University of Nairobi

School of Engineering

DEPARTMENT OF GEOSPATIAL AND SPACE TECHNOLOGY

ASSESSMENT OF SOIL EROSION DYNAMICS USING GEOSPATIAL TECHNOLOGY CASE STUDY OF LAKE BARINGO CATCHMENT.

BY

KEBUT DUNCAN KIPNGETICH

F56/7560/2017

A Project submitted in partial fulfilment for the Degree of Master of Science in Geographical Information Systems, in the Department of Geospatial and Space Technology of the University of Nairobi.

May, 2019

Declaration of Originality

Name of student: Kebut Duncan Kipngetich

Registration: F56/7560/2017.

College: College of Architecture and Engineering.

Faculty/School/Institute: School of Engineering.

Department: Department of Geospatial and Space Technology.

Course Name: Master of Science in Geographical Information Systems

Title of work: Assessment of Soil Erosion Dynamics using Geospatial Technology: Case study of Lake Baringo Catchment.

1) I understand what plagiarism is and I'm aware of the university policy in this regard
2) I declare that this research proposal is my original work and has not been submitted elsewhere for examination, award of a degree or publication. Where other works or my own work has been used, this has properly been acknowledged and referenced in accordance with the University of Nairobi's requirements
3) I have not sought or used the services of any professional agencies to produce this work
4) I have not allowed, and shall not allow anyone to copy my work with the intention of passing it off as his/her work
5) I understand that any false claim in respect of this work shall result in disciplinary action in accordance with University of Nairobi anti-plagiarism policy

Signature:

Date:

Turn it in report summary

STUDENT:

Kebut Duncan Kipngetich: SIGNATURE…………………………..DATE………………..……………..

SUPERVISOR:

Dr Faith Karanja: SIGNATURE…………………………..DATE………………..……………..

Acknowledgement

First and foremost I thank God for His grace and for giving me the strength to complete this project. I thank my supervisor, Dr.–Ing. Faith Karanja, for her guidance throughout the project, also I acknowledge Planet Labs through Spatial Ventures for providing me with data (images). Finally, I would like to thank my family, friends and classmates for their moral support and above all their prayers.

Abstract

Land degradation in form of soil erosion is a significant problem in arid and semi-arid region of Lake Baringo catchment. Soil erosion by water is one of the major contributors of reducing soil fertility, eutrophication and contamination of water resources experienced in the catchment. The goal of this research was to assess soil erosion in the area by combining object based image analysis to map erosion and spatial modelling to assess erosion risk. The development of remote sensing technology with regard to Geographic Object-Based Image Analysis (GEOBIA) gives new improved techniques to map erosion and associated features from high spatial resolution imagery. GEOBIA method was reviewed, developed and tested for its capability of mapping erosion. Assessment of the magnitude of the soil loss was incorporated as well through some form of modelling. Erosion modelling helped in pinpointing the vulnerable areas. Unit Stream Power-based Erosion Deposition Model (USPED) was used to capture the erosion and deposition process. The output of the GEOBIA which is the spatial patterns of erosion was combined with the output from the USPED erosion model which is a quantitative prediction of erosion risk to improve soil erosion assessment within the catchment.

Analysis of the USPED model results showed that around 56.5% of the catchment area is affected by erosion. Only 0.8% of the catchment is stable and not affected by either erosion or deposition process. Deposition occurs in the remaining 42.7%. Major erosion hotspots were found to be areas surrounding Radat, Kaptim, Kipcherera and Molo sirwe. GEOBIA classification results indicate that the method was able to detect the eroded areas in high resolution Rapid Eye image with a high level of accuracy. The results of the classification were checked against ground reference data in the area, resulting in an overall classification accuracy of 78.5%.From a conservation perspective, 10.8% of the watershed needs immediate watershed management intervention. Based on the results of this study, it is recommended that appropriate soil and water conservation measures should be implemented in these identified hotspots. This spatial information on the scale, severity level and exact coordinate location of badlands will give important insights to conservationists and stakeholders in planning and implementing mitigation measures.

Table of Contents

List of Figures

List of Tables

Abbreviations

GEOBIA: Geographic Object Based Image Analysis.

USPED: Unit Stream Power Erosion Deposition.

MAR: Mean Annual Rainfall.

NDVI: Normalized difference vegetation Index.

FAO: Food and Agriculture Organization.

USLE: Universal Soil Loss Equation.

RUSLE: Revised Universal Soil Loss Equation.

DEM: Digital Elevation Model.

UNCCD: United Nations Convention for Combating Desertification.

LS: Slope length and steepness factor.

SLT: Soil Loss Tolerance Value.

R-Factor: Rainfall-Runoff Erosivity Index Factor

REI: Rainfall Energy Intensity.

P Factor: Conservation Practice Factor.

K Factor: Soil Erodibility Factor.

C Factor: Cover Management Factor.

AFSIS: Africa Soil Information Service

CHAPTER 1: INTRODUCTION

1.1 Background

Human beings have adjusted their environment to suit their needs. The ever-increasing world population and demands have resulted in the degradation of limited earth resources. Land degradation has been defined as depletion in the economic or biological productive capacity of land (UNCCD, 1994). The major cause of land degradation is anthropogenic activities, however it is increased by naturally occurring processes and worsened by the climate change effects. Land degradation assessments have been conducted globally and indicate that "the percentage of earth surface that is degraded has increased from 15% in the year 1991 to 25% by 2011" (UNCCD, 2013).

One of the main causes of land degradation globally is soil erosion (Valentin et al., 2005). It is an earth surface process that occurs naturally. This process removes and carries soil particles through the action of its agents such as air, wind, gravity, and water. Naturally, the erosion process and the creation of new soil is balanced in nature, however anthropogenic activities have accelerated this process of erosion thereby causing an unsustainable imbalance in the cycle. Approximately 24 billion tons of productive soil are lost to erosion in the world's croplands (FAO, 2011). This destruction of the fertile land increases food insecurity. People living in rural areas are forced to migrate because of the destruction of fertile land resources which they depend on. At a global scale, water erosion is one of the most important land degradation problems (Eswaran et al., 2001).

Traditionally, GIS and remote sensing technologies have been applied in soil erosion assessment and research through conducting aerial surveys. Interpretation of aerial photos leads to detection of erosion. Model input data for analysis could also be obtained from the imagery. Technical developments in earth observation, such as availability of higher spectral and spatial resolution, the advancement of new digital image processing technology and analysis workflows, have created new opportunities for research in earth science, and especially spatial soil erosion assessment. The increasing availability of higher spatial resolution optical imagery has triggered a shift from traditional pixel based image classification methods to improve detection of erosion from imagery.

This research project focuses on using an improved approach for spatial soil erosion assessment by combining erosion modelling to quantitatively analyze soil erosion risk and Geographic Object Based Image Analysis (GEOBIA) to extract erosion from high spatial resolution imagery. Mapping eroded lands would assist in providing the current status of the patterns and severity levels of the badlands. Locating the potentially vulnerable areas through modelling of the soil loss will provide crucial information required for devising conservation plans and measures. Erosion modelling can effectively represent the behavior of the real world erosion phenomenon which will allow for the comparison of the image classification and simulated outputs. The fact that the spatial pattern of erosion from GEOBIA would be available opens the possibility to combine the GEOBIA output to soil erosion model output to further improve on the level of detail on erosion.

1.2 Problem Statement

Soil erosion is a big environmental concern across the globe, especially in developing countries. In Kenya, it is an increasing problem in Lake Baringo catchment. Water erosion is one of the most influential factors that determine catchment quality and is considered a significant form of land degradation that affects sustained land-use productivity.

Geospatial technologies like remote sensing and GIS have been used to assess soil erosion. However, in Kenya there is a lack of detailed spatial data with regards to the spatial extents of soil erosion at national scale. This study will attempt to address this problem of soil erosion assessment by combining soil erosion models and object based image analysis to improve detection and evaluation methods at the catchment.

The emergence of high resolution satellite sensors has offered the remote sensing community increased flexibility to study finer scale geographic phenomena anywhere on the Earth's surface. Geographic Object Based Image Analysis, a new paradigm shift in satellite image processing was used to map soil erosion and associated features. Classical pixel-based classification methods deliver results for land cover/use mapping that usually depend fully on the information of each pixel and the immediate neighborhood only (Vrieling, 2007). Other important information that implicitly exists like shape and texture within the image space is not put into consideration during classification. This information that is left out in pixel-based methods may solve several problems of mapping soil erosion features like gullies and rills in optical satellite data by including context as one main facet of expert knowledge. Although higher accuracy could be achieved by manual digitizing of erosion features from high spatial resolution imagery, it is extremely laborious and time consuming with lots of subjectivity during image interpretations. A study like this will be expensive to repeat for the whole of Kenya for monitoring purposes. It is therefore necessary to develop GEOBIA methodologies that will be less expensive to repeat.

Incorporating soil erosion models would enable a more precise soil loss value to be derived, which is crucial in devising an effective soil conservation plan and putting up strategies for sustainable development. In Lake Baringo catchment, so far soil erosion dynamics have not been assessed comprehensively. Quantitative assessment studies of erosion phenomena also do not exist in the catchment.

1.3 Objectives.

The main objective of this study was to assess soil erosion dynamics in Lake Baringo catchment through the application of geographic object based image analysis and spatial modelling.
The specific objectives of this study were to:

1) Review the application of object based image analysis for soil erosion assessment.
2) Identify suitable data for soil erosion assessment.
3) Map soil erosion by applying object-based image analysis.
4) Model soil erosion rates.

1.4 Justification of the Study

Most reports in the region point at alarming status of land degradation. This study has noted that no detailed GIS based degradation assessment and mapping efforts have been carried out to identify hotspot areas in the catchment. The only available studies have been done at national level with coarse resolution output.

With this shortcoming in mind, this study purposes to use an improved method combining spatially dynamic erosion modelling and object based image analysis to assess and map land degradation severity in the entire catchment at finer spatial scale. It is anticipated that this approach will result in finer resolution risk maps covering the entire catchment. Determining the erosion potential of an area would help conservationists target specific locations for appropriate initiation of conservation measures. The model's estimates of soil erosion would become an important component of sustainable land management plans (Bonilla, 2010). The estimates would help in prioritization of soil conservation based on severity levels in each region. These plans are designed to protect and recover soils. The spatial distribution of soil erosion and their severity levels are important input factors to be considered in watershed management and soil conservation planning (Kumar and Nair, 2006).

1.5 Scope of work.

The scope of this research project was to identify and map the extent and severity levels of land degradation. The study used an approach that combines object based image analysis and erosion model to assess and map soil erosion in the catchment.

Field survey would be carried out to validate the outputs of both object based image analysis and erosion models. The study area for this research is Lake Baringo catchment which was selected because of its agricultural and economic significance and the fact that it is one of the regions in Kenya that has suffered massive losses of productive land attributed to persistent land degradation which has also had direct implications to the ecosystem and livelihoods.

1.6 Organization of the Report.

This project report is organized into 5 chapters where Chapter 1 contains the background, problem statement, objectives, and justification of the study and scope of work. Chapter 2 discusses the previous literature written on the main aspects of the study i.e spatial assessment of soil erosion. Chapter 3 discusses the materials, data and the methods of data processing and analysis used during the study, chapter 4 focuses on the results of the data analysis processes and discussion of the results obtained with respect to the objectives. Chapter 5 gives conclusions drawn to the study in reference to the results obtained and objectives of the study and also recommendations provided to subsequent studies. Lastly the list of references is given after Chapter 5.

CHAPTER 2: LITERATURE REVIEW

2.1 Introduction

Soil erosion is a multiphase geomorphic process, involving the removal of topsoil from the earth surface and their transport by agents like wind and water. A third stage called deposition happens when enough power is no longer available to carry the soil particles (Morgan, 2005) . The most crucial detaching agent that starts the whole process chain is rain splash. Once the raindrops strike a bare earth surface, the soil particles are propelled through the air over distances of a few centimeters. This repeated exposure to intense rainstorm phenomenon considerably wears out the soil surface. The earth surface is further broken up by physical, chemical and biological weathering processes. The alternate freezing and thawing, wetting and drying, of the soil surface constitute mechanical weathering. Tillage activities on the farmland and stamping effects of livestock and people further disturb the earth surface. Wind and running water friction against earth surface also contributes to the detachment of soil particles. All these processes wear out the soil thereby enabling the agents of transport to remove it easily. The transporting agents consist of those that take action and contributes to the removal of a relatively uniform layer of soil and those that direct their action in water channels (Morgan, 2005).

There are three major types of soil erosion by water. The first one is splash erosion in which it happens when topsoil particles are removed and shifted because of the collision with the falling raindrops as explained above. Subsequently, sheet or inter-rill erosion takes away soil in the thin upper layers and is as a result of combined effects of surface runoff and splash erosion. The other type of water erosion is rill erosion, whereby the removal of soil particles is caused by concentrations of flowing water. Rill erosion eventually becomes gully erosion which occurs when a huge amount of topsoil is removed by the increased surface runoff. This runoff cumulatively leads to the formation of deeply incised and wide rills, referred to as gullies. (Morgan, 2005). Several factors control water erosion. They include topography, soil properties, climatic characteristics, land and vegetation management.

2.2 Sustainable Land Management.

Sustainable land use and management of earth resources plays an important role in human climate, and food security (Lal, 2001). Soil erosion is a global concern that threatens natural resources in both developing and developed countries. High levels of soil erosion rates has harmful ecological and economic effects (Lal, 1998). It creates both offsite and onsite impacts on productivity due to a decrease in the quality of soil health. According to UN's Institute for natural resources in Africa, “if current trends of land degradation continue, the continent might only be able to feed just a mere 25% of its total population by the year 2025”. This increase in land degradation over the past couple of years has led to a higher acknowledgement of the need for sustainable natural resource management. In response to this need, sustainable development goals (SDGs) were developed by the United Nations to direct a worldwide global development agenda. One of the sustainable development goals aims at “ protecting, restoring and promoting sustainable usage of terrestrial ecosystems, sustainably managing forests, combating desertification, halting and reversing land degradation, and stopping biodiversity loss” (UNDP, 2015). Therefore, SDGs provides a global dedicated effort towards combating land degradation and attaining degradation-free planet (Lal, 2012).

Kenya is a signatory and is bound by several international agreements such as the Convention on Biodiversity (CBD), the Kyoto Protocol on Climate Change, United Nations Convention to Combat Desertification (UNCCD) and the resultant UN Framework Convention on Climate Change. All these efforts directly and indirectly champion for the establishment of planet monitoring methods to better identify and map degraded land, evaluate the changes in degraded land over time and to understand the causes of land degradation. Additionally, Kenya Vision 2030, proposes the establishment of a GIS based system to aid in monitoring land use/cover changes. Vision 2030 prioritizes sustainable land management. The current land use practices in Kenya are conflicting with the ecological zones thereby catalyzing unsustainable use.

Kenya’s Constitution (2010) also captures the need for sustainable management of resources. According to article 60 of the constitution, the section on land and the environment states that “land in Kenya shall be held and used in such a way that is efficient, equitable and sustainable”. Two of the key principles of land use are captured in sub-article (c) and sub-article (e) which advocates for sustainable management of land resources; and sound conservation and protection of ecologically sensitive areas. Kenya has to manage and sustain its diverse natural resource base for it to be globally competitive. The country's economy significantly relies on tourism and agriculture for it to earn foreign exchange which contributes to GDP. Despite this fact, Kenya is experiencing many challenges with the environment. They include soil erosion, land degradation and deforestation. Three steps have been proposed to solve the land degradation problem. They include spatial assessment, monitoring changes and implementation of mitigating actions and technologies. Spatial assessment is necessary to guide on the suitable counter measures to curtail the worsening degradation problems. Spatial Information on the scale, severity level and exact coordinate location of badlands will give important insights to conservationists and stakeholders in planning and implementing mitigation measures.

2.3 Spatial Erosion Assessment.

GIS and remote sensing are essential technologies used in erosion assessment because they provide location specific insights. There are three different ways of conducting spatial assessment of soil erosion. Measurement of soil erosion rates at different locations on the earth surface using a measuring device or erosion plots is one of the ways according to (Hudson, 1993). Carrying out actual field measurements is a very intensive field survey activity. For one to achieve accurate and precise measurements it takes a lot of time. This manual method is very expensive and measurement equipment is not always available (Stroosnijder, 2005). Under the same circumstances, the measurement results may vary because of errors (Nearing, 1999). This method is most suitable for the determination of the role of a specific erosion factor, model design or validation. It is not suitable for spatial estimation of erosion.

Erosion field survey is the other method for assessment in which erosion and associated geomorphic features are identified. The features may include; pedestals, rills, gullies (Herweg, 1996). In this method quantitative information may be obtained through repeated mensuration of feature dimensions. This type of survey is qualitative in nature since classification of the amount of erosion is done based on the features encountered. Surveys allow for spatial erosion mapping for small catchments of about 2 square kilometers (Vigiak et al., 2005), but for bigger regions this becomes very difficult. The other form of erosion survey is a structured visual identification of geomorphic features from aerial photographs/imagery. This could be done for larger areas up to 50 square kilometers (Bergsma, 1974).

The third and most common technique for spatial erosion assessment is by integrating spatial data on erosion factors in some kind of modelling. The most widely accepted and used erosion model is the empirical Universal Soil Loss Equation (Wischmeier and Smith, 1978). However, it is important to note that many other erosion models have been developed and they also are used for spatial evaluation of erosion (Merritt et al., 2003).

Most models that capture the erosion process demand a big amount of detailed spatial data on a range of factors such as vegetation, soil, rainfall, and topography parameters. In most developing countries these data are not readily available or they have poor resolution. Recent development in the space technology and open data initiatives have improved availability of higher resolution data which is a huge benefit when conducting land degradation assessments.

When conducting an assessment by using erosion models, the outcome is a quantified risk that erosion would happen at a certain location as compared to other locations in the region mapped. High resolution rapid eye imagery was used to map the current extents of eroded land. The availability of the spatial pattern of erosion opens up the possibility to improve assessment by combining the two outputs. From the above studies there are huge potential opportunities for spatial erosion assessment combining the latest remote sensing technology and erosion models.

2.4 Geographic Object Based Image Analysis.

Interpretation of aerial photos has been the most extensively applied method for mapping erosion and associated features like rills and gullies. However, this method involves conducting an aerial survey and interpretation of images by humans. This method consumes a lot of time, is affected by human subjectivity and only covers a small area.

Remote sensing datasets have been effectively used for assessing eroded areas. In recent years pixel-based image classification techniques have been the main method used to map erosion from satellite imagery (Vrieling, 2007). A deep understanding of the region of interest and meticulous analysis of separability of spectral signatures is required during training and selection of adequate pixels. To add on this, spectral differences of the earth surface is affected by variability in mineral content, soil organic matter and moisture. This variation greatly affects the performance of pixel-based image classifications algorithms. Pixel by pixel analysis is able to detect erosion pixels, however the inexactness of whether an image feature is an eroded area or not may require further analysis in context. This brings about the need to use a more advanced object based image analysis techniques that utilize contextual data to aid in the detection of erosion.

In some studies already done, erosion types could be distinguished on satellite imagery based on derived vegetation cover and visual satellite image interpretation (Dwivedi and Ramana, 2003). Vegetation cover data and topographic attributes derived from additional data sources like DEM have also been used to map erosion (Yuliang and Yun, 2002).

A better option compared to visual satellite image interpretation method is the semi-automated extraction/mapping of eroded lands. Supervised maximum likelihood algorithm together with principal component analysis of Landsat TM imagery was used by (Floras and Sgouras, 1999) to map soil erosion classes (Bocco and Valenzuela, 1988) also used the supervised classification algorithm on SPOT and Landsat images to distinguish erosion and vegetation classes. From their research, it was discovered that multispectral bands of Landsat Thematic Mapper produced a superior result of land cover, however high resolution imagery from SPOT satellite achieved much better results in the classification of eroded regions.

(Dwivedi, 2018) ascertained that SPOT imagery provided superior quality classes of eroded lands than Landsat, however all Landsat bands were not used for the classification. An unsupervised classifier was applied to SPOT satellite data to extract four types of erosion (Serveney and Prat, 2003).

Advancement in remote sensing especially in terms of GEOBIA and availability of higher resolution satellite imagery offers more new possibilities to map erosion in less time and at an acceptable level of accuracy. Studies done before suggests that supervised classification technique such as maximum likelihood classifier could not detect eroded land at an acceptable level of accuracy because of spectral similarities with other non-erosion features (Pirie, 2009). Application of object based erosion extraction methods have proven to be more effective than the classical pixel based unsupervised and supervised classification technique. (Jetten, 2011) used eCognition an object based image analysis software to extract gullies in Morocco by using a combination of NDVI, slope, and catchment area thresholds. The accuracy assessment was good as it indicated negligible over estimation. In South Africa a study was done using eCognition to extract erosion gullies in tertiary catchment in eastern cape province. Vector segments representing homogenous landscape were derived by creating a bare soil mask. However segmentation was not done as it would have required a large amount of preprocessing especially at provincial scale. One of the advantages of using object oriented classification is that it uses both spectral and spatial patterns when classifying an image.

2.5 Soil Erosion Modelling.

Many soil erosion models have been designed to predict soil erosion. They can be divided into two major types namely: physically-based models and empirical models (Morgan, 1995). Empirical models have been developed with a statistical starting point. This is different from physically based models in which they describe the acting erosion processes on the basis of a storm event. However, most erosion models contain both physically-based and empirical parts. Empirical erosion models have been widely accepted and used worldwide. They play an important role in predicting soil erosion and supporting soil conservation management plans. In this study Unit Stream Power Based Erosion Deposition model (USPED) was used.

USPED is a two dimensional soil erosion model. It assumes soil erosion and deposition depends on the sediment transport capacity of the surface runoff, unlike the one dimensional revised universal soil loss equation (RUSLE) model, which assumes erosion mainly depends on detachment capacity of rain. According to USPED model, if soil particles are already broken off from the earth surface by rain, but the runoff is not enough to transport the soil particles because of the topography or vegetation cover, the actual amount of erosion will be notably lower (Mitalsova et al., 1997).

USPED model has been developed on the foundation of the empirical Universal Soil Loss Equation (USLE) and its improved version Revised Universal Soil Loss Equation (RUSLE). USLE models have been accepted widely and used worldwide for agricultural application, however they are wanting when a much more complex terrain is involved. The major advancement provided by the USPED model is the way in which it captures complex topography. The RUSLE model considers the earth surface to be a sequence of large planes. USPED model considers convergence and divergence of slope surface by modelling the entire upslope area that contributes to the overland flow of water across every point in the landscape in a GIS environment. This model comprehensively considers terrain complexity by including both the tangential curvature and profile curvature in the downhill direction. Computation of erosion and deposition is based on the change in sediment transport capacity in the direction of flow. Modelling of sediment deposition within the landscape is not possible with the empirical USLE/RUSLE equation.

According to the USPED model, (ED) erosion and deposition is calculated as a change in flow of sediment in the direction of flow (Mitalsova et al., 1997).

$$\mathrm{ED} = \mathrm{d}(\mathrm{T}\cos \mathrm{a})/\mathrm{dx} + \mathrm{d}(\mathrm{T}\sin \mathrm{a})/\mathrm{dy} \tag{2.1}$$

where: T is the flow of sediment at transport capacity, dx, dy is the grid resolution, and a is the terrain aspect (direction of flow) of surface in degrees; The output ED can be negative, showing soil erosion, or positive, indicating deposition of soil. Transport capacity is given as;

$$\mathrm{T} = \mathrm{RKCPA}^{\mathrm{m}}(\sin \mathrm{b})^{\mathrm{n}} \tag{2.2}$$

where: K is a soil erodibility index factor, R is a rainfall–runoff erosivity factor, C is a cover management factor, P is a support practice factor, A is the contributing area upslope, b is the terrain slope and n and m are constants. Transport capacity is defined as the highest amount of sediment that a given flow can carry without net deposition. Transport capacity and detachment capacity are correlated and it is their synergy that controls the magnitudes and patterns of both erosion and deposition (Slaymaker, 2003).

2.6 USPED Factors.

2.6.1 Rainfall-runoff erosivity Factor.

This factor is also called R-factor. Rainfall-runoff erosivity factor is an approximation of the erosivity effect of rainfall. It is calculated as the product of maximum 30-minute intensity (EI30) and storms kinetic energy. The product of the maximum 30-minute intensity (I30) of a storm and total kinetic energy of the storm (E) is directly proportional to storm soil loss from a rainfall rainfall event, when the other factors are kept constant (Arnoldus, 1980). This type of meteorological data is not available in Kenya, therefore mean annual and monthly rainfall data would be used as an alternative in calculating the R factor (Arnoldus, 1980).

Rainfall-Runoff erosivity (R) is expressed as a combined measure of the intensities and amounts of each rainstorm throughout the year (Hudson, 1981). If rainfall intensity data is available, equation 2.3 below is used;

$$\mathrm{R} = \frac{1}{n}\sum_{j=1}^{n}\left[\sum_{k=1}^{m} E(I30)\right] \tag{2.3}$$

where; R is rainfall runoff erosivity ($MJ.mm.ha^{-1}.h^{-1}.yr^{-1}$), I30 is maximum 30-min rainfall intensity (mm/h), E is the total storm kinetic energy (MJ/ha), j is the index of the number of years used to produce the average, m is the number of storms in each year, n is the number of years used to obtain average and k is the index of number of storms in a year.

In the absence of storm kinetic energy data and rainfall intensity, several different authors have come up with formulae that use mean annual rainfall data p, Fournier Index and monthly precipitation data pi as the inputs to calculate erosivity factor R (Arnoldus, 1980). Mean annual and monthly precipitation data of the area of interest would be obtained directly from CHIRPS and worldclim rainfall data, but the Fournier Index F is determined by using equation 2.4 as shown.

$$\mathbf{F} = \frac{1}{n}\sum_{j=1}^{n}\left[\sum_{i=1}^{i=12}\frac{{p_i}^2}{p}\right] \tag{2.4}$$

Many equations have been derived to determine the value of R-factor for a certain location. This brings about a new problem of selecting the right equation for a region because there is no guarantee that those model equation would work for all regions. To circumvent this issue, the different tested mathematical expressions were applied and the output rainfall erosivity indexes compared. To decide on the suitable equations that could be used at Lake Baringo catchment, nine equations given in Table 2.1 were tested based on the relationships between the Rainfall Erosivity (R) and Mean Annual Rainfall (MAR) show in Table 2.2 according to (Kassam et al., 1992).

Table 2.1: Tested R Factor Equations and their references (Kassam et al., 1992).

Case	***References/Source of the Equations***	***R and P or F Relationship***
1	Arnoldous (1980)	$R = 4.17F - 152$
2	YU & Rosewell, 1996	$R = 3.82\ F^{1.41}$
3	Arnoldus – Exponential, 1977	$R = 0.302\ F^{1.93}$
4	Renald & Freimun – F, 1994	$R = 0.739F^{1.847}$
5	Renald & Freimun – P, 1994	$R = 0.0483P^{1.61}$
6	Roose in Morgan and Davidson (1991)	$R = P \times 0.5$
7	Kassam et al.,1992	$R = 117.6\ (1.00105^{(MAR)})$ for < 2000mm
8	Singh et al., 1981	$R_{factor} = 79 + 0.363R$
9	Freimund (1994)	$R = 0.6120\ F^{1.56}$; Sicily-Italy $R = 0.264\ F^{1.50}$; the Morocco

Where;

R = rainfall erosivity factor (MJ/ha.mm/h)

MAR = mean annual rainfall (mm)

F = Founier index

P = Mean Annual Precipitation (mm)

Table 2.2: Relationship between Rainfall Erosivity and Mean Annual Rainfall (MAR) (Kassam et al., 1992).

MAR (mm)	*R*	*MAR (mm)*	*R*
170	140	913	307
212	146	998	335
256	153	1089	369
302	161	1189	409
350	170	1298	459
400	179	1419	522
453	189	1557	602
508	200	1711	708
566	213	1892	856
628	227	2108	1054
692	243	2376	1188
761	261	2729	1364
835	282	2878	1439

2.6.2 Cover Management Factor. (C- Factor)

C-factor is a general land cover factor that represents the collective effect of all interrelated land cover and management variables. Different land use types in terms of coverage and pattern influence the soil erosion potential of an area. This factor takes into account the earth surface protection against raindrop impact. This protection could be by vegetative cover at some height above the soil surface thereby reducing raindrop impact against the soil surface. It could also be protection against overland flow friction against the soil surface .C- factor has been described as the ratio of soil loss from continuous tilled bare fallow land to the corresponding loss from land maintained under specified conditions(Van der Knijff et al., 2000). Cover management factor values typically range from 0 for soils that are well protected to 1.5 for earth surface that has been finely tilled and generates much runoff, leaving it vulnerable to all types of erosion (Van der Knijff et al., 2000). Rapid eye satellite images were used for the approximation of C factor using NDVI because of the range of land cover types with temporal and spatial variations. The Normalized Difference Vegetation Index, NDVI is a dimensionless index that characterizes the difference between near-infrared and visible reflectance of vegetation cover. It is an indicator of vegetation health and vigor. NDVI was used in the below equation 2.6 to create the C factor layer for USPED erosion model (Zhou et al., 2008).

$$\mathrm{NDVI} = \frac{\mathrm{NIR} - \mathrm{RED}}{\mathrm{NIR} + \mathrm{RED}} \tag{2.5}$$

$$\mathrm{C} = \exp\left[-\propto \frac{NDVI}{(\beta - NDVI)}\right] \tag{2.6}$$

whereby where β and α are dimensionless variables which control the shape of the graph relating C factor and NDVI. The values of the variables β and α were determined to be 1 and 2 respectively. It was found out that this method of scaling produced more desirable results than when a linear relationship is assumed (Van der Knijff et al., 2000).

2.6.3 Soil Erodibility Factor. (K-factor)

Soil erodibility is an indicator of the ability of soils to withstand erosion. It is determined by the physical characteristics of the soil. This factor represents both susceptibility of the soil surface to rate of runoff and erosion when studied under typical unit plot condition. Soil erodibility is affected by two factors namely; structural stability and the infiltration capacity of the soil (Renard et al., 1997). Typical K factor model values vary from 0.01 to 1. Soils that have a high content of clay are resistant to detachment process and have very low soil erodibility values of ranging from 0.05 to 0.15. Soils that have a high content of fine sand have higher K-factor values. Soils with coarse texture are detached easily but have very low runoff thus contributing to low K factor values ranging between 0.05 to 0.2. Medium textured soils are moderately suscepetible to detachment and they have a moderate K values of about 0.04 to 0.25. The most erodible soils are the ones with high silt content. These soils are easily detached because they are not sticky. They also tend to crust and produce high runoff rates. K-factor values for this type of soil are more than 0.4.

K factor was approximated using the soil properties obtained from soil data from Africa Soil Information Service database by using equation 2.7 as proposed by (Williams, 1996). This equation was chosen because of the availability of soil properties data on sand, silt, organic carbon and clay content. K-factor equation is expressed as shown below:

$$K = A * B*\mathrm{C}*\mathrm{D} \tag{2.7}$$

$$A = (0.2 + 0.3\exp(-0.0256\,\mathrm{SAN}\,(1 - \mathrm{SIL}/100)) \tag{2.8}$$

$$B = \left(\frac{SIL}{CLA+SILT}\right) \tag{2.9}$$

$$C = \left(1 - \frac{0.0256C}{C + \exp(3.72\ - 2.95\ \mathrm{C})}\right) \tag{2.10}$$

$$D = \left(1 - \frac{0.7SN1}{\mathrm{SN1} + \exp(-5.51 + 22.9\,\mathrm{SN1})}\right) \tag{2.11}$$

where: SIL is silt, SAN is sand, C is organic carbon content of soil, CLA is clay, SN is (1-SAN/100).

2.6.4 Support Practice Factor.

This factor is also called the P-factor. Support practice factor considers the various land management control practices that assist in reducing erosion. These practices directly or indirectly influence the runoff velocity, runoff concentration, drainage patterns and runoff hydraulic force on the soil. P factor has been defined as the “ratio of soil that is lost within a specific support practice on croplands to the corresponding deficit with tillage up and down a slope" (Wischmeier and Smith, 1978). The effects of existing soil conservation practices such as terracing, strip cropping and contour farming on soil loss in an area are represented by this factor. These conservation practices affect erosion by water. They interfere with the direction of runoff, the pattern of flow thereby reducing speed and volume of runoff. P-factor model values reduce by embracing these supporting conservation practices as they reduce runoff impact and encourage the deposition of soil sediment on the slope surface of the hill. The better the management practice is for controlling soil erosion, the lower the P-factor value. Below table shows P factor values as designed by (Wischmeier and Smith, 1978).

Table 2.3 Typical P factor Values (Wischmeier and Smith 1978).

Land use	**Slope (%)**	**Value for P factor**
Agriculture	0-5	0.1
	5-10	0.12
	10-20	0.14
	20-30	0.19
	30-50	0.25
	50-100	0.33
Other Land Covers		1

CHAPTER 3: METHODOLOGY.

3.1: Introduction

This section introduces and discusses the entire workflow that will be used to achieve the study objectives. Specifically, it looks at the entire methodology used from study area identification, data acquisition, data processing, intermediate products derivation, USPED erosion modelling in GIS, erosion mapping using GEOBIA, and field validation all the way to the final product which is the erosion hotspots map. Figure 3.1 is a flowchart that summarises the methodology used in this study.

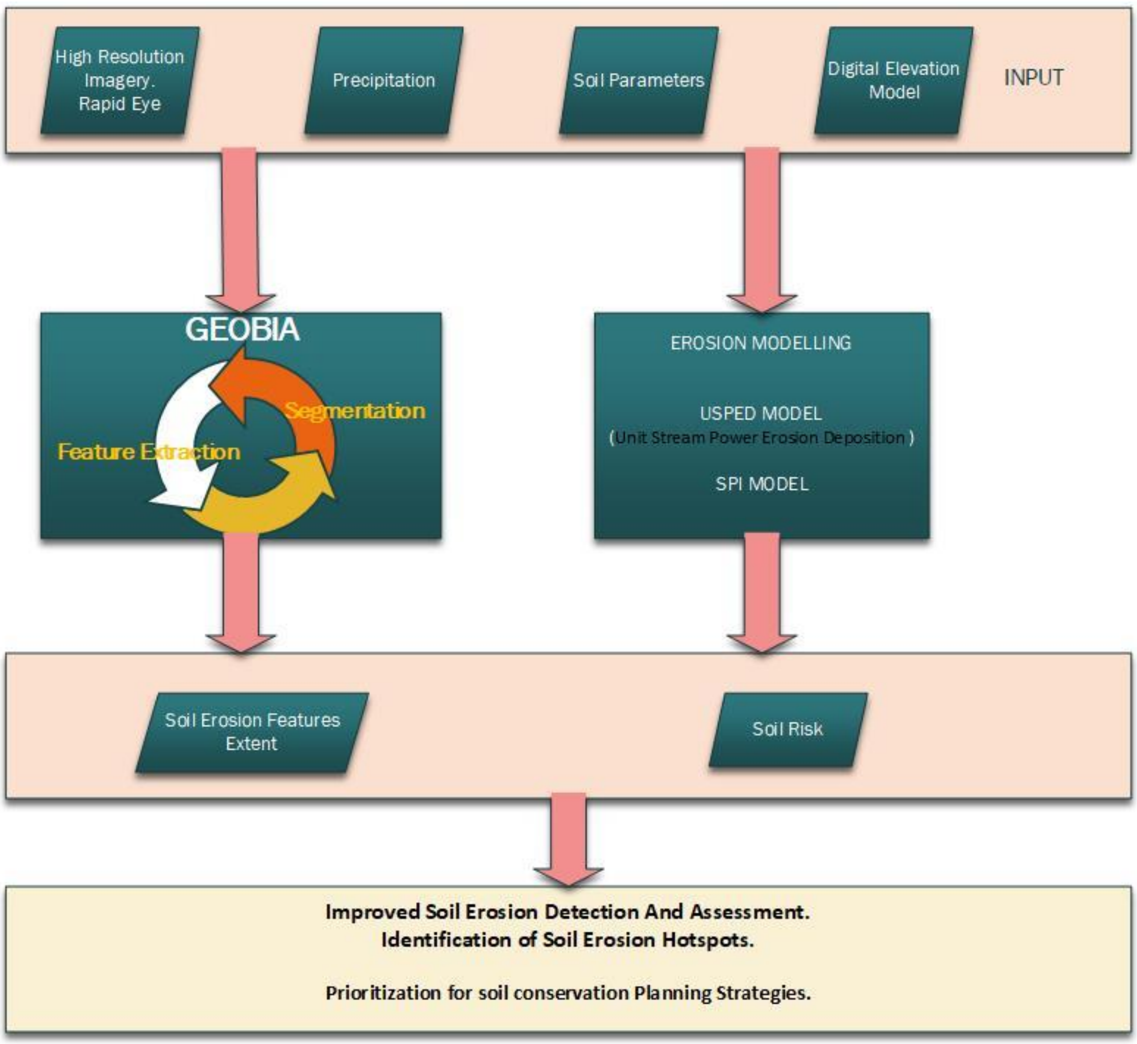


Figure 3.1 Summary of Methodology.

3.2: Study Area

This study was in Lake Baringo Catchment as shown in Figure 3.2.

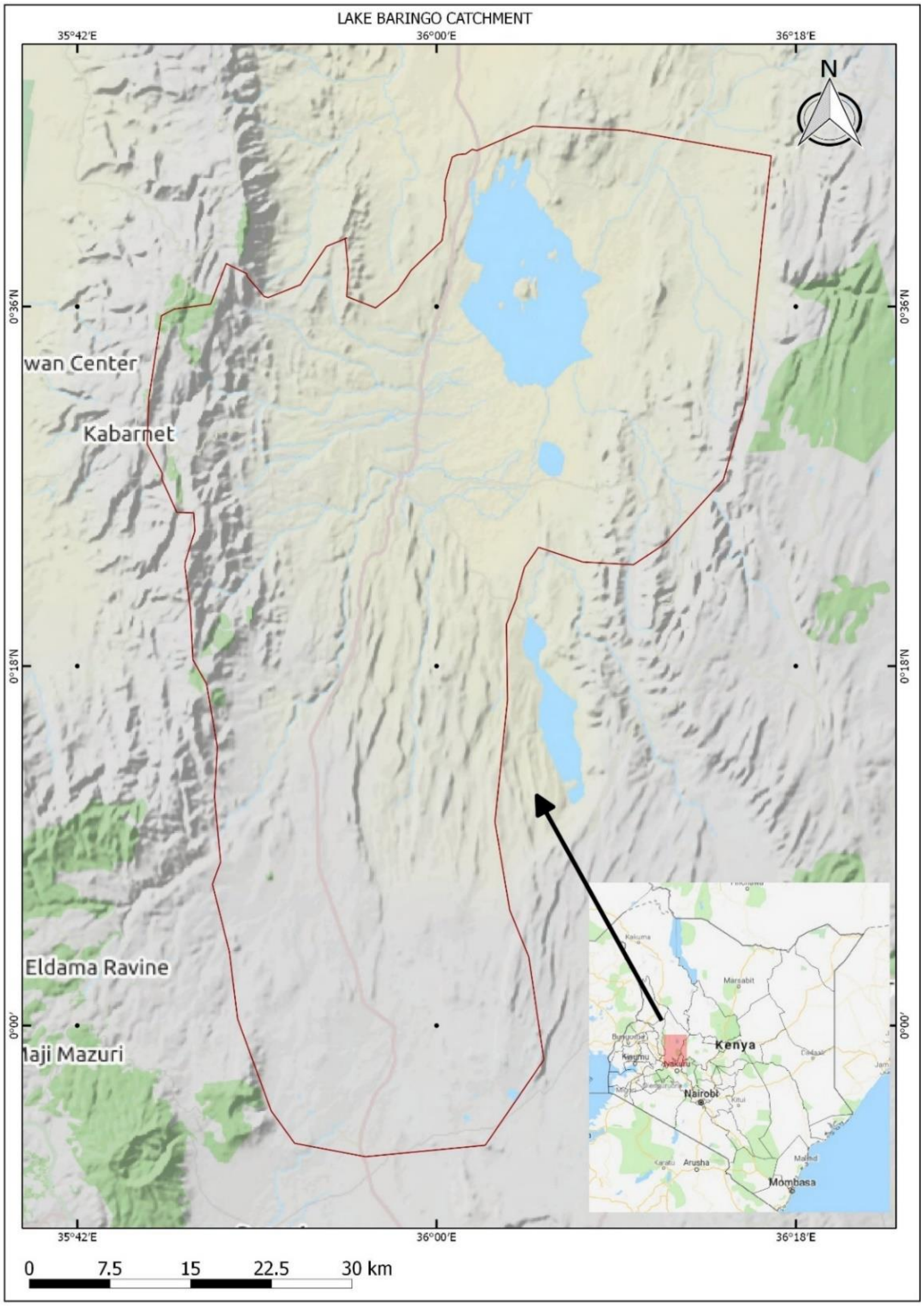


Figure 3.2 Area of study.

The climate of Lake Baringo catchment is classified as semiarid to arid with irregular dry and wet seasons. The dry season runs from September to February, while the rainy season is between

March and August. Mean annual rainfall ranges from about 600 mm on the east and south of the lake to 1500 mm on the western escarpment of the Rift Valley. The highland area of the catchment near the Tugen hills experiences a cool and wet climate, with an annual mean temperature of 25°C in combination with high precipitation. Along with the decreasing elevation, as the landscape is descending downhill towards the lake, the temperature gradually increases to an annual mean of 30°C and the drier climate characterizes the lower zones around the lake. Land cover of the catchment varies along with the topographic gradients. The highlands is characterized by temperate forests, whereas there exists desert shrubs, such as drier acacia-species, on the valley floors. The major livelihood activities in the southernmost part of the catchment and the highlands is agriculture. In the lower parts of the catchment, the major livelihood is herding animals like cattle, sheep but mainly goats and some irrigated and rainfed farming.

3.3: Data sources and Tools

The datasets and tools used for the study are discussed below:

3.3.1: Data Sources.

Spatial assessment of catchment wide degraded lands will utilise input data layers for various variables required to compute the required principal products required in modelling. The quantitative estimation of the soil erosion risk by USPED model is based on its component factors such as: digital elevation model (DEM), rainfall data, soil type map, land cover map and satellite images. Most of these input layers were computed from a combination of two or more other data layers, as described below:

i) High resolution satellite Imagery.

High resolution rapid eye satellite imagery will be used for geographic object based image analysis. Rapid Eye satellite captures images in 5 spectral bands with 5m spatial resolution. Table 3.1 shows the satellites spectral bands and the wavelength range.

Table 3.1 Rapid Eye Spectral Bands.

Spectral Band	Wavelength Range (nm)
Blue	440 – 510
Green	520 – 590
Red	630 – 685
Red Edge	690 – 730
NIR	760 – 850

ii) Rainfall.

WorldClim rainfall data would be used here. WorldClim is a set of gridded climate data in raster format with a spatial resolution of about 1 km. This data can be used for mapping and spatial modelling. Since the principal rainfall product i.e. rainfall erosivity required high temporal and spatial resolution rainfall data to calculate both rainfall depth and intensity, this rainfall data was found to be most representative. The dataset was further processed to provide the monthly mean and annual mean required as input in the computation of the rainfall erosivity index.

iii) Digital Elevation Model.

The DEM used was ALOS 10 meter resolution. It was generated from data collected from the JAXA's ALOS satellite.

iv) Soil.

The soil data for this study was obtained from Kenya Soil Survey offices at KALRO. The data is in grid format for the different soil horizons. The dataset has a resolution of 250m. The Soil erodibility factor for the model would be calculated from soil properties obtained from Africa Soil Information Service (AFSIS) database. The data contained soil properties on the percentage of clay, silt, sand and organic carbon content.

Table 3.2: List of data and data sources.

Data	Source	Access Link	Principal Product
Soil	Africa Soil Information Service project	KALRO	Soil Erodibility
Rainfall	USGS Chirps	ftp://ftp.chg.ucsb.edu/pub/org/chg/products/CHIRPS-2.0/africa_pentad/tifs/	Rainfall Erosivity
DEM	JAXA ALOS	KALRO	Topographic Factor
Satellite Imagery.	Rapid Eye	Planet labs.	Cover Management and Support Practice.
Baseline Data	Boundaries, towns, other (RCMRD)	http://geoportal.rcmrd.org	Baseline / Ancillary data

3.3.2: Tools.

The tools that were used in this study include the following;

Hardware – Personal computer.

Software – GRASS GIS, QGIS Software, eCognition Developer software, Microsoft Office.

3.4: Soil Erosion Assessment.

This subsection describes the steps used to assess soil erosion in Lake Baringo catchment. This assessment was done by combining soil erosion modelling and Geographic object based Image analysis technique. The model adopted for assessing soil erosion in this study is USPED. This section describes the processing stages of the various input parameters for the model i.e. vegetation cover condition, rainfall erosivity, terrain factor and soil erodibility.

3.5: Data Pre-processing.

These different spatial data obtained from different sources have different projections, formats, spatial resolution and quality. GIS will provide the framework necessary to standardize manage and manage these data. A thorough evaluation of these datasets is a must before they are used in modeling. This is because the uncertainties regarding data and its sources may bring about larger uncertainties in the form of errors in soil erosion estimates. Significant effort will be put to the assessment and pre-processing of data, such as data conversion, registration, interpolation and metadata. All the acquired spatial datasets will be converted to appropriate data formats for application in the extraction and modelling process. All data will be georeferenced in a standard coordinate reference system.

3.5.1 Generation of Watershed Boundary.

In generating the watershed boundary, the digital topographical maps and a DEM of the study area were used. The watershed boundary was then manually defined from the digital topographic maps using onscreen digitization. This was aided by features like the nature of the contour lines in the area of study and the general flow of rivers. The catchment boundary so generated was general and had to be further refined by use of hydrological tools provided in QGIS software.

For the purposes of refinement of the boundaries of the drainage, GRASS GIS software was used with a 30m raster SRTM DEM of the catchment area to achieve a more precise catchment area boundary.

The procedure first required that sinkholes or depressions on the DEM are filled in so that the boundaries are delineated properly. Then the FLOW DIRECTION function was executed. Conceptually this function defines which direction water would flow from each of the grid cells assuming the surface is impermeable. The output from the FLOW DIRECTION function then served as input for the next step of determining flow accumulation. The FLOW ACCUMULATION function was executed and defined the drainage network by calculating the contribution of each cell to its neighboring cells.

The final step was to run the WATERSHED function to automatically delineate the watershed boundary. Once the watershed boundary was delineated from the original DEM, the output data file was used as a template to cut out, or extract the area of interest from other digital maps.

3.6 USPED modelling.

The USPED model was run using QGIS and GRASS software. The various factors in the formulae were computed first. This will be done at 10 meters resolution. Raster layers having different resolution were resampled to 10m.

According to USPED model Erosion-Deposition is calculated as divergence of sediment flow transport capacity as shown below in equation 3.1

$$\mathrm{ED} = \mathrm{d}(\mathrm{T}\cos \mathrm{a})/\mathrm{dx} + \mathrm{d}(\mathrm{T}\sin \mathrm{a})/\mathrm{dy} \qquad (3.1)$$

where: T is the flow of sediment at transport capacity, dx, dy is the grid resolution, and a is the terrain aspect (direction of flow) of surface in degrees. Transport capacity is given as;

$$\mathrm{T} = \mathrm{RKCPA}^{\mathrm{m}}(\sin \mathrm{b})^{\mathrm{n}} \qquad (3.2)$$

where: K is a soil erodibility index factor, R is a rainfall–runoff erosivity factor, C is a cover management factor, P is a support practice factor, A is the contributing area upslope, b is the terrain slope and n and m are constants.

To compute specific land-surface parameters included in the model, such as directional derivatives and flow divergence, a map algebra module r.mapcalc and partial derivatives computed by the RST modules or r.slope.aspect was used in GRASS GIS.

First the sediment transport capacity in x and y directions were calculated using r.mapcalc tool in GRASS GIS.

```
r.mapcalc "flowtopo.dx=flowtopo * cos(aspect)"
```

```
r.mapcalc "flowtopo.dy=flowtopo * sin(aspect)"
```

This was then followed by deriving partial derivatives for sediment transport.

```
r.slope.aspect elev=flowtopo.dx dx=qs.dx

r.slope.aspect elev=flowtopo.dy dy=qs.dy
```

The net erosion deposition is then computed by the below equation:

```
r.mapcalc "topoindex = qs.dx + qs.dy"

mapcalc "erdep=qsx_dx + qsy_dy"
```

The sediment transport capacity was calculated by combining the rainfall erosivity factor, soil erodibility factor, cover management factor and support practice factor with the topographic sediment transport factor.

3.6.1 Processing Vegetation Cover Management Factor.

The vegetation cover management factor was calculated from NDVI values that were generated from Rapid Eye image of 23rd march 2018. The NDVI was then derived using QGIS software by applying equation 2.5 by using the raster calculator function. NDVI was further processed to generate C factor by applying equation 2.6.

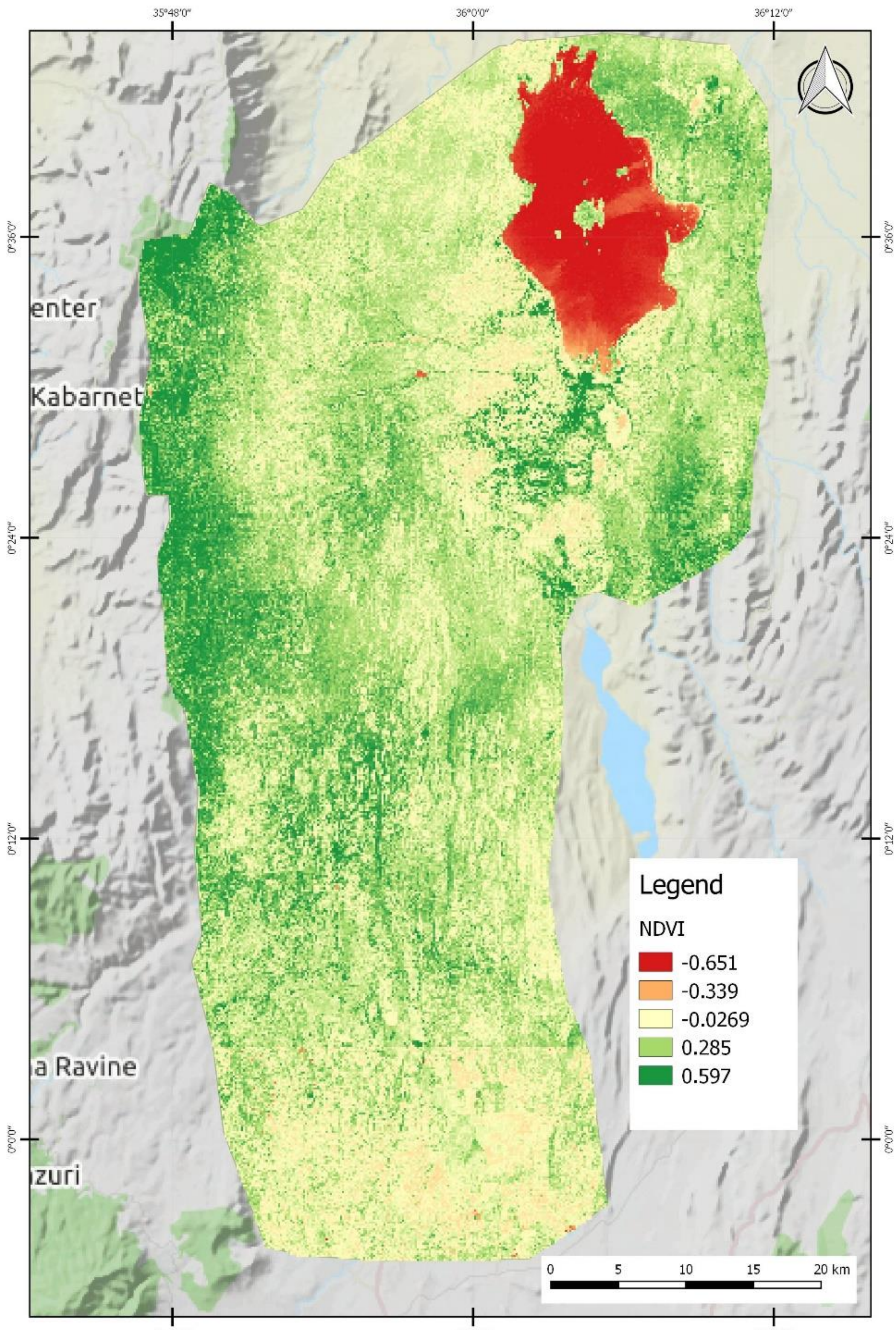


Figure 3.3 NDVI Lake Baringo Catchment

3.6.2 Processing Rainfall Erosivity Factor.

Rainfall and runoff play an important role in the process of soil erosion and were together expressed as the R factor. The greater the duration and intensity of a rain storm event, the higher the erosion potential. According to (Hudson 1981), rainfall- runoff erosivity factor (R) for any given period is obtained by summing for each rainstorm the product of total storm energy (E) and the maximum 40mm intensity. since the values for these factors were not available at standard meteorological stations, an alternative method using long term satellite rainfall estimates was used. For the computation of R factor two components were computed from the CHIRPS rainfall data: Mean monthly and mean annual rainfall. These mean values were used to compute the Fournier index by applying equation 2.4.

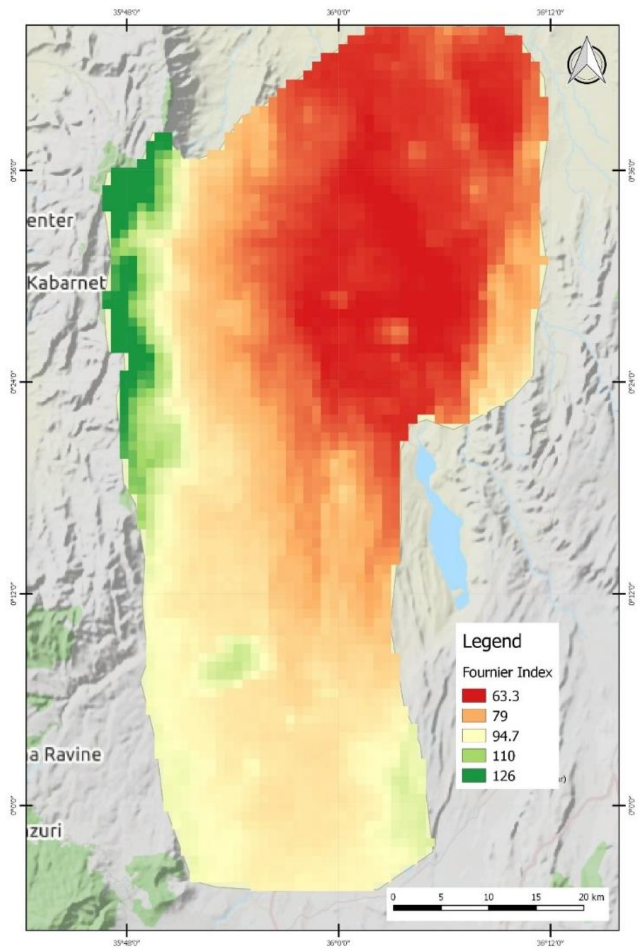


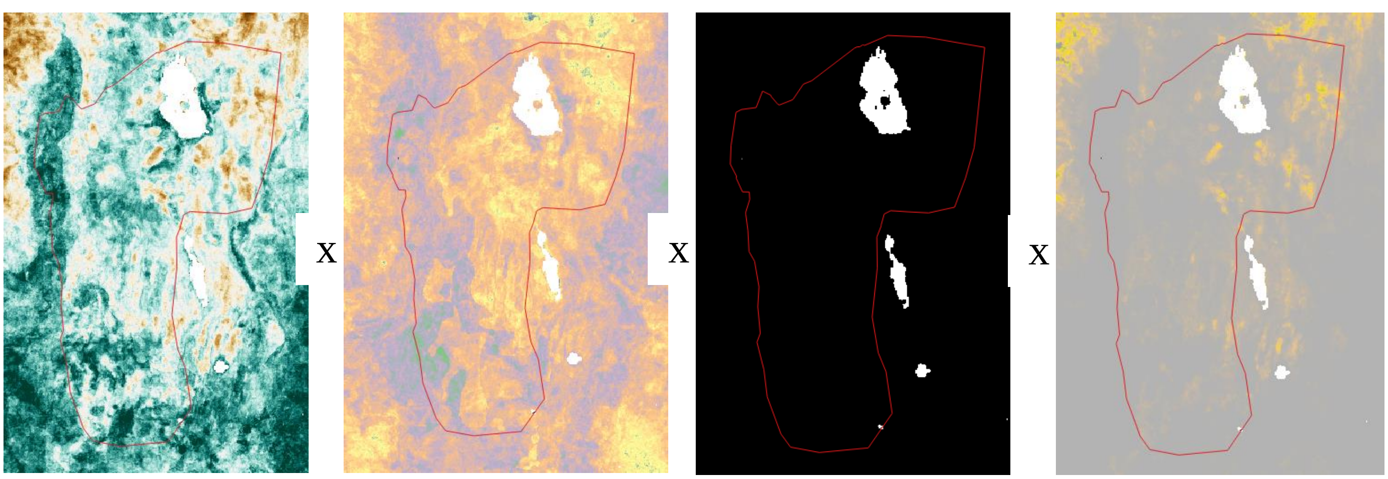
Figure 3.4 Fournier Index of Lake Baringo Catchment.

3.6.3 Processing Soil Erodibility Factor.

The K factor expresses the susceptibility of soil erodibility due to its soil properties. Soil texture, organic matter, gravel content and permeability (water holding capacity) are some of the factors that determines the erodibility of soil. K factor is an indicator of the change in the soil per unit of the applied external force of energy since it reflects the ease with which soil is detached by agents of erosion. It is related to the integrated effects of rainfall, runoff, and infiltration on soil loss, accounting for the influences of soil properties on soil loss during storm events on upland areas (George, 2013).

Soil erodibility factor of the catchment was estimated based on the sand, clay, silt and organic carbon fractions data obtained from the Africa Soil Information Service (AfSIS) data using equation 2.7.

Below shows intermediate products when calculating soil erodibility. Images A, B, C, D are products of applying equation 2.8, 2.9, 2.10 and 2.11 respectively.



A B C D

Figure 3.5 Intermediate Soil Erodibility factor products A, B, C, D.

3.7 Erosion Features Extraction.

Object-based image analysis (OBIA) for rapid eye satellite imagery using was done using eCognition Developer software. The application of GEOBIA for erosion classification can be categorized into a set of process steps as described below:

i) Segmentation.

In image segmentation, an image is grouped into objects based on spectral and/or spatial properties of an image (Wang et al., 2010). Several segmentation algorithms are available, whereas region-based algorithms are the ones most applicable within the field of remote sensing (Wang et al., 2010). The reason is its capability to merge pixels into spectrally homogeneous areas, and at multi-scales thus reflecting the human perception, which tends to group the geographic space into hierarchies of homogeneous objects. Segmentation process is essential in the development of OBIA procedure for mapping erosion. To come up with correctly segmented images, suitable multiresolution segmentation with a scale factor of 50, 0.3 shape factor and 0.5 compactness value. The above parameters were obtained after a series of repetitive trials and testing. Figure 3.5 shows the level 1 segmentation process. In this segmentation figure parameters are clearly captured.

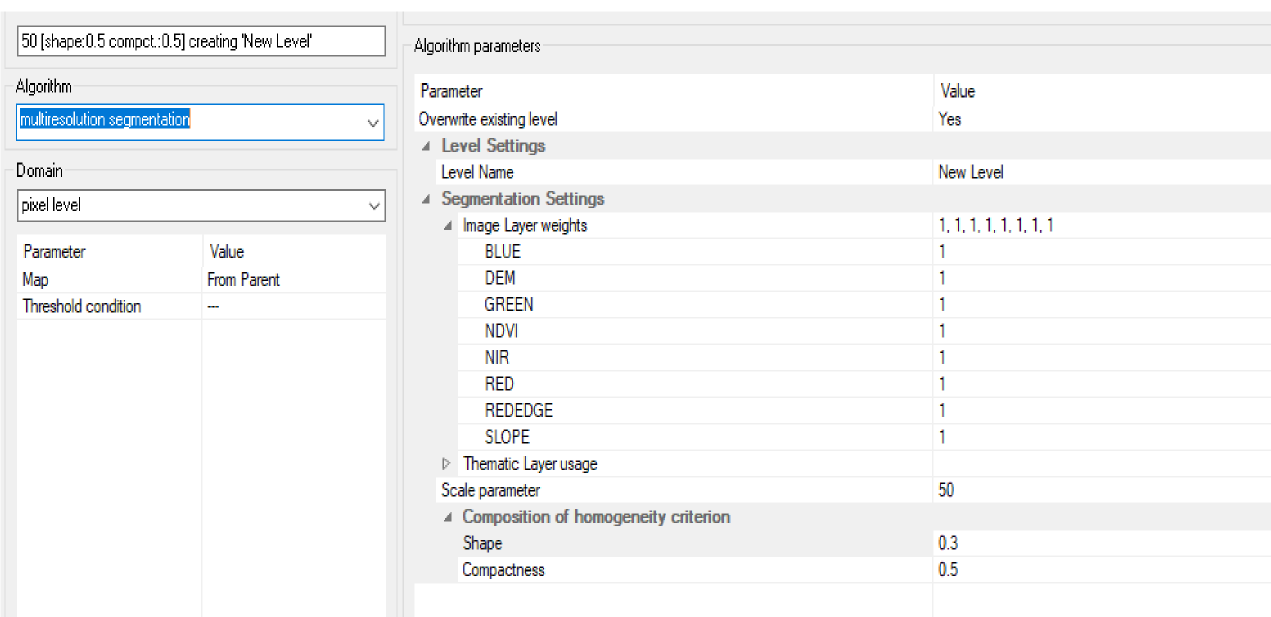


Figure 3.5 Segmentation parameters in eCognition software.

ii) Image Classification

The second step of the GEOBIA process was devoted to image classification. This step can be further divided into a set of subcategories. Calculating statistics is an important subcategory of image classification in order to successfully separate between different desired thematic classes. Statistics are generated primarily from the bands of the imagery in hand. Statistics of each band, such as mean, standard deviation, and ratio is calculated either locally for each object as generated from the antecedent step of image segmentation, or globally for a segmented image as a whole. These statistics are often referred to as features, feature statistics, object features.

To overcome the problem of colour (spectral) similarities of the imagery bands, some additional statistics, or features, are often needed. These additional features were size, mean NDVI, shape, texture, brightness and others, can be calculated from ancillary data, such as from elevation data, NDVI and similar. The purpose of feature statistics will be to add information so that objects can be easier merged by resemblance into thematic classes.

After the step of adding feature statistics to the analysis, the objects would be finally classified into a set of classes using some classification method. Object based classification methods can be divided into two types, namely supervised classification (using training data and classifier), and rule-based thresholding (Trimble, 2015). The former uses training data in the form of objects, selected for each class. The number of training data, or samples, selected for each class varies from case to case. Samples, which contain information about each feature calculated, should each one represent a typical characteristics of a particular class. Based on the object samples selected, a classification algorithm is applied so that to find similar objects that are merged into thematic classes. There are many types of algorithms, whereas for example Bayes, nearest neighbour (NN), and decision tree, are classifiers embedded in eCognition. The classification method based on training data and classifier is vital when a complex set of classes has to be classified, as it enables for a wide range of features to be incorporated in the analysis.

Support Vector Classification algorithm was chosen for supervised classification. This is because it has proven successful in binary classifications, is well adapted to deal with data of high dimensions, less expert knowledge is required in training data collection and it is also competitive as other classifiers.

Different from the above explained classification procedure is the rule-based methodology by thresholding. It simply divides objects into classes based on for example mean threshold as defined by different features. This is a preferred method if for example classes are easily separated using only a few features. This was not possible in Lake Baringo catchment because the area is semi-arid and coming up with thresholding criteria to map eroded areas would be difficult.

After classification was completed its accuracy was assessed according to (Lillesand et al., 2011). The accuracy assessment was carried out for the resulting image using ground reference data collected. A class with high accuracy indicates that the level of agreement between class assigned by the ground reference data and the class allocations by SVM classifier was of high degree. An error matrix (2*2) was prepared to express the accuracy. Assessment of the classification accuracy quantitatively was done by comparing two maps i.e. classification derived map and reference map. This referenced data was obtained from a combination of field collected point data and manually digitized eroded areas from higher resolution google earth imagery in an error matrix. The error matrix is a standard method of assessing the degree of accuracy and has been widely used in erosion classification accuracy assessment (Taruvinga, 2008). A total of 98 equalized random sample points (46 for non-erosion class and 50 for erosion class) were generated using eCognition tool for accuracy assessment. The results of the error matrix were interpreted using the overall classification accuracy statistics. The overall classification accuracy summarizes the producer's and the user's accuracy and is the ratio between the numbers of samples that are correctly classified and the total number of test samples.

3.8 Assessment of GEOBIA and models results.

Overlay analysis will be done on the two layers to help in the identification of vulnerable areas and hotspots according to the model and actual erosion status on the ground based on GEOBIA results. The common element for assessment would be spatial pattern and area coverage.

3.9 Field Validation.

Field validation was carried out to establish evidence of degradation. The field tools that were used included a camera for taking photos of degraded areas, note book and pen for jotting down the characteristics of hotspots based on observations and conversations with local communities and a handheld GPS for recording the coordinates of degraded spots. Due to budget limitations and the large size of the catchment, field validation was restricted to several hotspot areas.

CHAPTER 4: RESULTS AND DISCUSSIONS.

The combined use of GEOBIA and USPED erosion model has been used to assess the severity and spatial distribution of erosion in Lake Baringo catchment. For the USPED model the various model input parameters such as rainfall erosivity(R), vegetation cover management(C), soil erodibility (K) and topography factor were resolved. The results of USPED modelling and GEOBIA is shown in figure 4.3 and 4.4 respectively.

4.1 Spatial distribution of erosion.

4.1.1 Segmentation.

Segmentation process is needed in the development of OBIA method for detecting erosion. To come up with correctly classified images, suitable multiresolution segmentation with a scale factor of 50, 0.3 shape factor and 0.5 compactness value. Figure 4.1 shows the image obtained after level 1 segmentation process. In this segmentation eroded areas and vegetation cover have been captured.

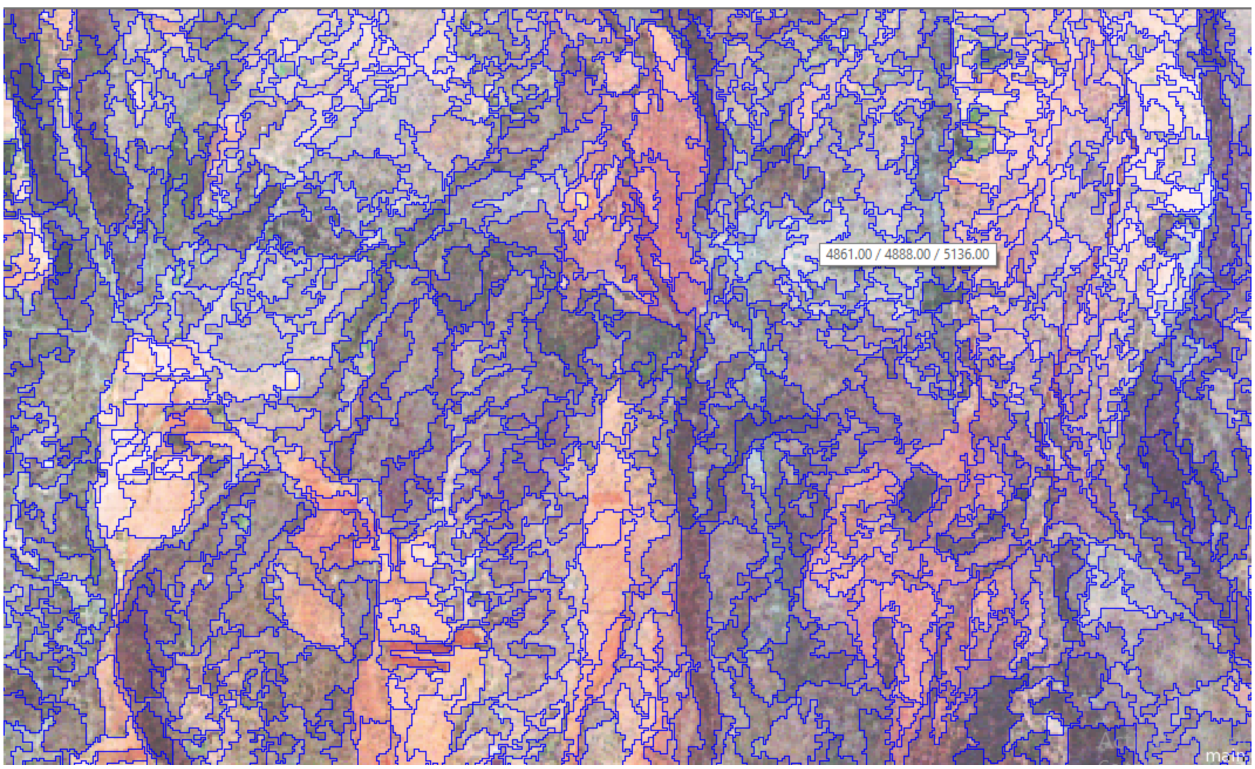
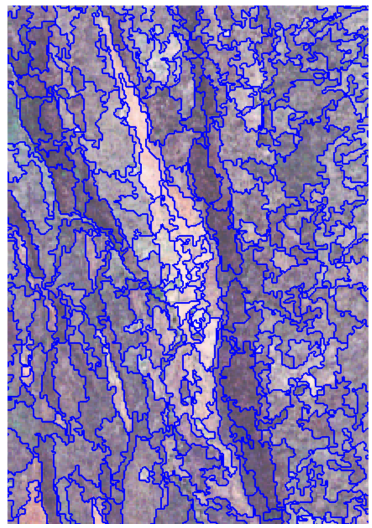


Figure 4.1 Level 1 segmentation results.

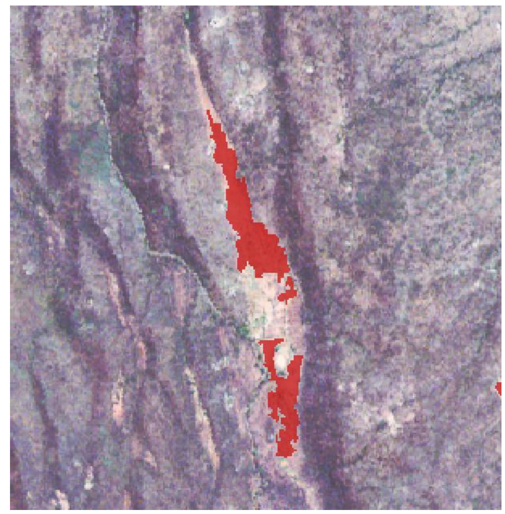
4.1.2 Classification.

GEOBIA classification approach led to a spatially exhaustive detection of erosion-affected areas. From classification results, the total land that is eroded is 123 km^2. These results show that eroded areas were able to be characterized and mapped as shown in figure 4.2.

RAPID EYE IMAGE SITE 1

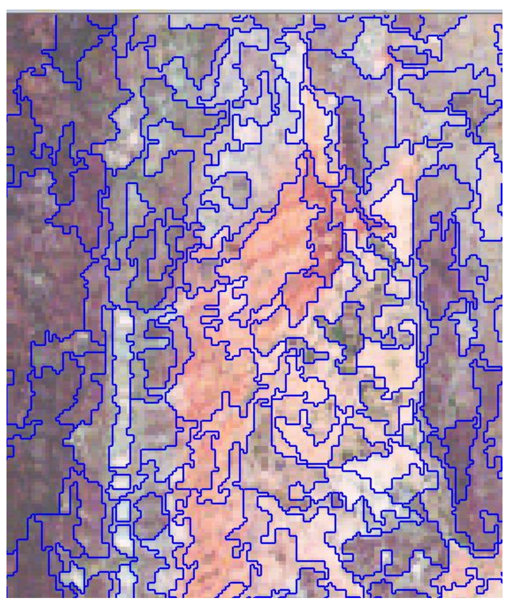


SEGMENTATION

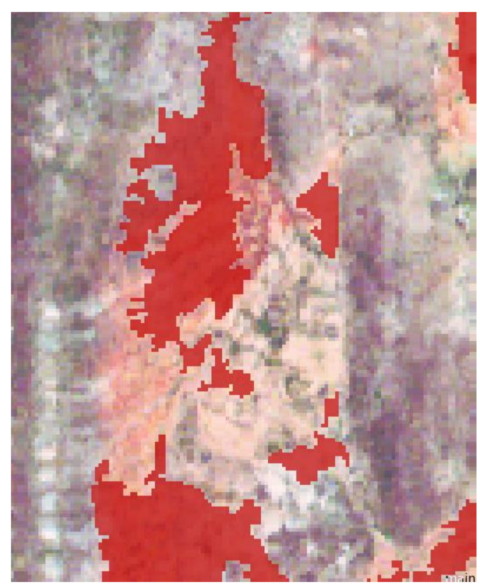


OBIA CLASSIFICATION RESULT

RAPID EYE IMAGE SITE 2

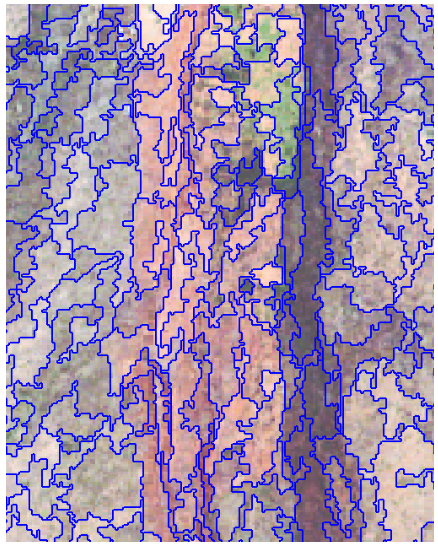


SEGMENTATION



OBIA CLASSIFICATION RESULT

RAPID EYE IMAGE SITE 3



SEGMENTATION

OBIA CLASSIFICATION RESULT

Figure 4.2 Zoomed in Screenshots showing OBIA results.

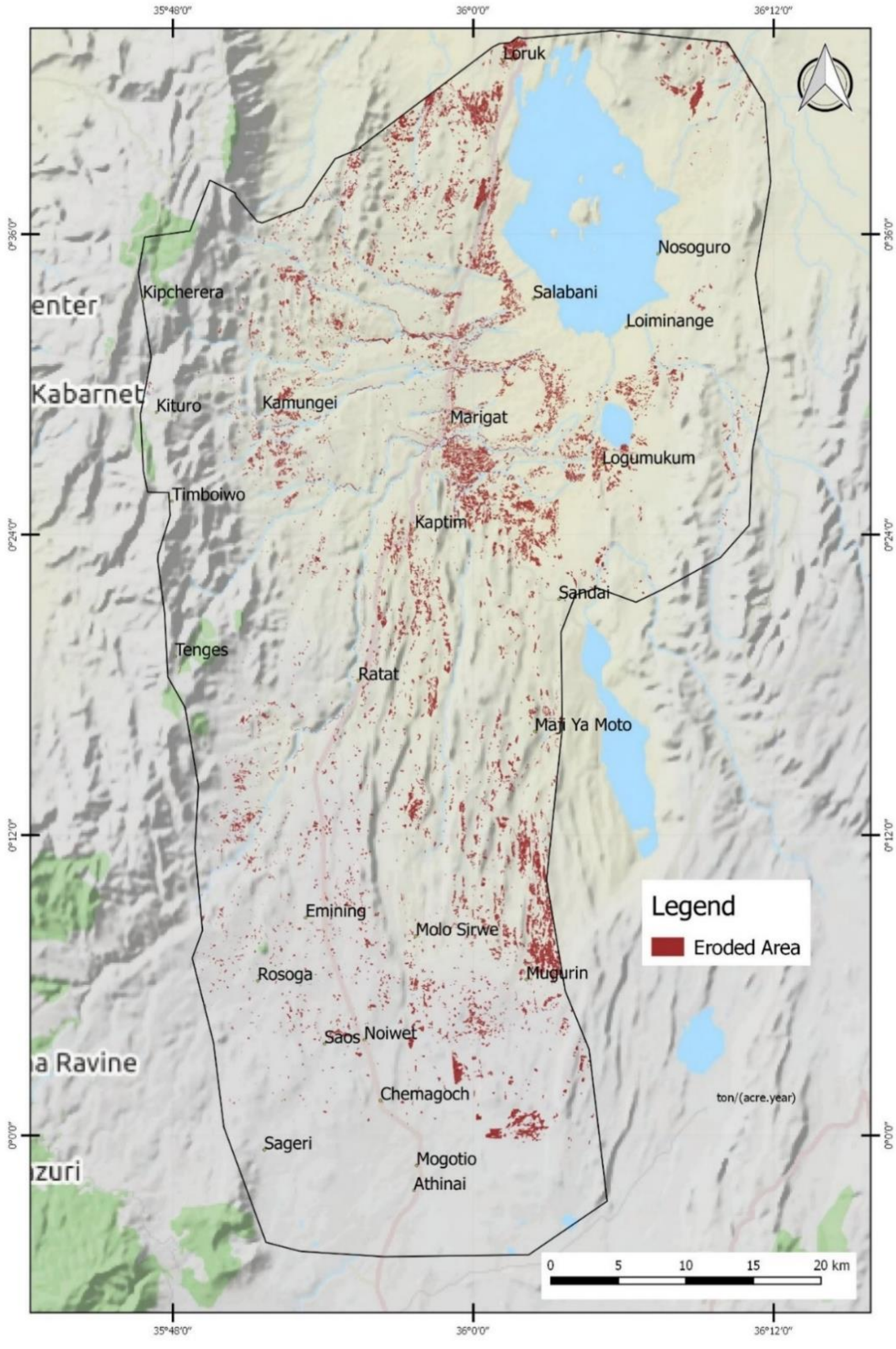


Figure 4.3 GEOBIA results spatial distribution of erosion for the whole Catchment.

4.1.3 Accuracy assessment Results.

Classification accuracy assessment enables a degree of confidence to be attached to the classification results. In this study, this was achieved by comparison between classification results with presumably correct information (ground reference) through conventional accuracy assessment. Table 4.1 below summarizes the accuracy statistics of derived erosion map in comparison with ground truth data. The GEOBIA map has the overall classification accuracy of 78.5%. The non-eroded class has the user's accuracy of 84.4%, the producer's accuracy of 76%. Erosion class has the user's and producer's of accuracy of 76.5% and 84.7% respectively.

Table 4.1 Summary of accuracy statistics.

		Reference Source		
Classified OBIA Map	Accuracy Report	Eroded Area	Non Eroded Area/other.	Total
	Eroded Area	39	12	51
	Non Eroded Area/other.	7	38	45
	Total	46	50	96

4.2 Erosion Model Results.

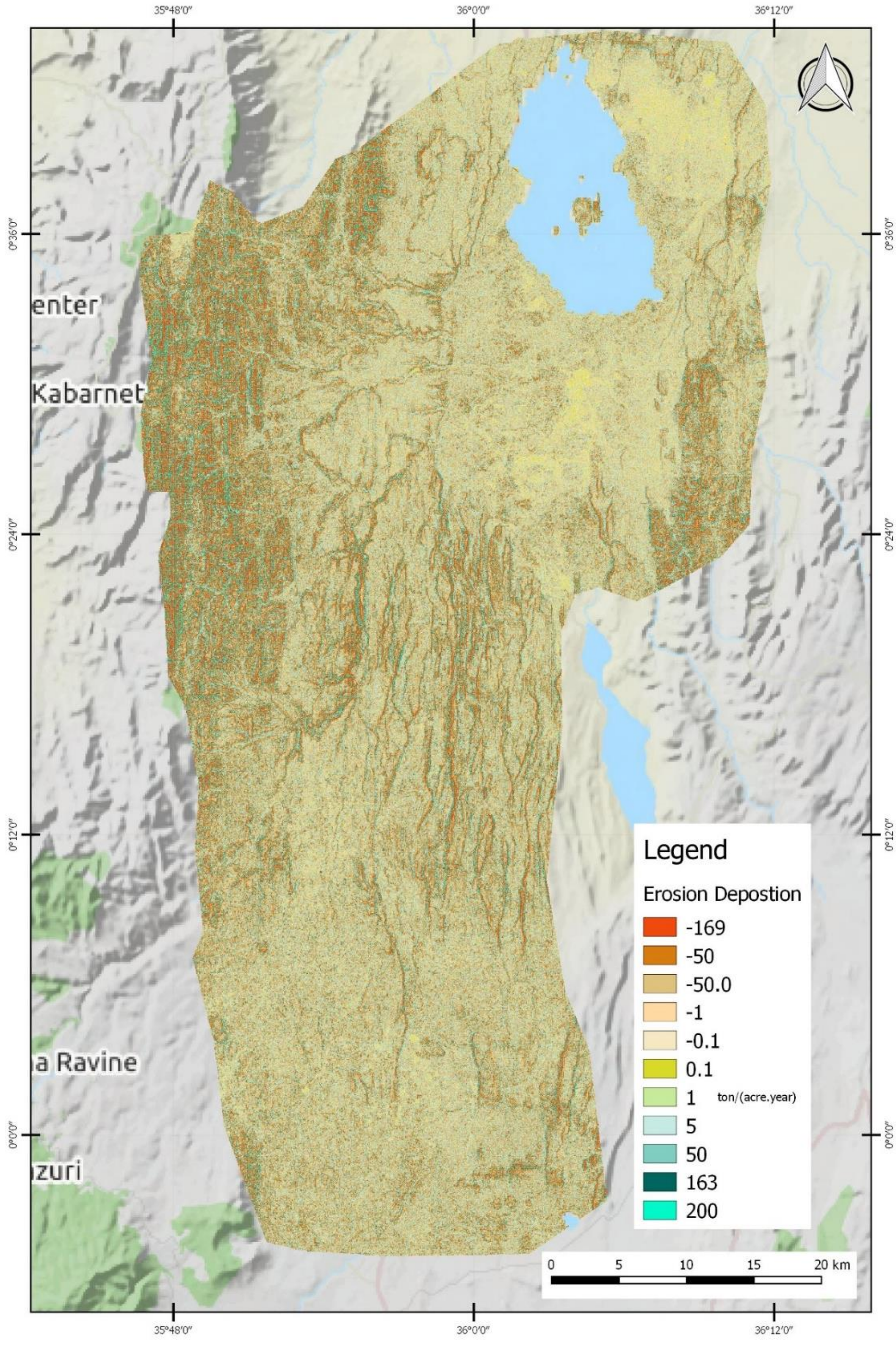


Figure 4.4 Spatial distribution of erosion-deposition (rates).

The resulting erosion-deposition USPED map shows a rich pattern of deposition and erosion typical for this catchment which has areas with complex topography and land cover. Variation in blue-green shades represents deposition whereas the orange-brown-yellow areas represent erosion and in figure 4.2. It has been observed that concentrated flow in river valleys and steep slopes for the highlands have the highest erosion rates, about one magnitude lower erosion is predicted in the agricultural fields.

Analysis of the USPED model results shows that around 56.5 % of the catchment area is affected by erosion. Only 0.8% of the catchment is stable and not affected by either erosion or deposition process. Deposition occurs in the remaining 42.7%. The stable areas and low erosion and deposition zones cover only 5.7 % of the area. Based on the model, erosion sites and deposition sites are adjacent to each other, especially near or within the stream networks. It is expected that not all of the eroded soil will be carried out of the fields as a substantial portion can be deposited directly in the field concave areas and at the border of the fields where water is slowed down by vegetative and the other land covers.

Based on the model results the total quantified erosion happening within the catchment is 59728.225 tonnes which is more than deposition 49603.05 tonnes yearly. This means that approximately 10125.18 tonnes of soil is deposited into the lake Baringo. This explains why during the last decade both the depth and the area of Lake Baringo have decreased dramatically due to siltation. The erosion model output was further reclassified to various classes based on the USPED design estimates as shown in table 4.1 and figure 4.5.

Major erosion hotspots were found to be areas surrounding around Radat, Kaptim, Kipcherera and Molo sirwe. The study further noted that the areas experiencing very low degradation were forested areas. These are areas occupied by the Tugen hills forest.

Table 4.2 USPED Classified Erosion Results.

Erosion Deposition **ton/(acre.year)**	**Description**	**Area(km^2)**	**Percentage (%)**
-169 - -50	Severe Erosion	300.8	10.8
-50 - -5	High Erosion	939.5	33.8
-5 - 1	Moderate Erosion	254.7	9.3
-1 - -0.1	Low Erosion	72.5	2.6
-0.1 - 0.1	Stable	23.0	0.8
0.1 - 1	Low Deposition	64.0	2.3
1 - 5	Moderate Deposition	203.2	7.4
5 - 50	High Deposition	632.3	22.7
50 - 200	Severe Deposition	287.0	10.3
	TOTAL	2776.8	100

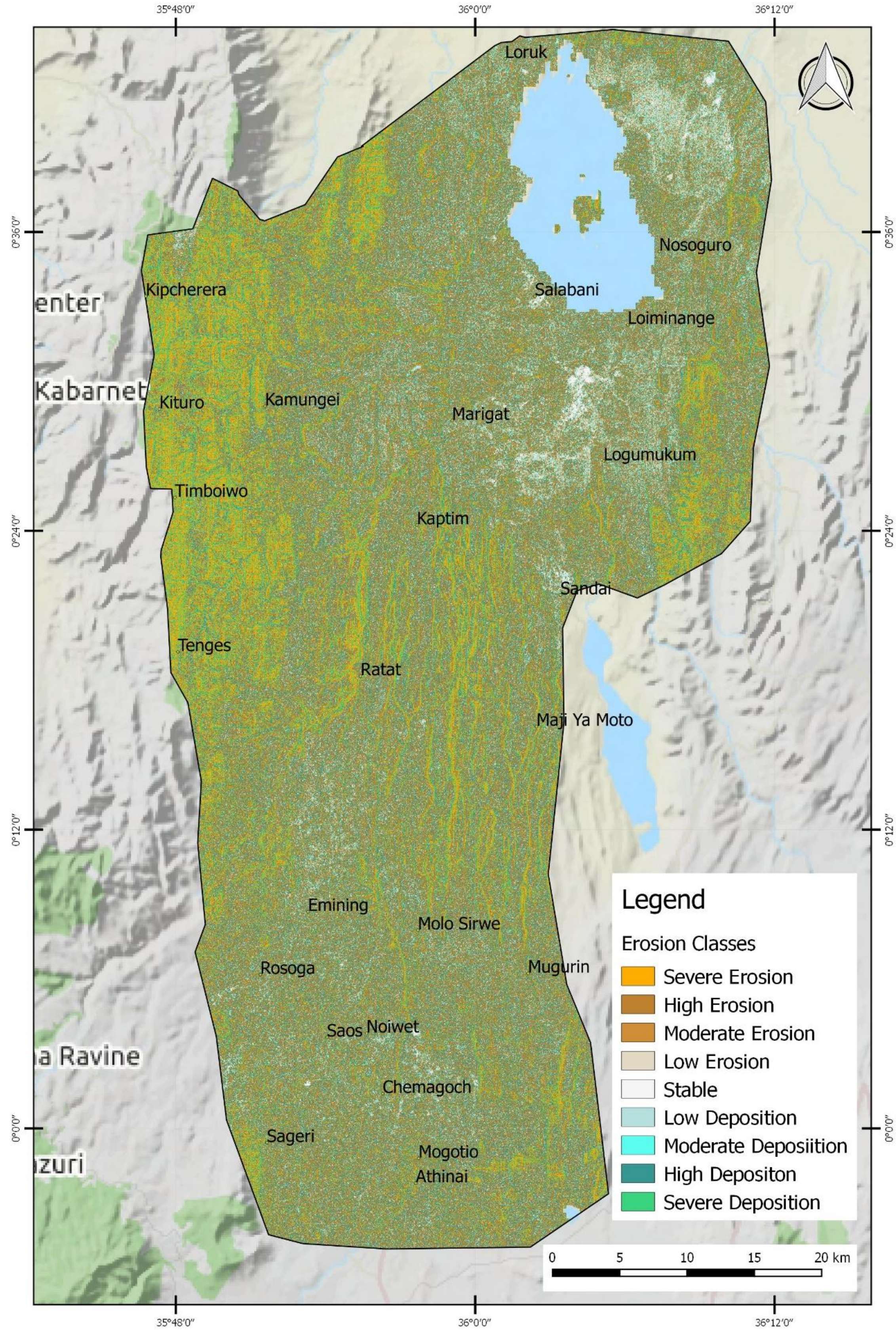

35°48'0"
36°0'0"
36°12'0"
0°36'0"
0°24'0"
0°12'0"
0°0'0"
Loruk
Nosoguro
Kipcherera
Salabani
Loiminange
enter
Kabarnet
Kituro
Kamungei
Marigat
Logumukum
Timboiwo
Kaptim
Sandai
Tenges
Ratat
Maji Ya Moto
Emining
Molo Sirwe
Rosoga
Mugurin
Saos
Noiwet
a Ravine
Chemagoch
Sageri
Mogotio
Athinai
zuri
Legend
Erosion Classes
Severe Erosion
High Erosion
Moderate Erosion
Low Erosion
Stable
Low Deposition
Moderate Deposiition
High Depositon
Severe Deposition
0
5
10
15
20 km

Figure 4.5 USPED Classified Erosion Results.

4.2.1 Rainfall Erosivity Factor.

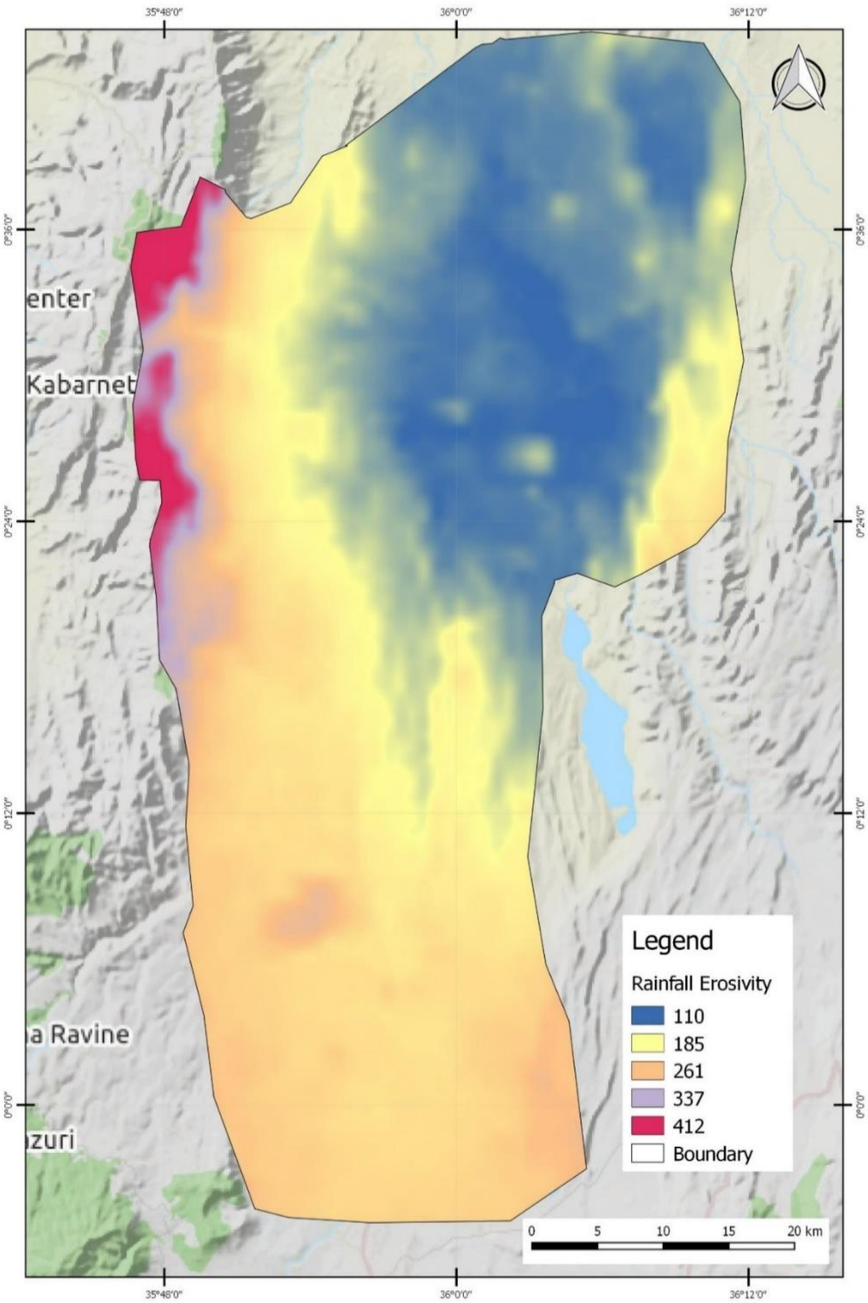


Figure 4.6 Erosivity Factor Map

The spatial distribution of the R factor for the area of study is shown in figure 4.6. The average annual R factor value varies from 110 to 412 $MJmmha^{-1}year^{-1}$.More rainfall erosivity was observed in the western part of the catchment with higher elevation (Tugen hills) as indicated with the red colour. If rainfall was the only factor affecting erosion then the western part of the catchment would be affected most in terms of the soil erosion.

4.2.2 Vegetation Cover management Factor.

The C factor represents the effect of cropping and agricultural management practices as well as the effect of tree and grass covers on reducing soil loss. As the vegetation cover increases, the soil loss decreases. In general it was noted that the C factor has an inverse relationship with NDVI. The C factor value varies from 0.04 to 1.4 and its mean is 0.73. As seen in figure 4.7, the far western and east region of the watershed have the lowest values. This is attributed to the presence of forest. Bareland has the highest values of C factor as indicated by the vibrant green colour.

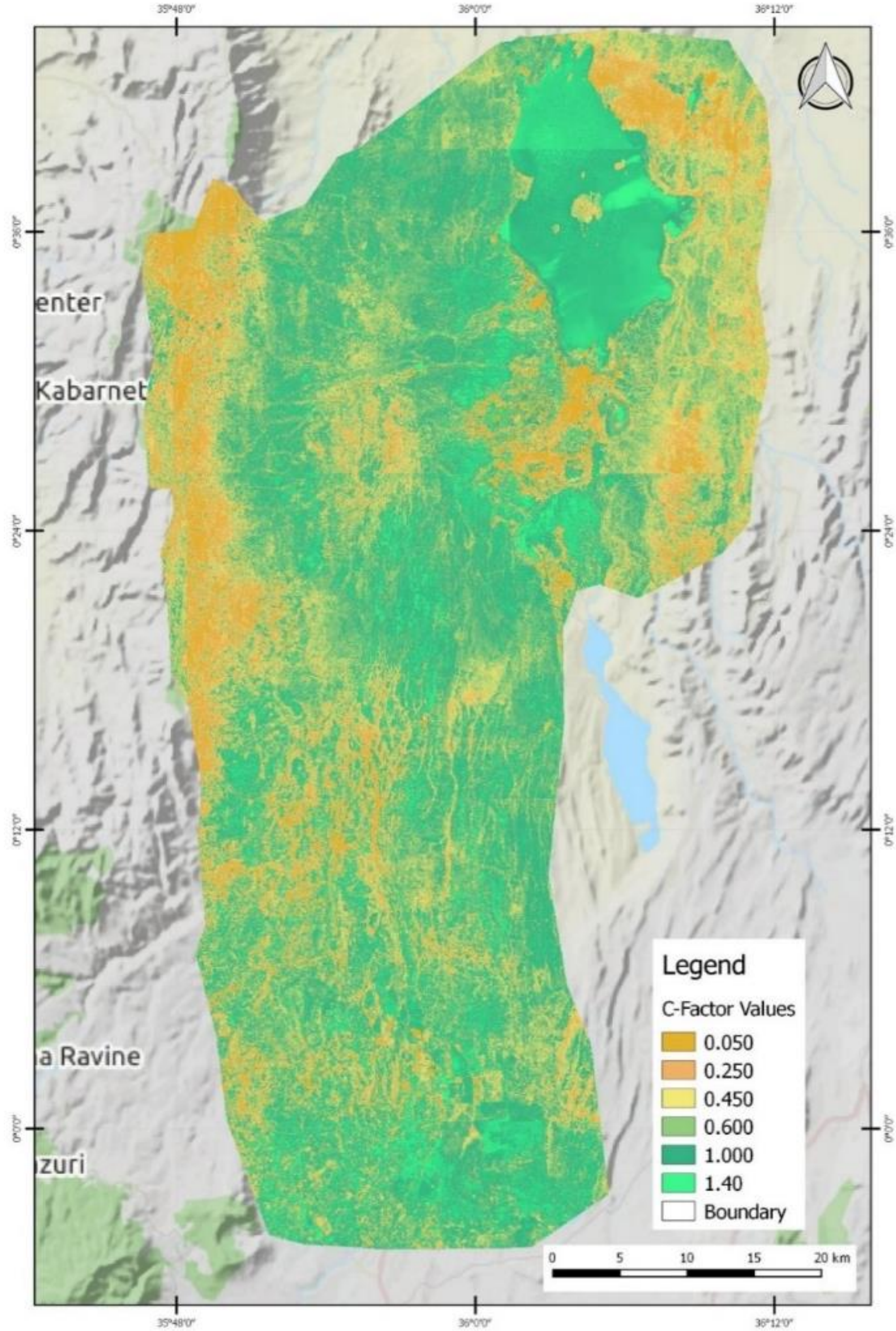


Figure 4.7 Cover Management Factor.

4.2.3 Soil Erodibility Factor.

The average soil erodibility factor value in the study area varies from 0.004 to 0.022 t ha h $MJ^{-1}ha^{-1}$ mm^{-1} and the mean value is 0.0167 t ha h $MJ^{-1}ha^{-1}$ mm^{-1} as shown in figure 4.8. The standard deviation is 0.0015. It can be seen from the soil erodibility map that the K factor value is higher in the some patches spread all over the catchment. These regions have a high content of silt except for some particular places.

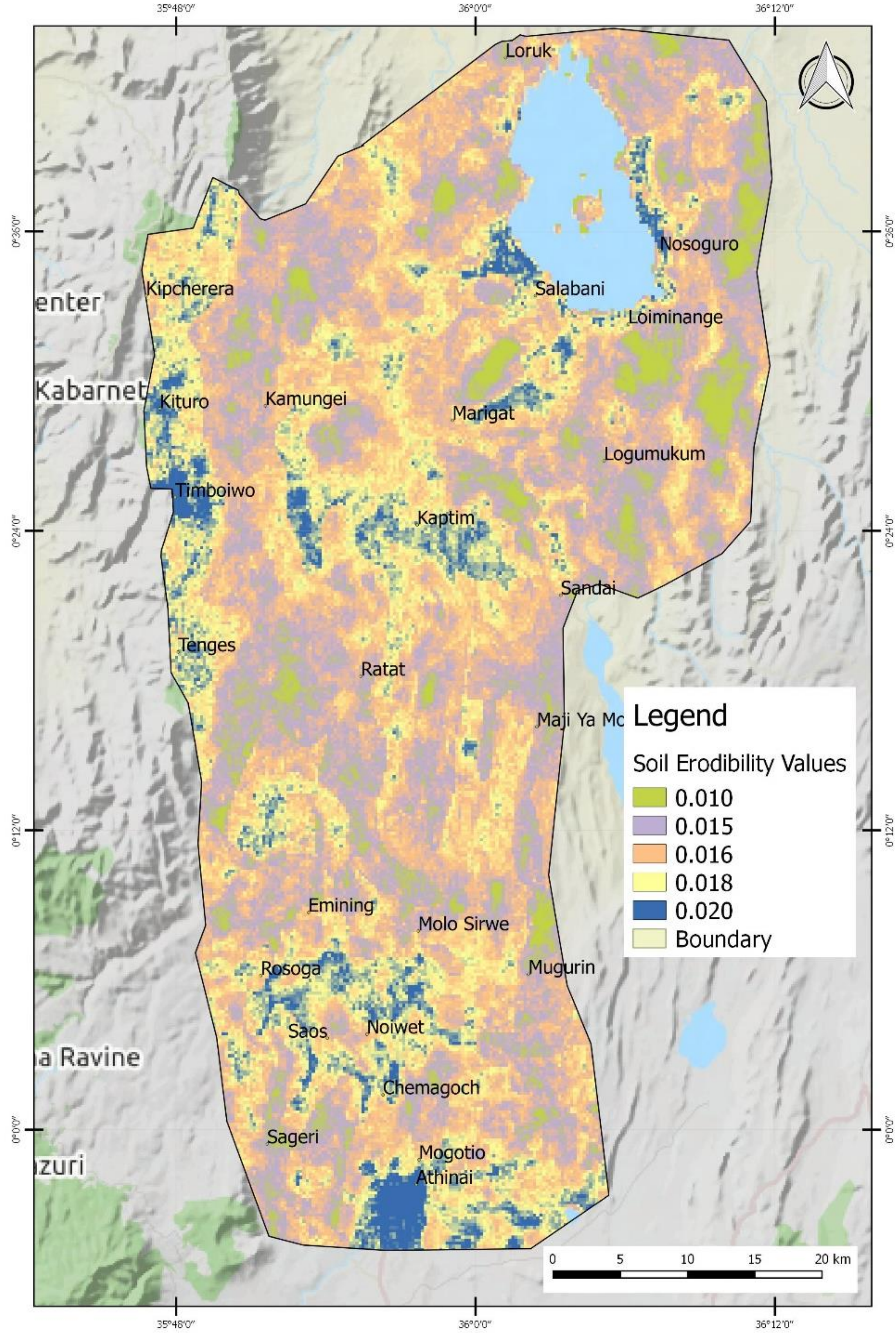


Figure 4.8 Soil Erodibility Factor.

4.2.4 Support Practice Factor.

Since data was lacking on permanent management factors and there were no management practices, P- factor values suggested by Wischmeier and Smith (1978); that consider only two types of land uses (agricultural and non-agricultural) and land slopes were used. Agricultural land was assigned values based on slope values as shown in table 3. Other land use classes were assigned a value of 1.

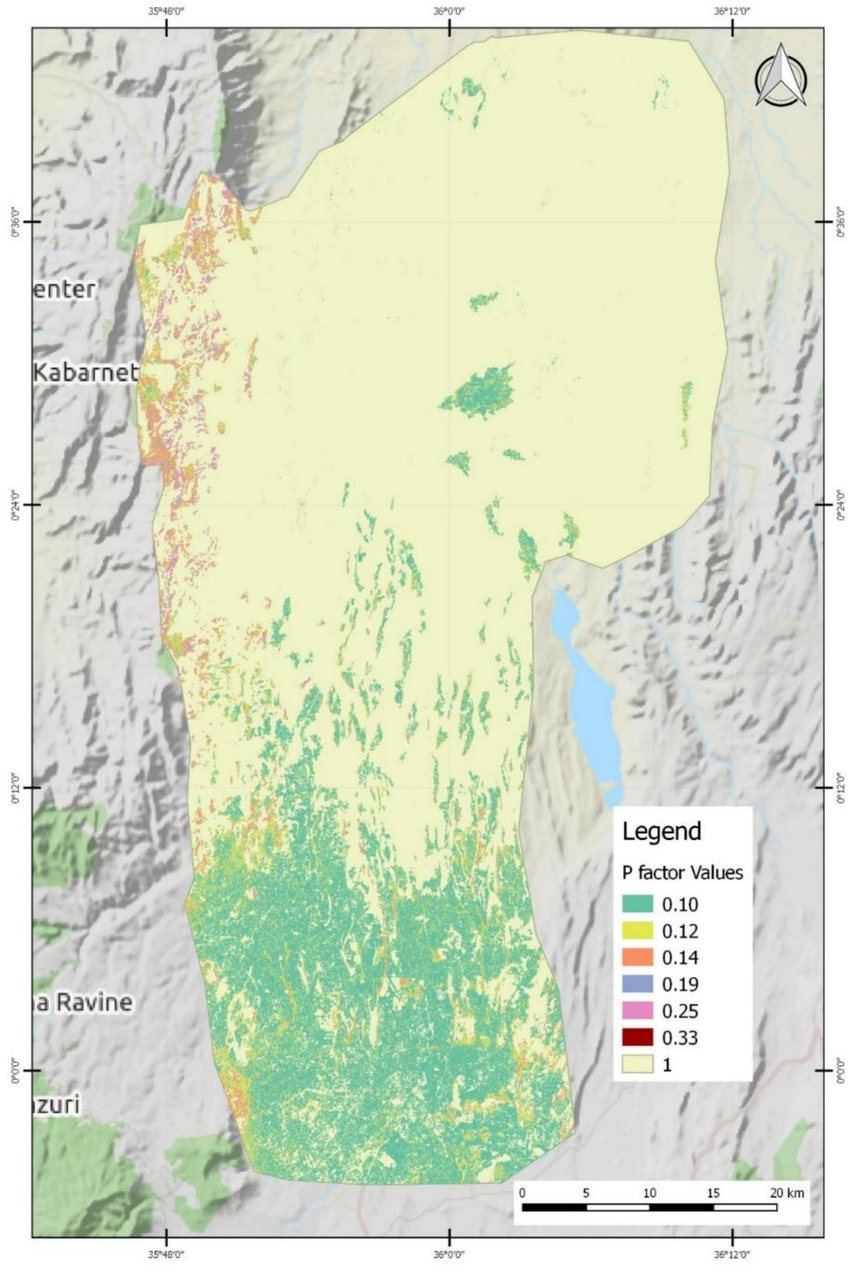


Figure 4.9 Support Practice Factor

4.3 Discussion of the results.

Overall and as observed by findings from field validation at Lake Baringo Catchment, massive land degradation through soil erosion in the catchment is experience in several locations as located by GEOBIA and USPED model. This is caused by a combination of poor agriculture practice in the basin which results in vegetation clearance and exposure of topsoil to erosion agents. A large part of the basin is occupied by small holder farmers practicing arable and mixed agriculture. Lack of awareness combined by poor agricultural extension services in the marginalized rural setups acts as the precursor to the hazard.

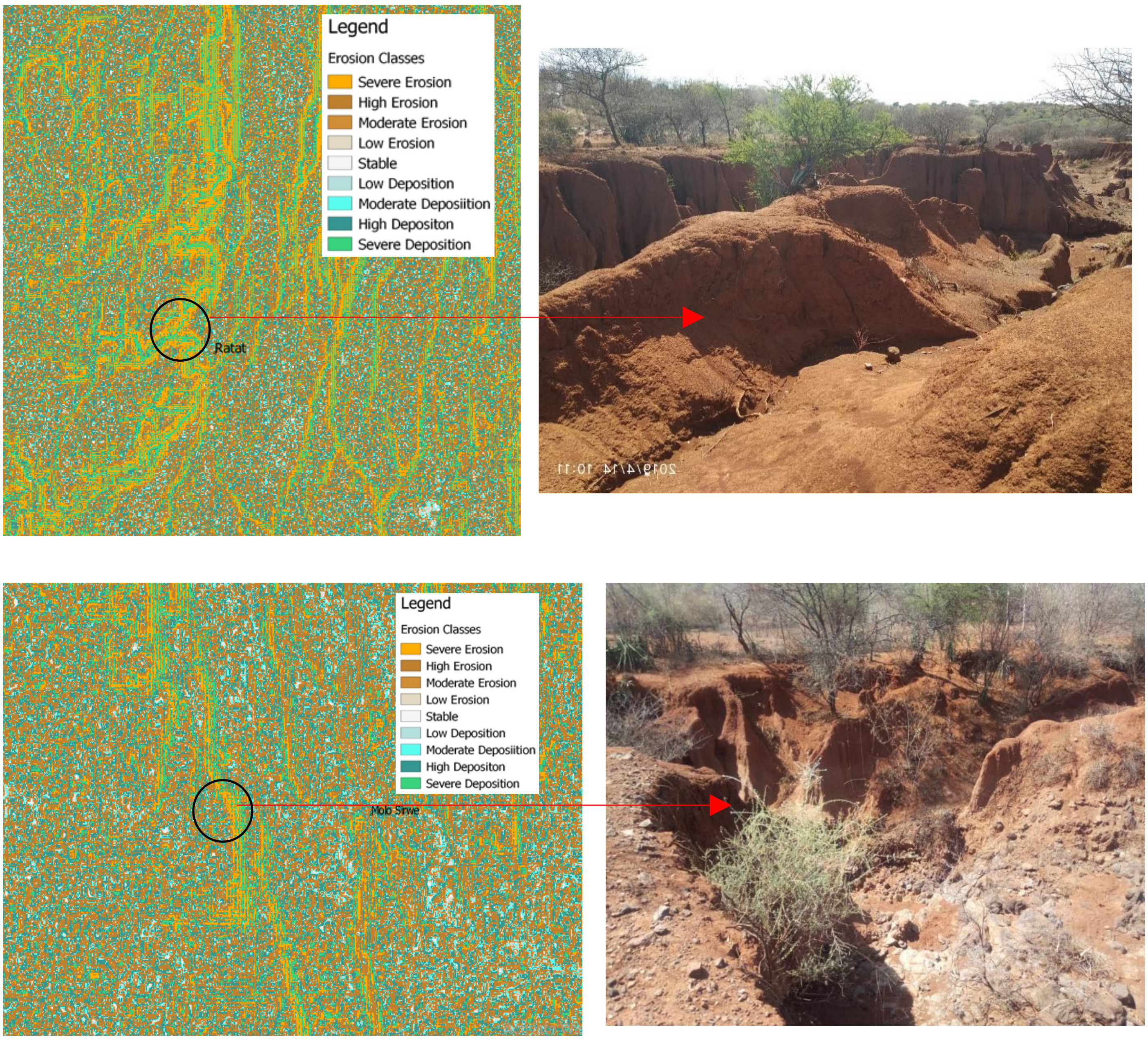


Figure 4.10 Erosion Hotspot at Ratat Area and Molo Sirwe at Lake Baringo Catchment.

The Erosion Deposition model result clearly shows that nearly 56.5 percent of the lake Baringo catchment area requires application of different soil conservation measures to promote sustainable management of land resources. Implementing of conservation measures could also be prioritized based on the different severity levels such that only selected areas that are severely affected are given more attention to help reduce soil loss. The lack of understanding among farmers of soil loss or their lack of participation in conservation measures may, however, limit the implementation of soil conservation technologies to a few priority areas only.

CHAPTER 5: CONCLUSIONS AND RECOMMENDATIONS

5.1 Conclusions

In this project, the use of GEOBIA and USPED erosion model has proved useful and effective in assessing land degradation in Lake Baringo catchment. The model output which is a quantified erosion risk map shows the spatial variation in soil erosion severity in the catchment enabling the study to point out the major land degradation hotspots in the catchment which are mainly found around these areas: Radat, Kaptim, Kipcherera and Molo sirwe. Stakeholders in erosion management can have added benefit of knowing areas to prioritize for soil conservation. This information on the nature, extent, severity and geographic distribution of degraded land is of paramount importance for planning reclamation strategies and setting up preventive measures for sustainable natural resource management. From a conservation perspective, 10.8% of the watershed needs immediate watershed management intervention.

GEOBIA method can be beneficial for erosion detection and mapping, not only in Kenya, but in other regions around the world. The potential of using GEOBIA to map areas of severe erosion provides a means of obtaining valuable information on the extent, nature and magnitude of erosion in rural areas. This study has demonstrated that GEOBIA can be used for the spatial assessment of the driving forces present at different scales which is considered to be fundamental in future steps towards controlling erosion in Kenya.

This improved assessment method that combines GEOBIA and USPED model can thus be applied in other parts of Kenya for assessment and delineation of erosion-prone areas for prioritization of areas for conservation. The method is an efficient use of limited resources with limited field work.

This study therefore has fully achieved its objectives which were to review the application of object based image analysis for soil erosion assessment; to identify suitable data for soil erosion assessment; to map soil erosion by applying object-based image analysis and to model soil erosion rates.

5.2 Recommendations.

Generally, this research study provided an approach for spatial assessment of soil erosion in Lake Baringo Catchment by using GEOBIA and USPED model. This is an improved technique to predict and map land degradation at catchment scale. However, when running the model an error occurrence in any of the input data or factor values will produce an equivalent error in the estimation of erosion and deposition. If each parameter is better estimated, the accuracy of the predicted erosion and deposition can be improved. For instance, R factor value can be improved by using rainfall intensity data and direct storm energy data which was not available during the study. The C factor and P factor can be improved by using a higher resolution satellite imagery. Verification with independent datasets is required to assess the accuracy of the produced model maps. This can be obtained from detailed soil surveys.

REFERENCES

Arnoldus, H. (1980). An approximation of the rainfall factor in the Universal Soil Loss Equation. *Assessment of Erosion, John Wiley and Sons, New York*, 127–132.

Bergsma, E. (1974). Soil erosion sequences on aerial photographs. *ITC Journal 3*, 342-376.

Bonilla, C. R. (2010). Water erosion prediction using the revised universal soil loss equation (RUSLE) in a GIS framework. *Chil. J. Agric*, 159-169.

Dwivedi, R. S. (2018). *Geospatial Technologies for Land Degradation Assessment and Management.* CRC Press .

Eswaran, H. &. (2001). Land degradation: An overview. Responses to Land Degradation. *2nd International Conference on Land Degradation and Desertification*, (pp. 20-35). KhonKaen, Thailand.

FAO. (2011). *The state of the world's land and water resources for food and agriculture (SOLAW) - Managing systems at risk.* Rome.: Food and Agriculture Organization of the United Nations & London, Earthscan.

Haghighat, A. M. (2010). Investigation of Some Methodologies in Providing Erosion Maps of Surface, Rill and Gully and Erosion Features. *International Journal of Geological and Environmental Engineering*.

Herweg, K. (1996). *Field Manual for Assessment of Current Erosion Damage.* Switzerland: 69 pp.: SCRP Ethiopia, and Centre for Development and Environment, University of Berne.

Hudson, N. (1981). *Soil Conservation..* London: Batsford.

Hudson, N. (1993). *Field measurement of soil erosion and runoff.* Rome, Italy: FAO Soils Bulletin, 68. Food and Agriculture Organization.

Jetten, B. S. (2011). Object-based gully feature extraction using high spatial resolution imagery. *Geomorphology 134*, 260-268.

Johansson, J. (2002). *Land Degradation In the semi-arid catchment of Lake Baringo, Kenya a minor field study of physical causes with a socioeconimic aspect.* Earth Science Centre.

Kassam, A. V. (1992). *Agro-ecological land resources assessment for agricultural development planning. A case study of Kenya. Resources data base and land productivity. Main Report.... Annex 1.* FAO.

Khoboso, E. S. (2018). Developments in the remote sensing of soil erosion in the perspective of sub-Saharan Africa. Implications on future food security and biodiversity. *Remote Sensing Applications: Society and Environment*, 100–106.

Knight, J. S. (2007). Large-Area, High-Resolution Remote Sensing Based Mapping of Alluvial Erosion in Australia's Tropical Rivers. *5th Australian Stream Management conference.* Griffith Research Online.

Koena, S. T. (2018). An appraisal on the progress of remote sensing applications in soil erosion mapping and monitoring. *Remote Sensing Applications: Society and Environment*, 1- 9.

Kumar, N. P. (2006). Tropical homegardens: a time-tested example of sustainable agroforestry. *Springer Science*, Dordrecht 380p.

Lal, R. (2001). Soil degradation by erosion. *Land Degradation & Development*, 519-539.

Lillesand, R. T. (2000). *Remote Sensing and Image Interpretation.* John Wiley and Sonc,Inc.

Merritt, W. L. (2003). A review of erosion and sediment transport models. *Environmental Modelling & Software 18 (8-9):* 761-799.

Mitas, L. a. (1998). Distributed soil erosion simulation for effective erosion prevention. *Water Resources Research 34(3)*, 505- 516.

Mitasova, H. &. (1997). Modeling topographic potential for erosion and deposition using GIS. *International Journal of Geographical Information Science.* .

Mitasova, H. H. (1996). Modeling topographic potential for erosion and deposition using GIS. *International Journal of GIS*, 629-641.

Mitasova, H. L. (1997). *GIS tools for erosion/deposition modeling and multidimensional visualization.* Geographic Modeling and Systems Laboratory, University of Illinois at Urbana-Champaign, Urbana, Illinois.

Morgan, R. P. (1995). *Soil Erosion and Conservation* . London: Longman Group Limited.

Morgan, R. P. (2005). *Soil Erosion and Conservation.* Wiley-Blackwell.

Nearing, M. G. (1999). Variability in soil erosion data from replicated plots. *Soil Science Society of America Journal 63 (6)*, 1829-1835.

Nigussie, H. A. (2017). Comprehensive assessment of soil erosion risk for better land use planning in river basins: Case study of the Upper Blue Nile River. *Science of the Total Environment*, 95 - 108.

Oltmanns, I. M. (2014). Detection of Gully-Affected Areas by Applying Object-Based Image Analysis (OBIA) in the Region of Taroudannt, Morocco. *Remote Sensing MDPI*, 8287-8309;.

Pirie, A. (2009). *Gully erosion mapping using SPOT 5 satellite imagery.* Pretoria, South Africa.: Honours research report, University of Pretoria.

Pistocchi, G. A. (2002). Use of the USPED model for mapping soil erosion and managing best land conservation practices. *International Congress on Environmental Modelling*.

RCMRD. (2015). *The Monitoring for Environment and Security in Africa programme (MESA) technical documentantation : Land Degradation Assesment Service.*

Renard, K. (1997). *Predicting Soil Loss: A Guide to Conservation Planning with the Revised Soil LossEquation (RUSLE). Handbook.* Washington DC, USA: US Dept Agriculture.

Sanyu. (2001). *The Study on the integrated Rural Development Project in the Baringo Semi Arid Land Area, Master Plan, Japan International Cooperation Agency (JICA),.* Ministry of Agriculture and Rural Development (MOARD).

Sebastian, D.-O., B. K., & Coenradie, B. (2011). An Object-Based Classification Approach for Mapping Migrant Housing in the Mega-Urban Area of the Pearl River Delta. *mdpi-remote sensing*, 1710-1723.

Servenay, A. (2003). Erosion extension of indurated volcanic soils of Mexico by aerial photographs and remote sensing analysis. . *Geoderma volume 117*, 367-375.

Shinde, K. N. (2010). Prioritization of micro watersheds on the basis of soilerosion hazard using remote sensing and geographic information system. *International Journal of Water Resources and Environmental Engineering Vol. 2(3),*, 130-136,.

Shruthi, N. K. (2011). Object-based gully feature extraction using high spatial resolution imagery. *Elsevier Geomorphology 134*, 260–268.

Slaymaker, O. (2003). The sediment budget as conceptual framework and management tool. . *Hydrobiologia 494.*, 71-82.

Stroosnijder, L. (2005). *Measurement of erosion: is it possible?* 162-173: Catena 64 (2-3).

Sutherland, B. R. (1986). Erodibility of soils in Baringo District. *Department ofGeography, University of Toronto, Canada.*

Sutherland, B. R. (1992). Accelerated Erosion in a Semi-arid Region: The Baringo District, Kenya, Soil Conservation for Survival. *Sixth International Soil Conservation Conference,.* Addis Ababa.

Trimble. (2015). *eCognition Developer 9.1 – User Guide (version 9.1.2).* Munich: Trimble Germany GmbH.

UNCCD. (1994). *United Nations Convention to Combat Desertification.* Retrieved from http://catalogue.unccd.int/936_UNCCD_Convention_ENG.pdf

UNCCD. (2013). *A Stronger UNCCD for a Land-Degradation Neutral World.*

UNDP. (2015). *Sustainable Development Goals*. Retrieved from http://www.ke.undp.org/content/kenya/en/home/sustainable-development-goals.html

Valentin, C. &. (2005). Gully erosion: Impacts, factors and control. *CATENA*.

Van der Knijff, J. J. (2000). *Soil Erosion risk Assessment in Europe.* European Commission, European Soil Bureau,.

Vigiak, O. O. (2005). Modelling catchment-scale erosion patterns in the East African highlands. . *Earth Surface Processes and Landforms 30 (2):*, 183-196.

Vrieling, S. G. (2006). Spatial evaluation of soil erosion risk in the West. *Land Degradation and Development*, 301-319.

Vrieling, S. C. (2007). Automatic identification of erosion gullies with ASTER imagery in the Brazilian Cerrados. *International Journal of Remote Sensing*, 2723–2738.

WAC. (2008). *Restoring Kenya's Degraded Land.* Retrieved from World Agrofestry Centre: http//www.worldagroforestry.org/ar2004/te_story02.asp.

Wang, Z. J. (2010). An automatic region-based image segmentation algorithm for remote sensing applications. *Environmental Modelling and Software*, 1149–1165.

Williams, J. M. (1996). Using soil erosion models for global change studies. *Journal of Soil and Water Conservation*, 381-385.

Wischmeier, W. H. (1976). *Predicting Rainfall Erosion Losses —A Guide To Conservation Planning.* United States Department of Agriculture,.

Xin Yang, W. D. (2017). Deriving Ephemeral Gullies from VHR Image inLoess Hilly Areas through Directional Edge Detection. *International Journal of Geoinformation*, 371.

Yuliang, Q. A. (2002). Fast soil erosion investigation and dynamic analysis in the Loess Plateau of China by using information composite technique. *Advances in Space Research 29 (1)*, 85-88.

Zhou, P. O. (2008). Effect of Vegetation Cover on Soil Erosion in a Mountainous Watershed. *Catena vol 75*, 319–325.

Zizala, T. Z. (2017). Assessment of Soil Degradation by Erosion Based on Analysis of Soil Properties UsingAerial Hyperspectral Images and AncillaryData, Czech Republic. *Remote Sensing*, 28.

.