International Journal of Agriculture, Environment and Bioresearch

Vol. 3, No. 06; 2018

ISSN: 2456-8643

ASSESSMENT OF LAND DEGRADATION BY RUSLE MODEL USING REMOTE SENSING AND GIS: A CASE STUDY OF KENYA'S LAKE VICTORIA BASIN

Siro Ali Abdallah
The University of Nairobi, Department of Geospatial and Space Technology
Tabitha Mukami Njoroge
The University of Nairobi, Department of Geospatial and Space Technology
John Odera Jaoko
Maseno University, School of Environment and Earth Sciences

ABSTRACT

The Lake Victoria Basin is facing major environmental challenges that have caused considerable hardship for the population depending on it for their livelihoods and have also reduced the biodiversity of the lake's flora and fauna. Deforestation coupled with bad agricultural practices has persistently exacerbated the problem of land degradation in the basin and sedimentation in the lake. Assessment of land degradation hazard is considered essential for soil conservation plans in the basin for sustainable development. The objective of this study was to identify and map the extent and severity levels of land degradation caused as a result of soil erosion by water on the Kenyan section of Lake Victoria basin (LVB) in order to support informed decisions for prioritizing and combating land degradation menace in the basin. We used Geospatial techniques and empirical soil erosion modeling techniques, mainly the Revised Universal Soil Loss Equation (RUSLE) Model that looked at five key soil erosion control parameters: vegetation cover, rainfall erosivity, slope factor, soil erodibility, and population density data as input variables. The results from modeling were subjected to field assessment in one of the identified hot spots in Bolo area in Kisumu County. Major erosion hotspots were found to be areas around Mumias, Bunyore, Kisumu, Kendu Bay, Ahero and south-western parts of Homa Bay. This study revealed that the lead contributing factor to soil erosion in the basin was soil erodibility component followed by rainfall erosivity, vegetation cover management, population density and finally slope factor. The study recommends comprehensive catchment level degradation assessment to be undertaken and prioritise the most affected areas.

Keywords: Land Degradation, RUSLE model, Lake Victoria Basin, GIS, Remote Sensing

1. INTRODUCTION

Land degradation is an enormous environmental challenge, in Africa, it is estimated that the annual decrease in productivity due to soil erosion is at 2-40% with an average of 19% of water reservoir being silted annually (Anderson, 2010). In Kenya, land degradation is widespread and affects millions of people who also experience poverty and repeated natural disasters such as drought and floods. According to UNEP (2002), weak knowledge of the nature, extent, and

severity of land degradation, and the inadequacy of tools and methods for assessment and monitoring of this phenomenon hamper the adoption of integrated resources use and management policies and rehabilitation programs.

Studies on spatial and temporal patterns of land degradation estimate increasing severity and extent in Kenya, according to Muchena (2008), over 20 per cent of all cultivated areas, 30 per cent of forests, and 10 per cent of grasslands have been subjected to degradation and primarily attributed to expansion of agriculture into marginal lands. Bai & Dent (2006) identified the dry lands around Lake Turkana in northern Kenya and marginal cropland in the Lake Victoria basin as the areas of sharpest decline. Lake Victoria, with a surface area of 68 000 km^2 is the world's second largest freshwater lake and is a main source of the River Nile. Accelerated soil erosion and nutrient runoff, urban and industrial pollution, and atmospheric deposition have induced a rapid rise in nutrient levels in the lake. This has, in turn, led to changes in the lake ecology, and a prolific growth of aquatic weeds dominated by the invasive water hyacinth (Bullock *et al.*, 1995). As a result, the fishery industry, the direct economic mainstay for half a million people in the lake basin, is in decline. The undermining of the integrity of the ecosystem coupled with poor farming practices have led to persistently growing land degradation in Lake Victoria basin and UNESCO (2006), attributes 45 percent of the Lake Victoria basin to being prone to water erosion leading to sediments deposited in the lake through mouths of rivers such as Nzoia and Kagera. In supporting this assertion WAC (2008) notes that since 1963, 3.2 million tons of soil (or the equivalent to one million truckloads) have been washed into Lake Victoria.

The need to quantify the amount of erosion in a spatially distributed form has become essential at the basin scale and in the implementation of conservation efforts (Fernandez *et al.*, 2003). In many situations, land managers and policymakers are more interested in the spatial distribution of soil erosion risk than in absolute values of soil erosion loss (Lu *et al.*, 2004). In addition, the use of conventional methods to soil erosion assessment tends to be expensive and time-consuming. Therefore, recent developments in assessing soil erosion recommend fusing of statistical techniques with the existing empirical techniques like the Universal Soil Loss Equation (USLE) and Revised Universal Soil Loss Equation (RUSLE) to effectively assess the sensitivity to soil erosion (Li *et al.*, 2006). Multi-criteria analysis has largely the causal factors. The RUSLE model can predict erosion potential on a cell-by-cell therefore, it is effective when attempting to identify the spatial pattern of the soil loss present within a large region. GIS techniques can be used to isolate and query these locations to identify the role of individual variables contributing to the observed erosion potential value. Keeping in view of the above aspects, the objectives of the present study are made (Ganasri & Ramesh, 2015). This study thus seeks to answer the problem by assessing and mapping land degradation severity levels in the Lake Victoria Basin using geospatial techniques.

2. DESCRIPTION OF THE STUDY AREA

The Lake Victoria Basin (LVB) is one of Africa's largest trans-boundary water resources covering an area of 68,800 km^2. The Kenyan part of the basin is 42,724 km^2. According to

LVBC (2007), the basin's geographical area is delineated by the watershed limits of the of surface and underground water flowing into the lake consisting of the following rivers: the Nzoia, Sio, Mara, Yala, Awach, Gucha, Migori and Sondu. The elevation of the entire Lake Victoria basin falls within 1078m to 4061m above sea levels with the lowest sides being around lake Victoria while the highest regions being the North Western sides of the basin around Mount Elgon.

2.1 Geology and Soils

The basin is surrounded by Precambrian bedrock however, the Winam Gulf is dorminated by Tertiary and Quaternary alkali volcanic and sedimentary units. River erosion has exposed lacustrine deposits to the west of Lake Victoria thus showing the origin of the Lake is as a result of the uplifting of the East African Rift Valley leading to back ponding of rivers that flowed westward (Okungu *et al.*, 2005). The Basin is characterized by different types of soils suitable for a variety of crops. Ferrosols are dominant within the lower parts of the Basin which are characterized by strong acidity and low in base saturation. Vertisols, which are also common, are dark-coloured-clays that expand and contract markedly with changes in moisture content and develop deep drying cracks. There is intensive cultivation in these soils. Acrisols, characterized by an argilic B horizon, containing alluvial clay and clay skin. Nitosols and cambisols are also common in the lower parts of the Basin (WAC, 2008).

2.2 Meteorological conditions

The basin falls under the equatorial hot and humid climate with a bi-annual rainfall pattern, where the long rains are experienced from March to May and short rains from October to December. July is the coolest month of the year and the warmest month is variable and fluctuates in the period from October to February. Rainfall varies considerably from one part of the Basin to another between 1,350 mm - 2,447 mm annually. The temperature in the Basin is maximum in February, just before the March equinox and reaches its lowest records in July after the June equinox maximum and range from 28.6˚ C – 28.7˚ C. The minimum temperature varies from 14.7˚ C to 18.2˚ C. Comparison of temperatures records for the period 1950-2000 to 2001-2005 show that maximum temperatures have increased by an average of 1˚ C. (LVEMP, 2005).

2.3 Vegetation

The vegetation cover around Lake Victoria basin comprises savanna and wetlands (MoEWN, 2014). Most of the natural vegetation of Lake Victoria Basin has disappeared because of intensive agricultural activities. Areas unsuitable for crop cultivation are planted to various species of trees, eucalyptus and cypress. Some areas within the lake basin are covered with shrubs. The biodiversity and ecosystem of the Lake Victoria basin provide a wide range of species of aquatic life, plant and forest cover. The soils, vegetation and landscapes vary widely with rainfall and altitude giving four main agro-ecological zones. The elevation of the entire Lake Victoria basin falls within 1078m to 4061m above sea levels with the lowest sides being around lake Victoria while the highest regions being the North Western sides of the basin around Mount Elgon.

Figure 2.0 Map of the study area

3. METHODOLOGY AND PARAMETER ESTIMATES

The advent of remote sensing and Geographic Information Systems (GIS) technologies accompanied with their integration with the USLE and RUSLE method has led to a simpler, cost-effective and efficient perception of erosion, and this integrated application has been applied by many researchers (See Ganasri & Ramesh. 2015). The prime input required for soil erosion modeling are terrain, slope gradient and slope length which can be generated by processing of Digital Elevation Models (DEM) in GIS. Multi-temporal remote sensing data (satellite imageries) provide valuable information related to seasonal land use dynamics. Satellite data can be used for derivation of erosional and depositional features, such as gullies, point bar, braided channel, abandoned channel, and vegetation cover factor (Surjit *et al.*, 2015).

3.1 The RUSLE parameter estimate

RUSLE is the method applied globally to predict long-term rates of inter-rill and rill erosion from field or farm size units subject to different management practices. The present study was started with delineation of Lake Victoria basin from). The underlying assumption in RUSLE is that the detachment and deposition are controlled by sediment content of the flow. The eroded material is not sourced limited, but the erosion is limited by the carrying capacity of the flow. When the sediment load reaches the carrying capacity of the flow, detachment can no longer occur. Sedimentation must also occur during the preceding portion of the hydrograph as the flow rate decreases (Kim, 2006). The basic form of RUSLE equation has remained the same, but

modifications in several of the factors have changed. In this study, RUSLE was used for the assessment of annual soil loss. RUSLE was designed to predict long-term annual averages of soil loss.

The Revised Universal Soil Loss Equation is presented in equation (i):

$$A = R \times K \times L \times S \times C \times P; \quad \ldots\ldots (i)$$

Where:

A - spatial average soil loss in tonnes per hectare per year (t/ha·yr);
R - rainfall runoff erosivity factor in millimeters per hectare per hour per year mm/ha·h·yr;
K - soil erodibility factor in t/ha per unit R;
L - the slope length factor;
S - steepness factor;
C - land cover management factor;
P - support practice factor defined by population density.

These factors (RKLSCP) were combined via the RUSLE in ArcGIS model builder for soil erosion prediction and, for these factors, individual maps were prepared in raster GIS.

Table 3.1 Data sources

Data	Source	Access Link	Principal Product
Soil	Harmonized World Soil Database (FAO HWSD, 2008, KENSOTER)	http://www.iiasa.ac.at/Research/LUC/External-World-soil-database/HWSD_Viewer/HWSD_viewer_setup.exe	Soil Erodibility
Rainfall	USGS Chirps (5km, Pentadol) gridded data.	ftp://ftp.chg.ucsb.edu/pub/org/chg/products/CHIRPS-2.0/africa_pentad/tifs/	Rainfall Erosivity
Slope	Shuttle Radar Topography Mission (SRTM) 90m	http://srtm.csi.cgiar.org/	Slope Factor
Population	Livestock Population: GLiPHA-FAO 2008 Cows, Goats, sheep density raster were used.	http://www.fao.org/Ag/againfo/resources/en/glw/GLW_dens.html	Population Factor
	Human Population: Afri-pop, 1km	http://www.afripop.org/	
Vegetation	LULC (RCMRD) NDVI (Spot VGT/ Proba	RCRMD SLEEK program eSTATION ICPAC	Vegetation Index

	V)		
Baseline Data	Boundaries, towns, other (RCMRD)	http://geoportal.rcmrd.org	Baseline / Ancillary data

RCMRD=Regional Centre for Mapping of Resources for Development; ICPAC= IGAD Climate Prediction and Applications Centre

Within the framework of RUSLE, individual indicators affecting soil erosion are mapped separately and later combined into a single scale, by adding or multiplying suitably weighted indicators for each individual factor. An overlay mathematical analysis in a geographical information system (GIS) as a factor-based assessment of risk is then performed. Input factors are then combined to estimate different categories of actual soil erosion risk as shown in figure 2.2.

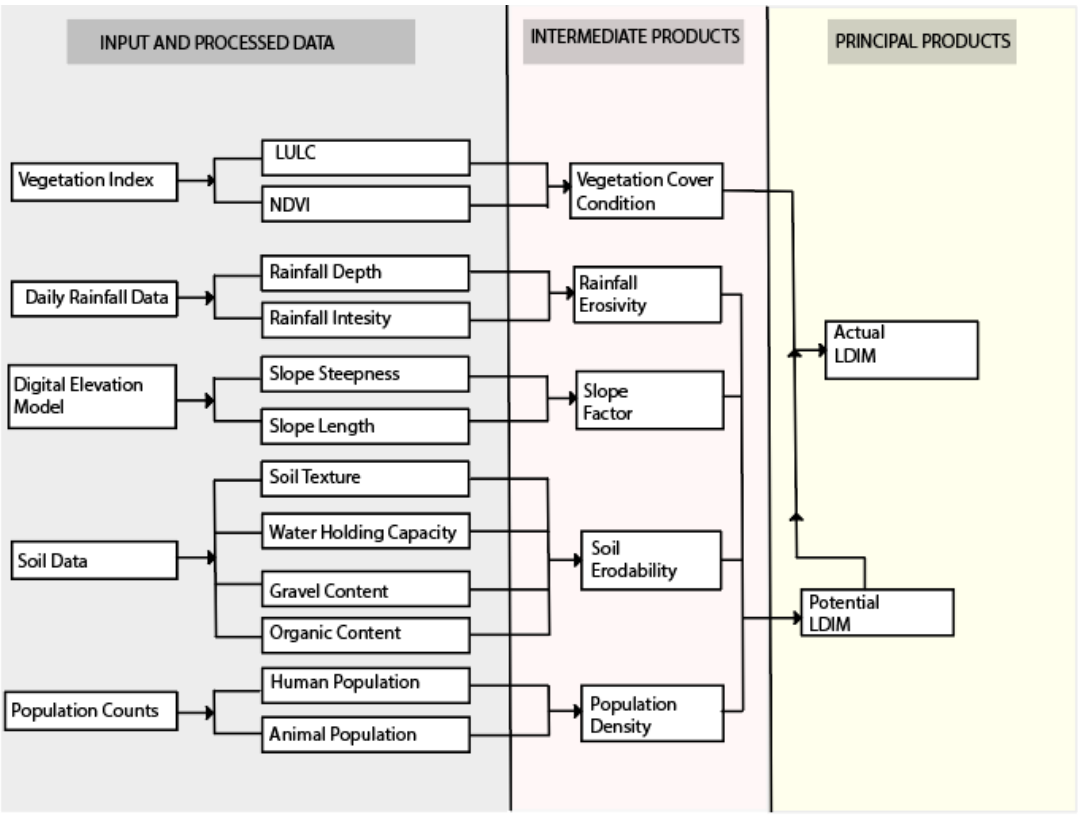


Figure 3.0: Soil erosion modelling flow process (indicator mapping and combination)

3.1.1 Rainfall Erosivity (R)

Rainfall and runoff play an important role in the process of soil erosion and are together usually expressed as the R factor. The greater the intensity and duration (depth) of the rainstorm, the higher the erosion potential. The RUSLE 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 (RCMRD, 2015). Unfortunately, the values of these factors are rarely available at standard meteorological stations. Fortunately, long-term average R-values are often correlated with more readily available satellite rainfall estimates values (Sadeghi *et al.*, 2011). For the computation of R factor, two components were computed from the Climate Hazards Group Infrared Precipitation with Stations rainfall dataset (CHIRPS) to get rainfall depth and intensity.

3.1.1.1 Computing rainfall depth

Rainfall depth calculation was meant to provide the total seasonal storm energy (E) in the basin. It was computed by summing up all the pentadol (5day rainfall average) CHIRPS gridded rainfall data for the entire season (March-May) using ArcGIS raster calculator. The cumulative seasonal rainfall depth (D) was then classified using natural breaks to 5 classes of erosion susceptibility (see fig 3.1) whereby very high rainfall totals implied very high susceptibility to soil erosion and vice versa.

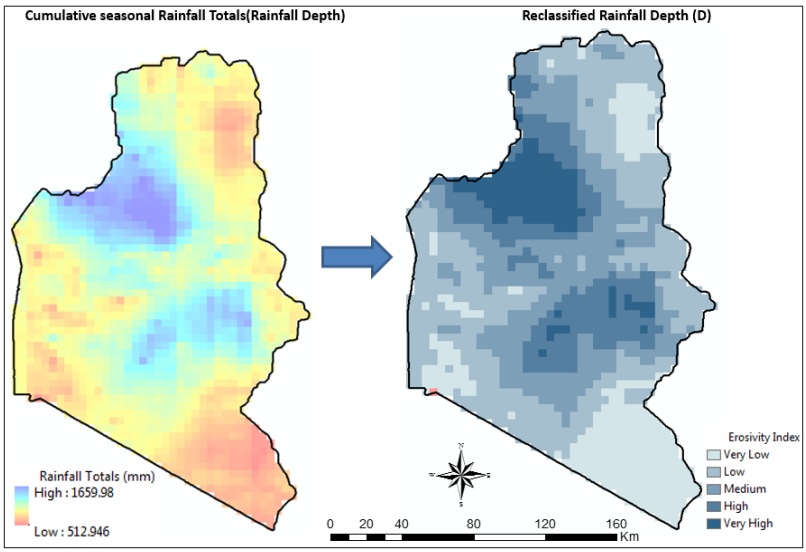


Figure 3.1: Cumulative seasonal rainfall depth

3.1.1.2 Computing rainfall intensity:

Rainfall intensity is defined as the ratio of the total amount of rain (rainfall depth) falling during a given period to the duration of the period (FAO, 2016). It is expressed in depth units per unit time, usually as millimeter per hour (mm/h). Studies suggest that, on average, around 50 percent of all rain occurs at intensities in excess of 20 mm/hour and 20-30 percent occurs at intensities in excess of 40 mm/hour (Adnan, 1978). This relationship appears to be independent of the long-term average rainfall at a particular location. This study adopted Adnan's assessment which compared with RCMRD (2015) derivation of rainfall intensity by assuming a rainfall intensity threshold of >= 40mm to possess enough kinetic energy to dislodge soil particles thus transporting them in the process initiating soil erosion. To compute rainfall intensity, for each pentadol, areas with rainfall above the threshold of 40 mm/pentadol were derived for the entire season. The processed pentadol files were then summed up to generate the cumulative seasonal rainfall intensity (I). The (I) was then classified into 5 classes of erosion susceptibility using the natural breaks as shown in figure 3.2.

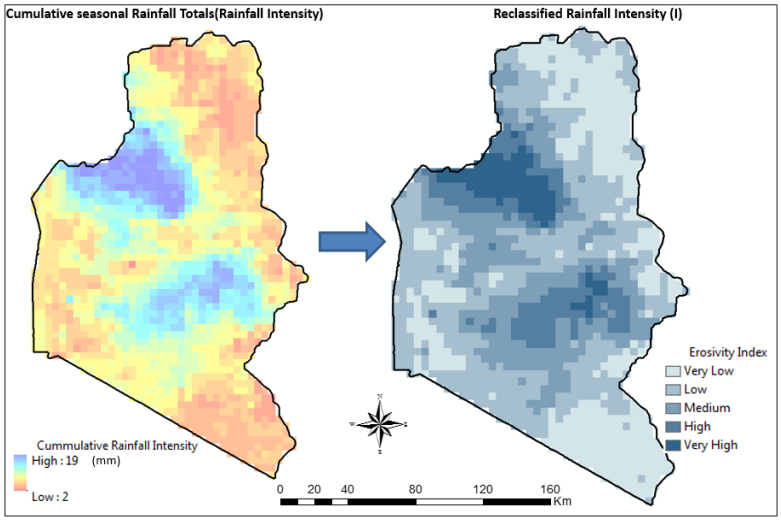


Figure 3.2: Cumulative seasonal rainfall intensity

The final rainfall erosivity (R) was obtained by combining rainfall depth (D) and rainfall intensity (I) using the weighted sum tool in Spatial Analyst using the formula (RCMRD 2015) below:

$$R = (0.4*D + 0.6*I) \quad \text{.....(ii)}$$

Where:
R - rainfall erosivity
D - rainfall depth
I - rainfall intensity

3.1.2 Soil Erodibility (K)

The Soil Erodibility (K) factor represents both susceptibility of soil to erosion and the amount and rate of runoff. Soil texture, organic matter, gravel content and permeability (water holding capacity) determine the erodibility of a particular soil (Efe *et al.*, 2008). The K factor reflects the ease with which the soil is detached by splash during rainfall and/or by surface flow, and therefore shows the change in the soil per unit of the applied external force of energy (Dumas & Printemps, 2010). 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). For computing the K- factor, the most updated version of the harmonized world soil database (HWSD) which integrates inputs from FAO-UNESCO soil map data and soil and terrain database for Kenya (KENSOTER) were selected. The advantage with HWSD was that the database had all the four components of soil (texture, organic matter, gravel, water holding capacity) that were of interest for processing (K) factor in this study. In order to process the four different soil components for soil erodibility (K), this study borrowed from RCMRD's methodology for processing the K factor in IGAD region land degradation assessment (RCMRD, 2015). The tables: 3.2 to 3.5 below show the processing and classification of the four soil components. Figure 3.3 shows the output of the four different soil components.

3.1.2.1 Processing soil organic content:

Organic Carbon is together with pH, the best simple indicator of the health status of the soil. Moderate to high amounts of organic carbon are associated with fertile soils with a good structure. Soils that are very poor in organic carbon (<0.2%), invariable need organic or inorganic fertilizer application to be productive. Soils with an organic matter content of less than 0.6% are considered poor in organic matter. The following classes were used to prepare maps of organic carbon status for mineral soils in the entire basin:

Table 3.2: Classification of soil organic carbon from HWSD

Code	Percentage organic carbon - PH	Erodibility Rating
1	< 0.2	Very high erodibility
2	0.2 – 0.6	High erodibility
3	0.6 – 1.2	Moderate erodibility
4	1.2 – 2.0	Low erodibility
5	> 2.0	Very low erodibility

Table 3.3: Classification of soil texture from HWSD

Texture class	Topsoil Texture Classification (T_USDA_TEX_ CLASS)	Erodibility Rating
1	C(h), SiC, C (HWSD class 1, 2, 3)	Very low erodibility

2	SiCL, CL, SCL (4,5, 8)	Low erodibility
3	L,SCL,LS (9,10,12)	Moderate erodibility
4	SiL, SL (7, 11)	High erodibility
5	Si, S (6, 13)	Very high erodibility

Textural Classification Where S = Sand, C = Clay, Si = Silt and L = Loam

Table 3.4: Classification of water holding capacity from HWSD

Water Holding Capacity (WHC) Class	Available water storage capacity (AWC) -mm	Erodibility Rating
1	> 125 (class 1,2,)	Very low erodibility
2	125-100 mm (class 3)	Low erodibility
3	100-75 mm (class 4)	Moderate erodibility
4	75-50 mm (class 5)	High erodibility
5	< 50 mm (class 6,7)	Very high erodibility

Table 3.5: Classification of soil organic carbon from HWSD

Stoniness class	Topsoil Gravel Content (T_GRAVEL) - %	Erodibility Rating
1	>50	Very low erodibility
2	50-30	Low erodibility
3	30-10	Moderate erodibility
4	10-1	High erodibility
5	<1	Very high erodibility

The four components were then summed together with equal weights in spatial analyst. The summed output raster was then reclassified into five classes of erodibility using the natural breaks classification to generate the final soil erodibility layer (K).

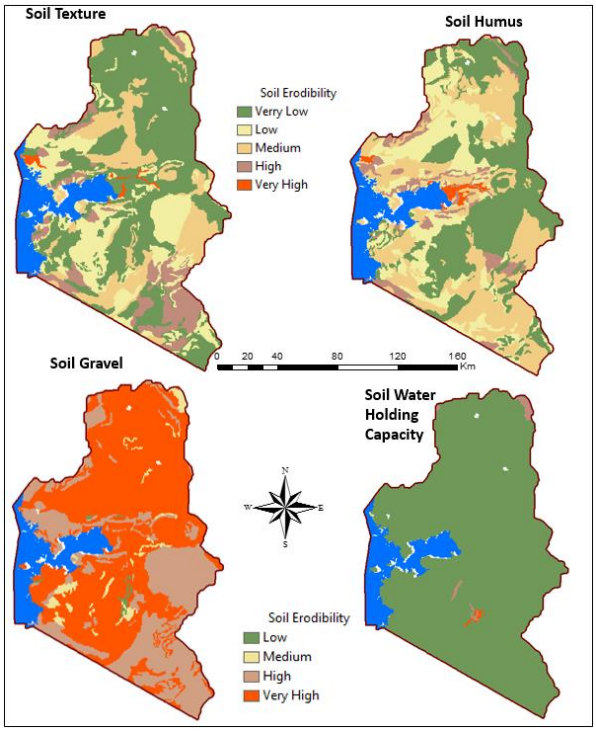


Figure 3.3: Mapped output of the four different soil components

3.1.3 Slope Factor (LS)

The L and S factors represent the effects of slope length (L) and slope steepness (S) on the erosion of a slope. The combination of the two factors expresses the effect of topography, specifically hillslope length and steepness, on soil erosion. An increase in hillslope length and steepness results in an increase in the LS factor (Karaburun, 2010). The slope length factor (L) is defined as the distance from the source of runoff to the point where either deposition begins or runoff enters a well-defined channel that may be part of a drainage network. On the other hand, the steepness factor(S) reflects the influence of slope steepness on erosion (George et.al, 2013). The longer the slope length, the greater the amount of cumulative runoff, and the steeper the slope of the land the higher the velocities of the runoff which contribute to erosion. This study utilised the 90m digital elevation model provided by Shuttle Radar Topography Mission (SRTM) as the input elevation for computation of slope factor (LS). For estimation and processing of the LS factor, this study adopted the expression (3.2) since it is integrated within ArcGIS and enables easier manipulation of the DEM (George, 2013).

$$LS = Pow([flow\ accumulation] * \frac{resolution}{22.1,0.4} * Pow(sin\frac{([slope\ of\ DEM])}{0.09,1.4}) * 1.4 \ldots\ldots\ldots\ldots \textbf{(iii)}$$

Where *Pow* (which means power) is a function in the ArcGIS Spatial Analyst.

Using the Spatial Analyst Extension in ArcGIS, the slope of the catchment area was derived from DEM. Sinks in the DEM were identified and filled. The filled DEM was used as input to determine the Flow Direction (FD) which was used as an input grid to derive the Flow Accumulation (FA). The LS factor was then computed using the Raster Calculator in ArcGIS to build an expression for estimating LS (3.2), based on flow accumulation and slope steepness (Mitasova et.al, 1996). The derived LS was then reclassified in the five soil erosion susceptibility classes with very steep areas being classified as very high and vice versa as shown in figure 3.4 below.

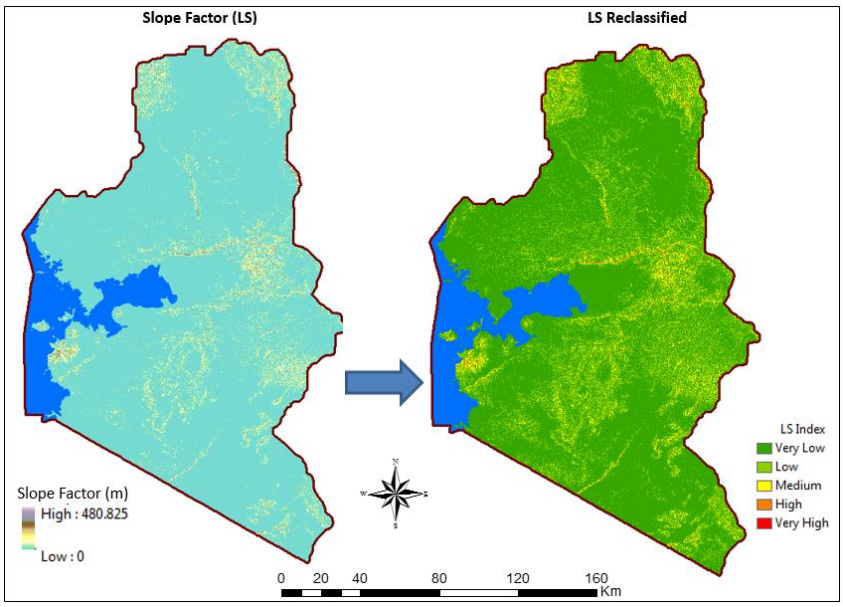


Figure 3.4: Processed slope factor (LS)

3.1.4 Vegetation Cover Management (C)

The Land Cover Management Factor (C) is used to express the effect of plants and soil cover. Plants can reduce the runoff velocity and protect surface pores. Since the satellite image data provide up to date information on land cover, the use of satellite images in the preparation of land cover maps is widely applied in natural resource surveys (Karaburun, 2010). More so, Since the Normalized Difference Vegetation Index (NDVI) values have a correlation with C factor many researchers fuse both land cover data derived from satellite imagery interpretation and NDVI to estimate C-factor values in erosion assessment (RCMRD, 2015). In this paper, Land cover data for 2015 sourced from RCMRD was combined with NDVI data obtained from SPOT VGT satellite system. The two datasets were first processed and aggregated separately in 5 classes ranging from 1 to 5 with 1 being very low potential for soil erosion and 5 being very high potential for soil erosion then later converted to raster grids resampled to 100m before being

combined in a weighted environment.

3.1.4.1 Processing Land cover

The different land cover types covering the entire basin were categorised into 5 classes of soil degradation susceptibility as shown in table 3.6 and figure 3.5 below, after which the land cover data was exported to raster grid of 100m spatial resolution using the reclass field as the export field:

Table 3.6: Aggregation of land cover types and their influence on soil erosion

Land_Cover	Reclass	Cartegorisation
Dense Forest	1	Very Low
Moderate Forest	1	Very Low
Open Forest	1	Very Low
Open Water	1	Very Low
Vegetated Wetland	2	Low
Perennial Cropland	2	Low
Open Grassland	3	Medium
Annual Cropland	3	Medium
Wooded Grassland	4	High
Otherland	5	Very High

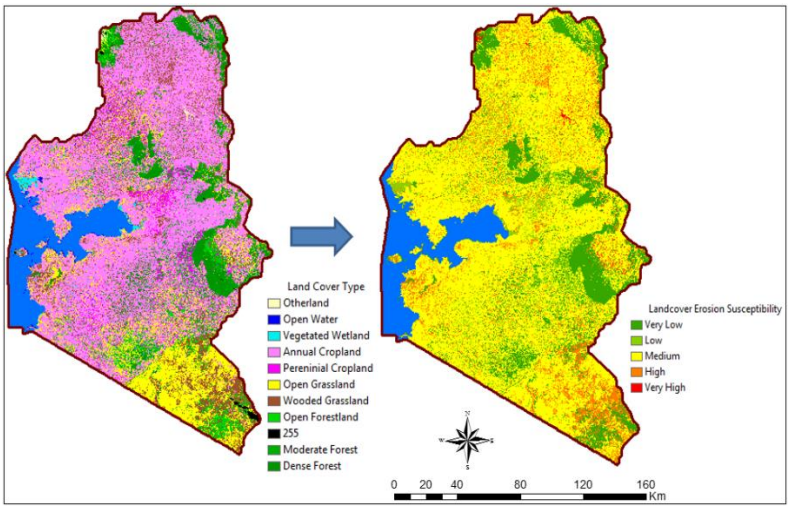


Figure 3.1: Aggregation of land cover to the 5 classes relating land cover type to its soil erosion susceptibility

3.1.4.2 Processing NDVI

Since NDVI dataset received had been organised into 10 day (decadal) means, the first processing step was to obtain seasonal average NDVI (March to September)for the entire basin. This was achieved by obtaining the MEAN for all the decadal NDVI data in the season using cell statistics by MEAN functionality in ArcGIS Spatial Analyst. The final seasonal NDVI_mean

data were classified into the 5 classes of erosion susceptibility as specified in the classification below (RCMRD, 2015) :

1. 0.68-0.98 Very Good
2. 0.5-0.68 Good
3. 0.3-0.5 Normal
4. 0.15-0.3 Poor
5. 0.1-0.15 Very Poor
6. = or < 0 Water bodies: needs to be masked out

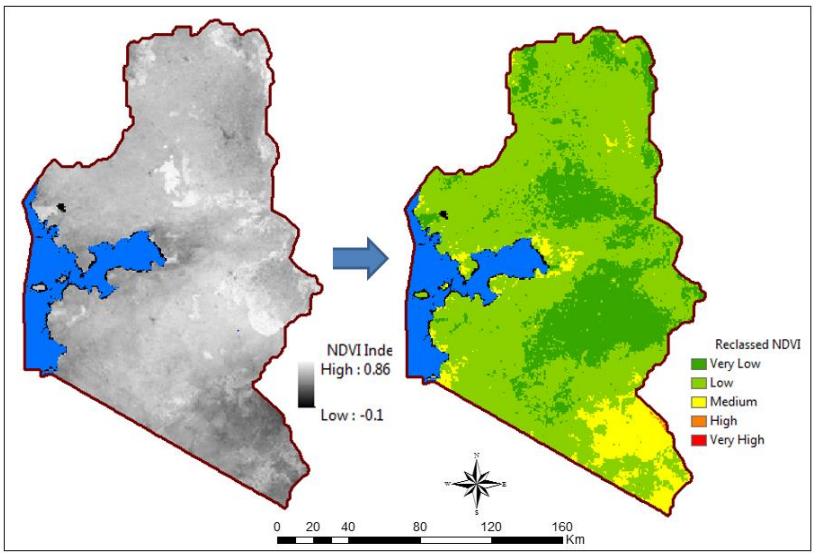


Figure 3.2: The processing of mean NDVI and the subsequent reclassification to the 5 classes relating land cover type to its soil erosion susceptibility.

The final vegetation cover management (C) was obtained by combining LULC and NDVI using the weighted sum tool in Spatial Analyst. Both LULC and NDVI had equal weights 1:1.

3.1.5 *Population Density (P)*

The soil conservation practice (P) factor describes the supporting effects of practices like contouring, strip cropping, and terraces other soil conservation efforts. Most often these datasets are not easy to obtain at an extensive geographical coverage and in most cases when computing the (P) factor in RUSLE, many studies have pointed at substituting the conservation data with human and livestock population data which is assumed to provide the indicator on cover management (George, 2013 and RCMRD, 2015). This study computed (P) by combining livestock density data (for common reared species mainly comprising the cattle, goats, and

sheep) provided by FAO gridded livestock data with human population density data provided by AfriPop.

3.1.5.1 Processing human population:

Since the population data as received had been processed to population density grids, the data was directly reclassified to five classes of erosion susceptibility as (shown in table 3.7 and figure 3.6):

Table 3.7: Population density classification

Class	Population Density Classification	Rating
1	0 – 2	Very Low
2	2 – 10	Low
3	10 - 40	Medium
4	40 - 100	High
5	> 100	Very High

3.1.5.2 Processing Livestock population:

This study summed up the population datasets for goats, cattle, and sheep since they are the predominant livestock domesticated in the Lake Victoria basin to derive the livestock population. The combined output was then reclassified into five classes of erosion susceptibility same as the human population as shown in table 3.7 and figure 3.6.

The final population density (P) was achieved by combining the livestock and human population data in a weighted ration of 0.6:0.4 respectively (RCMRD, 2015)

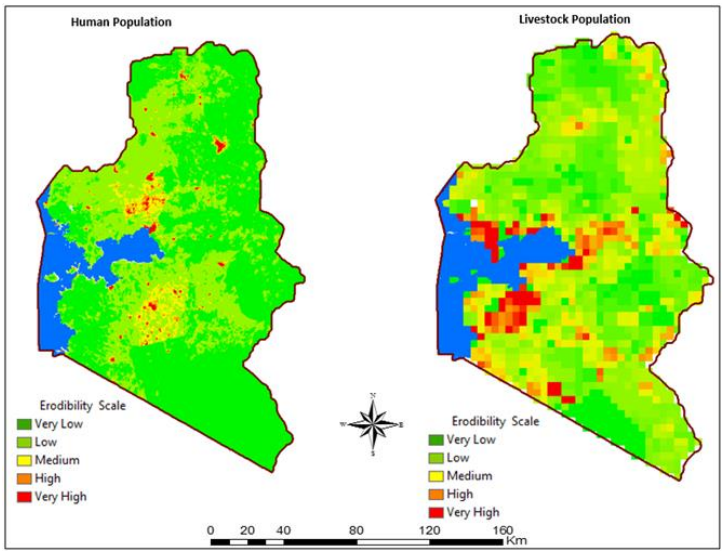


Figure 3.6: The reclassified human and livestock population

3.2 Factor weighting and combination (Overlay)

In order to derive the final soil erosion hotspots map, all the five processed soil erosion parameters have to be combined using their relative impact on land degradation. Therefore the basic pre-requisite for the assessment is the determination of weights and rating values representing the relative importance of factors and their categories. In this paper, the importance of classes was determined before assigning weights to the layers, and a suitable rating scale for each factor was defined from the experts' opinion. Assigning weights of influence requires comparing alternatives with respect to a set of criteria. Saaty Pairwise comparison enables ranking criteria in order of importance and to assign to the criteria some relative ranking indicating the degree of importance of each criterion with respect to the other criteria (GITTA 2016). This study utilized this approach by seeking views from two expert institution's teams; Regional Centre for Mapping of Resources for Development's (RCMRD's) Land degradation modeling team, and the Ministry of Environment, Water and Natural Resources state (MOEWN) department of Water, Directorate of Land Reclamation's team to subject all the 5 land degradation input parameters to ranking in order to derive individual weights leading to actual land degradation index. RCMRD and MOEWN ranked the 5 land degradation input parameters using the pairwise ranking approach. The outcome was a matrix similar to table 3.9 and the indicator weights as shown in figure 3.11:

Table 3.8: Pairwise Comparison Matrix for Land Degradation

Expert Opinion				
Land Degradation Input	**Team 1 RCMRD Experts**	**Team2 (MOEWN) Experts**	**Average Ranks**	**Weights**
Vegetation Index- **VI**	3	5	4	26.7
Slope Aspect- **S**	5	5	5	33.3
Soil Erodibility- **K**	2.5	3.5	3	20
Rainfall Erosivity-**R**	2	2	2	13.3
Population Density-**P**	1	1	1	6.7
TOTAL RANKING			15	100

To get weights the study used the formula: Weight=Rank/Total Weight * 100

Considering the above outcome the following weights were used for land degradation assessment.

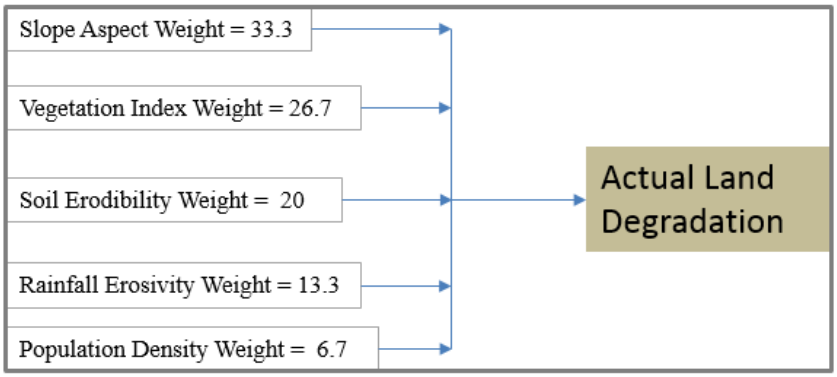


Figure 3.3: Weights used for the LDIM

To generate the final land degradation index, the 5 parameters were combined and specific weights implemented through weighted overlay performed with the model builder in ArcGIS spatial analyst as shown in figure 3.11.

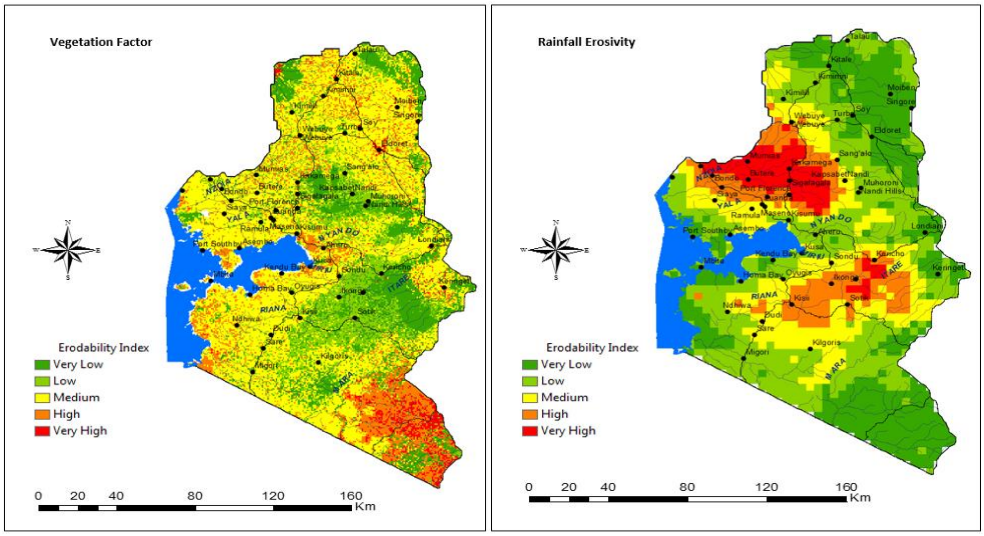
4.0 RESULTS

Five different erosion risk factors including vegetation cover management(C), rainfall erosivity(R), slope factor (LS), soil erodibility (k) and population density (P) were determined. The results of modeling these factors are discussed. The final land degradation map is shown in figure 4.2. The study learned that most parts of the Lake Victoria basin experience medium to high levels of degradation. The areas experiencing very low degradation are notably forested areas (see fig 4.1) in the northern parts and towards the eastern sides of the basin. These are areas occupied by the Mount Elgon forests, Kapsabet forest and parts of the Mau forests in Kericho all of which are reserved natural forests. The study also noted that the eastern parts of the basin registered low degradation levels and this could also be attributed to the tea plantations grown around these areas which provide perennial cover to the ground. This study noted that soil experts rated slope factor as the major contributing factor to land degradation by soil erosion in the basin followed by vegetation cover, soil erodibility, rainfall erosivity, and population density simultaneously (see table 3.8). However, while evaluating the key parameters that resulted to final land degradation hotspots map as outlined by RUSLE and as shown in figure 4.1, the leading factor to soil erosion in the basin and around the identified hotspots were found to be : soil erodibility component followed by rainfall erosivity , vegetation cover , population density and finally slope factor in that order.

The results of soil erodibility in the basin reflect the ease with which the soil is detached. However, figure 3.3 points to the fact that most soils in the basin have very low gravel content of <1% and this contributes highly to their susceptibility to erosion by run-off. There is a very close correlation between the soil erodibility map and the final land degradation severity map where in both cases, the hotspots are around the lake region.

In this study, rainfall erosivity stood out as the second most contributing factor to soil erosion in the basin. In modeling the rainfall erosivity, it can be seen that the greater the intensity and depth of the rainstorm, the higher the erosion potential. High rainfalls within the basin are received in the western parts of the basin mainly: Bungoma, Mumias and Kakamega region and subsequently, this has an inclination in the overall degradation in these regions.

The study further noted that areas practising smallholder agriculture (arable and mixed farming) in the basin most notably: Bungoma, Uasin Gishu, Kisii and Narok registered medium to high levels of degradation. The consistent disturbance of land and specifically top soils through tillage combined by unsustainable agricultural practice might be the precursor to growing soil erosion levels in these areas. The aspect of vegetation cover management provides an insight into the need for proper forest and vegetation cover protection and conservation in the basin in order to alleviate soil erosion and preserve the topsoil.



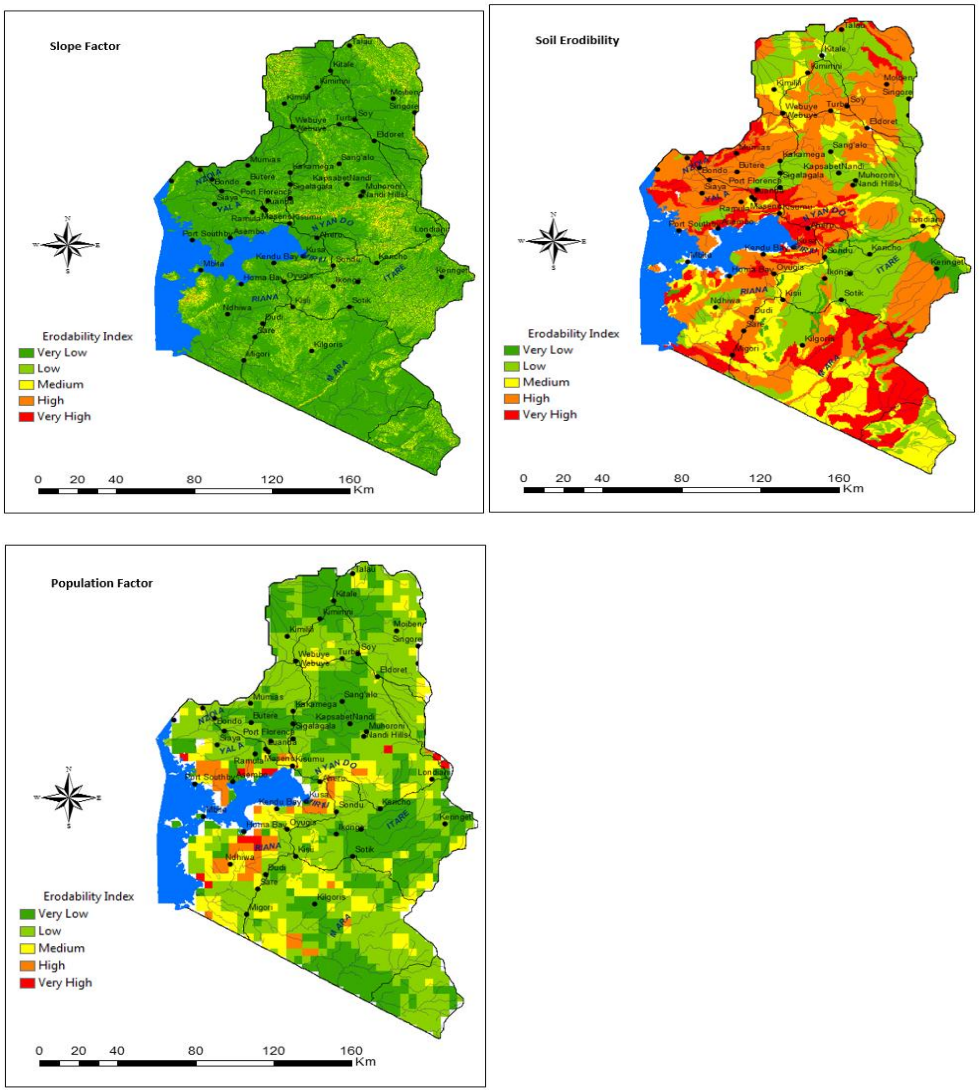


Figure 4.1: Erosion risk factor maps

In this paper, population factor was seen to provide modest impact in overall soil erosion in the basin. The population factor had high impact in the lake regions around Lake Victoria which had most population in the basin especially livestock population. The impact of the human population was widely distributed though.

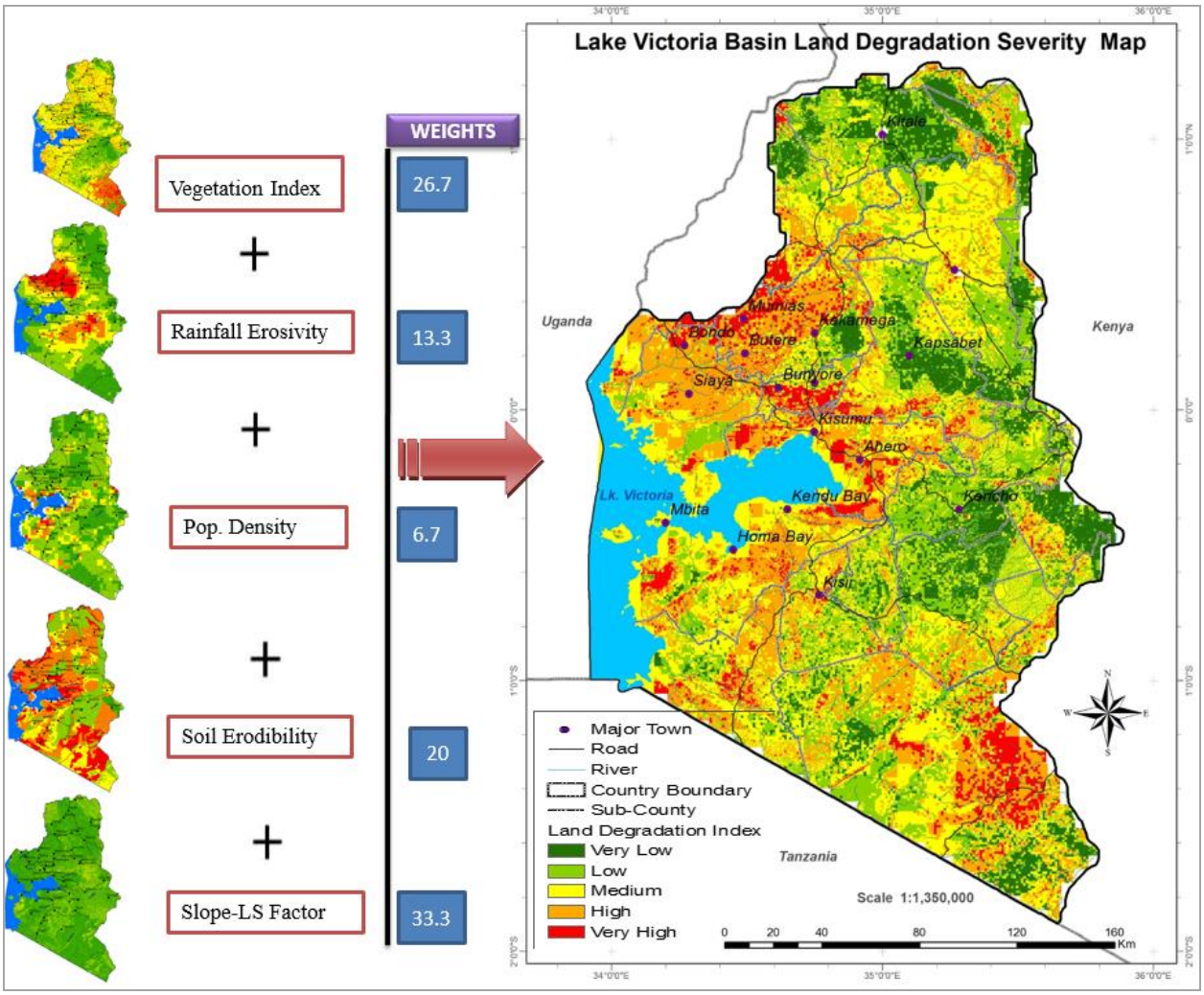


Figure 4.2: The RUSLE parameters leading to the final land degradation severity map.

Surprisingly, this study noted that despite the high weight allocated to slope factor, this particular parameter had little contribution to the overall land degradation in the basin. Further analysis on the slope layer revealed that it is in ridges, river lines, and stream areas that flow accumulation was high and that slope factor dictated very high soil erosion. The overall impression is that the gentle to near flat nature of slope in the entire basin bar the isolated mountainous regions of Elgon, Kapsabet and Mau regions meant that slope had little effect on soil erosion in the region.

Overall and as observed by findings from field validation at Bolo location in Kisumu county (see figure 4.3) , massive land degradation through soil erosion by surface runoff in the basin is caused by unsustainable agriculture practice in the basin which results to vegetation clearance

and exposure of topsoil to erosion agents. A large part of the basin is occupied by smallholder farmers practicing arable and mixed agriculture. Lack of awareness combined by poor agricultural extension services in the marginalised rural setups acts as the precursor to the hazard.

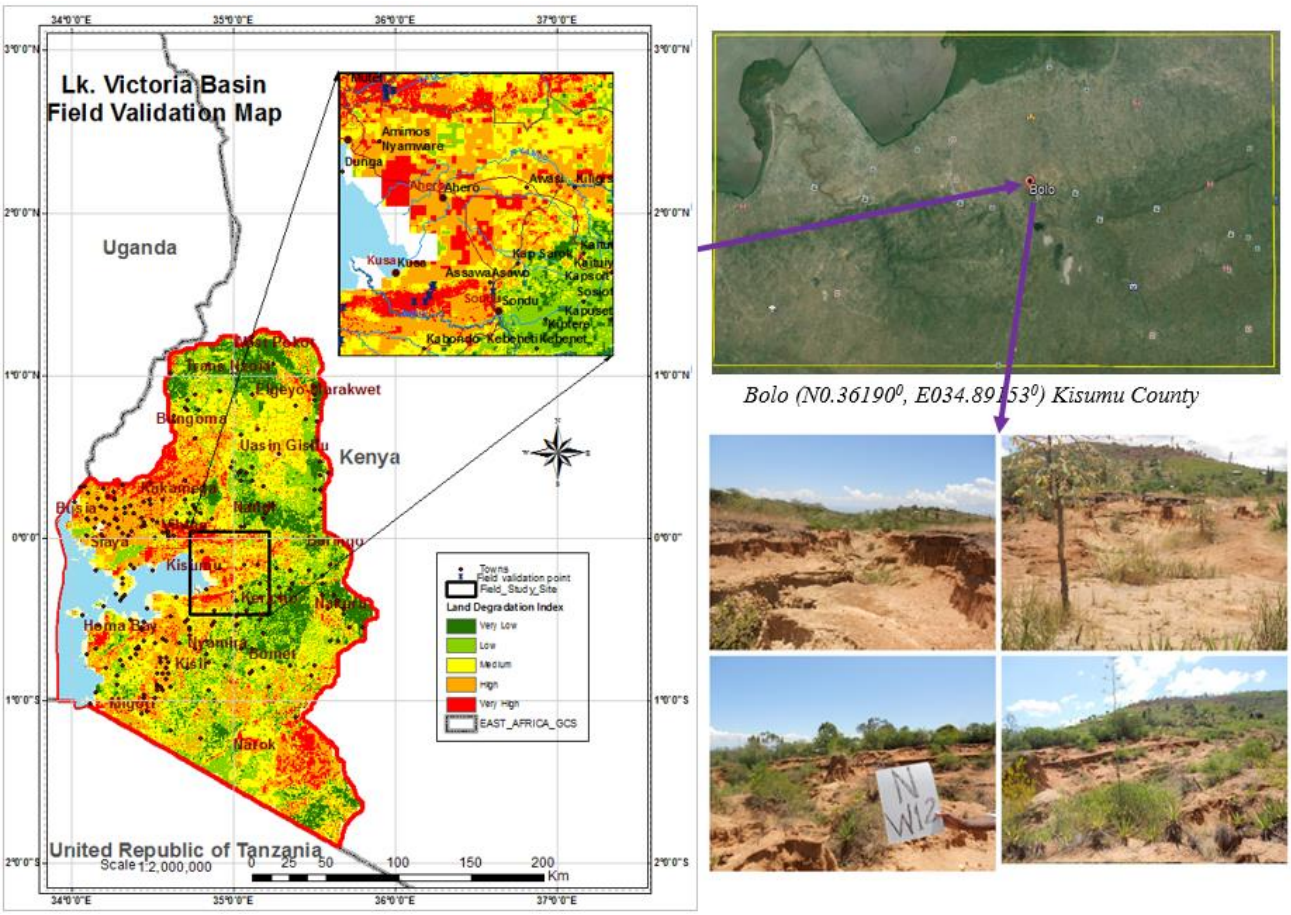


Figure 4.3: Degradation Hotspot at Bolo in Kisumu County

5. CONCLUSIONS

In this paper, empirical land degradation model for assessing soil erosion by surface runoff (RUSLE) and its integration with GIS tools have proved useful and effective in assessing land degradation in the entire Lake Victoria basin. The output which was a land degradation index map has shown the spatial variation in soil erosion severity in the basin enabling the study to point out the major land degradation hotspots in the basin which are mainly found around these areas: Mumias, Bunyore, Kisumu, Kendu Bay, Ahero and southwestern parts of Homa Bay. The

leading factors contributing to soil erosion in the basin have also been analysed and prioritized as follows: soil erodibility component followed by rainfall erosivity, vegetation cover management, population density and finally slope factor. This study hence fully achieved its objectives which were: to map the geographical variation of land degradation severity at the Lake Victoria basin; to establish the contributing factors to land degradation in the basin and to identify and recommend land degradation hotspots for further assessment at sub-basin level. Following the assessment of land degradation in the Lake Victoria basin complemented by carefully executed approach, the study draws the following recommendations to be used by key stakeholders like Lake Victoria Basin Commission (LVBC) and the county governments to contain land degradation and reclaim degraded lands in the basin: Undertake comprehensive catchment level degradation assessment prioritizing the most affected / hotspot areas (Mumias, Bunyore, Kisumu, Kendu Bay, Ahero and southwestern parts of Homa Bay). The information obtained from the assessment would include the level, severity, and extent of land degradation as well as sedimentations levels so that the information can be used for catchment conservation.

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