals the number of patches of the corresponding patch type (class).
3.	Patch Area (PA)	Equals the area (m^2) of the patch
4.	Patch Density (P.D)	Equals the number of patches of the corresponding patch type divided by total landscape area (m^2), multiplied by 10,000 and 100 (to convert to 100 hectares).
5.	Largest Patch Index (LPI)	An index used to quantify the percentage of total landscape area characterised by the largest patch
6.	Percentage of landscape (PLAND)	Useful in computing the proportional abundance for each of the patch type across the landscape
7.	Shanon Diversity Index (SHDI)	SHDI equals 1 minus the sum, across all patch types, of the proportional abundance of each patch type multiplied by that proportion.

Source: McGarigal (2015)

3.2.4.4 Soil analysis

Soil samples were air dried under shade to avoid contamination with foreign materials and then crushed with a wooden pestle. The samples were screened through a 2 mm sieve and the pebbles, stones and roots removed. About 0.5 to 1kg of air dried and crushed soil sample were reserved for analysis. The following soil parameters were assessed: pH, organic carbon (C), total nitrogen (N), nitrate-nitrogen (NO_3–N), ammonium-nitrogen (NH_4-N), available phosphorus (P), exchangeable potassium (K), and particle size (Sand %, Silt %, and Clay %,). The soil chemical parameters were picked because they are essential nutrients for plant growth. The physical properties (Sand %, Silt %, and Clay %), influence the level of nutrients (Karthika et al. 2018). The analysis of soil samples was done by using standard methods, that is; $pH_{(H20)}$ (1:2.5), EC (1:2.5), organic carbon (Walkley and Black 1934), total N (Bremner 1965), NO_3-N and NH_4-N (Grewling and Peech 1965), available P (Bray's No.-1) (Bray and Kurtz 1945), and exchangeable K (Alexander and Clark 1965).

3.2.4.5 Mapping of Soil Chemical and Physical parameters

To produce soil maps, quantities/concentrations of soil chemical and physical parameters for the 126 sample points were prepared in tabular format with the latitude and longitude as the location field for each plot. Ordinary Kriging was applied to interpolate the sample points over the entire study area using ArcGIS 10.3 software. Ordinary kriging is a widely used interpolation method that estimates a value at a point of a region for which a variogram is known, using data in the neighbourhood data. Geostatistical interpolation identified the spatial variability for the soil properties with best models fitted to semivariograms of the variables (Panday et al. 2018). The best model for C, NH_4-N and P was the Gaussian, Spherical for pH and K and the exponential for N and NH_3-N (Appendix E 1). The choice of model was based on the following criteria; standardized mean error (MSE) nearest to zero, the smallest root-mean-squared prediction error (RMSE), the average standard error (ASE) nearest the RMSE, and standardized root-mean-squared prediction error (RMSSE) nearest to 1 (Appendix E 1).

Similarly, the mean error (ME) and the RMSE were used for cross-validation to evaluate the accuracy using the ArcGIS Geostatistical tools, Validation / Prediction function. Of the 126 sample points, 60% (76 points) were used for training while 40 % (50 sample points) were used for cross validation. A ME value close to zero indicates that the interpolation method is unbiased while the lowest RMSE value indicates the best fit to the variogram model.

Validated soil chemical properties were used as the dependent variable in ANOVA. Physical properties, (Sand, Silt and clay) were used to produce a soil textural map using the raster calculator in ArcGIS based on the ranges provided by Natural Resources Conservation Service (NRCS 1993) of the USDA (Table 3.2). The twelve soil textural classes were reclassified into three soil categories; sandy, loamy and clayey soils and used as a fixed factor in ANOVA (Figure 3.3).

Table 3. 2. Reclassification of standard soil textural classes into soil categories

1	**2**	**3**	**4**	**5**	
Sand	**Silt**	**Clay**	**USDA Textural class**	**Applied Textural Categories**	**Code**
	%				
86-100	0-14	0-10	Sand	SANDY SOILS	**1**
70-86	0-30	0-15	Loamy sand		
50-70	0-50	0-20	Sandy loam	LOAMY SOILS	**2**
23-52	28-50	7-27	Loam		
20-50	74-88	0-27	Silty loam		
0-20	88-100	0-12	Silt		
20-45	15-52	27-40	Clay loam		
45-80	0-28	20-35	Sandy clay loam		
0-20	40-73	27-40	Silty clay loam		
45-65	0-20	35-55	Sandy clay	CLAYEY SOILS	**3**
0-20	40-60	40-60	Silty clay		
0-45	0-40	40-100	Clay		

Adapted from NRCS (1993)

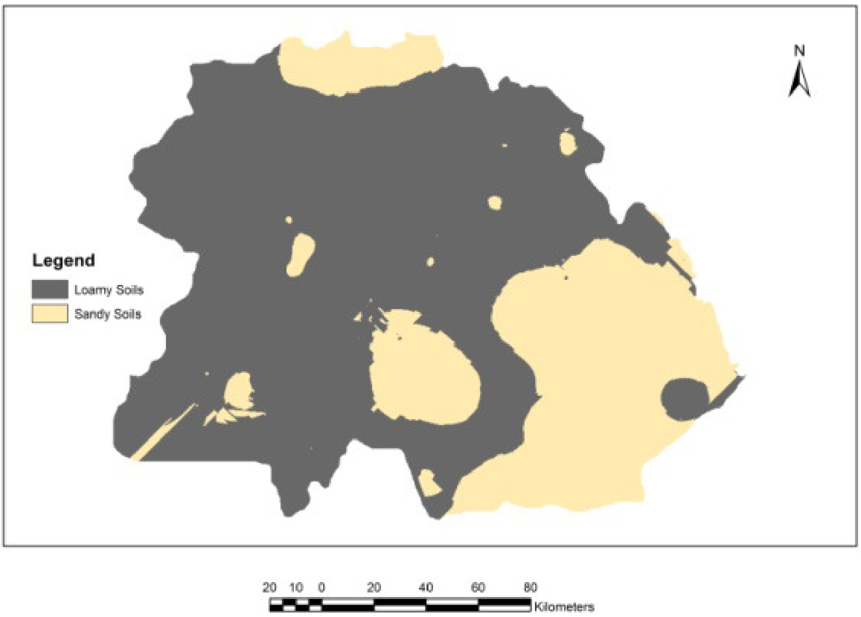

Figure 3. 3. Soil textural classes of the Copperbelt province derived from particle size analysis

3.2.4.6 Statistical analysis

The multivariate 2 – way ANOVA with interaction was applied in SPSS software to determine the variations in chemical parameters against all fixed factors at 95% confidence level. The total number of sample points assessed was 126 randomly distributed in the study area covering each fixed factor. We tested for significant differences in soil chemical properties between two forest fractal classes, FRAC-1 (≥ 1 to 1.25) and 2 (>1.25 to 1.5) and soil textural categories (Sandy and Loamy) using the ANOVA in the persistent forest category only (Figure 3.2 and 3.3). In ANOVA, all soil chemical properties were set as the dependent variables with FRAC and textural categories as fixed factors. Slope was assumed to be uniform across the study area and hence held constant.

3.3 Results

3.3.1 Landscape and class level metrics

The accuracy of LU/LC classification on which landscape metrics were computed for all years under review was above 87.04% (S1). At landscape level (considering all LU/LC classes), NP in the

Copperbelt province increased by 8.6% between 1984 and 2019. Similarly, the SHDI increased by 22.9% during the same period (Table 3.3, Figure 3.4a and d). At class level, Forestland had the highest LPI in 1984 (47.43%) but declined to 20.28% in 2016. The LPI increased slightly to 27.11% in 2019. The PLAND for Croplands increased by 12% between 1984 and 2016 and further increased from 18.40 in 2016 to 22.11% in 2019 (Table 3.3).

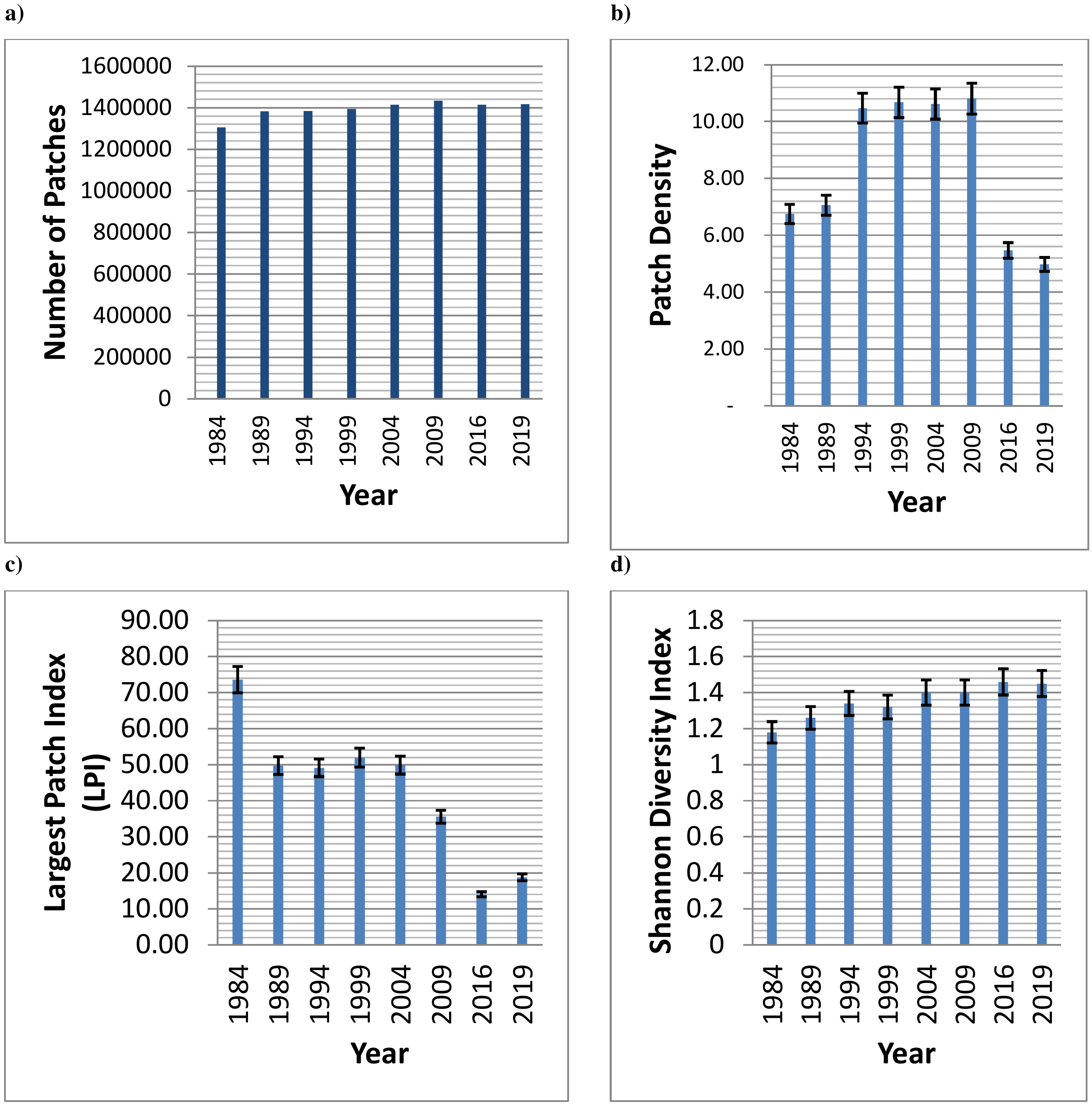

Figure 3. 4. Landscape fragmentation of the Copperbelt province a) Number of Patches (NP), b) Patch Density (PD), c) Largest Patch Index (LPI), d) Shannon Diversity Index (SHDI)
Note: Errors were calculated at 95% confidence level

Table 3. 3. Class metrics for the Copperbelt province from 1984 to 2019

	TYPE	**CA**	**PLAND**	**NP**	**PD**	**LPI**		**TYPE**	**CA**	**PLAND**	**NP**	**PD**	**LPI**
1984		2,035,539	64.86	137,416	4.38	47.73			347,872	11.08	362,063	11.54	0.27
1989		1,866,123	59.47	131,802	4.20	29.59		**5. Grassland**	410,956	13.10	415,708	13.25	0.50
1994	**1.Forestland**	1,730,363.	55.14	141,242	4.50	27.10			594,523	18.94	258,108	8.22	1.26
1999		1,728,105	55.07	152,340	4.85	28.62			319,380	10.18	315,114	10.04	0.29
2004		1,595,364	50.84	169,449	5.40	25.37			433,702	13.82	338,370	10.78	0.51
2009		1,554,617	49.54	168,025	5.35	17.62			295,138	9.40	248,480	7.92	0.16
2016		1,465,278	46.91	249,401	7.98	20.48			366,279	11.73	268,326	8.59	0.10
2019		1,492,143	47.54	255,104	2.11	27.36			274,901	8.76	329,407	10.50	0.11
1984		201,827	6.43	191,006	6.09	0.19			392,252	12.50	407,599	12.99	**0.18**
1989		320,260	10.21	216,408	6.90	0.33		**6. Dambo**	406,961	12.97	452,531	14.42	0.50
1994	**2. Cropland**	274,926	8.76	205,619	6.55	0.20			367,651	11.72	227,616	7.25	0.21
1999		457,700	14.59	215,787	6.88	1.62			498,565	15.89	213,299	6.80	1.65
2004		417,955	13.32	267,296	8.52	0.48			540,713	17.23	446,605	14.23	0.91
2009		482,597	15.38	331,211	10.55	0.58			650,522	20.73	522,387	16.65	1.19
2016		574,696	18.40	121,387	3.89	0.73			541,724	17.34	591,165	18.93	0.78
2019		694,061	22.11	246,394	7.85	1.44			477,767	15.22	179,065	5.70	0.72
1984		64,086	2.04	65,365	2.08	0.05			12,649	0.40	13,911	0.44	0.05
1989		33,963	1.08	45,984	1.47	0.10		**7.Bareland**	12,917	0.41	13,225	0.42	0.03
1994	**3.Water**	56,099	1.79	39,425	1.26	0.03			18,8833	0.60	21,919	0.70	0.06
1999		16,457	0.52	4,648	0.15	0.06			17,510	0.56	24,292	0.77	0.06
2004		32,181	1.03	25,056	0.80	0.02			13,044	0.42	9,574	0.31	0.07
2009		30,232	0.96	21,688	0.69	0.03			16,915	0.54	12,933	0.41	0.02
2016		48,445	1.55	76,908	2.46	0.05			14,333	0.46	5,801	0.19	0.04
2019		55,549	1.77	13,433	0.43	0.09			18,211	0.58	19,375	0.62	0.04
1984		37,624	1.20	86,177	2.75	0.09			46,471	1.48	42,463	1.35	0.10
1989		37,598	1.20	81,385	2.59	0.11			49,307	1.57	24,786	0.79	0.11
1994	**4. Settlement**	39,298	1.25	63,817	2.03	0.14		**8. Plantation**	56,524	1.80	25,838	0.82	0.15
1999		42,297	1.35	81,088	2.58	0.08			57,782	1.84	15,301	0.49	0.15
2004		56,072	1.79	140,664	4.48	0.15			49,053	1.56	17,077	0.54	0.12
2009		57,914	1.85	95,542	3.04	0.22			50,330	1.60	32,290	1.03	0.12
2016		60,876	1.95	92,045	2.95	0.25			51,859	1.66	8,947	0.29	0.15
2019		61,433	1.96	40,813	1.30	0.26			64,066	2.04	11,026	0.35	0.16

Note: CA is the Class Area; PLAND (Percent of Landscape); N.P, (number of patches); P.D, (Patch Density); LPI, (Largest Patch Index)

3.3.2 Forest fragmentation

The NP for the Forestland class increased by over 82% between 1984 and 2019 while the CA and PLAND declined by 27%, LPI by 75%, and PD by 26% in the same period. Between 2016 and 2019, the CA and PLAND increased by 1.3%, NP by 2% and LPI by 34% (Figure 3.5).

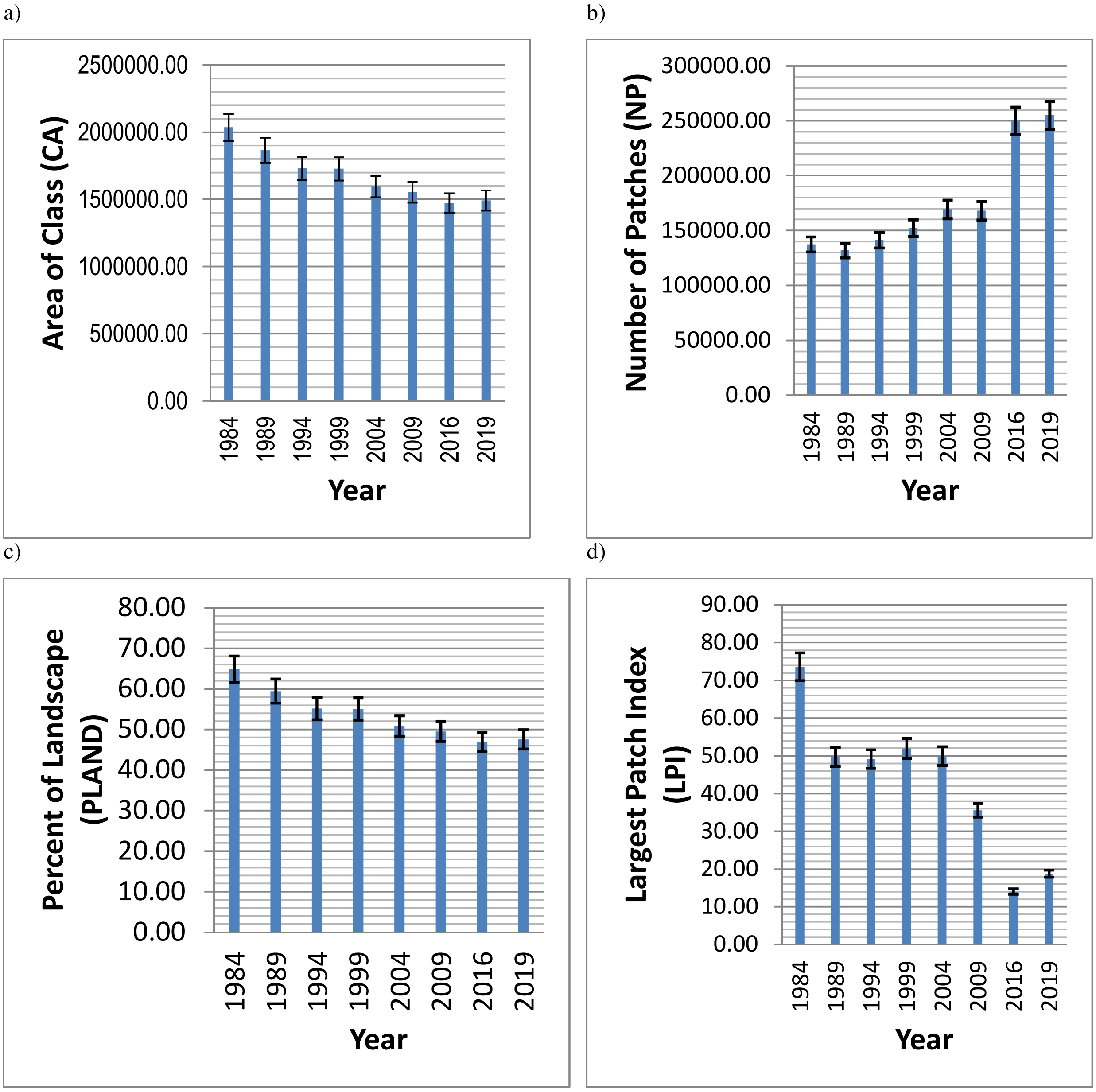

Figure 3. 5. Forestland metrics in the Copperbelt Province a) Total Area (CA), b) Number of patches (NP) c) Percent of Landscape (PLAND), and d) Largest patch Index (LPI)
Note: Errors were calculated at 95% confidence level

The FRAC metric for the persistent forest area in the province ranged from 1 to 1.5 (Figure 3.6).

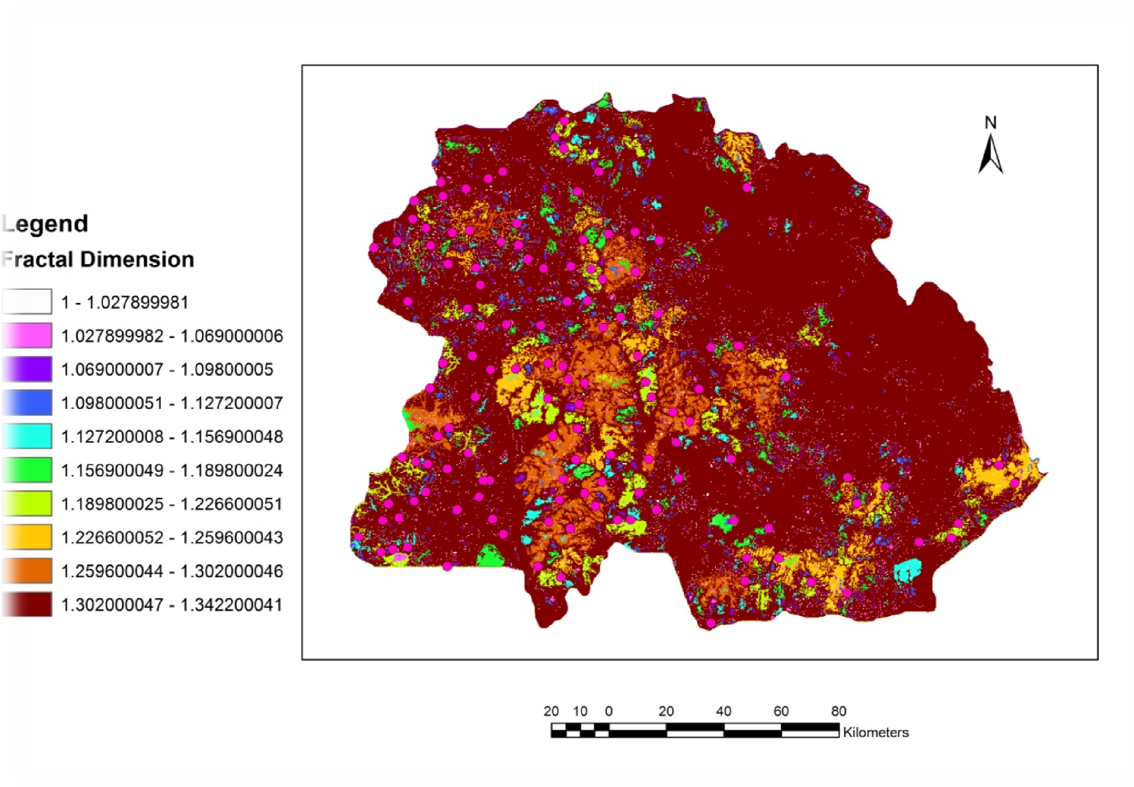

Figure 3. 6. Distribution of fractal dimension of the persistent forest (1984-2019) of the Copperbelt province

3.3.3 Quantities / Concentrations of soil chemical parameters

Results of soil nutrients concentrations from interpolation were validated by using the ME and the RMSE giving high levels of accuracy. The ME in the training and validation samples was close to 0 while the RMSE was low in both datasets. Figure 3.7 shows the mean values of soil chemical parameters in different soil textural categories within the FRAC-1 (≥ 1 to 1.25 range) and FRAC-2 (>1.25 to 1.5 range) metric areas. Loamy soils had higher mean values of C, N, NH_4-N, NO_3-N and K when compared to sandy soils for both FRAC metric scenarios (Figure 3.7a-e). However, P and pH had the opposite trend with high mean values in sandy soils on both metrics under review (Figure 3.7f, g). In fact amongst the soil parameters, the highest difference between loamy and sandy soil was observed for P.

The FRAC-1 metric range had higher values of (i) C (by 10% for loamy soils and by 11% for sandy soils); (ii) NH_4-N (by 1% for both soil types), N (by 8% for loamy and by 4% for sandy soil) when compared to FRAC-2 metric range. Similarly, the FRAC-1 metric category had higher concentrations of (i) NO_3-N (by 8% for loamy soils and 6% for sandy soils) and (ii) K (by 9% high in loamy soils and 3% for sandy soils) when compared to the FRAC-2 metric area (Figure 3.7). However, for P, areas within the FRAC-1 metric range had shown the highest variation in mean concentration; by 19% in loamy soils and 35% in Sandy soils while for pH, the mean level was higher by 1% in both soils in the FRAC-1 when compared to the FRAC-2 metric range. P had shown the biggest difference in the FRAC-1 metric areas with 49% higher values in sandy soils when compared to loamy soils. Table 3.4 shows results for the test between and within subject /factors indicated by the interaction of FRAC and soil textural classes.

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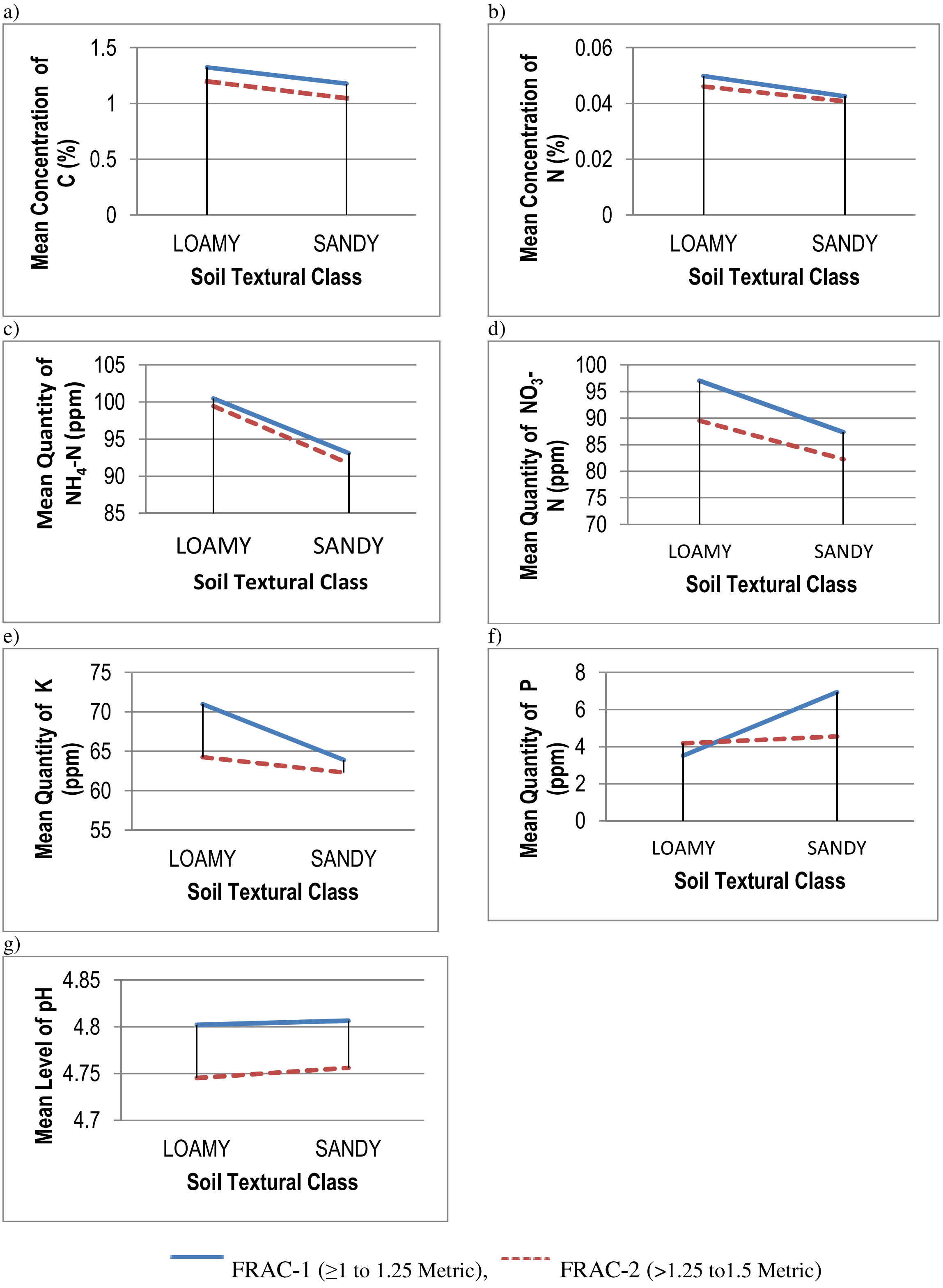

Figure 3. 7. Mean quantities/concentrations of soil chemical parameters in loamy and sandy soils of FRAC-1 and FRAC-2 metric areas a) Carbon (C); b) Nitrogen (N), c) NH_4-N (Ammonium Nitrogen), d) NO_3-N (Nitrate Nitrogen), K (Potassium), P (Phosphorus) and pH

Table 3. 4. Reconstructed table of test between-subject effects results of ANOVA

Source	**Dependent Variable**	**Type III Sum of Squares**	**df**	**Mean Square**	**F**	**Sig.**	**Partial Eta Squared**	**Noncent. Parameter**
Soil Textural Class * FRAC (Interaction)	C	0.72[a]	3	0.24	2.64	0.05	0.06	7.92
	NH_4-N	1223.26[b]	3	407.75	5.12	0.00	0.11	15.35
	N	0.00[c]	3	0.00	4.26	0.01	0.1	12.79
	NO_3-N	2245.17[d]	3	748.39	6.38	0.00	0.14	19.10
	P	141.37[e]	3	47.12	9.05	0.00	0.18	27.14
	pH	0.1[f]	3	0.03	2.25	0.09	0.05	6.75
	K	1115.64[g]	3	371.88	1.99	0.12	0.05	5.96
Error	C	11.00	121	0.09				
	NH_4-N	9642.64	121	79.69				
	N	0.01	121	7.396E-5				
	NO_3-N	14193.62	121	117.30				
	P	630.40	121	5.21				
	pH	1.73	121	0.01				
	K	22665.60	121	187.32				

a. R Squared = .061 (Adjusted R Squared = 0.04)
b. Computed using alpha = .05
c. R Squared = 0.113 (Adjusted R Squared = 0.09)
d. R Squared = 0.096 (Adjusted R Squared = 0.07)
e. R Squared = 0.137 (Adjusted R Squared = 0.12)
f. R Squared = 0.183 (Adjusted R Squared = 0.16)
g. R Squared = 0.053 (Adjusted R Squared = 0.03)
h. R Squared = 0.047 (Adjusted R Squared = 0.02)

Note: the table excludes rows for Corrected model, Intercept, total and Corrected total. C is (Carbon), NH_4-N (Ammonium Nitrogen), N (Nitrogen), NO_3-N (Nitrate Nitrogen), P (Phosphorus), K (Potassium).

The influence of soil textural class and FRAC was statistically significant for NH_4-N (p=0.002); N (p=0.007); NO_3-N (p=0.000) and P (p=0.000). However, the interaction between FRAC and Soil textural class was insignificant for C (p=0.053); pH (p=0.086) and K (p =0.120).

3.4 Discussion

3.4.1 Landscape and forest fragmentation between 1984 and 2019

Extensive LULCC occurred in the Copperbelt province between 1984 and 2019 leading to landscape fragmentation. These changes were caused by an increase in settlements, construction, agricultural expansion, industrialisation, woodfuel demand, logging and population (Dam 2017, Gondwe et al. 2020, Handavu et al. 2019, Mzuza et al. 2019, Shackleton 2015). The pressure on forest resources was triggered by the impact of economic liberalization, privatization of mines and companies, and the Structural Adjustment Programme (SAP) initiated by the Zambian government in the 1990s (Funsani et al. 2016, MAL 2013, Mulungushi 2007). The impact on forest resources is confirmed by an increase in the NP and a decline in the LPI for the Forestland class, suggesting a break-up into smaller patches between 1984 and 2019 (Figure 3.4, Table 3.3).

According to Nel et al. (2017), agricultural employment increased from 16.8 to 37% of all jobs in the Copperbelt province, thereby confirming findings of the current study that, the PLAND and CA increased for Croplands (Figure 3.4). Nevertheless, by 2016, the NP for Croplands reduced indicating that, initially crop fields were small and dispersed but as their size increased, fragmentation for this class reduced partly because some neighbouring boundaries were now touching each other. It was observed that agricultural activities were practiced in Forestlands, Dambos and along water bodies. This explains why the NP for Water and Dambo classes also increased during the period, indicating a rise in fragmentation (Table 3.3). These results are consistent with findings by Gondwe et al. (2020), Mabeza and Mawere (2012), Mbanze et al. (2019), Mwita (2013), Nyamadzawo et al. (2014), Ojoyi et al. (2016). LULCC gradually reduced the area of the persistent forests (Figure 3.6) where the mean quantities of soil chemical parameters were assessed.

3.4.2 Impact of forest fractal dimension on the level of soil chemical parameters

According to Compton and Boone (2000), Dupouey et al. (2002), Foster et al. (2003), Verheyen et al. (1999), land use history has long term effects on vegetation and soil properties. Even though information on the effect of forest fractal geometry on soil properties were not available, fragmentation analysis results (Table 3.3, Figure 3.6); supported by findings by (Didham and Lawton 1999, Medina et al. 2012, Newmark 2005) showed that forest areas falling within the FRAC-2 metric were characterised by many small patches of increasing shape complexities indicating higher fragmentation. On the other hand, areas within the FRAC-1 metric had larger and less complex shapes of patches which formed a more continuous and closed canopy (Figure 3.6). The presence of many small patches within the FRAC-2 metric areas increased the edge effect that altered biotic and abiotic factors (microclimatic factors) such as light intensity and duration, air temperature, relative humidity and wind leading to lower mean levels of the soil chemical parameters under review. This view agrees with Didham and Lawton (1999), Newmark (2005), Schmidt et al. (2017) who also found that higher fragmentation increased the edge effect which altered the micro environment.

Variations in the levels of NH_4+ and NO_3-were notable between textural classes and FRAC metric scenarios. The dominance of NH_4-N in the persistent forest (Figure 3.7) are supported by Cui and Song (2007) who made similar conclusions that soils in primary forests are typically dominated by NH_4+ rather than NO_3-. Lower levels of NO_3-N (Figure 3.7e and f) in these forests generally correspond to low net rates of nitrification caused by low pH associated with older forestlands. This is consistent with findings of this study where lower pH characterised FRAC-2 metric areas (Figure 3.7). The low levels of pH in the FRAC-2 metric areas is a result of increased soil respiration rates caused by higher temperature and moist conditions that promoted the production of organic (acetic, citric, malic, oxalic, tartaric, malonic) (Li et al. 2018) and carbonic acid (Fujii 2014, Harter 2007, Newmark 2005). This suggests that cations are released quickly and leached from the soil by heavy rains that are common in the Copperbelt province. Kacholi (2013), Logah et al. (2010), Norton and Ouyang (2019) reported similar reasons for the variations in pH, C, total N and available P. Ammonium on the other hand is positively charged and competes with K, C, and Magnesium (Mg). Leaching is especially high in sandy soils due to their low cation exchange capacity (CEC) and low water holding capacity compared to loamy soils. This is the reason why the mean levels of N, NH_4-N, NO_3-N, C and K were higher in loamy soils of both FRAC metrics as shown by the interaction values in the ANOVA (Table 3.4). However, the vegetation in FRAC-2 metric areas had more open, small and complex spaces/shapes hence allowed more runoff, wind and erosion thus the lower quantity/concentrations of nutrients along this metric in both soils categories (Figure 3.6, 3.7). These results further suggests that the intensity of rain interception was higher in the FRAC-1 metric areas leading to reduced impact of rain/ runoff compared with the more spaced vegetation in the FRAC-2 metric.

The low pH in many Miombo soils results in binding of P with iron and aluminium (Medina et al. 2012). The results suggest that as the forest canopy developed; in the case of FRAC-1 metric, the micro-environment below the forest became wetter and shadier, which increased chemical weathering of parent material, and therefore soil P was lost at a higher rate compared to the FRAC-2 metric areas. These results agree with Liu et al. (2010), Wardle et al. (2004) who reported that P becomes limiting to plant growth in the old growth forest largely due to depletion by plants and loss through erosion and runoff. High soil acidity plus high concentrations of aluminium and iron in sandy soils result in phosphorus fixation (Zhang et al. 2001). This is the reason why P levels were lower in loamy and higher in sandy soils of both metric categories (Figure 3.7).

3.4.3 Implication

Miombo soils are acidic and generally poor in essential nutrients. It is therefore imperative that interventions to maintain or improve the soils through forest pattern management are put in place. Millions of people in Tanzania, Angola, Mozambique, Malawi, Zambia and Zimbabwe depend on the Miombo ecosystems (Gumbo et al. 2018a). Deterioration in soil fertility and loss of forests would therefore have devastating effects on food security and climate in the region. Unfortunately, findings have shown that the CA for Forestland declined while that of Croplands increased (Figure 3.4, Table 3.3). These findings are worrying especially that the world population living in urban areas is expected to increase from the current 50% to 60% by the year 2030 and this will lead to increased exploitation of natural resources (Ahmed et al. 2013). The need to conserve soils and vegetation pattern is especially important at the time when mitigation and adaptation measures against climate change have taken centre stage (Li et al. 2013, Willim et al. 2020). Results of landscape pattern analysis (Table 3.3) indicated an increase in forest fragmentation in the province and if the trend continues, existing persistent forests will be affected. Such action would lead to loss or alterations in the geometric pattern of vegetation with negative impacts on soil properties (Medina et al. 2012). The study found significant variations in soil chemical properties attributed to forest geometric pattern (FRAC-1 and 2) (Table 3.4). These results imply that the application of fractal theory would improve the management of forest areas, enhance their interaction with soil properties and form the basis for accurate simulation in restoration programmes and decision making (Aguilar et al. 2008, Dibble and Thomaz 2009, Kacholi 2013, Ojoyi et al. 2016).

3.5 Conclusion

The Copperbelt province landscape had changed extensively with an increase in NP indicating a rise in fragmentation. An increase in SHDI from 1984 to 2019 further confirmed the formation of smaller and diverse patches in the landscape. Anthropogenic induced classes such as Croplands and Settlements had shown increasing PLAND while that of Forestlands, Water and Dambos declined. Weak implementation of existing land use plans / laws meant that there has been inadequate control on expansion of activities such as agriculture and settlements leading to haphazard opening up of land for new developments. The study further concluded that within a given persistent forest, knowledge on fractal geometry has the potential to improve the management and understanding of the impacts on soil properties as the study had found significant variations attributed to forest pattern.The study demonstrated that maintaining lower FRAC values of below 1.25 appear to maintain higher levels of C, N, NH_4-N, NO_3-N and K, in loamy soils. However, higher levels of P and pH would be maintained in sandy soils of FRAC-1 areas. These results imply that strict reference should be made to soil texture and forest geometry when deciding LU/LC because of the significant variations attributed to the factors. Therefore, incorporating fragmentation analysis in land use planning can assist in early detection of practices (such as Agriculture) that increase FRAC of forests. The study recommends that more research should be carried out on developing mechanisms for prescribing and implementing specific forest/vegetation geometry patterns for application in restoration / defragmentation programmes.

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CHAPTER 4: Extent of soil loss and the impact of fractal geometry of two competing land uses (Cropland and Forestland) on erosion severity in the Miombo ecosystem of the Copperbelt Zambia

Abstract

A rapid rise in the exploitation of forest resources largely attributed to an increase in agricultural activities has led to more fragmented landscapes and soil erosion in developing countries. Yet, the impact of fractal geometry of the two competing land use land cover (LU/LC); forestland and cropland on soil loss is not well understood. The objectives of this study are to quantify the extent of soil loss and to determine the impact of fractal dimension (FRAC) of Persistent Forests and Croplands on erosion severity in sandy and loamy soils of the Copperbelt province of Zambia. The Revised Universal Soil Loss Equation (RUSLE) was applied in ArcGIS 10.3. LU/LC maps (1984 to 2019) were produced by supervised classification and used in fragmentation analysis in FRAGSTATS. The extent of the Low Erosion Severity class (<5 $t.ha^{-1}yr^{-1}$) had a net reduction in area by 15.05% between 1984 and 2019. The mean soil loss (MSL) in FRAC-1 (1 to 1.25 FRAC) metric category was higher by 10.2% and 18% in Croplands and Forestlands, respectively, than in FRAC-2 (> 1.25 ≤ 1.5 FRAC) areas of loamy soils. However, the soil loss in loamy soils of FRAC-2 areas was higher by 41.4% and 32.8% in Croplands and Forestland respectively, than in sandy soils. Overall, the MSL in Croplands was 95% higher than in Forestlands considering all fixed factors. Cropland and Forestland geometric pattern affected soil loss, therefore, it is suggested that fragmentation analysis should be incorporated into land use planning for sustainable agriculture, soil, water and forest management.

KEYWORDS: **Fractal Geometry, Soil Loss, Erosion Severity, Miombo, Copperbelt, Soil Texture, RUSLE**

4.1 Introduction

Soil is an important resource vital for enhancing biodiversity, regulating climate, carbon sequestration, filtering contaminants, providing nutrients and producing food (Panagos et al. 2020). Globally, soils are constantly degraded because of population growth, economic development, and climate change (Montanarella et al. 2016). More than 1 billion hectares are affected by water or wind erosion (Lal 2003); thus, soil erosion is widely recognized as a serious environmental problem globally (Osei and Kabwe 2018, Sanchez and Swaminathan 2005). Soil erosion by water (the focus of this study) is defined as the wearing away of the earth's surface by the force of water and gravity, and the process involves soil particle dislodgement, entrainment, transport, and deposition (Gao et al. 2020, McCool and Williams 2008). Soil erosion dominates on areas with scanty vegetative cover and on agricultural lands (Ravi et al. 2010). The erosion of top soil costs billions of dollars worldwide and has caused the displacement of people who end up as environmental refugees each year. According to GSP (2017), 75 billion tonnes of soil are eroded every year from arable lands worldwide, which equates to an estimated US $400 billion per year in financial loss (Borrelli et al. 2017, Sartori et al. 2019). Erosion is a threat to soil functions (FAO and ITPS 2015, Montanarella et al. 2016), risking food security, water quality and climate change mitigation. The loss of forests through anthropogenic activities entails loss of plants that anchor the soil and protect from nutrient loss which are also common in the Miombo ecosystems.

The Miombo ecosystem is found in the Tropical region and covers over 2.7 million km^2, or, 10% of the African landmass (Malmer and Nyberg 2008, Syampungani et al. 2020). Miombo woodlands are dominated by *Isoberlinia, Julbernadia* and *Brachystegia* tree species (Backéus et al. 2006, Dewees et al. 2010). This ecosystem is important for carbon sequestration, controls flooding, moderates climate conditions, filters pollutants, maintains biodiversity, protects soils from erosion, provides food (Alberti 2010, Gökyer 2013, Shackleton and

Gumbo 2010) and supports the economic livelihood of millions of people (Gumbo et al. 2018b, Ryan et al. 2016). Despite the benefits provided by the Miombo, the ecosystem is affected by anthropogenic activities such as timber harvesting, settlements, charcoal production, firewood collection, and fires leading to land use land cover change (LULCC), forest fragmentation and soil loss (Syampungani et al. 2020, Tembo et al. 2015). Population growth and high poverty levels have exacerbated the situation causing an increase in the rate of forest clearance leading to high soil erosion risk.

Water-driven soil erosion has been widely studied as the most dominant form of soil degradation worldwide (García-Ruiz et al. 2017, Li and Fang 2016, Xiong et al. 2018). Soil erosion assessments therefore serve as a scientific base for soil conservation and watershed management (Patil 2018). Theoretically, water erosion is caused by runoff energy, which depends on runoff volume and its squared speed. According to the theory by Horton (1945), runoff starts when rainfall intensity exceeds soil absorption capacity. Further, the soil saturation theory states that runoff starts when all the pores in the soil are filled with water. Overland flow (surface run-off) occurs through the Hortonian and the saturation overland flow. Hortonian overland flow occurs when the intensity of precipitation that reaches the surface exceeds the infiltration capacity of the soil (Barman et al. 2021). On the other hand, saturation overland flow occurs when the combination of precipitation intensity and duration (and run-on from higher areas) saturates the soil and raises the water table to the surface. In the Miombo ecosystem, storm flows are influenced by both Hortonian and saturation overland flow depending on the land cover, soil properties and ground water at a point (McCartney et al. 1998).

Studies on soil use and management, especially predictive models, are fundamental for conservation planning processes (Carvalho et al. 2014, Kinnell 2010, Zhuang et al. 2015).

While various soil erosion assessment models have been developed; the universal soil loss equation (USLE) (Wischmeier and Smith 1978) and its revised version (RUSLE) (Renard 1997) have been widely applied to assess past and future soil erosion (Borrelli et al. 2017, Correa et al. 2016, Li et al. 2017, Naipal et al. 2015, Panagos et al. 2015, Xiong et al. 2019). This is because of their simple structure and empirical basis. Some studies have researched on the effects of soil erosion on ecosystem services (Guerra et al. 2014, Jiang et al. 2018, Peng et al. 2017) and on biogeochemical cycles, such as the carbon cycle (Borrelli et al. 2017, Doetterl et al. 2012) at varying scales. On the other hand, Borrelli et al. (2017) worked on the effects of anthropogenic activities on erosion and found a 2.5% increase in soil loss attributed to human activities between 2001 and 2012 globally.

The link between soil loss, LULCC and the intensity of fragmentation is important. Fragmentation describes landscape-level process in which a large intact parcel of land is progressively divided into smaller, geometrically altered and isolated patches (Carranza et al. 2014, Fahrig 2003, Forman and Godron 1986) altering the fractal geometry. Spatial pattern metrics such as FRAC among numerous other metrics, allow researchers to quantify size/shape relationship of vegetation patches (Franklin and Forman 1987, Krummel et al. 1987, Loehle 1983, Mandelbrot 1982, Medina et al. 2012, O'neill et al. 1988, Zhang et al. 2007). Fractal theories have been employed in studying soil characteristics (Karami et al. 2017, Li et al. 2016, Miloš and Bensa 2017, Oleschko et al. 2008, Tuffour 2015, Yu et al. 2015, Zhang et al. 2013). For instance, Wang et al. (2008) found that the, fractal dimensions of soil particle size distribution were influenced by land use and management practices. Wang et al. (2007), Wang et al. (2010) also concluded that fractal parameters provided potential indicators of soil quality and are capable of characterizing spatial and temporal differences in different land-use patterns. Nevertheless, studies focusing on the impact of forest and cropland fractal geometry on soil loss are rare and the gap is particularly large in the Miombo ecosystem leaving substantial uncertainty.

The objectives of the study were to: i) quantify the extent of soil loss in the Copperbelt province between 1984 and 2019; ii) determine the impact of fractal dimension of forests and croplands on the rate of erosion severity. The study is based on the hypothesis that significant spatial variations in soil loss are influenced by the geometric pattern of the two competing LU/LC. We used the Copperbelt province as a case study because this predominantly mining region has undergone massive changes since the privatisation and structural adjustment programme of the 1990s and yet information on LULCC and forest fragmentation; and their impacts on soil loss are absent. This trend in lack of information on soils loss has potential to impact on regional and global food security and climate.

4.2 Methods

4.2.1 Study area

The Copperbelt is one of Zambia's ten provinces with a total land surface area of 31,3281 km^2 (3.1328 million ha); 4.2% of the total area of the country. The province lies between latitude S12º to S13º 50'and longitude E27º to E29º (ACCC 2010) and is bounded by the Democratic Republic of Congo (DRC) to the north and east; within the country, with Central and North Western provinces. The Copperbelt province consists of ten (10) districts namely; Chililabombwe, Chingola, Kalulushi, Kitwe, Luanshya and Lufwanyama. Masaiti, Mpongwe, Mufulira and Ndola (Figure 4.1) (GRZ 2016). The province has a high population density (63.0 persons per square kilometre) and has experienced increased pressure on natural resources that have become an alternative source of livelihood thereby impacting on the environment of the area (CSO 2014). According to CSO (2014), the population of the province was 1,972,317 (15.2% of Zambia's total population) with about 81% and 19%

living in urban and rural areas respectively. Land use in the province are influenced by livelihood activities that are based on agriculture, forestry and mining. The unemployment rate of the province is over 22% (CSO 2014). The topography of the province is gently undulating with an elevation of between 1250 and 1400 m. The Kafue is the major River flowing in the southward direction through the province. The soils in the Copperbelt province comprise of red lateritic soils with sandy topsoil overlying more loamy clayey subsoil.

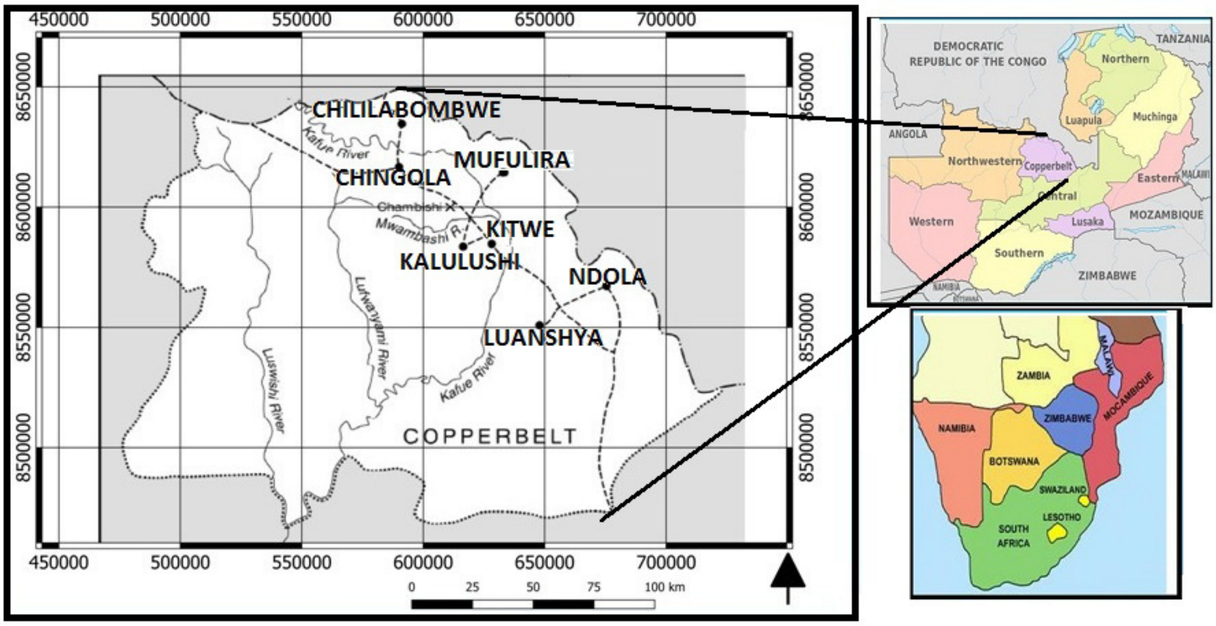


Figure 4. 1. The Location of the Copperbelt province, Zambia

Because of the high rainfall in the Copperbelt, the soils are strongly leached, have low base saturation and plant nutrients reserve. The soils are only suitable for climatically adapted crops under fertilization and good management. The high rainfall in the Copperbelt has induced vigorous tree growth (GRZ 2016). The climate of the Copperbelt province is controlled largely by the north-south migration of the Inter Tropical Convergence Zone (ITCZ). Total annual average rainfall is approximately 1,309.1 mm, with the majority falling during the summer months between November and April. The temperature ranges from 19.1 °C, with warm to hot summers reaching 31.9 °C in October.

4.2.2 Data collection

Data collected in this study was used in modelling soil loss, erosion severity and landscape metrics. Soil loss modelling was based on the interactions between rainfall runoff-erosivity (R); soil erodibility ($K_{er,}$), slope length (L); slope steepness (S), cover and management (C_{mt}) and the support practice (P_{sp}) factors for rill and sheet erosion as applied in the RUSLE (Renard 1997). In this study, the FRAC metric was computed using LU/LC maps to determine the geometric pattern of the Persistent Forest and Croplands.

4.2.2.1 Factors of erosion- rainfall runoff-erosivity (R), soil erodibility (K_{er}) and slope length and steepness (LS)

In the RUSLE, the K_{er}-Factor reflects the rate at which different soil types erode and it is a measure of the vulnerability of soil particles to transport by runoff. This is influenced by the amount of organic matter, soil structure, texture and percentage of silt, sand and clay (Williams et al. 1984, Wischmeier and Smith 1978). Data for computing the K_{er}-Factor was derived from Sand, Silt and Clay percent raster layers created through kriging interpolation of 126 random sample points collected from the study area. The sample points were generated using the “Create Random Points” tool in ArcGIS 10.3. Soil sample locations were marked using Global Positioning System (GPS) unit by recording the latitude and the longitude. At the centre of each plot, one composite soil sample was obtained from 0 cm and 20 cm depth, collected using a 5 cm diameter soil auger.

The LS-Factor expresses the effect of topography on soil erosion (Karaburun 2010). This index is the measure of the distance from the point of origin to the point where either deposition begins or slope gradient reduced and is influenced by the slope (Wischmeier and Smith 1978). Data used in computing the LS-Factor was calculated from a Digital Elevation Model (DEM) of the province obtained from the Space Shuttle Radar Topography Mission

(SRTM) hosted at the United States Geological Survey (USGS) website (ESRI 2020). The DEMs are at 30 m resolution. In addition, the R-Factor is determined as a function of storm effect on surface soils (Lee and Lee 2006). The R-Factor was computed by using the mean annual precipitation map obtained from USGS/EROS Climate Hazards Group Infrared Precipitation with Station (Center and Hazards 2017).

4.2.2.2 Data on cover and management (C_{mt}), support practice factors (P_{sp}) and landscape metrics (FRAC)

Deriving the C_{mt} and P_{sp} factors, and landscape metrics (FRAC) involved acquisition and pre-processing of Landsat images. Landsat images covering path/row: 172/69, 172/70, 173/69, and 173/68 for 1984 based on Landsat 5-TM images and Landsat 8 for 2019 were obtained from the United States Geological Survey (USGS) website (ESRI 2016). The P_{sp}-Factor is the function of soil conservation measures that may be adopted to mitigate soil loss. The P_{sp} value ranges from 0 to 1, where 1 represents no conservation and 0 means measures resulting in high resistance to erosion (Renard 1997). This factor has been noted by Mishra et al. (2006) as practice that retained eroded particles and prevents them from further transport. In this study, Shin (1999) support practice factor was adopted for P_{sp}-value estimation which relates cultivation method to slope. On the other hand, the C_{mt} index is the cover management factor and refers to the influence of LU/LC on soil erodibility.

4.2.3 Data analysis

4.2.3.1 Analysis of factors of erosion

Soil loss was assessed for rill and sheet erosion by applying the RUSLE model as outlined by Renard (1997). All raster maps of factors applied in the RUSLE model (Eqn 1) were resampled to 250 m resolution. In the RUSLE, A is the mean annual soil loss in $t.ha^{-1}yr^{-1}$, R is the rainfall runoff-erosivity ($MJ.mmha^{-1}hr^{-1}yr^{-1}$); K_{er}, (soil erodibility); L (slope length); S, (slope steepness) (dimensionless); C_{mt}, (cover and management) (dimensionless); and P_{sp} (support practices) (dimensionless) factor. The Mean Soil Loss (MSL) was computed using eqn 2 adapted from (Das 2017).

$$A = R x K_{er} x L/S x C_{mt} x P_{sp} \quad (1)$$

$$\mathrm{MSL} = \sum_{i}^{n} \left(\frac{\mathrm{Pv\ x\ Pa}}{\mathrm{Ta}} \right) \quad (2)$$

Where Pv = Pixel Value, Pa = Pixel area, Ta = Total Study Area, n = n^{th} Pixel

The Total Soil Loss (TSL) was calculated as a product of MSL and the Ta (Eqn 3) in the Raster calculator.

$$\mathrm{TSL} = Ta\ x\ MSL \quad (3)$$

1. Calculating the rainfall–runoff erosivity factor (R)

Eqn 4 was applied to compute the rainfall erosivity factor the Raster calculator in ArcGIS 10.3 (Eqn 4).

$$R = 38.5 + 0.35\ x\ Pr \quad (4)$$

Where, R is the Rainfall Erosivity Factor, Pr is the annual average rainfall in (mm/year).

2. Soil Erodibility factor (K_{er})

Particle size (Sand, Silt, and Clay % values) data from the field was prepared in tabular format with XY coordinate fields. Kriging interpolation was applied to create raster layers. This study adopted the alternative soil erodibility factor (ERFAC)-K equation by Geleta (2011) and in the Raster calculator in ArcGIS 10.3 (Eqn 5) with Sand, Silt and Clay rasters as inputs. This is an alternative method for estimating K_{er} for dynamic environments where data sources are scarce.

$$\mathrm{K}_{er} = 0.32\ x\ (\frac{\%\ Silt}{\%\ Sand + \%\ Clay})\text{^}0.27 \qquad (5)$$

Where K_{er} is the ERFAC-K = Proposed alternative soil erodibility factor; % Silt = percentage silt content in the soil %; Clay = percentage clay content in the Soil %; Sand = percentage sand content in the soil.

3. Slope length (L) and slope steepness (S) factor;

The combined topographic LS-factor was computed (Figure 4.2) with the slope angle (%) and the slope length (overland flow length) as input rasters. In this study, the slope length was generated using the Integrated Land and Water Information System (ILWIS 3.3) academic while the slope angle was computed using ArcGIS 10.3. The flow accumulation raster (Step 3) was used as an input grid in the Drainage Network Extraction process. The Drainage Network Extraction operation extracts a basic drainage network (a True and False Boolean raster map). In calculating the drainage network, a limit in the number of cells draining into a particular cell was assumed. In this study, the slope length limit was set to 150 m which is considered as being the upper bound when concentrated flow would generally occur (Mbugua 2009, Renard 1997). The Drainage Network Ordering operation (Step 5) was done to examine all drainage lines in the drainage network map, find the nodes where two or more streams meet, and assigns a unique ID to each stream in between these nodes. In this operation, a minimum drainage length was specified as 150 m; which is the value for the minimum length (m) that a stream should have to remain in the drainage network (Mbugua 2009). The Overland Flow Length was then computed with the Drainage Network Ordering as the input raster in the Raster calculator of ArcGIS. The Slope % and Overland Flow Length were used as input in calculating the LS-Factor using the equation recommended by Morgan and Davidson (1991) (Eqn 6).

$$A = \sqrt{\frac{L}{22}(0.065 + 0.045\, xs + 0.0065\, xs^2)} \qquad (6)$$

Where L is Slope length and S is the Steepness factor

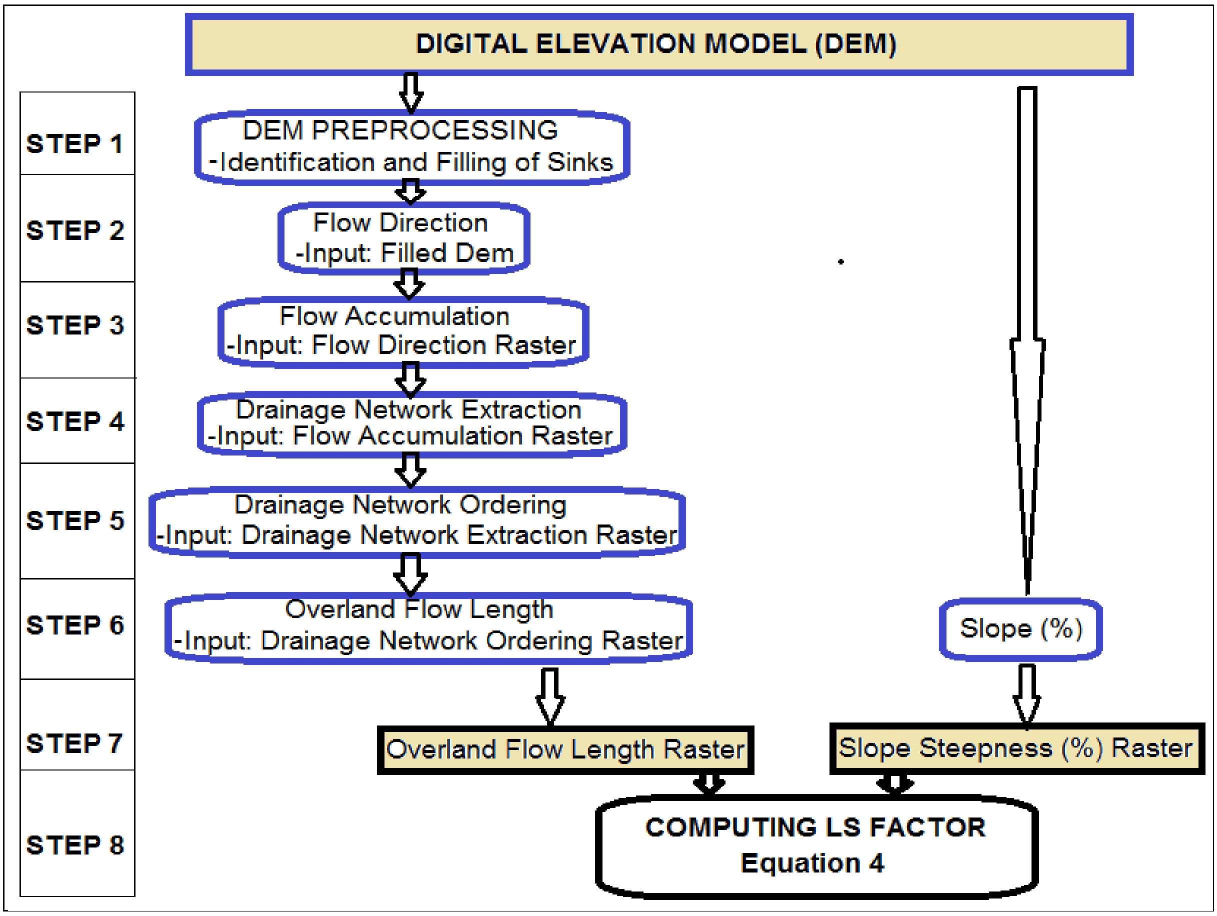


Figure 4. 2. Flow chat for computing the slope length and slope steepness factor
Adapted from (Mbugua 2009)

4. Cover management factor (C_{mt}) and support practice factor (P_{sp})

The C_{mt} and P_{sp} factors were calculated based on LU/LC maps produced in ArGIS 10.3 through supervised image classification (Table 4.1). The Landsat images were geometrically corrected and projected to the Universal Transverse Mercator zone 35s coordinate system and the World Geodetic System (WGS) 84 datum. Training site data were selected in easily identifiable areas of classes such as water; indigenous and plantation forest; and non-forest classes such as Bareland and Settlements, using a GPS receiver and Google Earth. Representative sites were visited and their locations recorded with a GPS unit as ground truth points in order to match the land use class with the digital number (DN) in each band (Millard and Richardson 2015). Classes adapted from IPCC (2003) and Münch et al. (2017) were applied and are described as follows: Dambo (depressions with grasses and seasonal water); Woodland/Forestland (land of >0.5 ha with trees ≥5m and a canopy ≥10%); Settlement (urban, industrial land covers with buildings and roads); Bareland (barren land, bare soil and rock outcrops); Grassland (grasses, shrubs, pasture or herbaceous rangeland); Cropland (agricultural land with standing or harvested crops including livestock); Water (water bodies such as ponds, lakes, rivers, streams and canals); and Plantation (felled or standing trees of pine, eucalyptus and other exotic tree species). The overall accuracy was computed through kappa statistic by dividing the correctly classified points by the total number of points multiplied by 100% using ENVI 4.7 software. An overall accuracy of 85% was acceptable in the study (Kamusoko and Aniya 2007).

For the C_{mt}-Factor, each LU/LC class was reclassified using the “Reclassify” function in the Spatial Analysts Extension of ArcGIS 10.3 according to the values provided in Table 4.1 for 1984 and 2019. In the case of the P_{sp}-Factor, Forestlands, Barelands, Water, Grasslands, Dambo and Settlement classes were merged into Other land (Non Agricultural class) while Plantations were merged into the Croplands class (Table 4.1). All non Agricultural areas were assigned 1 while Croplands were assigned 0.5 since there were no adopted conservation methods in the study area (Morgan 1995).

Table 4. 1. Cover management factor (C_{mt}) and support practice factor (P_{sp})

Land Use	C_{mt}-Factor	C_{mt}-Factor Area (%)		P_{sp}-Factor	P_{sp}-Factor Area (%)	
		1984	2019		1984	2019
Forestland	0.003[2]	64.86	32.64	1[3]	93.57	84.18
Settlement	0.003[2]	1.2	1.34			
Bareland	1[1]	0.4	0.4			
Grassland	0.0152	11.08	6.01			
Water	0[1]	2.04	1.22			
Dambo	0[1]	12.5	10.45			
Plantation	0.2[2]	1.48	1.40			
Cropland	0.2[2]	6.43	15.18	0.5[3]	6.43	15.18

[1] (Ko et al. 2013), [2] (Panagos et al. 2015), [3] (Chadli 2016)

4.2.3.2 Change in erosion severity between 1984 and 2019

Changes in soil severity used the “Postclassification” function in ENVI 4.7 with the 1984 and 2019 soil loss rasters as the initial and final year respectively. These images were compared using cross-tabulation in determining the changes between 1984 and 2019 on a pixel basis. Soil erosion severity was categorized into three classes namely; Low Erosion Severity (<5 $t.ha^{-1}.yr^{-1}$), Moderate (5-12 $t.ha^{-1}.yr^{-1}$), and High Erosion Severity (>12 $t.ha^{-1}.yr^{-1}$). The magnitude and percentage of changes are expressed in equation 7 and 8:

$$sK = sF - s\mathrm{I} \qquad (7)$$

$$\mathrm{sA} = \frac{(sF - sI)}{\mathrm{sI}} X\ 100 \qquad (8)$$

Where sK = magnitude of changes in erosion severity between the initial year (1984) and the final year (2019) in hectares; sA = percentage of changes in erosion severity; sF= erosion severity in Final year, and sI = the erosion severity in initial year (Mahmud and Achide 2012). Additional change detection parameters as outlined in (Aldwaik and Pontius Jr. 2012) and (Pontius Jr. 2019) where adapted into the methods (equation 9, 10, 11, 12 and 13).

$$\mathrm{sL_X} = \mathrm{CT}F_{\mathrm{x}} - \mathrm{sP_x} \qquad (9)$$

$$\mathrm{sG_X} = \mathrm{CT}I_{\mathrm{x}} - \mathrm{sP_x} \qquad (10)$$

$$\mathrm{NQC_X} = s\mathrm{G_x} - \mathrm{sL_x} \tag{11}$$

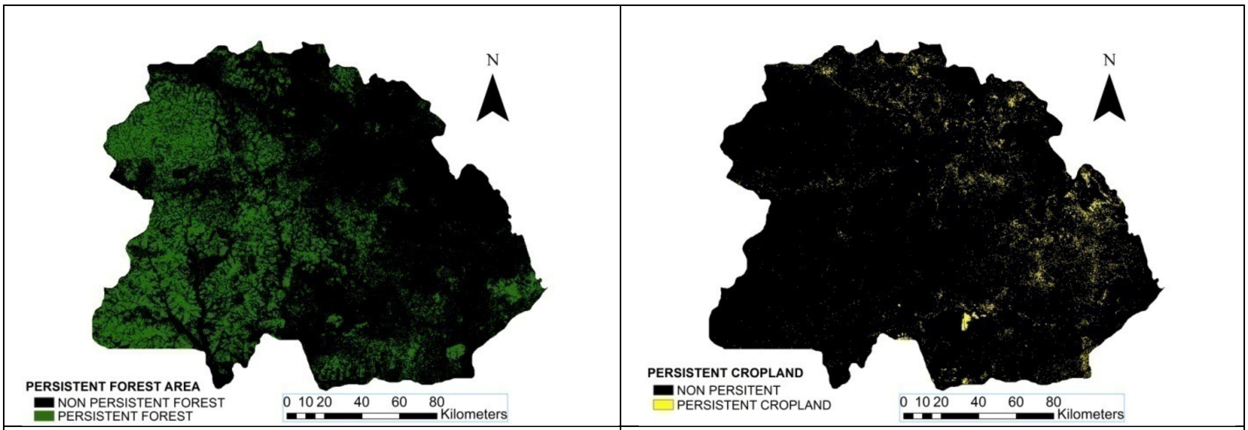
$$\mathrm{sS_X} = (\mathrm{sG_X} + \mathrm{sL_x}) - \mathrm{NQC_x} \tag{12}$$

$$\mathrm{sTC_X} = \mathrm{sS_x} + \mathrm{NQC_x} \tag{13}$$

Where $\mathrm{sL_x}$= the loss in area of severity class (i.e. the class change) given by the difference between the Class total for the Initial year and the unchanged area (persistence) for erosion severity class x; $\mathrm{CT}F_\mathrm{x}$ = the Class total for the Final year of erosion severity class x; $\mathrm{sP_x}$ =the area of unchanged pixels for erosion severity class x between the Initial and Final year; $\mathrm{sG_x}$= the gain in area for erosion severity class x given by subtracting the Persistence from the Class total of the Final year for erosion severity class x; $\mathrm{CT}I_\mathrm{x}$= the Class total of the Initial year for erosion severity class x; $\mathrm{NQC_x}$ (image difference) = the Net Quantity Change for erosion severity class x given by the sum of Gain and Loss between the Initial and Final year; $\mathrm{sS_x}$ = the swap in area between the Final and Initial year for erosion severity class x given by the difference between the sum of gains + losses and NQC; $\mathrm{sTC_x}$= the total change in area between the Initial year and Final year for erosion severity class x given by the sum of the swap and NQC.

4.2.3.3 Quantifying fractal geometry (FRAC)

FRAC, was computed from LU/LC maps produced in ArcGIS 10.3 and ENVI 4.7 using FRAGSTATSs 4.2 application at three spatial levels: patch, class, and landscape (McGarigal and Marks 1995). FRAC Equals 2 times the logarithm of patch perimeter (m) divided by the logarithm of patch area (m^2); the perimeter is adjusted to correct for the raster bias in perimeter. FRAC approaches 1 for shapes with very simple perimeters such as squares, and approaches 2 for shapes with highly convoluted, plane-filling perimeters (McGarigal (2015). FRAC was computed in the Persistent Forest and Croplands only (Figure 4.3). Persistent forests included all forest areas (pixels) that never changed from 1984 to 2019 created by intersecting all Forestland pixels for all years under review using the "And" Boolean operation in ArcGIS. Similarly, the Persistent Cropland areas included areas that were under agriculture without changing to any other land use between 1984 and 2019 (Appendix B1). The Persistent categories were created in order to isolate the influence of other land uses so that the only factor contributing to the variation in soil loss was the geometric pattern (FRAC) of Forestlands and Croplands. All imput Landsat images were resampled to 250 m grain scale because according to Tian et al. (2019) this grain scale provided more accurate results. The fractal dimension was divided into two scales; FRAC-1 (≥ 1 to 1.25) and FRAC-2 (>1.25 to ≤1.5) metrics indicating high and low degrees of shape/pattern complexities, respectively. FRAC values were applied as fixed factors in ANOVA. The advantage of fractal analysis is that it can be applied to spatial features over a wide variety of scales (Mandelbrot 1977, Mandelbrot 1982).



(a) (b)

Figure 4. 3. Persistent areas between 1984 – 2019 in the Copperbelt province (a) Persistent Forestland; (b) Persistent Cropland

4.2.3.4 Statistical analysis

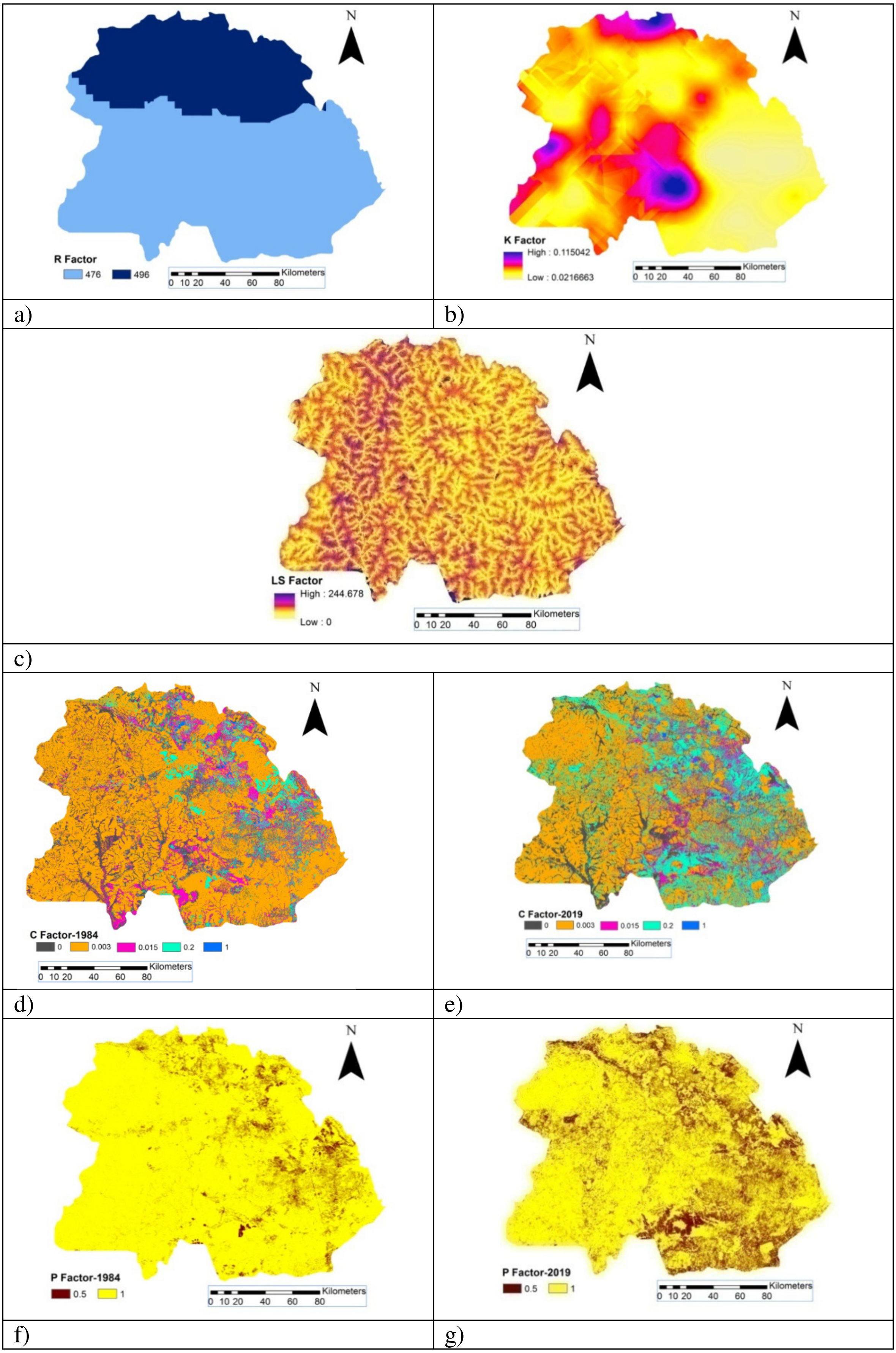
Two independent samples of all points contained in the Persistent Cropland and Forestland rasters, were extracted from the attribute table using the Value field. The XY coordinates were added to each sample set using the "Add XY coordinates" function in ArcGIS 10.3.

This procedure ensured that all available sample points / pixels were included in the statistical analysis with referenced X,Y locations. The "Extract Multi Values to Points" function in ArcGIS 10.3 was employed to extract variables. We tested for significant differences in soil loss (dependent variable) between two fractal classes (FRAC-1 and FRAC-2), and soil texture as fixed factors in Persistent Forest and Cropland areas. This was done in agricultural suitable slope areas of <20%. The Univariate ANOVA with interaction was applied in SPSS software to determine the variations in soil loss against all fixed factors at 95% confidence level. In this study, data on slope %, stoniness, drainage and the type and extent of erosion were recorded for validation purposes at each of the 126 sample points.

4.3 Results

4.3.1 Results on erosion factors

The R-factor ranged from 476 to 496 ($MJ.mmha^{-1}hr^{-1}yr^{-1}$) while the K_{er}-factor values had minimum values of 0.0217 and maximums of 0.11504 ($t.ha.hr.ha^{-1}.MJ.mm^{-1}$) (Figure 4.4a). The LS-Factor was between 0 to 244.678 (Figure 4.4c). The C_{mt}-Factor for 1984 and 2019 hard shown an increase in areas with values of 0.2 and a reduction in areas with 0.003 index (Figure 4.4d, e). Similarly, the P_{sp}-Factor exhibited an increase in areas with values of 0.5 (Agriculture) compared to other lands (Non agricultural areas) of factor 1 (Figure 4.4f, g)).



a) b)

c)

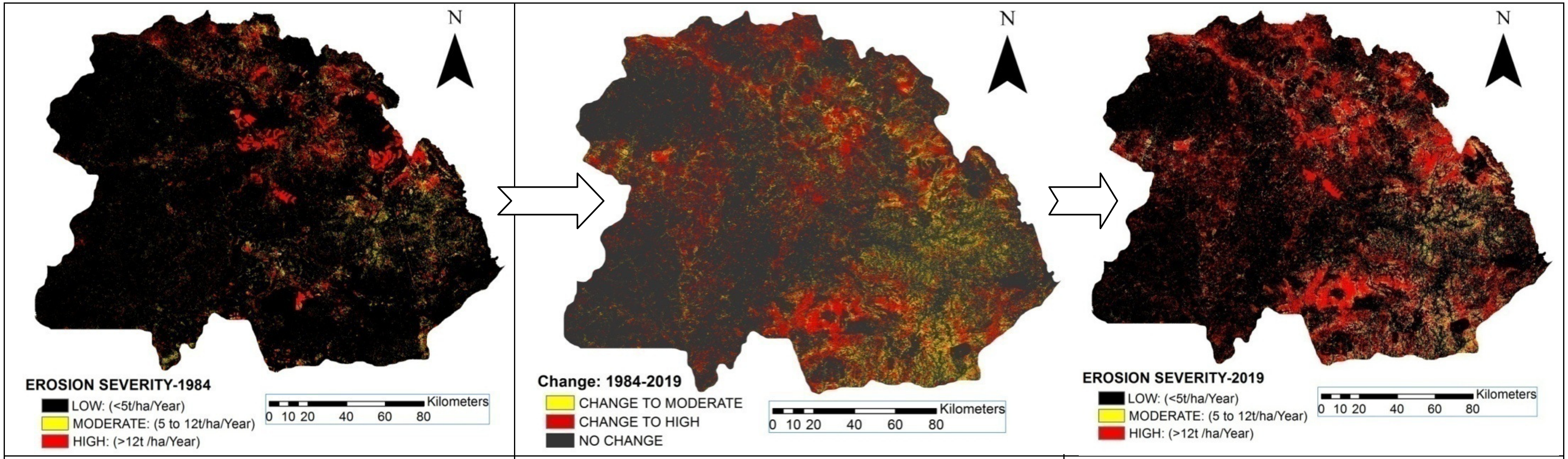
d) e)

f) g)

Figure 4. 4. Factors used in soil loss modelling a) Rainfall erosivity, b) Soil Erodability, c) Slope Length and Slope Steepness, d) Cover and Management-1984, e) Cover and Management Factor-2019 f) Support Practice - 1984 g) Support Practice Factor-2019

4.3.2 Changes in the extent of soil Loss and erosion severity between 1984 and 2019

The results showed an increase in soil loss and erosion severity between 1984 and 2019. The overall MSL for the province was 3 $t.ha^{-1}yr^{-1}$in 1984 and 6 $t.ha^{-1}yr^{-1}$in 2019. The TLS increased from 9.4Mt in 1984 to 20.6 $Mt.ha^{-1}yr^{-1}$in 2019. The extent of the Low Erosion Severity class reduced by 15.05% between 1984 and 2019. Similarly, the area of the Moderate Severity class reduced by 3.81%; from 7.17% in 1984 to 2.33% in 2019. The area under High Erosion Severity increased by 11.24% between the years under review. In fact, the highest loss in the area of the Low Erosion Severity class was to the High Erosion Severity category (13.35%) followed by the conversion to Moderate Severity (6.04%). Between 1984 and 2019, 72.07% for Low, 1% for Moderate and 2.69% for High Erosion Severity classes remained unchanged (Persisted) (Figure 4.5, Table 4.2).



(a) (b) (c)

Figure 4. 5. Extent of erosion severity in the Copperbelt province (a) Erosion severity in 1984; (b) Change map of erosion severity between 1984 and 2019 (c) Extent of erosion severity in 2019

Table 4. 2. Reconstructed table of the change in the area of erosion severity classes between 1984 and 2019.

	Area Under Severity Class in 2019 (t.ha^{-1}yr^{-1})				
	LOW	**MODERATE**	**HIGH**	**Area in 1984**	**Loss (L)**
LOW	**2,262,074.40 (72.07)**	189,421.92 (6.04)	418,894.74 (13.35)	2,870,391.06 (91.46)	608,316.66 (19.38)
MODERATE	61,407.90 (1.96)	**32,332.86 (1.03)**	11,839.77 (0.38)	105,580.53 (3.36)	73,247.67 (2.33)
HIGH	74,738.07 (2.38)	3,364.83 (0.11)	**84,488.31 (2.69)**	162,591.21 (5.18)	78,102.90 (2.49)
Area in 2019	**2,398,220.28 (76.41)**	**225,119.61 (7.17)**	**515,222.82 (16.42)**	3,138,562.80 (100)	
Total Gain (G)	136,146.06 (4.34)	192,786.75 (6.14)	430,734.51 (13.72)		
Total Change (TC)	744,462.72 (23.72)	266,034.42 (8.48)	508,837.41 (16.21)		
Swap (S)	1,216,633.32 (38.76)	146,495.34 (4.67)	156,205.80 (4.98)		
Net Quantity Change (NQC)	-472,170.60 (-15.04)	119,539.08 (3.81)	352,631.61 (11.24)		

Note: Figures in parenthesis are percentages –NQC indicates Net Decline, +NQC shows Net Increase

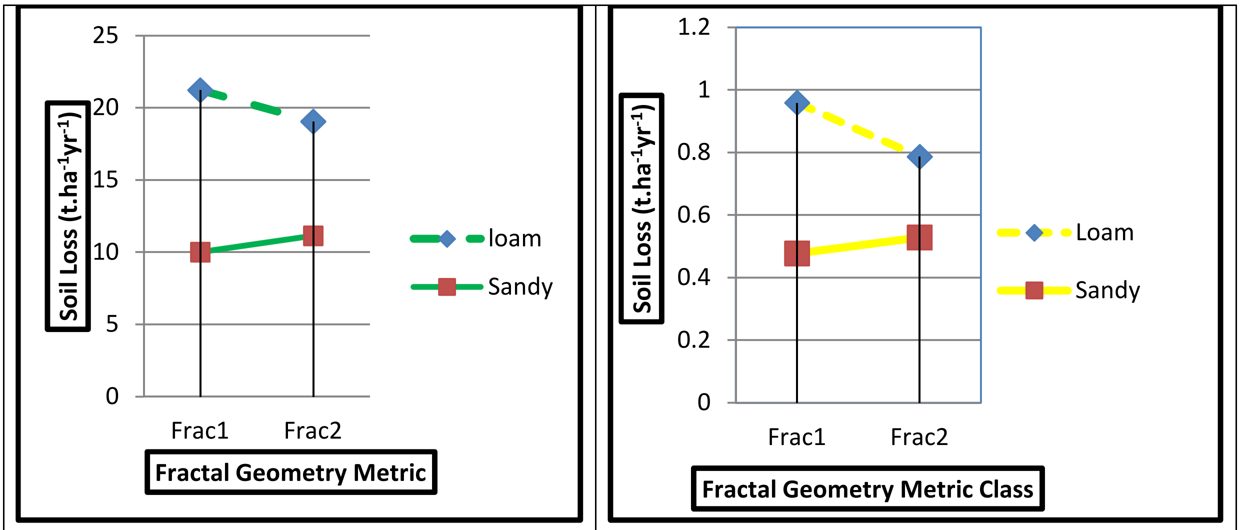
4.3.3 Effect of fractal geometry of croplands and forestlands on soil loss

In the persistent Cropland, the MSL was higher by 10.2% in FRAC-1 than in FRAC-2 metric areas of loamy soils. However, erosion was higher by 10.13% in FRAC-2 than in FRAC-1 metric areas of sandy soils. The MSL was higher by 52.83% and 41.4% in FRAC-1 and FRAC-2 metric areas of Loamy soils respectively, than in sandy soils (Table 4.3-A, Figure 4.6).

In the persistent Forestland category, the MSL was 18% higher in FRAC-1 compared to FRAC-2 areas in loamy soils. However, soil loss was 9.6% higher in FRAC-2 than in FRAC-1 metric areas in sandy soils. Erosion in loamy soils was 50.2% and 32.8% higher in FRAC-1 and FRAC-2 metric areas respectively, than in sandy soils (Table 4.3-B). Overall, the MSL was higher in Croplands by 95% when compared to Forestlands (Table 4.3-C).

Table 4. 3. Difference in mean soil loss between Cropland and Forestland in FRAC-1 and FRAC-2 metric areas in sandy and loamy soils

	Fractal Dimension	**Sandy** (t.ha^{-1}yr^{-1})	**Loamy** (t.ha^{-1}yr^{-1})	**Difference** (t.ha^{-1}yr^{-1})
A.				
Persistent Cropland	FRAC-1	10.0072	21.2168	11.2096 52.83% Higher in Loamy Soils
	FRAC-2	11.1346	19.0440	7.9094 41.4% Higher in Loamy Soils
Difference Within Cropland		1.1274 10.13% Higher in FRAC-2	2.1728 10.24% Higher in FRAC-1	
B.				
Persistent Forestland	FRAC-1	0.4774	0.9588	0.4814 50.2% Higher in Loamy Soils
	FRAC-2	0.5281	0.7861	0.258 32.82% Higher in Loamy Soils
Difference Within Forestland		0.0507 9.6% Higher in FRAC-2	0.1727 18% Higher in FRAC-1	
C.				
Difference between Cropland and Forestland	FRAC-1	9.5298 95% Higher in Cropland	20.258 95.48% Higher in Cropland	
	FRAC-2	10.6065 95.26% Higher in Cropland	18.2579 95.87% Higher in Cropland	



a) a)

Figure 4. 6. Variations in mean soil loss in FRAC-1 and 2 areas and soil textural categories in persistent (a) Forestlands (b) Croplands

4.3.3.1 Analysis of variance-persistent croplands

The study revealed that the effect of soil textural class and the interaction (FRAC + Textural Class) was statistically significant at 95% CI. The effect of FRAC alone on soil loss was statistically insignificant (p=0.083) (Table 4.4).

Table 4. 4. Tests of between-subjects effects-Croplands

Source	Type III Sum of Squares	df	Mean Square	F	Sig.
Corrected Model	356,618.163[a]	3	118,872.721	554.495	0.000
Intercept	2,224,108.994	1	2,224,108.994	1.037E4	0.000
FRAC * Soil Texture	6,424.664	1	6,424.664	29.969	0.000
FRAC	644.758	1	644.758	3.008	0.083
Soil Texture	215,632.429	1	215,632.429	1.006E3	0.000
Error	2,811,379.157	13114	214.380		
Total	6,644,611.996	13118			
Corrected Total	3,167,997.320	13117			

a. R Squared = 0.113 (Adjusted R Squared = 0.112)

4.3.3.2 Analysis of variance-persistent Forestlands

In the Persistent Forest area, the effect of FRAC, soil texture and the interaction was statistically significant at 95% CI (Table 4.5).

Table 4. 5. Tests of between-subjects effects-Forestlands

Source	Type III Sum of Squares	df	Mean Square	F	Sig.
Corrected Model	2,223.456[a]	3	741.152	92.873	0.000
Intercept	20,966.193	1	20,966.193	2.627E3	0.000
Soil Texture * FRAC	138.178	1	138.178	17.315	0.000
Soil Texture	1,515.173	1	1,515.173	189.864	0.000
FRAC	41.232	1	41.232	5.167	0.023
Error	907,494.372	113,717	7.980		
Total	983,992.590	113,721			
Corrected Total	909,717.828	113,720			

a. R Squared = 0.002 (Adjusted R Squared = .002)

4.4 Discussion

4.4.1 Factors of soil loss

In this study, the dominant LU/LC were Cropland, Grasslands and Forestlands with the remaining part classified under, Plantation, Settlement, Barelands, and water bodies. Generally, the C_{mt}-Factor for Forestland, Dambo, Water, and Settlements had the lowest values implying higher protection ability from water erosion (Sun et al. 2014). Although the C_{mt}-Factor has the power to influence the erosion risk, they can be artificially modified except for LU/LC that occurs naturally; such as Water and Dambos to mitigate erosion (Figure 4.4d, e). This suggests that information on LU/LC and C_{mt}-Factors would be vital for developmental planning and erosion risk mitigation. On the other hand, the P_{sp}-Factor had values ranging from 0.5 (Agriculture) to 1 where no supportive erosion practices were implemented (Figure 4.4f, g). In most developing countries, few to no support practice interventions are in place hence soil loss attributed to lack of conservation is widespread as reported by Osei and Kabwe (2018).

In the case of the R-Factor, the study area falls in a high precipitation area which receives average rainfall of 1,300 mm (Figure 4.4a). This suggests that the rainfall erosivity had greater weight than the other four factors (K_{er}, LS, C_{mt}, and P_{sp}); logical because we are studying soil erosion by water (Mahalingam et al. 2015, Mair and Fares 2011). High rainfall coupled with high population, lack of support practice interventions and increasing depletion of covers such as Forestlands explains why erosion in the north and eastern sections of the province are dominated by the High Erosion Severity class in 1984 and 2019 (Figure 4.5). This is especially so because the northern and eastern parts of the province are also dominated by major mining industries and population centres.

The K_{er}-Factor is influenced by the inherent characteristics of the parent materials, that is the percentage of sand, silt, clay and organic matter (Anache et al. 2016, Neitsch et al. 2011). The courser texture (Sandy) is the more tolerable or less erodible than finest soil texture (Loamy). K_{er} values in the study area ranged from 0.11 to 0.02 t.ha^{-1}.yr^{-1} with low values indicting low erodibility (Figure 4.4b). In terms of the LS factor, Gelagay and Minale (2016) reported that it is the most influential factor in water erosion modelling after the rainfall erosivity factor . The soil loss variation by LS-Factor ranged from 0 to 244 (Figure 4.4c). This suggests that areas with high LS values are located on the steep slope, gully and river bank regions and these areas are sensitive to erosion.

4.4.2 Extent of soil loss and erosion severity between 1984 and 2019

According Foster et al. (2005), the uncertainty of the RUSLE goes up very rapidly for soil loss values less than 1 ton ac-^{1} yr-^{1} (1 ton per 0.4 ha). However, the MSL and TLS in this study were all above 1 ton ac-^{1} yr-^{1} meaning that the results were accurate and reliable.

Identifying the severity of erosion is essential for selection and implementation of appropriate soil and water conservation measures (Meshesha et al. 2012, Sun et al. 2014). In this study, we found a gradual conversion from Low to the High Erosion Severity class (Table 4.2, Figure 4.5). This increase in soil loss is attributed to the extensive LULCC that occurred in the Copperbelt province between 1984 and 2019 which modified the C_{mt} and P_{sp}-Factors. These changes were caused by an increase in settlements, construction, agricultural expansion, industrialisation, woodfuel demand, logging and population (Dam 2017, Gondwe et al. 2020, Handavu et al. 2019, Mzuza et al. 2019). The LULCC were triggered by the impact of economic liberalization, privatization of mines and companies, and the Structural Adjustment Programme (SAP) initiated by the Zambian government in the 1990s (Funsani et al. 2016, MAL 2013, Mulungushi 2007). Similar results on soil loss were found by (Gelagay and Minale 2016). However, the results of this study are different from findings by Osei and Kabwe (2018) who reported very low soil loss values of between 0 and 0.0000000011 $t.ha^{-1}yr^{-1}$ compared to our results (0 – 5,369 for 1984 and 0 – 2,871 for 2019) in the province.

The overall MSL for the province was 3 $t.ha^{-1}yr^{-1}$ (1984) and 6.6 $t.ha^{-1}yr^{-1}$ for 2019 (Figure 4.5, Table 4.2). According to the USDA, the tolerable erosion limits ranges from 2 to $5t.ha^{-1}yr^{-1}$ (Wischmeier and Smith 1978). This means that the MSL in 1984 was within the tolerable limit while 2019 was above by 1.65 $t.ha^{-1}yr^{-1}$). However, comparing the MSL for the study area with other regions revealed differences. For instance, the MSL for Europe is between (0.7 – 17.9 t.ha−1 yr−1) while it is between 10.8 – 146 t.ha−1 yr−1 for Africa (Maetens et al. 2012). The TSL of 9.4 $t.ha^{-1}yr^{-1}$ (1984) and 20.4 (2019) for the study area appear to be comparatively lower than other countries such as Nepal which was reported to have TSL of 369 $Mt.yr^{-1}$ (Koirala et al. 2019). By 2019, more than 23% of the area of the province fell within the Moderate and High Erosion Severity classes compared to 8.54% for the same categories in 1984 (Figure 4.5, Table 4.2) justifying calls for urgent action. The impact of the anthropogenic activities are observed in the increase in area for Croplands and a decline in Forestlands, Water and Dambos (Figure 4.5, Table 4.1). According to Nel et al. (2017), agricultural employment increased from 16.8 to 37% of all jobs in the Copperbelt province and this contributed to the increase in erosion.

4.4.3 Impact of fractal geometry on soil loss in persistent Cropland and Forestlands

4.4.3.1 Variations in mean soil loss between Croplands and Forestlands

According to Compton and Boone (2000), Dupouey et al. (2002), Foster et al. (2003), Verheyen et al. (1999), land use history has long term effects on vegetation and soil properties. The MSL was higher in loamy soils of both metric categories (FRAC-1 and FRAC-2) when compared to the levels in sandy soils (Figure 4.6, Table 4.3) in persistent Forests and Croplands. Soil textural class accounted for the difference as observed in the ANOVA results (Table 4.4, 4.5). According to (O'geen 2006), silty soils tend to be highly erosive, clayey and loamy soils tend to have moderate erodibility, and sandy soils generally have low erodibility. This explains why soil loss was higher in loamy soils compared to sandy soils in both Croplands and Forestlands. The second factor accounting for the difference relates to activities performed in the persistent areas under review. In Croplands, the land is tilled to prepare the soil for seeding (Kusumandari 2014). This means that tillage accelerates soil erosion by disrupting soil structure, and reducing the crop residue which help to cushion the force of pounding raindrops / splash erosion (Reicosky et al. 2011, Van Dijk et al. 2015). We found that the MSL in Croplands was higher by 95% in both sandy and loamy soils and FRAC categories when compared to Forestland areas (Table 4.3-C). This view is supported by (Koirala et al. 2019) who also found that the highest mean erosion rate was in barren lands followed by agricultural lands with lower values in forests.

The low MSL observed in Forestlands can be attributed to rainfall interception and lack of tillage. Canopy interception is the amount of rain that is intercepted by a canopy and then evaporates (Xiao et al. 2000). Evaporation from wet canopies can return up to half of incident rainfall back into the atmosphere meaning that the full impact of raindrops does not hit the surface (Yang et al. 2019). Therefore, understanding tree canopy geometry and the effect of rainfall interception is important (Baptista et al. 2018, Xiao and McPherson 2016) and this is influenced by vegetation geometry (FRAC-1 and FRAC-2). According to Yang et al. (2019), the soil below is further protected from the impact of Throughfall and splash erosion through litter and humus on the surface. This explains why the MSL was 50% higher in Loamy soils of Croplands and Forestlands of FRAC-1 areas than in sandy soils (Table 4.3-A, B).

4.4.3.2 Variations in soil Loss between FRAC metrics and soil textural classes

The mean soil loss in FRAC-1 areas of loamy soils decreased towards FRAC-2 regions in Forestlands and Croplands. However, the opposite trend was true in Sandy soils where the mean soil loss increased from FRAC-1 to FRAC-2 metric areas (Table 4.3, Figure 4.6). Even though information on the effect of Forest and Cropland fractal geometry on soil loss were not available, fragmentation analysis results (Table 4.3, 4.4, 4.5, Figure 4.6); supported by findings by (Didham and Lawton 1999, Medina et al. 2012, Newmark 2005) showed that areas within the FRAC-2 metric were characterised by many small patches of increasing shape complexities indicating higher fragmentation and wider spacing in the canopy. On the other hand, areas within the FRAC-1 metric had larger and less complex shapes of patches which formed a more continuous and closed canopy (Figure 4.6). The presence of many small patches within the FRAC-2 metric areas of both Forestlands and Croplands increased the edge effect that altered biotic and abiotic factors (microclimatic factors) such as light intensity and duration, air temperature, relative humidity and wind which affected the factors of erosion leading the differences in the MSL.

Due to the denser vegetation, it was expected that loamy soils in FRAC-1 areas would be consistently moist leading the higher initial moisture for soils that inherently, have high water holding capacity (Holz et al. 2015). This means that loamy soils would saturate faster given a rainstorm and hence experience more erosion. The other reason for high soil loss in loamy soils of the FRAC-1 metric is attributed to the effect of splash erosion associated with rainfall interception common in denser and closed vegetation. According to Yang et al. (2019), during a rainstorm, raindrops will be intercepted by leaves of trees but the intercepted water may fall to the ground (Throughfall) and cause splash erosion which could have greater impact. The third reason is attributed to chemical reactions associated with loamy soils covered by dense vegetation (FRAC-1). These results suggest that the micro-environment in FRAC-1 metric areas are wetter and shadier, which increases chemical weathering through the generation of weathering agents, biocycling of cations, and the production of biogenic minerals (Balogh-Brunstad et al. 2008, Finlay et al. 2020, Kelly et al. 1998) .

In FRAC-1 areas of sandy soils, the opposite effect was observed. Splash erosion experienced in FRAC-1 areas of loamy soils may still occur here (Figure 4.6). However, the impact is reduced due to the low erodibility of sandy soil (O'geen 2006). This suggests that the soil loss increase from FRAC-1 towards FRAC-2 metric areas are partly due to the low chemical weathering taking place in sandy soils because of higher pH, and low organic content associated with the type of soil. In FRAC-2 areas of sandy soils, higher soil loss is recorded because of the wider spacing of the canopy, more raindrops reach the surface thereby increasing the runoff capable of dislodging the particles causing higher soil loss in FRAC-2 areas. While FRAC-1 areas are also highly shaded in sandy soils just like in loamy soils, the soil moisture is much lower due to high percolation properties of sand. Therefore, the sandy soils in FRAC-1 areas of both LU/LC take time to saturate hence runoff is lower leading to low erosion. Leaching is also high in sandy soils due to their low cation exchange capacity (’CEC) and low water holding capacity compared to loamy soils. Soil loss is particularly higher in Croplands (by 95%) due to tilling that loosens the soil (Ma et al. 2014).

The lack of information on soil loss and erosion severity and the effect of the geometric pattern of Forests and Croplands could impact on planning for mitigation of soil erosion at national and regional level (Liniger et al. 2011). If not addressed, significant amounts of topsoil would be lost leading to a decline in agricultural production and this would compromise the already unstable food security situation (Bastida et al. 2018) in these acidic and nutrient poor soils of the Miombo ecosystem (Gumbo et al. 2018a). Further, sediments from erosion carry bound nutrients which contribute to the eutrophication of freshwater resources (Rabalais et al. 2010). Eroded soil cause damage to hydroelectricity, irrigation facilities, and reservoirs raising the risk of flooding and damage to marine life (Vanmaercke et al. 2011), loss of vital ecosystem services (Lal 2014) and associated economic costs (Kirui and Mirzabaev 2014).

4.5 Conclusion

The study concluded that within a given Persistent Forest and Cropland, knowledge on fractal geometry has the potential to improve the interaction between agricultural and forest activities. The study had found significant variations in soil loss attributed to the geometric pattern of Forestlands and Croplands. The study demonstrated that maintaining lower metric (FRAC-1) appear to reduce the MSL in sandy soils of Forestlands and Croplands. However, lower levels of soil loss are achieved by maintaining FRAC-2 metric values in loamy soils. These results imply that strict reference should be made to soil texture and geometry when deciding LU/LC as these affect the factors of erosion. Therefore, incorporating fragmentation analysis in land use, soil and water conservation planning can assist in early detection of practices (such as Agriculture) that alter the geometry and factors of erosion. Fractal theory therefore presents an opportunity to address the soil erosion problem through manipulation of the geometric pattern of Forestlands and Croplands. The study recommends that more research should be carried out on developing mechanisms for prescribing and implementation of specific forest/vegetation cropland geometry patterns for sustainable agriculture and forest landscapes.

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CHAPTER 5: Modelling the pattern and morphological characteristics of Forest and Cropland patches for use as indicators in spatial planning

Abstract

Land use land cover (LU/LC) and other landscape features have different morphological/geometric properties, but studies that model these characteristics are scarce making it difficult to accurately restore or mimic sustainable landscapes. This study conducted the morphological spatial pattern analysis (MSPA) on persistent (1984 to 2019) forest and cropland areas in the Copperbelt province of Zambia. These persistent land use classes were divided into two fractal dimension (FRAC) categories: FRAC-1=1≤1.25 and FRAC-2=1.25≤1.5. LU/LC maps used in the study were analysed in ArcGIS and ENVI. The MSPA used GUIDOS 3.0 to compute the Cores, Islets, Loops, Bridges, Perforations, Edges, Branches and Contortion. Shape descriptors (Roundness, Circularity, Convexity, Elongation, Width, Length, Number of Holes and Directionality) were computed in ImageJ1.53 software. The study revealed that FRAC-1 and FRAC-2 Forest areas recorded the highest number of Core areas (over 13%) while Croplands had the highest quantity of Islets with over 63%. FRACs of forest areas had lower average Elongation and Convexity index than Cropland FRACs. However, Forest areas recorded higher Contortion index than Croplands suggesting more complex patch shapes in natural landscapes. FRAC-1 Forestland areas had longer average length and width of patches by between 29-36%. This study concluded that the spatial and temporal morphology of natural landscapes (Forestlands) differed significantly with human induced land uses (Croplands) at 95% confidence level. This has implications on ecological connectivity which could affect the provision of ecosystem services. The study recommends that pattern and morphology of landscapes / patches should be incorporated for accurate mimicking of sustainable landscapes or in restoration programmes.

KEYWORDS: **landscape metrics, forest geometry, Shape descriptor, morphometrics, mspa, patches shape**

5.1 Introduction

Ecological processes are influenced by landscape pattern shaped by the morphology of patches that may exist in different ecosystems. Landscape and morphological metrics/indices have been developed to provide indicators in monitoring of global, and regional biological and ecological changes (Ostapowicz et al. 2008, Soille 2013). Morphometry is the quantitative analysis of form, a concept that encompasses size and shape of entities (Dryden and Mardia 2016). The morphology of a landscape /patch has a direct influence on ecosystem services and functions such as on the movement of water, physical and chemical properties of soil, vegetation cover and distribution (Dujardin 2017). The morphology further influences humans when there is shaping and reshaping of the landscape in which social and cultural entities are established. While the natural landscape is influenced by a combination of forms shaped by climate, water, land and vegetation through time, the cultural landscape is formed by anthropogenic activities such as settlements, agriculture, transport networks and industries (Dujardin 2017).

The characteristic morphology of landscapes can be described by the size and shape of objects, their relative area share and their spatial configuration which may allow distinguishing between different land-use classes (Vanderhaegen and Canters 2010). For instance, Tropical forests cover 13% of the world while Miombo woodlands (found within Tropical forests) cover 10% of the African landmass and are dominated by *Isoberlinia, Julbernardia* and *Brachystegia* tree species. These forests have unique morphormetric characteristics that influence the provision of ecosystem services (Dujardin 2017). Natural landscapes such as forests are vital elements in the provision of ecosystem services that include timber, habitats, maintaining water supply and quality, carbon sequestration, and recreation (Luque and Iverson 2016) and in reducing the risks of global climate change, since they buffer carbon emissions (FAO 2010). However, forests are dynamic environments that change over time and across geographic areas leading to changes in their morphology and geometric pattern (Ghazoul and Chazdon 2017, Moghaddam 2018).

On the other hand, the areas under agriculture globally is 5 billion hectares (38% of global surface area) (FAO 2020). Agriculture is vital for the survival of man on earth and is often cited as a major cause of forest decline and land use land cover change (LULCC). Changes in a landscape may result from both natural and artificial causes. For instance, biotic processes such as forest succession, insect outbreaks, wind throw, flooding, droughts, regeneration and human activities such as increase in settlements, agricultural expansion, pollution, charcoal production and firewood collection are the primary vectors in changing the composition and distribution of landscapes which in turn shape their characteristic morphology (Camarretta et al. 2018, Moghaddam 2018). Therefore, estimating and understanding these changes can provide essential ecological information for policy-making in the protection of species diversity, forest resource conservation and management (Camarretta et al. 2018, Ferrara et al. 2016, Rabalais et al. 2010).

Three general approaches can be distinguished in morphological studies; traditional, landmark and outline-based morphometrics. In traditional morphometrics, lengths, widths, masses, angles, ratios and areas are analysed (Henderson 2006, Rohlf and Bookstein 1990). Landmark-based geometric morphometrics takes care of the spatial information missing from traditional morphometrics because the data are coordinates of landmarks. In the outline analysis approach, coefficients of mathematical functions are fitted to points sampled along the outline. Morphometrics were initially performed on biological studies involving organisms (Baab 2011, Parés-Casanova 2017). However, many morphometrical concepts have now been generalized to encompass non-biological hypotheses such as geomorphometry (Guth 2011) and archaeometry (Borel et al. 2017). Moghaddam (2018) applied the MSPA and found differences in the temporal morphological pattern and spatial changes in forest disturbance within the boreal biome of Canada. Vogt et al. (2007) also used the MSPA to analyze land cover pattern on raster maps. Ostapowicz et al. (2008) and Vogt et al. (2009) quantified structural and functional connectivity while Ostapowicz et al. (2006) worked on forest fragmentation. Ye et al. (2020) established important ecological corridors based on the MSPA in Tomur World Natural Heritage Region of China. Shape metrics have been applied to classify objects to land use categories (Frohn 2006). Zhou et al. (1995) employed a shape index to discriminate spectrally similar land-cover classes while Lewis et al. (1997) used shape descriptors such as eccentricity, elongatedness and complexity in cloud classification from satellite imagery. A study by Jiao and Liu (2012) analyzed the shape characteristics of land use classes in remote sensing imagery and found that all typical shape properties of land use segments can be quantitatively described by shape metrics.

It is widely believed that landscape features take numerous morphological properties but attempts to quantify these differences are scarce. The objective of this study was to carry out a morphological spatial pattern analysis (MSPA) of patches and then quantified the differences in shape characteristics between undisturbed (Persistent) Forests and Croplands for use as indicators in spatial planning.

5.2 Materials and methods

5.2.1 Study area

The study was conducted in the Copperbelt Province of Zambia (latitude S12° to S13° 50'and longitude E27° to E29°) (ACCC 2010) The province has a high population density (63.0 persons per square kilometre) and has experienced increased pressure on natural resources that have become an alternative source of livelihood thereby impacting on the environment of the area (Handavu et al. 2019). We used the Copperbelt province as a case study because this predominantly mining region has undergone massive changes since the privatisation and structural adjustment programme of the 1990s and yet information on the morphology of patches, their directionality in the landscape; and the potential impacts on ecological connectivity are absent.

According to the Central Statistics Office, CSO (2014) and the Zambia Statistics Agency, Ministry of Health and Inner City Fund, ZSA/MOH/ICF (2019) the population of the province was 1,972,317 (15.2% of Zambia's total population) with about 81% and 19% living in urban and rural areas respectively. Land use in the province is influenced by livelihood activities that are based on agriculture, forestry and mining. The unemployment rate of the province is over 22% (CSO 2014, ZSA/MOH/ICF 2019).

The province lies on the eastern central African plateau that is characterised by a gently undulating plateau of between 1,200m and 1,455m above sea level. The Kafue is the major River and it flows in the southward direction through the province. The climate of the Copperbelt Province is controlled largely by the north-south migration of the Inter Tropical Convergence Zone (ITCZ). Total annual rainfall is approximately 1,309.1 mm, with the majority falling during the summer months between November and April. The temperature ranges from 19.1 °C, with warm to hot summers reaching 31.9 °C in October. The combination of high rainfall and temperature averages has induced vigorous tree growth in the province (GRZ 2016)

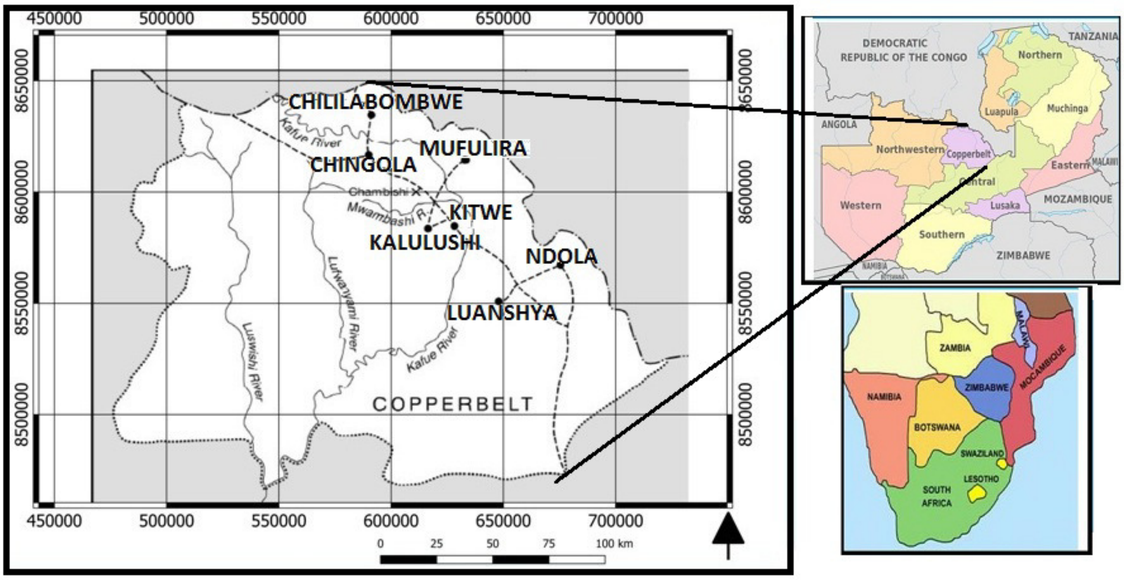


Figure 5. 1. The Location of the Copperbelt Province, Zambia, Southern Africa

5.2.2 Image acquisition and pre-processing

Landsat images covering path/row: 172/69, 172/70, 173/69, and 173/68 from 1984 to 2019 were obtained from the United States Geological Survey (USGS) website (ESRI 2016) and used for preparation of land use maps used in fragmentation and morphometrics analysis. These images were based on Landsat 5-TM images for 1984, 1989 and 1999; Landsat 7-ETM for 2004, and 2009 and Landsat 8 images for 2016 and 2019. The images were geometrically corrected and projected to the Universal Transverse Mercator zone 35s coordinate system and the World Geodetic System (WGS) 84 datum. Radiometric correction and normalization of the images was done in order to ensure that the changes in pixel values from various images reflect actual changes on the surface (Du et al. 2002). ArcGIS 10.3 and ENVI 4.7 software were employed in the analysis process using both raster and vector data.

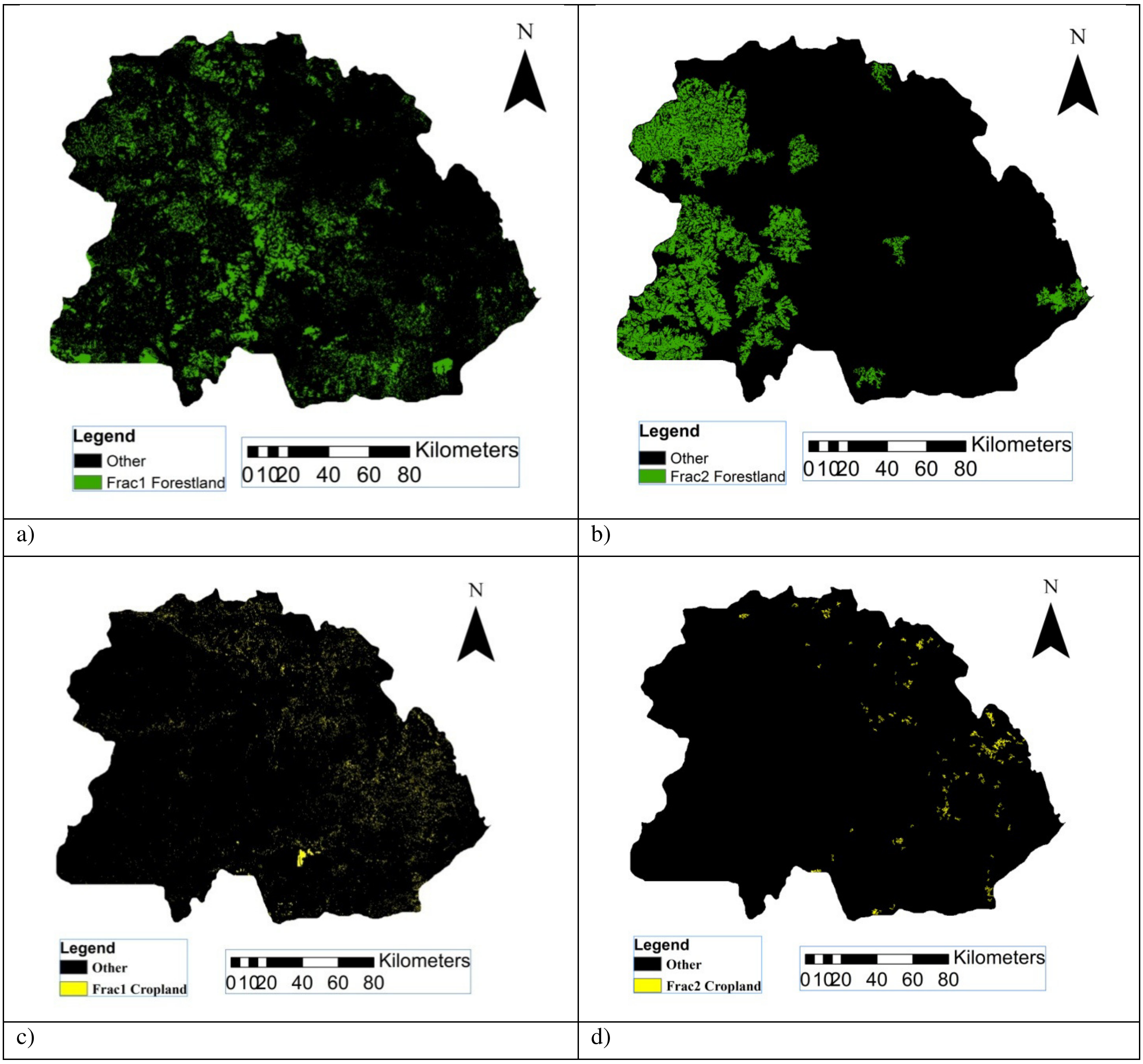
5.2.3 Data analysis

5.2.3.1 Land cover classification

Landsat images were classified through supervised image classification using the maximum likelihood classification method (ESRI 2012). As outlined in Malunga et al. (2021), training site data were selected in easily identifiable areas of classes such as water; indigenous and plantation forest; and non-forest areas such as bare soil and built-up areas, using a GPS receiver and Google Earth. Representative sites were visited and their locations recorded with a GPS unit as ground truth points in order to match the land use class with the digital number (DN) in each band (Millard and Richardson 2015). Classes adapted from IPCC (2003) and Münch et al. (2017) were applied and are described as follows: Dambo (depressions with grasses and seasonal water); Forestland/Woodland (land of >0.5 ha with trees ≥5m and a canopy ≥10%); Settlement (urban, industrial land covers with buildings and roads); Bareland (barren land, bare soil and rock outcrops); Grassland (grasses, shrubs, pasture or herbaceous rangeland); Cropland (agricultural land with standing or harvested crops including livestock); Water (water bodies such as ponds, lakes, rivers, streams and canals); and Plantation (felled or standing trees of pine, eucalyptus and other exotic tree species).

All the data was validated using the confusion matix in ENVI 4.7. Forestlands and Croplands were further categorised into Persistent classes covering 1984 to 2019. Persistent / undisturbed forests included all forest areas (pixels) that never changed from 1984 to 2019 created by intersecting all Forestland pixels for all years under review using the “And” Boolean operation in ArcGIS. Similarly, the Persistent Cropland areas included areas that were under agriculture without changing to any other land use, over the same period. The Persistent categories were created in order to isolate the influence of other land uses so that the only factor contributing to the variation in the morphology / geometry of patches was Forestlands and Cropland activities.

Fractal Dimension (FRAC) for each persistent layer was computed in FRAGSTATS 4.2 at a spatial resolution of 250 m because according to Tian et al. (2019), this grain scale provided more accurate results in landscape metrics (LM). The resulting FRAC rasters were used in morphological analysis of patches. The FRACs were divided into two scales; FRAC-1 ($\geq$ 1 to 1.25) and FRAC-2 ($>$1.25 to $\leq$1.5) metrics indicating high and low degrees of shape/pattern complexities, respectively. FRAC equals two times the logarithm of patch perimeter divided by the logarithm of patch area (m^2); the perimeter is adjusted to correct for the raster bias in perimeter. FRAC approaches 1 for shapes with very simple perimeters such as squares, and approaches 2 for shapes with highly convoluted, plane-filling perimeters (McGarigal 2015) (Figure 5.2).



a) b)

c) d)

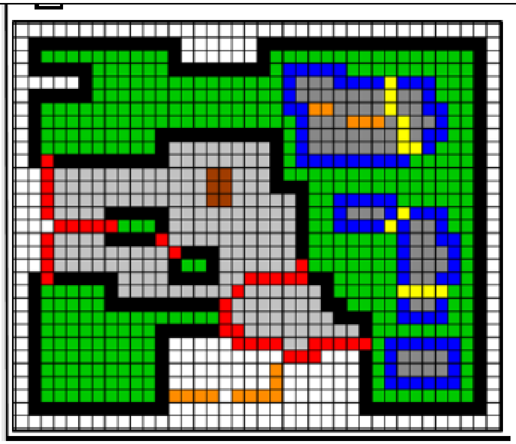
Figure 5 2. Categories of forest and Cropland areas assessed; a) FRAC-1 Forestlands, b) FRAC-2 Forestlands, c) FRAC-1 Croplands, d) FRAC-2 Croplands

5.2.3.2 Morphological spatial pattern analysis and shape characteristics of patches

To characterise the morphology and pattern of Forestland and Cropland patches, LM were initially computed in FRAGSTATS 4.2 software (McGarigal et al. 2012) (Table 5.1). To complement the LM assessment from FRAGSTATS, GUIDOS 3.0 (Graphical User Interface for the Detection of Objects and Shapes) Toolbox, (Soille and Vogt 2009, Vogt and Riitters 2017) and IMAGEJ-FIJI 1.53J (Schindelin et al. 2012) software were used for morphological analysis of patches. The GUIDOS and IMAGEJ software contains a wide variety of raster image processing routines. In pre-processing for GUIDOS and IMAGEJ, two-byte images were prepared by importing the images into ARCGIS and exporting them as 1-bit monochrome TIFFs. Monochrome thresholding was adjusted to distinguish between the foreground (white); Forestland and Cropland Patch layer and background; and the non-forest/cropland layer.

In GUIDOS, morphological analysis was done by fixing the MSPA parameter as follows: Foreground Connectivity- 8/4 (default setting); Edge Width- 5 (adjusted until 'core' classification features resembled closely; Transition-set to 'off'; Intext-set to 'on' (default setting). The foreground area of a binary image was analysed and classified into seven generic MSPA classes: Core, Islet, Perforation, Edge, Loop, Bridge, and Branches (Table 5.1) and further calculated the contortion of patches. Other shape descriptors such as Circularity, Roundness, Elongation, Convexity, Number of Holes, length and width were computed using IMAGE FIJI software through the Shape Filter and Measure ROI PA plugins (Table 5.1). To test for significance in the difference in sample means for shape descriptors between FRAC-1-Forest : FRAC-1-Cropland-and FRAC-2 Forest : FRAC-2 Cropland at 95% confidence level, the Levine's test for equality of variances and the Independent sample t-test were applied in SPSS software.

Table 5. 1. Description of indices applied in the study

				Description
A	**MORPHOLOGICAL SPATIAL PATTERN ANALYSIS (MSPA)**			
1.		🟩	**Core**	Pixels entirely surrounded by other foreground pixels
2		🟫	**Islet**	Foreground pixels too small to be recognised as cores
3		🟨	**Loop**	Connects one area of one core patch to itself
4		🟥	**Bridge**	Connects two areas of different core patches
5		🟦	**Perforation**	Inner boundary of the core patches that are located inside of another core patch (also known as Hole)
6		⬛	**Edge**	Outer boundary pixels of core patches, separating core patch from non-core patches
7		🟧	**Branch**	Pixels that do not belong to any other morphological class.
8		⬜		Background Area outside foreground
9		░		Border-Opening along Edge
10		▒		Core-Opening within perforations
11		▓		Foreground, Objects of interest
12	**Contortion**			Describes the degree of irregularity of a foreground object perimeter value corresponding to the number of times an object perimeter changes direction
				Source: (Soille P and P 2009, Vogt and Riitters 2017)
B	**SHAPE DESCRIPTORS**			
1.	Roundness			*Round* (roundness) equals 4*area/(π*major_axis^2), or the inverse of the aspect ratio.
2.	Convexity			The relative amount that an object differs from a convex object. An object takes the value of 1 for a convex object, and will be less than 1 if the object is not convex,
3.	Circularity			obtained as the ratio of the area of an object to the area of a circle with the same convex perimeter: The formula for circularity is 4pi(area/perimeter^2)
4.	Elongation			The ratio between the length and width of the object bounding box: given as a value between 0 and 1. If the ratio is equal to 1, the object is roughly square or circularly shaped.
5.	Width and length			The length is defined as the greatest distance between any two points on the perimeter (Feret's diameter), and the ROI width is largest separation between points measured perpendicular to the axis defining the length.
6.	Number of Holes			The number of holes inside an object or patch
7.	Directionality			Computes a histogram indicating the amount of structures oriented in a given direction

Source: (Schindelin et al. 2012)

5.3 Results

5.3.1 Morphological spatial pattern of patches

The MSPA from GUIDOS quantified the Cores, Islets, Perforations, Edge, Bridge, Branches, Loops and the Contortion index. FRAC-2 Forests recorded the highest number of core areas (22.39%) followed by FRAC-1 Forestlands with 13.93% (Figures 5.3 and 5.4). The difference in the number of core areas between Forest and Cropland FRAC classes was over 11%. Cropland FRAC areas had the highest number of Islets with 93.81% (FRAC-1) and 63.17% (FRAC-2). FRAC-1 Cropland areas recorded 42.41% while no Islets were recorded in FRAC-2 Forest areas. Perforations were recorded in FRAC-2 Forest areas only. Similary, the propotion of edges was higher in forested areas, being 17.3% (FRAC-1) and 36.46% (FRAC-2). Forest areas had more edges by 19% compared to Cropland FRAC areas. In terms of bridges, FRAC-2 forest areas had a high proportion of Bridges with 24.33% compared to FRAC-1 forest and FRAC-2 croplands with just above 6%.

In terms of Branches, FRAC-1 and FRAC-2 Forests and FRAC-2 Croplands had equal values of branches with 15%. However, FRAC-2 Cropland, had 15% higher number of Bridges campared to FRAC-1 Croplands. In terms of the Number of Holes, FRAC-2 Forests had the highest Numbers of Holes (276) followed by FRAC-1 Cropland with 10 holes. FRAC-1 Forest and FRAC-2 Croplands had the lowest average Number of Holes with 1 and 3 respectively (Figure 5). FRAC-2 Croplands had the highest proportion of Loops (6%) followed by FRAC-1 Forests with 5%. FRAC-2 Forests had 2% while FRAC-1 Cropland had less than 1% of Loops. FRAC-1 Cropland category had the lowest values of Edge, Loop, Bridges and Branches but had the highest number of Islets. FRAC-2 Croplands had the lowest quantity of Cores, Perforations with higher quantities of Loops and Branches. FRAC-2 Forests had the lowest number of Islets but had high quantities of Cores, Perforations, Bridges and Number of Holes.

5.3.2 Description of shape in FRAC-1 and 2 between Forestlands and Croplands

FRAC-1 and FRAC-2 Forest areas had lower average values of Elongation and Convexity index than FRAC-1 and FRAC-2 Croplands. However, Forest areas recorded higher Contortion index than Croplands implying more complex shapes in natural landscapes (Figure 5.5). For the Number of Holes, Contortion index and average width and length, within the same FRAC category; FRAC-1 and FRAC-2 Forest areas recorded higher values than FRAC-1 and FRAC-2 Croplands, respectively. However in opposite FRAC areas, FRAC-1 and FRAC-2 Forestlands had lower values of Number of Holes, Elongation, Convexity index and average width and length when compared to FRAC-2 and FRAC-1 Croplands respectively. FRAC-2 Forest areas had lower values of Roundness, Circularity and convexity index when compared to FRAC-1 and 2 Croplands. Similarly, FRAC-1 Forests had lower values of Roundness, Circularity and Convexity when compared to FRAC-1 Croplands. However, for FRAC-1 Forest areas, values for Roundness, Circularity and Contortion index were higher than for FRAC-2 Croplands except for Convexity which recorded lower values for the two categories.

The highest difference between FRAC-1 Forests and FRAC-1 Croplands was the Elongation index with 39% lower values than FRAC-1 Cropland areas (Figure 5.6). In terms of Directionality of patches, FRAC-1 and 2 Forests and FRAC1 Croplands were oriented between 0— -5 degree (Generally the East-West orientation). FRAC-2 Croplands were oriented in north-west / South-east orientation at -40 degrees (Figure 5.5 and 5.6). The difference in means of all shape descriptors (Circularity, Round, Length, Width, Elongation, Number of Holes, Convexity) were statically significant ($p<0.001$) between FRAC-1 Forests and FRAC-1 Croplands. However, for the FRAC-2-Forest and FRAC-2-Croplands, only the mean difference in circularity, length and width of patches were statistically significant.

5.3.3 Description of shape in FRAC-1 and 2 within Forestlands and Croplands

Within the Forest Class, FRAC-1 Forest had higher values for Circularity by 96%, Roundness by 15% and Convexity by 71%. However, FRAC-1 Forest areas recorded lower values in Elongation by 21%. The biggest difference was Circularity with 96.4 % difference. FRAC-1 Forest areas recorded lower width and length by 64-78% and also lower Number of Holes by 78.34%. In Croplands, FRAC-1 Cropland areas had higher difference for all shape descriptors ranging from 2% to 75% with the biggest difference on Circularity (75%). FRAC-1 Cropland had lower width and length by at least 76% but had a high Number Holes by 73.3%.

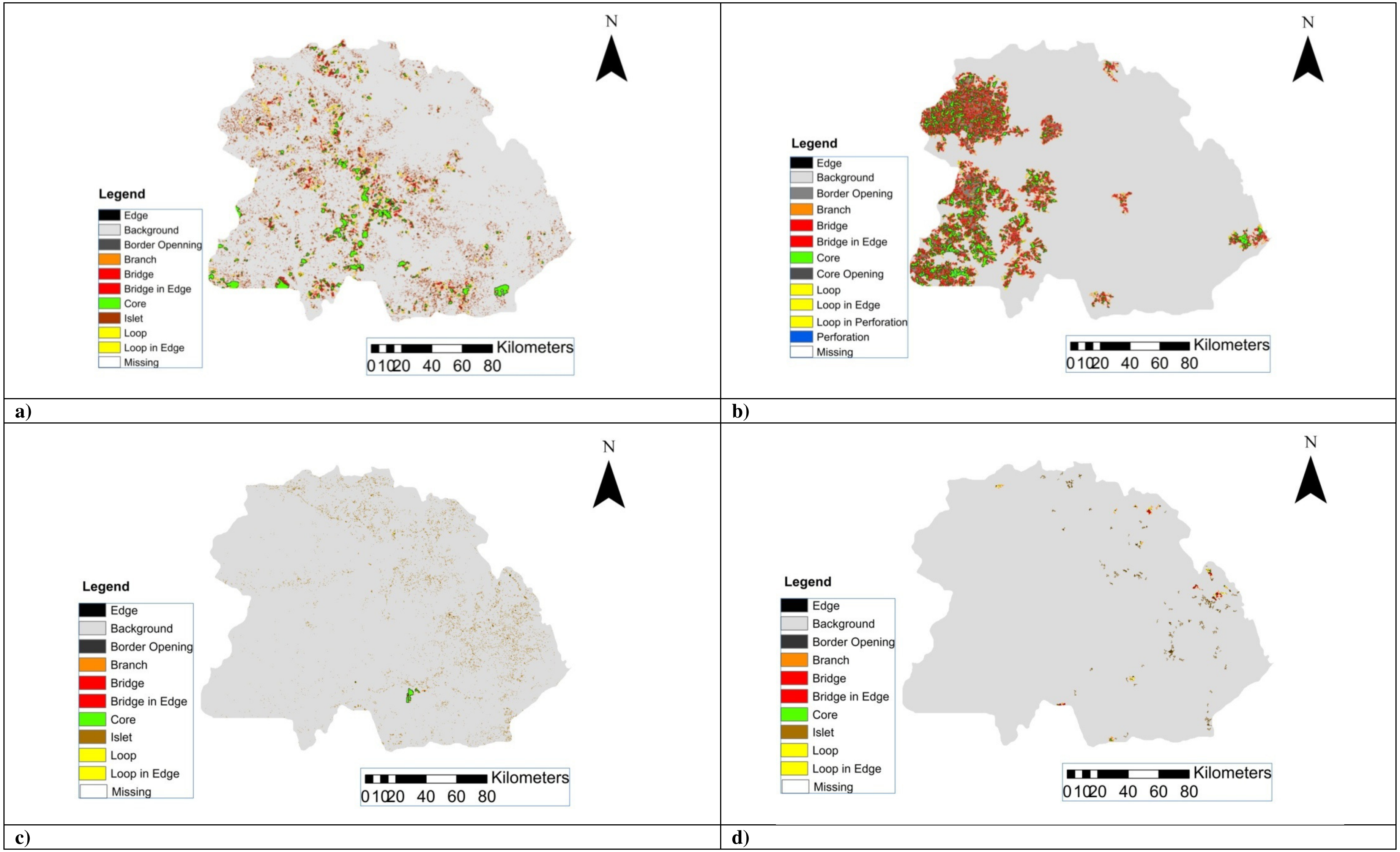


Figure 5 3. Distribution of MSPA parameters in persistent Forestlands and Croplands a)FRAC-1 Forestland, b) FRAC-2 Forestland, c) FRAC-1 Cropland, d) FRAC-2 Cropland

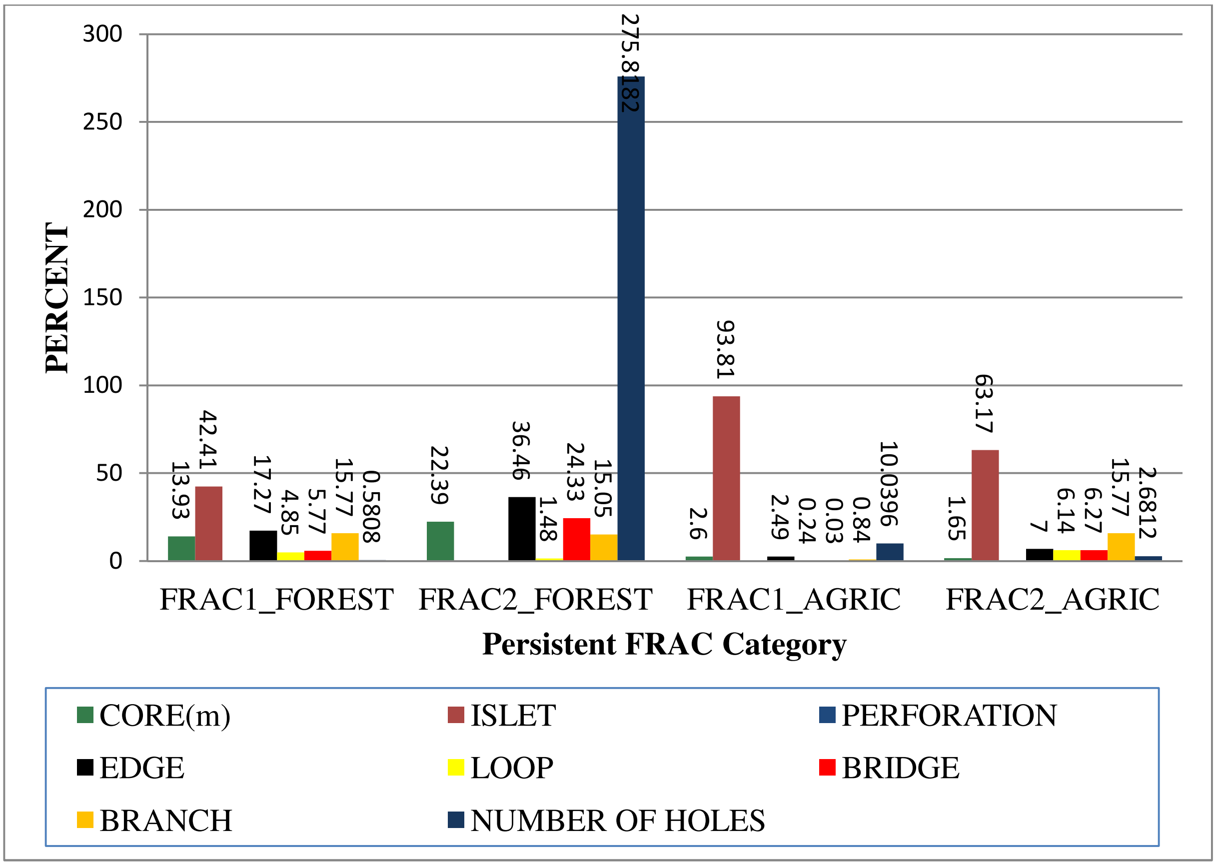


Figure 5 4. Intensity of MSPA parameters in persistent Forest and Cropland classes

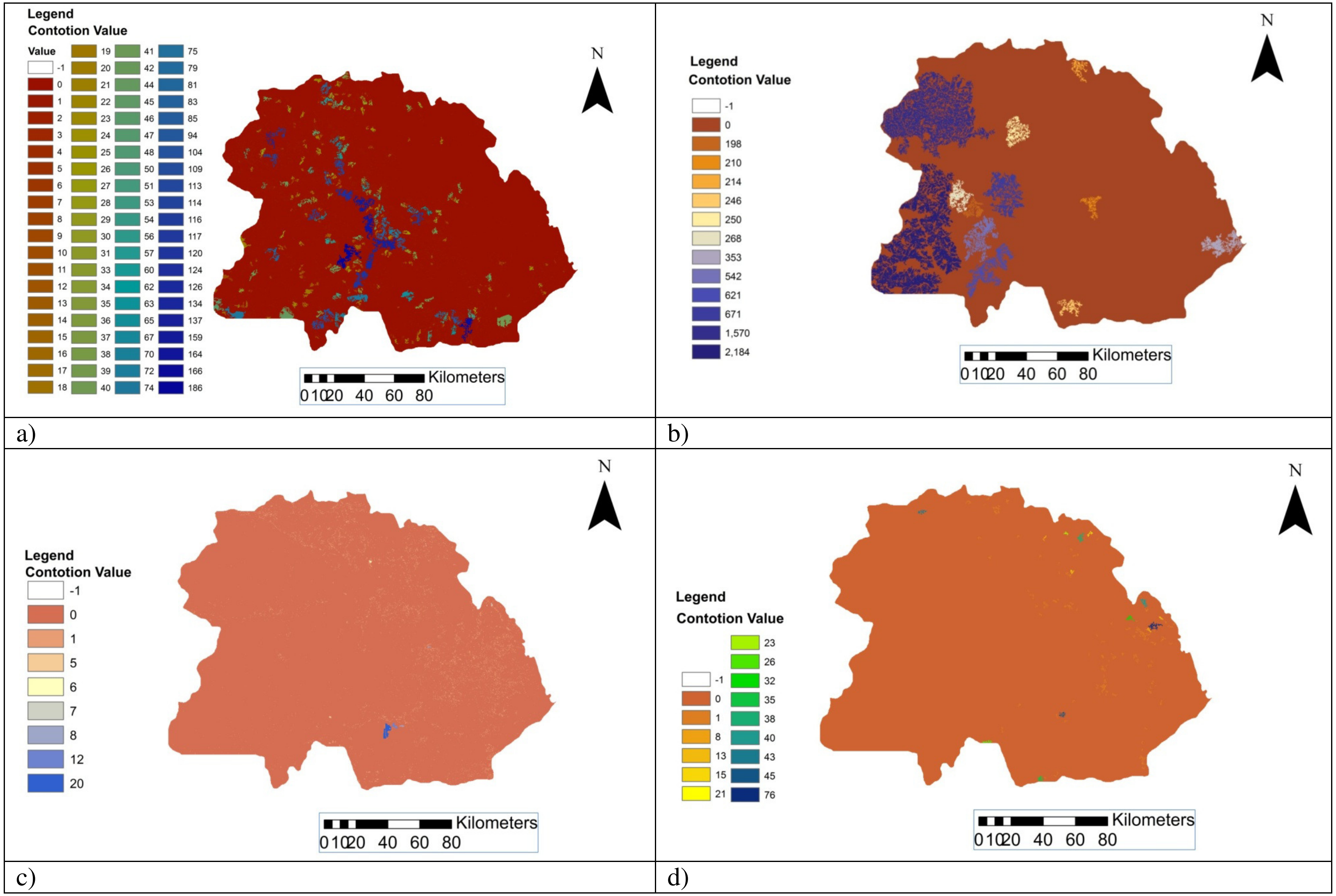
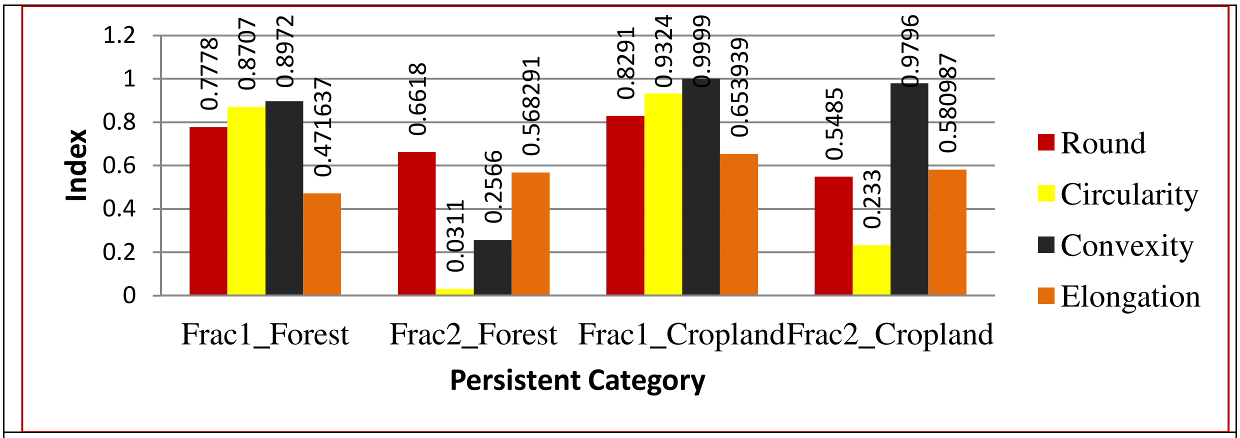
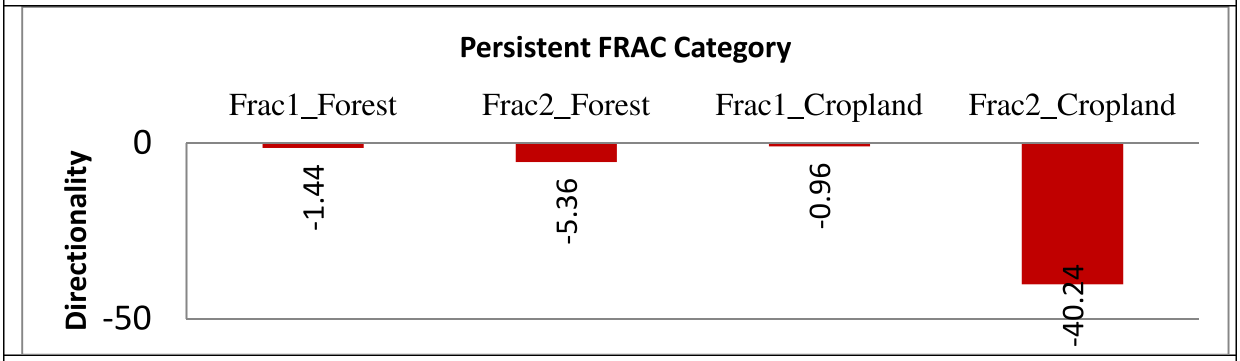


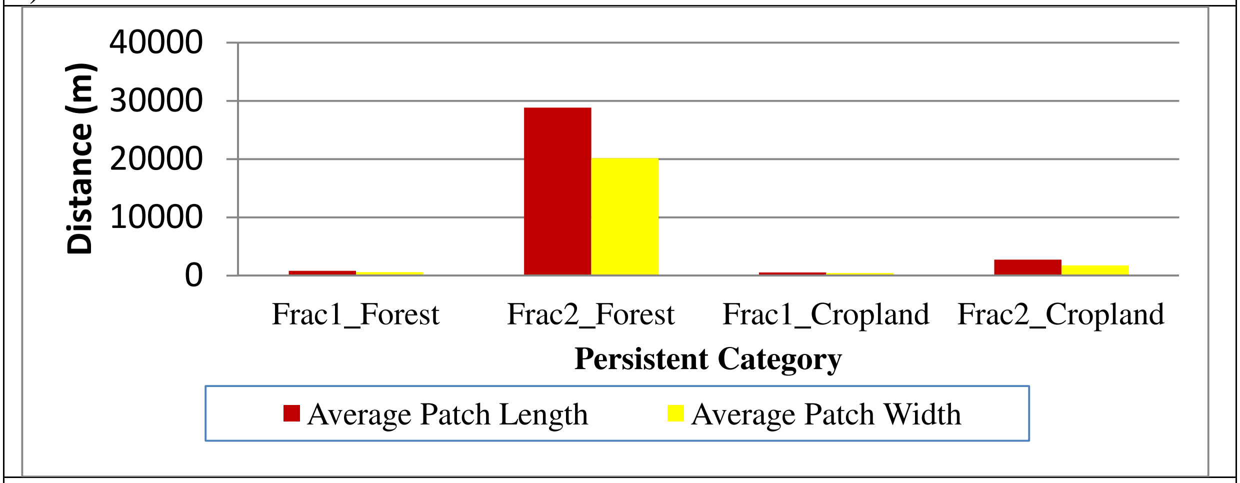
Figure 5 5. Distribution of contortion parameters in persistent Forestlands and Croplands a) FRAC-1 Forestland, b) FRAC-2 Forestland, c) FRAC-1 Cropland, d) FRAC-2 Cropland



a)



b)



C)

Figure 5 6. Intensity of shape descriptors in persistent FRAC categories a) Convexity, Roundness, Circularity Elongation, b) Directionality c) Average length and Width of patches [2]

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[2] **t-test for equality of means between Frac1 and 2 Forestlands and Croplands Shape descriptors**

Index	FRAC1 Forest	FRAC1 Cropland	FRAC2 Forest	FRAC2 Cropland
Circularity	**$t_{(13338.77)}$=-18.244, P<0.001**		**$t_{(74.459)}$=-21.898, P<0.001**	
Round	**$t_{(11498.852}$=-11.143, P<0.001**		$t_{(126)}$=2.129, p=0.035	
Length	**$t_{(10097.989)}$=21.213, P<0.001**		**$t_{(1.011)}$, 5.017, p<0.001**	
Width	**$t_{(9375.7.7)}$=21.005, P<0.001**		**$t_{(1.010)}$, 4.915, p<0.001**	
Elongation	**$t_{(1818.088)}$ =-15.668, P<0.001**		$t_{(147)}$=-127, P=0.9	
Number of Holes	**$t_{(504.774)}$=-5.369, P<0.001**		$t_{(10)}$=1.85, P=0.084	
Convexity	**$t_{(2347.691)}$=-35.880, p<0.001**		$t_{(147)}$=-41.441, p<0.001[2]	

5.4 Discussion

5.4.1 Morphological spatial pattern analysis

Significant differences were found between Forestlands and Croplands (Figure 5.3, 5.4, 5.5) in the MSPA and shape descriptor analysis. According to Pino and Marull (2012), functional connectivity in a landscape is ensured when existing habitat units are physically adjacent, and other connecting elements (Edges, Bridges, Loops and Branches) allow particular organisms / ecosystem elements to move between habitats that may be physically distant. Lack of landscape connectivity and subsequent isolation of habitat patches (influenced by the morphological spatial pattern) can interfere with ecological processes such as nutrient flow, pollination, seed dispersal, gene flow, wildlife migration and reproduction (Bodin and Saura 2010, Moilanen and Hanski 2001). In this study, the dominance of forest core areas would entail a source of a variety of ecological processes-and biodiversity protection in these areas. Core areas dominated the FRAC-2 Forest areas concentrated in the western regions of the study area (Figure 5.2 and 5.3). Forest Core areas were scarce in the eastern and southern portion because these are areas dominated by huge human settlements hence prone to anthropogenic activities (Malunga 2009). This is the reason why the eastern and southern portions of the province are dominated by Cropland Islets suggesting poor forest habitat connectivity in the area (Figure 5.3).

According to Ye et al. (2020), Islets are small patches, which are independent of each other and have low connectivity, are less likely to communicate with other patches in terms of material and energy. The high number of Cropland Islets is possible in this part because according to Shitima (2005) the province experienced an increase in agriculture activities and population between 1990 and 2010 due to massive job losses from the Structural Adjustment Programme (SAP) and privatisation implemented by the Zambian government in the 1990s.

The high unemployment rate at the time led to an increase in the number people involved in charcoal production and firewood collection, agriculture and timber logging activities in the Copperbelt region of Zambia (Handavu et al. 2019, Mzuza et al. 2019). LULCC is therefore a key driver of global change, and has important implications for environment policy issues particularly, in densely populated and fast developing continents (Jiao and Liu 2012, Ozesmi and Bauer 2002). Landscapes in populated areas are heavily influenced by human activities. According to CSO (2014), and ZSA/MOH/ICF (2019) the population of the Copperbelt province had the highest population of people living in urban (81%) compared to rural areas (19%). The rapid urbanization process, accompanied by the high‐intensive land development, constantly encroaches on new habitat patches (in rural and urban areas), making them increasingly fragmented and isolated, which directly influences the regional landscape pattern (Jiao and Liu 2012, Ye et al. 2020). This calls for timely monitoring of LULCC for early identification of the pattern of transformations.

The state of the habitat connectivity also depends on the quantity of Perforations, Edges, Loops, Branches and Bridges which connect Cores and Islets (Figure 5.3). In case of Forestlands, forest edges are vital because they serve as the transition zone between core areas and the peripheral non-green landscape area, which can reduce the impact brought by the external environment and human disturbance (Ye et al. 2020). This explanation favours the Forest class which had a higher proportion of Edges than cropland areas. In addition, Forest Bridges are the narrow and long areas connecting the patches of different core areas, which have the characteristics of ecological corridors and are mostly green belts, conducive to the migration of species and the connection of landscape within the territory (Ye et al. 2020). Again, the area of Forest connection Bridge for FRAC-2 Forest areas was higher with 24.33% compared to FRAC-1 Forest and FRAC-2 Croplands with just above 6%. A reduction in landscape connectivity (e.g. Core areas), would have the effect of blocking the migration of species and the spread of the material energy, and impairs the health of ecosystem integrity, leading to reduction in ecosystem services (Saura et al. 2011a).

5.4.2 Description of the shape of Cropland and Forest patches

The shape of land use patches is determined by both natural and anthropogenic forces resulting in specific spatial and morphological characteristics. For example, Jiao and Liu (2012) found that roads are elongated, and cultivated lands are more regular-shaped. On the other hand, natural features such as Rivers and Forests are less influenced by humans and hence preserve more natural boundaries. This explains why FRAC-1 and FRAC-2 Forest areas had lower values of Elongation and Convexity index than FRAC-1 and FRAC-2 Croplands. However, Forest areas recorded higher Contortion index than Croplands suggesting more complex shapes in natural landscapes (Figure 5.5, Appendix D1). For the Number of Holes, Contortion index and average width and length, within the same FRAC category; FRAC-1 and FRAC-2 Forest areas recorded higher values than FRAC-1 and FRAC-2 Croplands, respectively. According to Jiao and Liu (2012) Cultivated lands are often regularly shaped, while forest and grasslands have more complex boundaries hence the higher contortion index for forestlands. FRAC-2 Forest areas had lower values of Roundness, Circularity, and Convexity index when compared to FRAC-1 and 2 Croplands. Similarly, FRAC-1 forests had lower values of Roundness, Circularity, and Convexity when compared to FRAC-1 Croplands. Zdilla et al. (2016) citing Jiao and Liu (2012) explained that Roundness and Elongation indicate how well the polygon can be described by a circle and a rectangle, respectively (Figure 5.7).

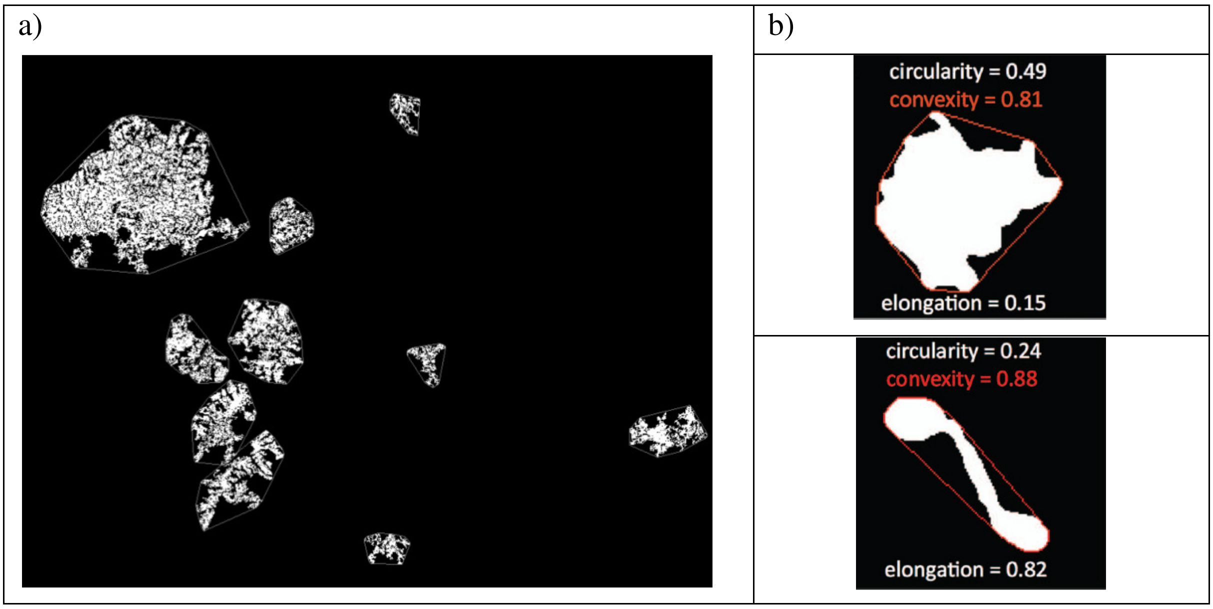

Figure 5. 7. A Snapshot of FRAC2 Forest patches outlined in Imagej for computation of shape descriptors, b) An illustration of shape descriptor index adapted from (Bogan et al. 2010)

The results of the study also agree with Jiao and Liu (2012) who found that human features such as cultivated lands and ponds had the highest Roundness index (>0.5). In relation to directionality, it was observed that the FRAC-1 category for Forestland and Cropland patches were oriented in east-west direction (0 -1^{0}) while FRAC-2 areas ranged from -5^{0} (East-west) to -40^{0} (North-West/ South-East). However, due to limited information in the field of study, it was difficult to find existing literature on directionality of landscapes. Therefore, identifying the morphology would provide insights into ways in which isolated and broken ecological patches can be restored so that there is continuous exchanges of genetic material and species between patches, and this would effectively improve ecosystem services provision (Richter and Behnisch 2019). The core of ecological corridors is influenced by the condition of Cores, Islets, Loops bridges and other MSPA parameters that further manifest into shape of patches (Saura et al. 2011b). Alterations in the MSPA and shape characteristics would further affect the provision of ecosystem services such as water, purifying pollutants, and reducing the heat island effect (Zang et al. 2002). In terms of Agricultural lands, the MSPA and shape characteristics would also influence nutrient flows that could lead to reduced agricultural production.

5.5 Conclusion

The MSPA and shape descriptors can aid in the identification and description of structural/geometric variation between natural and artificial landscapes and give insights into approaches/ framework for mimicking / restoration. The study concluded that the shape characteristics of Croplands were influenced by human activities and this affected the area of Cores, Islets, Edges and shape descriptor indices. The spatial and temporal morphology of forest pattern within the Copperbelt province differed significantly with Croplands. This study therefore sets a promising direction for future work in which each of the shape and pattern identified would be explored in more detail and applied in spatial planning. The study recommends that attention should be paid to the pattern and morphology of landscapes / patches in restoration programmes.

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CHAPTER 6: Synthesis of the impact of landscape metrics on soil parameters, soil loss, erosion severity and patch morphology

6.1 Background

This chapter provides a synthesis of the research on LULCC in the Copperbelt Province of Zambia and the resulting fragmentation, impacts on soil chemical parameters, soil loss, erosion severity and finally modelling the morphological characteristics of Forestland and Cropland patches. The methods applied in each of the four specific objectives to accomplish the conceptual framework (Figure 1.1) have been evaluated, and conclusions and recommendations on management approaches, policy implications and suggestions for future studies have also been provided.

6.2 Introduction

The Miombo woodlands provide vital ecosystem services. This ecosystem hosts about 43% of the world's tropical dry forests (Kalaba et al. 2012, Mittermeier et al. 2003) and contain over 8,500 species of higher plants of which 54% are endemic (Chirwa et al. 2008, Mittermeier et al. 2003). The ecosystem maintains soil fertility, carbon stocks, modifies the hydrological cycle, controls soil erosion and therefore regulates climate. The Miombo ecosystem supports livelihoods of more than 100 million people within and outside the region (Chidumayo and Gumbo 2010, Jew et al. 2016, Ryan et al. 2016). Maintaining the structure and pattern would entail a guided and sustained provision of ecosystem services.

Locally, it is widely appreciated that Zambia is one of the most forested countries in Africa, with about 50 million out of the 75 million hectares (ha) total land area under some form of forest cover (GRZ 2014, Kalinda et al. 2013). However, the country also has one of the highest rates of deforestation and degradation in the world, estimated at 250,000-300,000 ha of forest loss per annum (Handavu et al. 2019, Vinya et al. 2011) leading to fragmentation. The exact forest coverage and LULCC is uncertain because there has been no recent comprehensive forest inventory since the last one was conducted from 1952 to 1967. The change in the condition and extent of forest cover affected by human activities and the level of fragmentation is also not known. While forest cover continues to decline (Gondwe et al. 2020, Munthali et al. 2019), very little investment has been made in sustainable woodland management in Zambia. This makes it difficult to manage the natural resources. The situation is worsened by a rising demand for land used for settlements, and agricultural activities and the increasing consumption of firewood, charcoal and timber as the population continues to grow (ZSA/MOH/ICF 2019).

High rates of forest degradation and fragmentation have therefore negatively affected the climate, soil properties, fauna and flora. This disturbance has led to the occurrence of extreme weather events such as rising temperature, floods, and droughts which further affects soil properties, agricultural productivity and subsequently impacts on food security. Soil erosion has been reported to impact on hydropower plants such as the Kariba Power station, irrigation systems and aquatic ecosystems due to sedimentation in river systems. Solutions based on the restoration of forest landscapes through the manipulation / management of the geometric pattern would provide a cost effective and environmentally friendly approach to this problem. However, there is lack of information on morphological indicators, limited application of landscape metrics (LM) and lack of spatial planning in forest management.

The link between LU/LC, LULCC, intensity of fragmentation and soil parameters is important. This is because LU/LC activities lead to LULCC which influences the geometry

(FRAC) of the landscape that cause land exposure and potential degradation in the forms of nutrient and soil loss and erosion severity. Yet the shapes that form can be applied to mitigate the impacts of LULCC and fragmentation on provision of ecosystem services. Fragmentation describes landscape-level process in which a large intact parcel of land is progressively divided into smaller, geometrically altered and isolated patches (Carranza et al. 2014, Fahrig 2003, Luque and Iverson 2016).

6.3 Reflecting on the conceptual framework

The hypothesis of this study was that the geometric pattern (FRAC) of land use that evolves out of Forestlands, over time (Chapter 2) has influence on the level of soil fertility parameters, soil loss and erosion severity (Chapters 3 and 4) in different soil-textural classes. This is because LU/LC activities leads to LULCC which in turn alter the geometry of the landscape and this causes land exposure and potential degradation to the ecosystem. In order to determine the LM and the geometric pattern, land cover classification from 1984 to 2016, and predicted to 2050 was carried out (Chapter 2). LU/LC maps from Chapter 2 were then used as input in subsequent Chapters 3-5 using the Persistent Forest and Cropland layers accumulated from 1984 to 2019. The use of the persistent layers ensured that the only factor causing the variation in soil parameters and erosion severity was the difference in the geometric pattern (FRAC-1 and FRAC-2) (Chapter 3). Through the morphological spatial pattern analysis (MSPA) and LM analysis (Chapter 3, 4 and 5), the study established that FRAC-1 areas ($1 \leq 1.25$ Frac index) were characterized by simple shapes of patches which formed a more continuous and closed canopy. FRAC-2 areas ($> 1.25 \leq 1.5$ Frac index) were composed of more open, numerous patches caused by the high number of holes (Chapter 5).

The study clearly demonstrates that the extent of soil loss and erosion severity differed according to variations in geometric pattern of Forestlands and Croplands (Chapter 4) and this had implications on the levels of soil chemical parameters (Chapter 3). Finally, the LULCC observed in Chapter 2 led to modelling the differences in the morphological pattern of patches which would be useful as indicators in spatial planning in Chapter 5 where the MSPA and shape descriptors were quantified and identified. The identification of morphological / shape characteristics presents actual measurement units for implementing patch geometry in environmental programme and this is a new approach in spatial planning.

6.4 Assessment of the materials and methods used in the study

In this study, a mixture of methods including Remote Sensing and GIS using Landsat images to explore LULCC in the Copperbelt province were used (Chapter 2, 3, 4 and 5). Landsat images from the United States Geological Survey (USGS) were preferred because of the long temporal dataset (since 1972) global coverage; and 30m resolution which meant sufficient spatial cover for the study area. The maximum likelihood classifier (MLC) in a supervised classification was used. The accuracy assessment used the error-adjusted matrices (Jeon et al. 2014, Olofsson et al. 2014) and found negligible classification errors giving robust results (Appendices A1, A2, A3 and B2). However, findings of this study could have been affected by lack of consistent cloud free multitemporal Landsat data from the same season for some years and scenes under review.

Furthermore, misclassification arising from similarity in classes such as Dambos and Grasslands also caused difficulties in visual interpretation and the classification process. Nevertheless, the LU/LC classification accuracy results were above 87%. According to Kamusoko and Aniya (2007), LU/LC accuracires of above 85% are considered reliable. In modelling to 2050, the availability and choice of socio-economic and biophysical data used as factors and constraints was challenging. This may have created some uncertainty in predicting LULCC to 2050 and could have further affected the precision of the model. Similar challenges were pointed out by Aburas et al. (2016) and Amthor et al. (2001) who reported that these limitations also affected testing and validation of models. Despite the limitation, modelling accuracy results in this study indicated strong association between the predicted map and the observed map because according to Zheng et al. (2015), kappa values >0.8 show strong association or agreement**.**

The extent of LM and variations in soil parameters (Chapter 3), magnitude of soil loss and variations in erosion severity (Chapter 4) initially used remote sensing data from Chapter 2. Soil chemical and physical analysis results were obtained from standard laboratory tests after which GIS and RS was applied to produce maps through interpolation. Geospatial techniques and statistical packages were applied to carry out further analysis. For the MSPA and shape descriptor modelling (Chapter 5), binary maps of the Forestland and Cropland classes from LU/LC maps were used as input in GUIDOS and IMAGEJ software. The MSPA was applied to explore the morphological and shape characteristics of patches. The inadequate application of morphometrics in forestry meant that it was difficult to find reference information to support some of the findings in this chapter.

6.5 Linking major findings and their implications in management strategies.

This study revealed that between 1984 to 2016 and 2050, natural landscapes such as Forestlands and Dambos had shown a declining trend while human induced land uses (Settlements, Barelands, Plantations, Grasslands and Croplands) increased in area (Malunga et al. 2021). Conversion to Cropland accounted for more than 54 % of the total area of Woodlands and Dambos lost. This indicates an increasing demand for agricultural land to meet the needs of the growing population in the province. These results further show that, Forestlands and Dambos are used as safety nets for livelihoods especially in the dry season due to their fertile and wetter conditions that are ideal for agricultural production. If used unsustainably, forest and Dambo ecosystems are at risk of degradation further worsening the impact of climate change.

Unfortunately, there are currently no significant efforts put in place to address the decline in forestlands and Dambos, and this will have a negative impact on the provision of ecosystem services. This is because the degradation of Dambos, water bodies and Forestlands affect the hydrological system of an area by altering the rainfall, evaporation and runoff balance (Nyirongo 2009), increases stream flow, evapotranspiration and erosion and reduces infiltration and flood control ability (Mumeka 1986, Nyirongo 2009) (Chapter 4). Therefore, disturbances induced by LULCC will have wider impact on water systems such as the Kafue river basin and would subsequently affect countries like Mozambique, Angola, Namibia, Botswana, Zimbabwe and Malawi.

LULCC (Chapter 2) affected soil properties, erosion severity and the morphology of patches. The impact of LULCC was evident in forestlands were the CA decreased, but the same parameter increased in the Cropland class between 1984 and 2019. Conversely, the NP of forestlands increased while a decline was recorded in croplands. These results show that forest areas were increasingly fragmented compared to croplands resulting in negative impacts on soil loss, erosion severity and nutrients (Chapter 3, 4). Soil loss was particularly high with MSL rising from 3 $t.ha^{-1}yr^{-1}$ in 1984 to 6 $t.ha^{-1}yr^{-1}$ in 2019 and TLS increasing from 9.4Mt (1984) to 20.6 $Mt.ha^{-1}yr^{-1}$ (2019). Cultivated areas had 95% higher rates of soil loss compared to forest areas because tillage associated with cropping, loosens the soil making it vulnerable to erosive forces.

Similarly, significant variations in the concentration of soil chemical parameters, soil loss and erosion severity were found between persistent FRAC categories in different soil textural classes (Chapter 3 and 4). For instance, higher concentrations of N, NH_4-N, NO_3-N, C and K would be maintained in loamy soils of areas with simple geometric shapes (FRAC-1). However, higher levels of P and pH, would be maintained in sand soils of FRAC-1 areas. This means that personnel such as Agricultural Extension officers should consider the FRAC of the intended LU/LC and soil textural class when making land use decisions as this has implications on the future of soil nutrients, loss and erosion severity. The study had also shown that the mean soil loss (MSL) in FRAC-1 metric category was higher by 10.2% and 18% in Croplands and Forestlands, respectively, than in FRAC-2 areas of loamy soils. Conversely, the MSL was higher in the FRAC-2 metric by 10.13% and 9.6% in Croplands and Forestland respectively, than in FRAC-1 areas of sandy soils. Therefore, continued LULCC would entail alterations to the persistent Forest areas which could result in changes to the geometry of the landscape and subsequently variations in the concentration of nutrients, soil loss and erosion severity of the area. If the situation is not addressed, significant amounts of topsoil would be lost and this will lead to a decline in agricultural production and compromise the already unstable food security situation (Bastida et al. 2018) in these acidic and nutrient poor soils of the Miombo ecosystem (Gumbo et al. 2018).

In modelling the MSPA and shape characteristics, the implication of these results is that landscape connectivity is reduced by a decline in Core areas in the forest class, which blocks the migration of species, affects ecosystem integrity and nutrient flows leading to reduction in the provision of ecosystem services (Saura et al. 2011). On the other hand, the presence of more Islets in cropland areas entails more fragmentation in a land use which is already 95% more susceptable to erosion. The reduction in the area of the Low Erosion Severity class between 1984 and 2019 is also worrying. It would be desirable to have a bigger area of the Low erosion severity compared to the medium and high severity category in order to minimise soil and nutrient loss but this is not the case. By 2019, the total area covered by the Low erosion severity class shrunk while the area for the high and moderate erosion severity classes increased (Chapter 4).

It is therefore critical to consider soil texture, FRAC and morphological factors before deciding on land use activities. Specific geometry and morphometric characteristics (Chapter 5) would be applied in restoration projects as a new approach in spatial planning. This calls for timely monitoring of LULCC (Chapter 2) for identification of the patterns of transformations (Chapter 3, 5). The need to conserve soils using vegetation pattern is especially important at the time when mitigation and adaptation measures against climate change have taken centre stage (Li et al. 2013, Willim et al. 2020). The rapid recovery of woodlands and Dambos in abandoned areas observed in the study and by Geldenhuys (2010), Gonçalves et al. (2017), Syampungani et al. (2017) provides the motivation to manage deforested areas through regeneration. What would be critical is the management / manipulation of the geometric pattern of the regenerating stands. Regeneration / reforestation programmes in degraded areas should therefore be implemented with reference to previous / desired FRAC geometry and morphology of the patch / landscape. For instance, through morphometric parameters established in this study (Chapter 5), FRAC-1 forest areas would be restored by ensuring an average patch length and width of 800 m x 588 m respectively; with a maximum contortion index of 188 (Appendix D). In the case of FRAC-2 Forest areas, the mean length and width is about 28,818 m x 20,169 m with a contortion index of over 2,000 corners. While the average dimensions for FRAC-2 forest patches appear to be longer / larger, they are highly perforated as indicated by the Number of holes, which ranged from 42 to 1,733. This combination of shape / morphometric parameters confirm that objects with a bigger Frac index (>1.25, towards 2) are characterised by complex shapes with irregular / complex boundaries, high contortion index and more open spaces within the patch (Number of holes) (Appendix D1).

The use of Dambos and forestlands for agricultural activities also indicates a potential that should be optimised. Dambos and woodlands should be zoned based on FRAC and soil textural classes using GIS and RS in order to minimise impacts by implementing the coupe system. In the coupe system, a portion of the forest or Dambo would be prescribed for anthropogenic activities for specified period of time followed by a fallow period to allow for recovery in a specific / prescribed geometric pattern (FRAC 1 or FRAC 2). To successfully carryout such programmes, capacity building in the human resource and the geospatial infrastructure in relevant institutions is key.

The overall conclusion of the study was that the geometric pattern of Forestlands had significant impact on soil quality, loss and erosion severity. This means that soil quality, loss and erosion severity can be managed by manipulating the geometric and morphological characteristics of patches / landscapes which presents a new approach to ecosystem management. Years of uncoordinated and uncontrolled land use activities will reduce the area of persistent forests and if the situation is not addressed, significant amounts of topsoil / nutrients, vegetation would be lost. The loss of nutrients will lead to a decline in agricultural production which will compromise the already unstable food security situation in the area. Therefore, there is urgent need to incorporate FRAC analysis in land use planning.

6.6 Policy direction

Sustainable development requires a balance between the social, economic, physical and environmental systems. Therefore, mitigating the impacts of LULCC and the resulting geometric / morphological changes on soil properties, loss and erosion severity requires an integrated management approach that relies on up to date geospatial data. Currently, monitoring / management of forest resources is not effective because the Forest Department (FD) and other responsible institutions remain under-funded, and lack tools and equipment. The sector is also characterised by inadequate investment in science and technology which is vital to finding solutions. Therefore, policies should encourage research and development (R and D) by attracting more funding to the sector. For instance, practical steps should be taken towards the development, improvement and implementation of climate smart and safe agricultural techniques such as the use of quality planting stock adapted to the area, sustainable biodiversity management including Agroforestry, integrated pest management, water, soil and land management, sustainable mechanization (using renewable energy with reduced impact on environment). Other practices to consider would include the use of improved manure and nutrient recycling techniques, conservation agriculture using minimum tillage, and energy conservation systems such as biogas, solar, and wind.

High levels of poverty, increase in population and high energy demand have worsened the situation especially that there is no collaboration among institutions to enable integrated management. Such collaboration would link several ministries / departments and agencies responsible for managing agriculture, wildlife, forests and other natural resources. Therefore, efforts should be made towards establishing a platform that facilitates a multi-sectoral spatial decision support system (Keenan and Jankowski 2019). This would ensure that planning is done with reference to existing land use activities in collaboration with other institutions.

This would reduce conflicting allocation / implementation of activities in undesignated areas (such as high erosion severity areas). Land use planning policies should incorporate the concept of geometric pattern (FRAC) and morphometrics, as factors of evaluation in land use planning. For instance, FRAC and soil textural class ranges should be considered when making LU/LC decisions. Such spatial data would be critical in accurate mimicking / restoration of landscapes because significant variations in soil nutrients and erosion severity have been attributed to the geometric pattern.

Policies should also aim at strengthening the capacity of the geospatial infrastructure and personnel through investment in the sector. Future polices and laws should aim at strengthening the financial and administrative autonomy of institutions to enable them return a portion of the money they generate for reinvestment and implementation of the management plans. Policy changes should also ensure that the utilisation of carbon tax and other related revenues are realigned so that the resources are used for carbon sequestration / natural resources management activities.

6.7 Recommendations

It is recommended that interventions to curb the increase in LULCC, landscape fragmentation and its impact on soil parameters, loss, erosion severity, and on the morphology and shape characteristics of patches should be put in place through the following:

1. Fragmentation analysis should form a key part of the land use planning process. Land use planners, environmental / natural resources managers (including FD and ZAFFICO personnel, famers, Agricultural extension officers) should be trained in fragmentation analysis. This will ensure effective incorporation of FRAC in

designing, restoration, managing or harvesting of specific croplands, plantation or natural stands.

2. Base maps of FRACS, soil nutrients, textural classes and erosion severity should be used as tools / indicators in planning and decision making on land use issues.
3. Land zoning of woodlands / Dambos should be done according to the desired FRAC and in reference to soil texture and erosion severity class of the land unit being zoned;
4. Safe and climate smart agricultural practices should be implemented to curb impacts of LULCC and climate change;
5. Effective enforcement and sensitisation of communities on land and water use policies and laws should be carried out regularly aimed at increasing compliance;
6. The capacity of institutions responsible for natural resources / environmental management should be enhanced so that human, material and financial resources are available for effective management. An enabling environment for private sector and civil society participation should be promoted.
7. There should be more investment in natural resources management institutions / sector through the channeling of the existing revenues raised from environmental or biodiversity fiscal measures and taxes (such as carbon tax) to natural resources and environmental management programmes.

6.8 Consideration for future studies

More research should be carried out on developing and refining mechanisms for prescribing and implementing specific forest/vegetation and cropland geometric patterns for application in restoration / defragmentation programmes. Future research should look at the identification and development of factors beyond forest/vegetation and cropland geometry that could influence natural resources management. Other studies should focus on identifying the requirements for the establishment of a multi-sectoral spatial decision support platform that would bring together key players in natural resources management.

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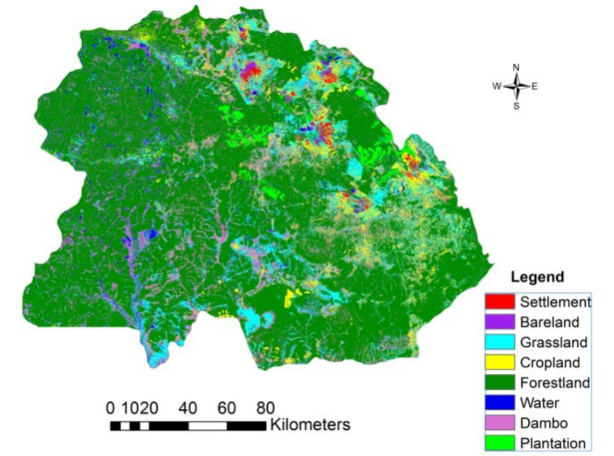
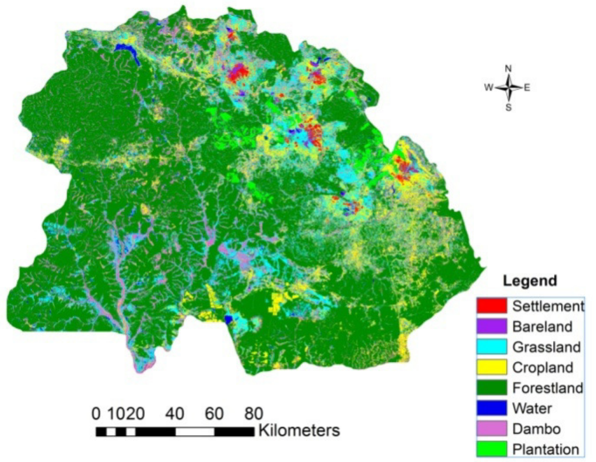
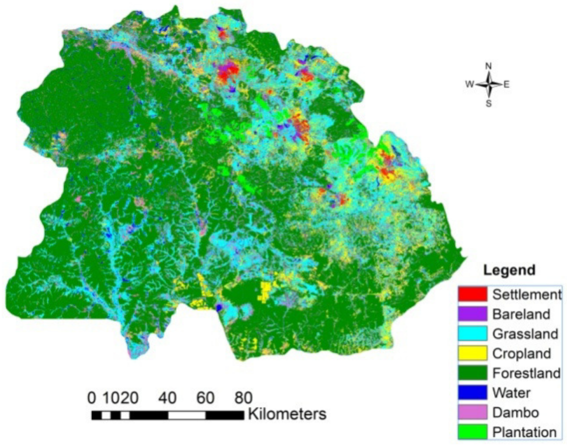
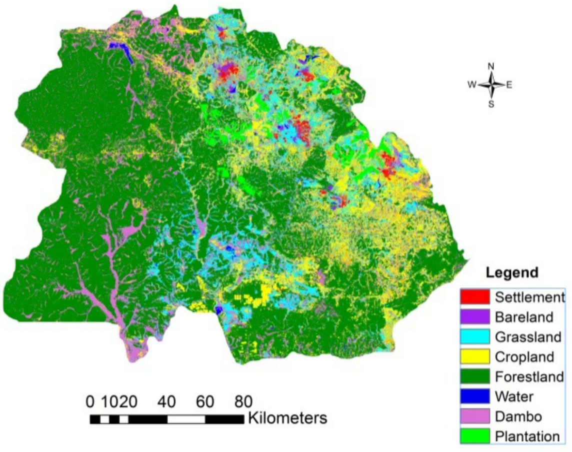
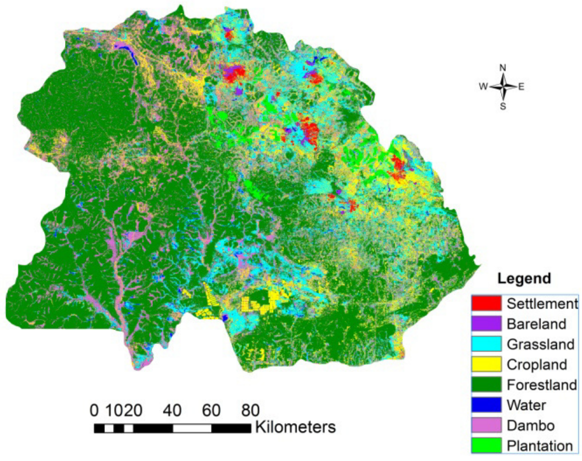
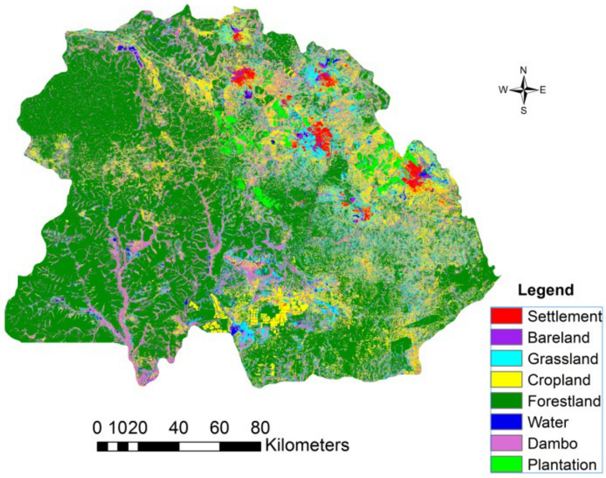
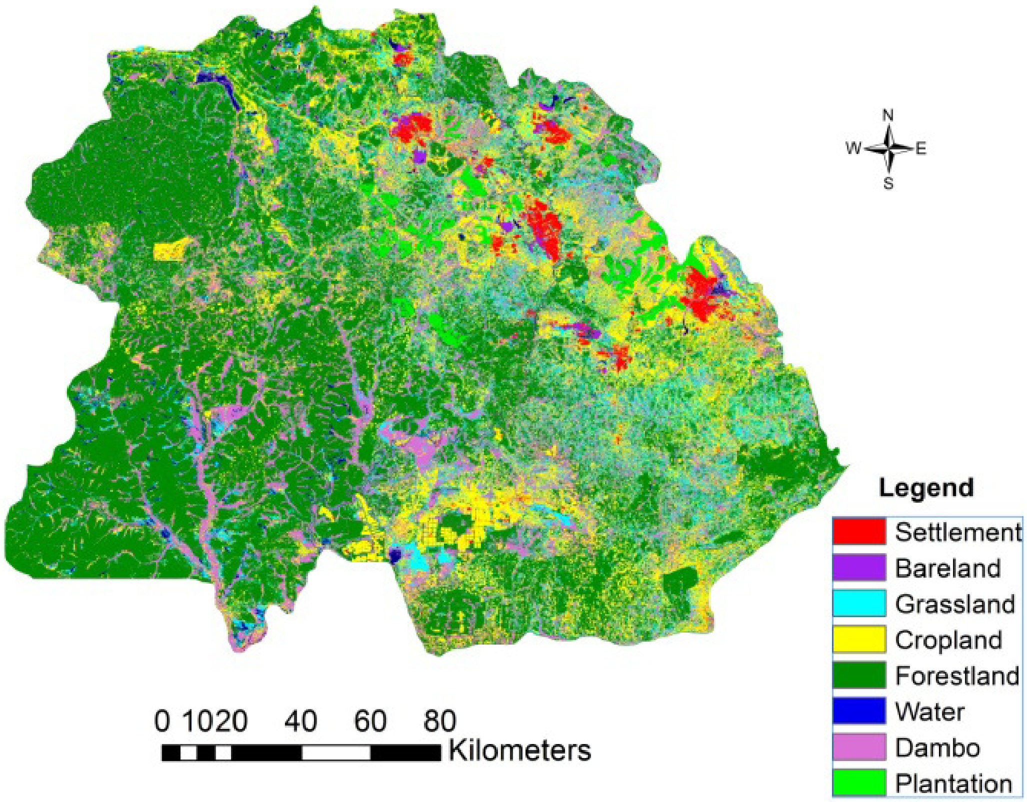
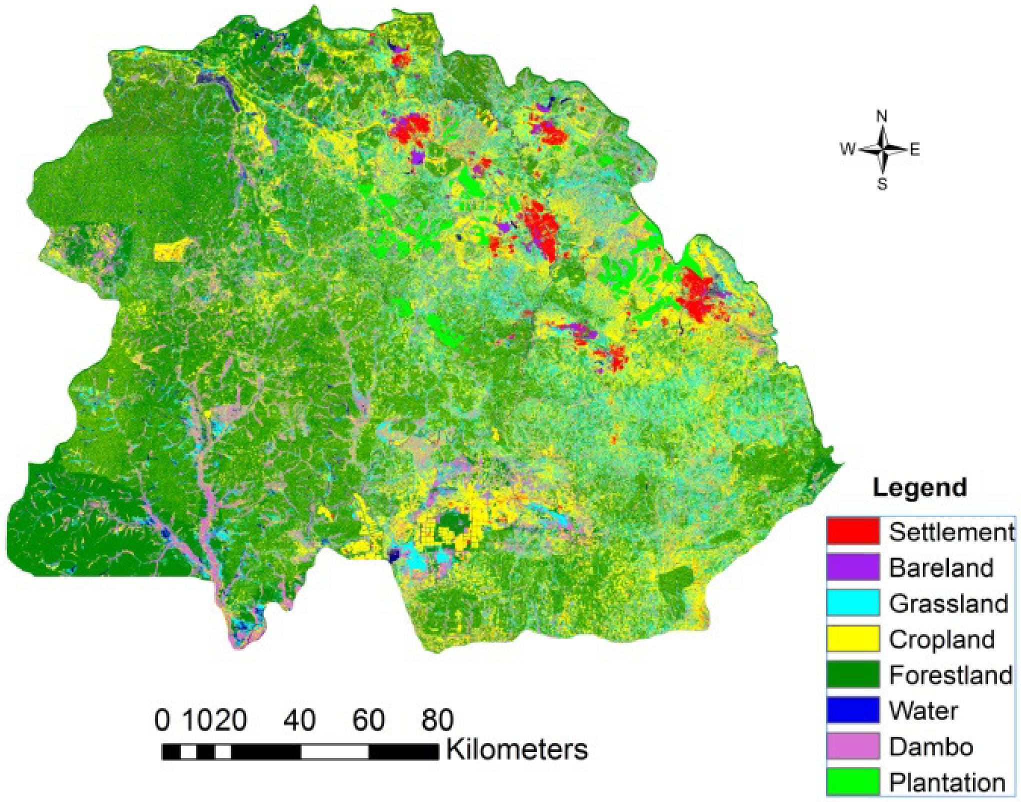
APPENDICES

Appendix A 1: Land use land cover maps from 1984, 2016, 2050

	
1984-LULC, Copperbelt province	1989- LULC, Copperbelt province
	
1994- LULC, Copperbelt province	1999- LULC, Copperbelt province
	
2004- LULC, Copperbelt province	2009- LULC, Copperbelt province



2016- LULC, Copperbelt province



Predicted 2050-LULC, Copperbelt province

Appendix A 2: Summary of training, validation data and overall accuracy for the various years between 1984 and 2019

	Training number of pixels							**Validation number of pixels**								
Cover classes	1984	1989	1994	1999	2004	2009	2016	2019	1984	1989	1994	1999	2004	2009	2016	2019
Dambo	936	1,125	1,114	2,090	609	461	1,125	1868	301	260	211	286	281	231	591	245
Forestland	133,396	49,009	30,285	26,742	26,764	20,705	29,671	7714	5,916	6,135	5,759	5,586	4,466	3,811	2,350	249
Settlements	99	637	270	92	527	1,150	833	1485	489	1,053	399	498	493	599	821	585
Bareland	643	659	143	145	173	34	583	623	1,095	348	921	851	785	710	486	367
Grassland	421	3116	305	403	957	455	638	286	448	446	279	294	284	223	612	252
Cropland	8,768	9,547	7,646	12,352	12,318	20,291	27,041	5691	267	303	432	380	342	294	363	260
Water	421	600	335	840	394	1,083	938	1784	445	418	398	446	443	412	268	275
Plantation	127	113	100	118	75	97	119	30	1,742	2,149	1,501	1,053	749	675	644	2507
Area Adjusted (Actual) Overall Accuracy									97.63	98.71	98.48	99.51	97.35	98.90	99.95	96.90

Confusion matrix for 1984-LULC

1984		**REFERENCE (pixels)**										
Class	**Cropland (nij)**	**Grassland**	**Forestland**	**Dambo**	**Water**	**Settlement**	**Bareland**	**Plantation**	**total (ni)**	**wi (Ami/Atot)**	**map area (ha)**	**user acc**
Cropland (nij)	265	0	2	0	0	0	0	0	267	**0.064**	201,837.51	99.3
Grassland	0	422	24	2	0	0	0	0	448	**0.111**	347,898.15	94.2
Forestland	0	0	5911	0	0	0	0	5	5916	**0.649**	2,035,694.25	99.9
Dambo	0	0	35	262	0	0	0	4	301	**0.125**	392,280.84	87.0
Water	0	0	0	0	445	0	0	0	445	**0.020**	64,147.50	100.0
Settlement	0	0	0	0	0	487	2	0	489	**0.012**	37,624.95	99.6
Bareland	0	0	0	0	0	0	1095	0	1095	**0.004**	12,649.86	100.0
Plantation	0	0	4	0	0	0	0	1738	1742	**0.015**	46,471.77	99.8
Total	**265**	**422**	**5976**	**264**	**445**	**487**	**1097**	**1747**	**10703**		3,138,604.83	
Producer acc	100	100	98.91	99.24	100	100	99.82	99.49			overall accuracy	99.27
Class	**Cropland (nij)**	Grassland	Forestland	Dambo	Water	Settlement	Bareland	Plantation	row total	user acc		
Cropland (nij)	0.06	0.00	0.00	0.00	0.00	0.00	0.00	0.00	**0.06**	99.25	0.99	0.0000
Grassland	0.00	0.10	0.01	0.00	0.00	0.00	0.00	0.00	**0.11**	94.20	0.94	0.0000
Forestland	0.00	0.00	0.65	0.00	0.00	0.00	0.00	0.00	**0.65**	99.92	1.00	0.0000
Dambo	0.00	0.00	0.01	0.11	0.00	0.00	0.00	0.00	**0.12**	87.04	0.87	0.0000
Water	0.00	0.00	0.00	0.00	0.02	0.00	0.00	0.00	**0.02**	100.00	1.00	0.0000
Settlement	0.00	0.00	0.00	0.00	0.00	0.01	0.00	0.00	**0.01**	99.59	1.00	0.0000
Bareland	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	**0.00**	100.00	1.00	0.0000
Plantation	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	**0.01**	99.77	1.00	0.0000
col Total	**0.06**	**0.10**	**0.67**	**0.11**	**0.02**	**0.01**	**0.00**	**0.02**	**1.00**			0.0000
Aj (unbiased estimator of area)	200,325.62	327,707.63	2,099,843.80	343,006.87	64,147.50	37,471.06	12,803.75	53,298.59	**3,138,604.83**		actual overall accuracy	
Producer acc	100.00	100.00	96.86	99.55	100.00	100.00	98.80	86.99			97.63	

Confusion matrix for 1989-LULC

1989		**REFERENCE (pixels)**										
Class	**Forestland (nij)**	**Cropland**	**Grassland**	**Dambo**	**Water**	**Settlement**	**Bareland**	**Plantation**	**total (ni)**	**wi (Ami/Atot)**	**map area (ha)**	**user acc**
Forestland (nij)	6124	0	0	0	0	0	0	11	6135	**0.595**	1,866,506.13	99.8
Cropland	4	298	0	1	0	0	0	0	303	**0.102**	320,298.48	98.3
Grassland	2	0	444	0	0	0	0	0	446	**0.131**	410,991.57	99.6
Dambo	17	0	0	241	0	0	0	2	260	**0.130**	407,047.23	92.7
Water	0	0	0	0	418	0	0	0	418	**0.011**	33,978.15	100.0
Settlement	3	0	1	0	0	1048	0	1	1053	**0.012**	37,598.76	99.5
Bareland	0	0	0	0	0	3	345	0	348	**0.004**	12,916.89	99.1
Plantation	1	0	0	0	0	0	0	2148	2149	**0.016**	49,307.94	100.0
Total	**6151**	**298**	**445**	**242**	**418**	**1051**	**345**	**2162**	**11112**		3138645.15	
Producer acc	99.56	100.00	99.78	99.59	100.00	99.71	100.00	99.35			overall accuracy	99.59
Class	**Forestland (nij)**	Cropland	Grassland	Dambo	Water	Settlement	Bareland	Plantation	row total	user acc		
Forestland (nij)	0.5936190	0.00000000	0.00000000	0.00000000	0.00000000	0.00000000	0.0000000	0.00106627	**0.59468529**	99.82	0.9982	0.0000
Cropland	0.0013471	0.10036593	0.00000000	0.00033680	0.00000000	0.00000000	0.0000000	0.00000000	**0.10204991**	98.35	0.9835	0.0000
Grassland	0.0005872	0.00000000	0.13035834	0.00000000	0.00000000	0.00000000	0.0000000	0.00000000	**0.13094553**	99.55	0.9955	0.0000
Dambo	0.0084796	0.00000000	0.00000000	0.12021157	0.00000000	0.00000000	0.0000000	0.00099761	**0.12968883**	92.69	0.9269	0.0000
Water	0.0000000	0.00000000	0.00000000	0.00000000	0.01082574	0.00000000	0.0000000	0.00000000	**0.01082573**	100.00	1.0000	0.0000
Settlement	0.0000341	0.00000000	0.00001138	0.00000000	0.00000000	0.01192241	0.0000000	0.00001138	**0.01197929**	99.53	0.9953	0.0000
Bareland	0.0000000	0.00000000	0.00000000	0.00000000	0.00000000	0.00003548	0.0040799	0.00000000	**0.00411543**	99.14	0.9914	0.0000
Plantation	0.0000073	0.00000000	0.00000000	0.00000000	0.00000000	0.00000000	0.0000000	0.01570263	**0.01570994**	99.95	0.9995	0.0000
col Total	**0.604074521**	**0.100365926**	**0.130369712**	**0.120548372**	**0.010825738**	**0.011957892**	**0.00407995**	**0.017777882**	**1**			0.0000
Aj (unbiased estimator of area)	1895976	315013	409184	378359	33978	37532	12806	55798	**3138645**		actual overall accuracy	
Producer acc	98.27	100.00	99.99	99.72	100.00	99.70	100.00	88.33			98.71	

Confusion matrix for 1994-LULC

1994	**REFERENCE (pixels)**											
Class	**Forestland (nij)**	**Cropland**	**Grassland**	**Dambo**	**Water**	**Settlement**	**Bareland**	**Plantation**	**total (ni)**	**wi (Ami/Atot)**	**map area (ha)**	**user acc**
Forestland (nij)	5749	0	0	3	0	1	0	6	5759	**0.551**	1,730,530.26	99.8
Cropland	1	422	0	5	0	2	2	0	432	**0.088**	274,948.38	97.7
Grassland	2	0	275	2	0	0	0	0	279	**0.189**	594,561.60	98.6
Dambo	13	0	0	194	0	4	0	0	211	**0.117**	367,678.62	91.9
Water	0	0	0	0	398	0	0	0	398	**0.018**	56,104.74	100.0
Settlement	0	0	0	0	0	399	0	0	399	**0.013**	39,300.75	100.0
Bareland	0	0	0	0	0	0	921	0	921	**0.006**	18,882.99	100.0
Plantation	2	0	0	0	0	0	0	1499	1501	**0.018**	56,526.30	99.9
Total	**5767**	**422**	**275**	**204**	**398**	**406**	**923**	**1505**	**9900**		3138533.64	
Producer acc	99.69	100.00	100.00	95.10	100.00	98.28	99.78	99.60			overall accuracy	99.57
Class	Forestland (nij)	Cropland	Grassland	Dambo	Water	Settlement	Bareland	Plantation	row total	user acc		
Forestland (nij)	0.550424	0.000000	0.000000	0.000287	0.000000	0.000096	0.000000	0.000574	**0.551382**	99.83	1.00	0.00000
Cropland	0.000203	0.085576	0.000000	0.001014	0.000000	0.000406	0.000406	0.000000	**0.087604**	97.69	0.98	0.00000
Grassland	0.001358	0.000000	0.186723	0.001358	0.000000	0.000000	0.000000	0.000000	**0.189439**	98.57	0.99	0.00000
Dambo	0.007218	0.000000	0.000000	0.107711	0.000000	0.002221	0.000000	0.000000	**0.117150**	91.94	0.92	0.00000
Water	0.000000	0.000000	0.000000	0.000000	0.017876	0.000000	0.000000	0.000000	**0.017876**	100.00	1.00	0.00000
Settlement	0.000000	0.000000	0.000000	0.000000	0.000000	0.012522	0.000000	0.000000	**0.012522**	100.00	1.00	0.00000
Bareland	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.006017	0.000000	**0.006017**	100.00	1.00	0
Plantation	0.000024	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.017986	**0.018010**	99.87	1.00	0.00000
col Total	**0.559227**	**0.085576**	**0.186723**	**0.110370**	**0.017876**	**0.015244**	**0.006422**	**0.018561**	**1.000000**			0.00001
Aj (unbiased estimator of area)	1755152	268584	586037	346401	56105	47844	20156	58254	**3138534**		actual overall accuracy	
Producer acc	98.43	100.00	100.00	97.59	100.00	82.14	93.68	96.91			98.48	

Confusion matrix for 1999-LULC

1999		**REFERENCE (pixels)**										
Class	**Forestland (nij)**	**Cropland**	**Grassland**	**Dambo**	**Water**	**Settlement**	**Bareland**	**Plantation**	**total (ni)**	**wi (Ami/Atot)**	**map area (ha)**	**user acc**
Forestland (nij)	5586	0	0	0	0	0	0	0	5586	**0.543**	1,703,637.81	100.0
Cropland	0	379	1	0	0	0	0	0	380	**0.140**	439,894.50	99.7
Grassland	6	0	287	1	0	0	0	0	294	**0.116**	362,997.27	97.6
Dambo	21	0	0	265	0	0	0	0	286	**0.160**	503,334.54	92.7
Water	0	0	0	0	446	0	0	0	446	**0.005**	16,225.74	100.0
Settlement	0	0	0	0	0	498	0	0	498	**0.013**	41,328.36	100.0
Bareland	0	0	0	0	0	1	850	0	851	**0.006**	17,437.95	99.9
Plantation	0	0	0	0	0	0	0	1053	1053	**0.017**	53,228.07	100.0
Total	**5613**	**379**	**288**	**266**	**446**	**499**	**850**	**1053**	**9394**		3,138,084.24	
Producer acc	99.52	100.00	99.65	99.62	100.00	99.80	100.00	100.00			overall accuracy	99.68
Class	Forestland (nij)	Cropland	Grassland	Dambo	Water	Settlement	Bareland	Plantation	row total	user acc		
Forestland (nij)	0.543	0.000	0.000	0.000	0.000	0.000	0.000	0.000	**0.54**	100.00	1.00	0
Cropland	0.000	0.140	0.000	0.000	0.000	0.000	0.000	0.000	**0.14**	99.74	1.00	0.000
Grassland	0.002	0.000	0.113	0.000	0.000	0.000	0.000	0.000	**0.12**	97.62	0.98	0.000
Dambo	0.012	0.000	0.000	0.149	0.000	0.000	0.000	0.000	**0.16**	92.66	0.93	0.000
Water	0.000	0.000	0.000	0.000	0.005	0.000	0.000	0.000	**0.01**	100.00	1.00	0.000
Settlement	0.000	0.000	0.000	0.000	0.000	0.013	0.000	0.000	**0.01**	100.00	1.00	0.000
Bareland	0.000	0.000	0.000	0.000	0.000	0.000	0.006	0.000	**0.01**	99.88	1.00	0.000
Plantation	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.017	**0.02**	100.00	1.00	0.000
col Total	**0.557**	**0.140**	**0.113**	**0.149**	**0.005**	**0.013**	**0.006**	**0.017**	**1.00**			0.000
Aj (unbiased estimator of area)	1,748,004.05	438,736.88	355,512.09	467,611.09	16,225.74	41,348.85	17,417.46	53,228.07	**3,138,084.24**		actual overall accuracy	
Producer acc	97.46	100.00	99.67	99.74	100.00	99.95	100.00	100.00			98.51	

Confusion matrix for 2004-LULC

2004		**REFERENCE (pixels)**										
Class	**Forestland (nij)**	**Cropland**	**Grassland**	**Dambo**	**Water**	**Settlement**	**Bareland**	**Plantation**	**total (ni)**	**wi (Ami/Atot)**	**map area (ha)**	**user acc**
Forestland (nij)	4463	0	0	0	0	0	0	3	4466	**0.508**	1,595,696.31	99.9
Cropland	0	339	1	0	0	1	0	1	342	**0.133**	418,006.44	99.1
Grassland	6	1	276	0	0	0	0	1	284	**0.138**	433,729.17	97.2
Dambo	32	2	0	247	0	0	0	0	281	**0.172**	540,823.05	87.9
Water	0	0	1	0	442	0	0	0	443	**0.010**	32,183.82	99.8
Settlement	0	2	0	0	0	490	1	0	493	**0.018**	56,074.50	99.4
Bareland	0	0	0	0	0	1	784	0	785	**0.004**	13,076.64	99.9
Plantation	0	0	0	0	3	0	0	746	749	**0.016**	49,055.22	99.6
Total	**4501**	**344**	**278**	**247**	**445**	**492**	**785**	**751**	**7843**		3138645.15	
Producer acc	99.16	98.55	99.28	100.00	99.33	99.59	99.87	99.33			overall accuracy	99.29
Class	**Forestland (nij)**	Cropland	Grassland	Dambo	Water	Settlement	Bareland	Plantation	row total	user acc		
Forestland (nij)	0.50806	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00034	**0.50840**	99.93283	0.99933	0.00000
Cropland	0.00000	0.13201	0.00039	0.00000	0.00000	0.00039	0.00000	0.00039	**0.13318**	99.12281	0.99123	0.00000
Grassland	0.00292	0.00049	0.13430	0.00000	0.00000	0.00000	0.00000	0.00049	**0.13819**	97.18310	0.97183	0.00000
Dambo	0.01962	0.00123	0.00000	0.15146	0.00000	0.00000	0.00000	0.00000	**0.17231**	87.90036	0.87900	0.00001
Water	0.00000	0.00000	0.00002	0.00000	0.01023	0.00000	0.00000	0.00000	**0.01025**	99.77427	0.99774	0.00000
Settlement	0.00000	0.00007	0.00000	0.00000	0.00000	0.01776	0.00004	0.00000	**0.01787**	99.39148	0.99391	0.00000
Bareland	0.00000	0.00000	0.00000	0.00000	0.00000	0.00001	0.00416	0.00000	**0.00417**	99.87261	0.99873	0.00000
Plantation	0.00000	0.00000	0.00000	0.00000	0.00006	0.00000	0.00000	0.01557	**0.01563**	99.59947	0.99599	0.00000
col Total	**0.53060**	**0.13380**	**0.13471**	**0.15146**	**0.01029**	**0.01815**	**0.00420**	**0.01678**	**1.00000**			0.00001
Aj (unbiased estimator of area)	1665376	419944	422806	475385	32308	56972	13174	52680	**3138645**		actual overall accuracy	
Producer acc	95.75	98.67	99.69	100.00	99.39	97.83	99.14	92.75			97.35	

Confusion matrix for 2009-LULC

2009		**REFERENCE (pixels)**										
Class	**Forestland (nij)**	**Cropland**	**Dambo**	**Water**	**Settlements**	**Bareland**	**Plantation**	**Grassland**	**total (ni)**	**wi (Ami/Atot)**	**map area (ha)**	**user acc**
Forestland (nij)	3808	0	0	0	0	2	1	0	3811	**0.495**	1,554,765.12	99.9
Cropland	0	293	0	1	0	0	0	0	294	**0.154**	482,637.15	99.7
Dambo	10	1	220	0	0	0	0	0	231	**0.207**	650,581.65	95.2
Water	0	0	0	412	0	0	0	0	412	**0.010**	30,233.97	100.0
Settlements	0	0	0	0	595	4	0	0	599	**0.018**	57,916.71	99.3
Bareland	0	0	0	0	0	710	0	0	710	**0.005**	16,915.23	100.0
Plantation	5	0	0	0	0	0	670	0	675	**0.016**	50,332.86	99.3
Grassland	0	0	0	0	0	0	0	223	223	**0.094**	295,148.97	100.0
Total	**3823**	**294**	**220**	**413**	**595**	**716**	**671**	**223**	**6955**		3138531.66	
Producer acc	99.61	99.66	100.00	99.76	100.00	99.16	99.85	100.00			overall accuracy	99.65

Class	**Forestland (nij)**	Cropland	Dambo	Water	Settlements	Bareland	Plantation	Grassland	row total	user acc		
Forestland (nij)	0.49499	0.00000	0.00000	0.00000	0.00000	0.00026	0.00013	0.00000	**0.49538**	99.92128	0.99921	0.00000
Cropland	0.00000	0.15325	0.00000	0.00052	0.00000	0.00000	0.00000	0.00000	**0.15378**	99.65986	0.99660	0.00000
Dambo	0.00897	0.00090	0.19742	0.00000	0.00000	0.00000	0.00000	0.00000	**0.20729**	95.23810	0.95238	0.00001
Water	0.00000	0.00000	0.00000	0.00963	0.00000	0.00000	0.00000	0.00000	**0.00963**	100.00000	1.00000	0.00000
Settlements	0.00000	0.00000	0.00000	0.00000	0.01833	0.00012	0.00000	0.00000	**0.01845**	99.33222	0.99332	0.00000
Bareland	0.00000	0.00000	0.00000	0.00000	0.00000	0.00539	0.00000	0.00000	**0.00539**	100.00000	1.00000	0.00000
Plantation	0.00012	0.00000	0.00000	0.00000	0.00000	0.00000	0.01592	0.00000	**0.01604**	99.25926	0.99259	0.00000
Grassland	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.09404	**0.09404**	100.00000	1.00000	0.00000
col Total	**0.50408**	**0.15415**	**0.19742**	**0.01016**	**0.01833**	**0.00577**	**0.01605**	**0.09404**	**1.00000**			0.00001
Aj (unbiased estimator of area)	1582077.76	483811.90	619601.57	31875.59	57529.95	18117.92	50367.99	295148.97	**3138531.66**		actual overall accuracy	
Producer acc	98.20	99.42	100.00	94.85	100.00	93.36	99.19	100.00			98.90	

Confusion matrix for 2016-LULC

2016		**REFERENCE (pixels)**										
Class	**Forestland (nij)**	**Cropland**	**Grassland**	**Dambo**	**Water**	**Settlement**	**Bareland**	**Plantation**	**total (ni)**	**wi (Ami/Atot)**	**map area (ha)**	**user acc**
Forestland (nij)	2349	0	0	0	0	0	0	1	2350	**0.469**	1,473,405.75	100.0
Cropland	0	363	0	0	0	0	0	0	363	**0.184**	577,004.94	100.0
Grassland	0	0	612	0	0	0	0	0	612	**0.117**	367,444.80	100.0
Dambo	0	1	0	590	0	0	0	0	591	**0.174**	544,883.40	99.8
Water	0	0	0	0	268	0	0	0	268	**0.015**	48,644.82	100.0
Settlement	0	2	0	0	0	819	0	0	821	**0.019**	60,991.47	99.8
Bareland	0	0	0	0	0	0	486	0	486	**0.005**	14,349.96	100.0
Plantation	0	0	0	0	0	0	0	644	644	**0.017**	51,879.96	100.0
Total	**2349**	**366**	**612**	**590**	**268**	**819**	**486**	**645**	**6135**		3,138,605.10	
Producer acc	100.00	99.18	100.00	100.00	100.00	100.00	100.00	99.84			overall accuracy	99.93480033
Class	**Forestland (nij)**	Cropland	Grassland	Dambo	Water	Settlement	Bareland	Plantation	row total	user acc		
Forestland (nij)	0.46925	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00020	**0.46945**	99.95745	0.99957	0.00000
Cropland	0.00000	0.18384	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	**0.18384**	100.00000	1.00000	0.00000
Grassland	0.00000	0.00000	0.11707	0.00000	0.00000	0.00000	0.00000	0.00000	**0.11707**	100.00000	1.00000	0.00000
Dambo	0.00000	0.00029	0.00000	0.17331	0.00000	0.00000	0.00000	0.00000	**0.17361**	99.83080	0.99831	0.00000
Water	0.00000	0.00000	0.00000	0.00000	0.01550	0.00000	0.00000	0.00000	**0.01550**	100.00000	1.00000	0.00000
Settlement	0.00000	0.00005	0.00000	0.00000	0.00000	0.01939	0.00000	0.00000	**0.01943**	99.75639	0.99756	0.00000
Bareland	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00457	0.00000	**0.00457**	100.00000	1.00000	0.00000
Plantation	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.01653	**0.01653**	100.00000	1.00000	0.00000
col Total	**0.46925**	**0.18418**	**0.11707**	**0.17331**	**0.01550**	**0.01939**	**0.00457**	**0.01673**	**1.00000**			0.00000
Aj (unbiased estimator of area)	1,472,778.77	578,075.49	367,444.80	543,961.43	48,644.82	60,842.89	14,349.96	52,506.94	**3,138,605.10**		actual overall accuracy	
Producer acc	100.00	99.81	100.00	100.00	100.00	100.00	100.00	98.81			99.95	

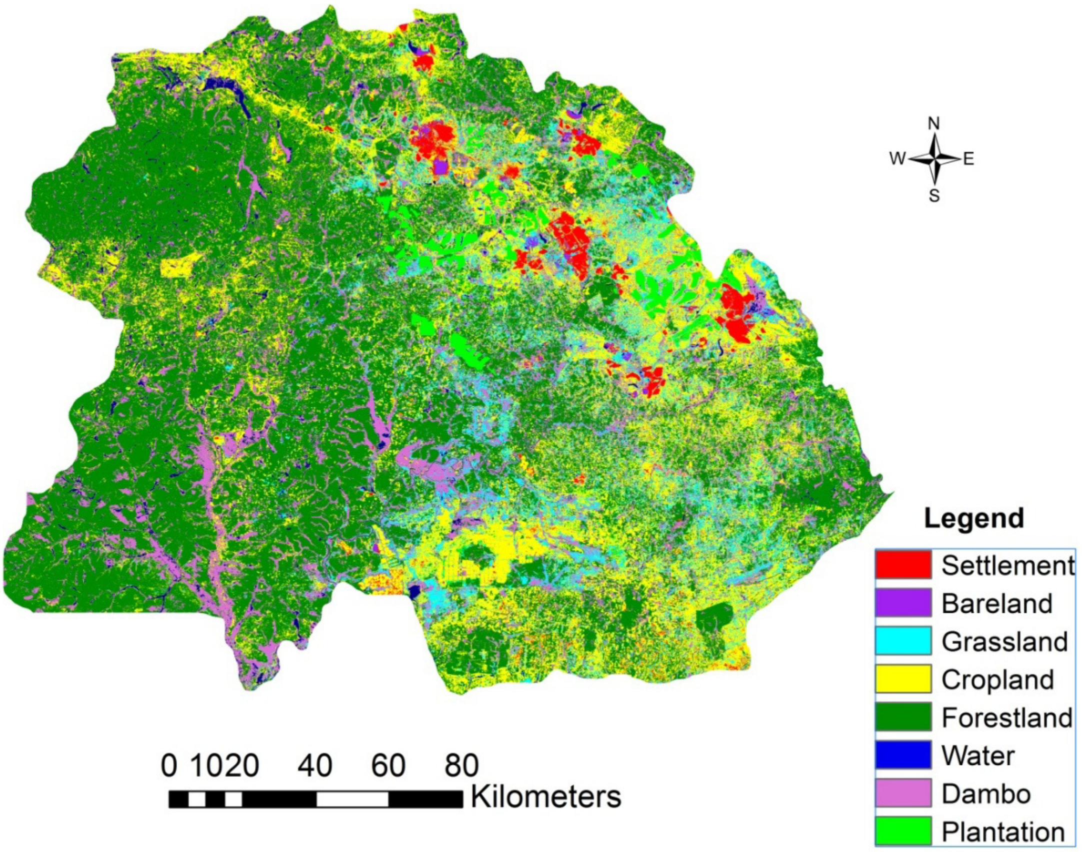
Appendix A 3: Accuracy of driver variables used in transition potential modeling in the Copperbelt province, Zambia

Forcing one Independent Variable Constant at a time	**Skills Measure**	**Accuracy**	**Influence order**
With all variables	0.688	76.63696	N/A
Var. 1 constant (Highways)	0.043	28.15231	1 (Most influential)
Var. 2 constant (Rivers)	0.258	44.31386	2
Var. 3 constant (Slope)	0.688	76.63696	3
Var. 4 constant (Soils)	0.54	65.5118	4 (Least influential)

Model accuracy and skill measure per transition in the multi-layer perception (MLP) for the Copperbelt province, Zambia

(a)	**Class**	**Skill measure**	**Accuracy**
1)	Transition : Forestland to Cropland	0.84	85.868
2)	Transition : Forestland to Settlement	0.84	85.868
3)	Transition : Water to Cropland	0.84	85.868
4)	Transition : Water to Settlement	0.84	85.868
5)	Transition : Dambo to Cropland	0.84	85.868
6)	Transition : Dambo to Water	0.84	85.868
7)	Transition : Dambo to Settlement	0.57	61.453
8)	Transition : Dambo to Grassland	0.84	85.868

Appendix B 1: Land use land cover for 2019



Appendix B 2: Validation / Confusion matrix for 2019

2019	REFERENCE (pixels)											
Class	**Forestland (nij)**	**Cropland**	**Grassland**	**Dambo**	**Water**	**Settlement**	**Bareland**	**Plantation**	**total (ni)**	**wi (Ami/Atot)**	**map area (ha)**	**user acc**
Forestland (nij)	233	0	0	0	0	0	0	0	233	**0**	1,492,274.25	100.0
Cropland	0	246	3	0	0	5	0	0	254	**0**	694,137.42	96.9
Grassland	0	1	239	17	0	0	3	0	260	**0**	274,929.75	91.9
Dambo	16	0	10	226	1	0	0	0	253	**0**	477,793.26	89.3
Water	0	0	0	2	274	0	0	0	276	**0**	55,555.65	99.3
Settlement	0	13	0	0	0	579	3	0	595	**0**	61,437.69	97.3
Bareland	0	0	0	0	0	1	361	0	362	**0**	18,213.57	99.7
Plantation	0	0	0	0	0	0	0	2507	2507	**0**	64,067.58	100.0
Total	**249**	**260**	**252**	**245**	**275**	**585**	**367**	**2507**	**4740**		3,138,409.17	
Producer acc	93.57	94.62	94.84	92.24	99.64	98.97	98.37	100.00			overall accuracy: 98.418	
Class	Forestland (nij)	Cropland	Grassland	Dambo	Water	Settlement	Bareland	Plantation	row total	user acc		
Forestland (nij)	0.475	0.000	0.000	0.000	0.000	0.000	0.000	0.000	**0.475**	100.00	1.000	0
Cropland	0.000	0.214	0.003	0.000	0.000	0.004	0.000	0.000	**0.221**	96.85	0.969	5.9E-06
Grassland	0.000	0.000	0.081	0.006	0.000	0.000	0.001	0.000	**0.088**	91.92	0.919	2.2E-06
Dambo	0.010	0.000	0.006	0.136	0.001	0.000	0.000	0.000	**0.152**	89.33	0.893	8.77E-06
Water	0.000	0.000	0.000	0.000	0.018	0.000	0.000	0.000	**0.018**	99.28	0.993	8.2E-09
Settlement	0.000	0.000	0.000	0.000	0.000	0.019	0.000	0.000	**0.020**	97.31	0.973	1.69E-08
Bareland	0.000	0.000	0.000	0.000	0.000	0.000	0.006	0.000	**0.006**	99.72	0.997	2.57E-10
Plantation	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.020	**0.020**	100.00	1.000	0
col Total	**0.485**	**0.215**	**0.089**	**0.142**	**0.018**	**0.023**	**0.007**	**0.020**	**1.000**			1.69E-05
Aj (unbiased estimator of area)	1,522,490	674,675	279,807	445,182	57,042	73,500	21,645	64,068	**3,138,409**		actual overall accuracy	
Producer acc	98.02	99.64	90.32	95.87	96.69	81.34	83.91	100.00			96.90	

Appendix C 1: Data collection tools / sheets

Ground Truthing-Form 1

Name of Recorder: UTM Zone: Datum:

LULC Date: / / 2017

	LOCATION OF LULC PIXEL (Gutman et al.)		GPS WAYPOINT NAME	ACTUAL /VERIFIED LULC	PHOTO ID + DIR.	COMMENT
	LATITUDE	LONGITUDE				
1.						
1.						
2.						
3.						
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36.						
37.						

Data collection tools / sheets-patch landscape structure and composition-Form-2

Recorder: ____ UTM Zone: ____ Datum: ____

MZ ____ Patch Number ____ Latitude ____ Date: / / 2017

Longitude ____

LULC Class of Patch		Patch Type		Patch Size…	
Actual LULC at Patch					
LANDSCAPE CHARACTERISTICS					
Elements: Biophysical Features:		Causes of Patch / Major Activities:			
1. 2. 3. 4. 5.	6. 7. 8. 9. 10.	1. 2. 3. 4. 5.		6. 7. 8. 9. 10.	

General Description of Landscape Structure at Patch	Shape of Land forms:	1. Smooth	(Tick √) ☐	3. Irregular	(Tick √) ☐	5. Other…	
		2. Rugged	☐	4. Rounded	☐	Photo ID + Dir.	
	Shape of Vegetation:	1. Irregular	☐	3. Other…			
		2. Geometric	☐	Photo ID + Dir.			

VEGETATION INFORMATION			
Most Affected Tree Species		State of Disturbance	State of Succession
1. 2. 3. 4.	5. 6. 7. 8.		

Recorded / Observable LULC Transitions					
①	②	③	④	⑤	⑥
⑦	⑧	⑨	⑩		

Data collection tools / sheets-Forest inventory Main Plot-Form-2.1A

Recorder: UTM Zone: Datum: DATE: / /2017

MZ PATCH NUMBER LATITUDE
PLOT NO. PATCH TYPE LONGITUDE
PLOT TYPE ELEVATION

TREE NO.	SPECIES NAME	≥5 cm DBH	HEIGHT (m)	TREE HEALTH* / STATUS		COMMENT
				CONDITION	CAUSING ELEMENT	

Coding for Health Condition*

Bor:	*Boring*	***Brk:***	*Broken*	***Chw:***	*Chewing*	***Dd:***	*Dead*	***Def:***	*Defoliation*	***Disc:***	*Discoloration*
H:	*Healthy*	***St:***	*Stunting*	***Web:***	*Webbing*	***Ds:***	*Disease*	**Dc**	*Decay*	**Dib**	*Die Bark*
Bb:	*Brocken Branches*	***Mb:***	*Missing Bark*	***Lb:***	*Lack of Balance*	***Fl:***	*Flagging*	**Ln**	*Leaning*		

Data collection tools / sheets-Forest inventory-Regeneration-Form-2.1B

Recorder: UTM Zone: Datum: DATE: / /2017

MZ
PATCH NUMBER
LATITUDE
PLOT NO.
PATCH TYPE
LONGITUDE
PLOT TYPE
ELEVATION

NO.	SPECIES NAME (≤ 5 cm DBH)	COLLAR DIAMETER (mm)	NO.	SPECIES NAME (≤ 5 cm DBH)	COLLAR DIAMETER (mm)

Comment:

Appendix C1: Data collection tools / Sheets-soil data record-Form-2.1C

Recorder: UTM Zone: Datum:

MZ PATCH NUMBER LATITUDE DATE: / / 2017

SOIL SAMPLE PLOT NO. PATCH TYPE LONGITUDE ELEVATION

Soil Type		**Soil Texture:**	Very Coarse		Coarse		Medium		Fine		Very Fine	

BEDROCK (Tick ✓)		**LANDFORM CLASSIFICATION (Tick ✓) MINERAL TERRAIN SURFACE FORMS**				**PARENT MATERIAL (MINERAL SOILS) (Tick ✓)**				**STONINESS (Tick ✓)**	
Igneous	☐	Inclined	☐	Pitted	☐	Fluvial	☐	Organic	☐	Not stony	☐
Sedimentary	☐	Veneer	☐	Level	☐	Colluvial	☐	Residual	☐	Slightly stony	☐
Metamorphic	☐	Undulating	☐	Fan	☐	Fluvioeolian	☐	Other:		Moderately stony	☐
Other:		Terrace	☐	Delta	☐	Fluviomarine	☐			Very stony	☐
		Rolling	☐	Blanket	☐	Lacustrine	☐			Exceedingly stony	☐
		Ridged	☐	Other:		Marine	☐			Excessively stony	☐

SLOPE %	**CLASS**	**SAMPLE SITE POSITION ON SLOPE**		**DRAINAGE**		**SOIL SAMPLE PLOT LOCATION (Gutman et al.)**	
0 to < 0.5 0.5 to < 2 2 to < 5 5 to < 9 9 to < 15 15 to < 30 30 to < 60 60 +	1 2 3 4 5 6 7 8	Crest	☐	Very rapidly drained	☐	**Latitude**	**Longitude**
		Upper slope	☐	Rapidly drained	☐		
		Middle	☐	Well drained	☐	**Mass of Composite Sample (g)**	
		Lower slope	☐	Moderately well drained Imperfectly drained	☐		
		Toe	☐	Poorly drained	☐		
		Depression	☐	Very poorly drained	☐		

Erosion Condition:	
Comment:	

MZ: Soil Management Zone

Appendix D 1: Shape descriptors for FRAC-1 and 2 Forest and Croplands

	Shape Descriptor						
Forestland FRAC-1							
Label	**Round**	**Circularity**	**Convexity**	**Elongation**	**Patch Length**	**Patch Width**	**Number of Holes**
Mean	**0.7778**	**0.8707**	**0.8972**	**0.471642**	**800.6936**	**587.684**	**0.5808**
SD	0.2643	0.2357	0.1382	0.354954	1127.2306	703.8506	2.3604
Min	0.1667	0.0246	0.3002	0	353.5527	353.5527	0
Max	1	1	1	0.9516	18,676.4871	14,446.5857	34
Forestland FRAC-2							
Mean	**0.6618**	**0.0311**	**0.2566**	**0.5683**	**28,818.2724**	**20,169.2496**	**275.8182**
SD	0.1442	0.0169	0.0567	0.1315	17,259.1581	12,455.5758	489.7234
Min	0.3732	0.0127	0.1783	0.3464	14,989.4721	11,220.5096	42
Max	0.8613	0.0706	0.3291	0.8055	73,680.3511	55,559.7324	1733
Cropland FRAC-1							
Mean	**0.8291**	**0.9324**	**0.9999**	0.653939209	**10.0396**	**517.1104**	**416.2786**
SD	0.257	0.1549	0.0028	**0.167648124**	39.5778	334.2051	165.0722
Min	0.1796	0.2362	0.9377	0.000000015	0	353.5534	353.5534
Max	1	1	1	0.7247	462	9,708.2439	4,751.1167
Cropland FRAC-2							
Mean	**0.5485**	**0.233**	**0.9796**	0.5809869	**2.6812**	**2,703.8983**	**1,708.0066**
SD	0.1707	0.0832	0.0556	0.2230397	6.9018	1,347.0087	888.4716
Min	0.2135	0.042	0.6995	0.00000001	0	1,100.8335	675.4406
Max	0.9322	0.5267	1	0.8349	54	8,916.0715	5,474.0461

Appendix E 1: Cross validation of ordinary kriging for interpolating soil parameters

MODEL	**SOIL PROPERTY**						
SPHERICAL	**C**	**PH**	**K**	**P**	**N**	**NH3**	**NH4**
Mean (ME)	-0.004007255	-0.005515757	0.222464676	0.122894993	0.000735866	1.384646287	0.080358499
Root-Mean-Square (RMSE)	0.86605128	0.467395628	49.48688208	10.23863075	0.018904815	48.8666498	29.02037185
Mean Standardized (MSE)	**-0.004453924**	-0.011709875	0.004090419	0.011407944	0.03935993	0.031468326	0.004378548
Root-Mean-Square Standardized (RMSSE)	1.070876007	1.006162728	1.079015172	0.997599341	1.024299117	1.033855978	0.96788278
Average Standard Error (ASE)	0.807627396	0.465111006	45.8220898	10.27611973	0.018461936	47.17947582	30.03974514
• ASE closest to RMSE	-0.058423884	**-0.002284622**	-3.664792281	0.037488979	-0.000442879	-1.687173976	1.019373295
• RMSSE nearest to 1	-0.070876007	**-0.006162728**	-0.079015172	0.002400659	-0.024299117	-0.033855978	0.03211722
EXPONENTIAL							
ME	-0.003675061	-0.005197089	0.220110574	0.122894993	0.000711641	1.228057992	0.042912049
RMSE	0.87653752	0.470809844	49.6567312	10.23863075	**0.018892688**	49.18926188	28.60102678
MSE	-0.00447167	**-0.010853833**	0.003912628	0.011407944	**0.038009091**	**0.0278873**	0.002792409
RMSSE	1.077327887	1.008528048	1.073298154	0.997599341	1.022465745	1.026122638	**0.951253965**
ASE	0.815650376	0.467733618	46.28192039	10.27611973	0.018484516	47.56611853	30.16988883
• ASE closest to RMSE	-0.060887144	-0.003076226	**-3.3748108**	0.037488979	**-0.000408172**	**-1.623143352**	1.568862054
• RMSSE nearest to 1	-0.077327887	-0.008528048	**-0.073298154**	0.002400659	**-0.022465745**	**-0.026122638**	0.048746035
GAUSSIUN							
ME	-0.00465444	-0.006475256	0.169952731	0.122894993	0.000781143	1.320035778	-0.036121399
RMSE	**0.853839682**	**0.464925685**	**49.29354148**	10.23863075	0.018927278	49.0176835	29.04258547
MSE	-0.004637949	-0.01396115	**0.003220396**	0.011407944	0.041761865	0.03050742	**0.000845237**
RMSSE	1.054441662	1.008316931	1.076824668	0.997599341	1.024075172	1.029353292	0.967930288
ASE	0.805822895	0.461351724	45.64958876	10.27611973	0.018485611	47.34284747	30.03139114
• ASE closest to RMSE	**-0.048016788**	-0.003573961	-3.643952725	0.037488979	-0.000441668	-1.674836027	**0.988805662**
• RMSSE nearest to 1	**-0.054441662**	-0.008316931	-0.076824668	0.002400659	-0.024075172	-0.029353292	**0.032069712**
BEST FIT MODEL PER SOIL PARAMETER	GAUSSIUN	SPHERICAL	GAUSSIUN OR EXPONENTIAL	ANY OF THE FOUR MODELS	EXPONENTIAL	EXPONENTIAL	GAUSSIUN

CRITERIA: 1. Standardized mean (MSE) nearest to zero 2. The smallest root-mean-squared prediction error (RMSE) 3. The average standard error (ASE) nearest the root-mean-squared prediction error (RMSE) 4. Standardized root-mean-squared prediction error (RMSSE) nearest to 1

- **Bold numbers indicate statistics meeting criteria 1 to 4**