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Analytical Hierarchical Process of Soil Erosion Risk Assessment in Ondo State, Nigeria

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Abstract Soil erosion risk assessment and landuse planning strategies have become increasingly more data-intensive, sophisticated and highly complex involving myriads of quantitative and qualitative techniques. One of the methods that can help in synchronizing all these diverse data sets within a decision making framework is the analytical hierarchical process (AHP) developed by Satty. AHP provides a better technique for the comparison of factors based on decision matrices. It also provides structured methods for the incorporation of experts' opinions in the ranking of factors. This study examines the use of the AHP in modelling soil erosion risk using Universal Soil Loss Equation (USLE). Rainfall data, landuse/landcover, digital elevation data, soil erosivity index, supporting practices and expert opinions were integrated using AHP to identify areas with varying degrees of erosion risk potential. A pairwise comparison of the four factors identified by experts and supported by the USLE model was performed by means of Saaty's square it is a reciprocal matrix with unit rank whose eigenvector solution gives the priority or the relative importance, or dominance, of the elements on a ratio scale. The inputs to the matrix were derived from field survey and expert opinions on the relative dominance of the elements within each pair by using a nine-point scale. The approach retains the quantitative conceptual elements of the USLE methodology while allowing for a qualitative assessment and ranking of pertinent factors of soil erosion at micro level. The study shows that hilly areas with high rainfall particularly in the urban areas have the highest erosion risk potential while the natural forest areas have the least. It therefore shows the utility of AHP in coupling existing models with expert opinions as well as some subjective indicators in decision making. The method was capable of ranking ecosystems in terms of environmental conditions and suggesting cumulative impacts across a large region.

Keywords Soil erosion, Weighted linear combinations, decision making, erodibility, erosivity

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Introduction

Erosion is the gradual removal of soils by wind or water and this is exacerbated by land clearing practices related to farming, residential or industrial development, road building, logging and other anthropogenic influences. It is part of denudation process which includes the physical breakdown, chemical solution and transportation of material from the surface of the Earth. Soil erosion is one the major causes of land degradation which is the reduction and loss of biological or economic productivity caused by land-use change processes, physical processes or a combination of the two. These include processes arising from human activities and habitation patterns, such as soil erosion, deterioration of the physical, chemical and biological or economic properties of the soil, and long-term loss of vegetation [1]. Models and theories abound in the literature that provide explanation for causes and consequences of soil erosion, however, one major limitation with almost all these models is that they do not consider interactions among soil erosion factors apart from their intensive data requirements and hence each factor is treated independently in the model [2]. The factors are treated as if they contribute equally to precipitate soil erosion. It is however evident that the number of factors as well as their contribution to soil erosion varies both in time and space. Prominent soil erosion inducing factors such as rainfall, topography, nature of soils and landuse cannot be treated equally because each contribute differently to soil erosion depending on the local and regional condition prevailing. Factor weights may therefore be used to specify the relative importance of each factor in determining their susceptibility to erosion. In effect, factor weights serve to define to what extent a high score on one factor can compensate for or tradeoff with a low score on another factor. For example, a not-so-important factor with a very high suitability but low factor weight cannot make up for a very important factor that has a low score and high factor weight [3].

The use of Analytical Hierarchical process (AHP) which was developed by Satty in 1987 to assess the risk of soil erosion is becoming increasingly wide spread. Historically, AHP is a theory of measurement and practically a technique of dealing with multi-criteria, multi-objective, multi-person, multi-attribute, multi-period, multiple alternatives and multiple social interests and preferences hierarchically for decision making purposes [4,5,6,7,8). It was developed to promote improved decision-making for a specific class of problems that involve prioritization of potential alternate solutions through evaluation of a set of criteria elements. It involves the identification of the decision issues and its subsequent decomposition into hierarchies with each strata consisting of several elements [9]. It provides a fundamental scale of relative magnitudes expressed in dominance units through a pairwise comparison of decision variables (e.g., objectives, alternatives) according to some attribute they share or a criterion they should meet in order to represent judgments. Pairwise comparisons of the element (usually, alternatives and attributes) can be established using a scale indicating the strength with which one element dominates another with respect to a higher-level element. This scaling process is then translated into priority weights or scores [9]. Two features of the AHP which differentiate it from other decision-making approaches are (a) its ability to handle both tangible and intangible attributes and (b) is its ability to monitor the consistency with which a decision-maker makes his judgments [9].

It has been noted that the method is a multi-criteria decision-making tool that has been used in almost all the applications related to decision-making [10]. AHP suits a wide range of applications including transport study, technological choice, resource allocation and organization planning [8]. It has gained popularity as a viable decision-support tool in a number of fields such as economics, politics, marketing, sociology and management [11, 12]. Recent applications include the urban housing prioritization in the United States [13], prediction of advanced manufacturing technology [14]. The use of AHP in dealing with fuzziness, factor diversity and complexity in problems of land evaluation involving the location of a public facility within a geographic information system environment was evaluated [15]. The method has also been used to incorporate stakeholder objectives in the 'Wonga Wetlands' on the Murray River [16]. However, one of the most recent applications of the technique in soil erosion is the work of Wu and Wang [17) who used it to develop an analytical risk assessment model to evaluate the risk index for soil erosion by water. Some of the dominant factors that have been evaluated include the soil type, rainstorm intensity, landform accounting for physiognomy type, ravine density, and land slope, vegetation coverage, mining area, level of water and soil conservation, and type of land uses. The weight of each thematic layer is determined through the AHP technique. This model is then applied in predicting development of soil erosion at a typical scenario. In addition a fuzzy ranking method and the AHP can be combined for integrating ecological indicators using data on land cover, population, roads, streams, air pollution, and topography with a view to identifying areas vulnerable to future deterioration. [18]

Soil erosion is one of the major environmental problems in the South West and South Eastern parts of Nigeria [19,20]. It has resulted in large scale degradation of soils with attendant consequence on food productivity and human life. Inadequate knowledge about the interaction between and among soil erosion inducing factors is one of the main challenges confronting its effective management. The objective of this paper is to improve understanding of the relationships among soil erosion factors through the integration of rule based and subjective models. In view of this therefore, this study employed the procedure of hierarchical analytical procedures (AHP) coupled with the existing rule based erosion model (Universal Soil Loss Equation) and expert opinions to identify and quantify areas susceptible to soil erosion risk in Ondo state, Nigeria (Figure 1). The approach will provide a spatial insight on soil erosion risk assessment.

Materials and Methods

The identification of erosion risk areas using the AHP involves the collection of both quantitative and qualitative data on factors that predispose an environment to soil erosion. To generate the selected factors, remote sensing, analytical hierarchy process (AHP) and GIS techniques along with spatial models were applied. To standardize all of the factors and establish the factor weights, the AHP method was adopted. A major component in the data collection involves the use of participatory approach in collecting expert's opinions on the causes of soil erosion as well as the ranking of each of the identified factors in order of importance. Household heads, community leaders and soil scientists in the vicinity of the areas experiencing gully erosion constituted the expert team. They were asked to identify factors that predispose a location to soil erosion and eight factors were identified. These eight factors were further reviewed and were subsequently reduced to five major factors corresponding to those identified in their Universal Soil Loss Equation (USLE) [1]. Three factors dropped because of their inherent presence in others include nearness to road network, rivers/streams and closeness to foot of hills.

The factors of erosion specified in the USLE developed by Wischmeier and Smith therefore provide the basis for data compilation. Although, the model's limitations have been extensively documented, the equation remains the basis for varieties of soil and sediment erosion applications including estimating watershed wide sediment transport [21]. Mathematically, the equation is defined as: A = R* K* L* S* C* P. where, A is soil loss in tons per acre, R is rainfall-erosivity index, K is soil erodibility index, L represents slope length, S is the slope steepness factor, C is a land cover management factor, and P is a supporting practices factor. Table 1 shows the input data parameters and the various sources from where the data were collected. The focus here is not with the estimation of erosion tons rather, the identification and prioritization of areas that are susceptible to erosion risk and this require a slight modification of the USLE model in order for it to be suitable for this purpose.

Table 1 Model Input Data Sources and Associated Equation Factors

	Input Data	Corresponding Equation Factor	Data Source
1	Rainfall Data	R Factor Derived	Federal Meteorological Service, Oshodi, Nigeria
2	Landuse/Landcover	C Factor Derived	Landsat ETM 2005
3	DEM	LS Factor Derived	1:50,000 Topographical Map
4	Soil Erosivity Index	K Factor Derived	1:1million Soil map
5	Supporting Practice	P-Factor Derived	Landuse/Landcover Map

The Runoff Erosivity factor R quantifies the effect of raindrop impact and also reflects the amount and rate of runoff likely to be associated with precipitation. Typically, the R-Factor is calculated as total storm energy (E) times the maximum 30-minutes intensity (I_{30}), or EI, and is expressed as the rainfall erosion index [30]. For the purpose of this study, the determination of the R factor employed the Fournier approach which is based on the computation of climate index as a surrogate measure for the rainfall erosivity factor [22]. The climate index takes the form of: C=r2/p. Where r is the amount of rainfall in the wettest month and P is the annual rainfall amount. To estimate the R-Factor, it is common to use the rainfall intensity for the two most wettest months, however, in the study area as in other part of South Western Nigeria, the onset and cessation of rainy season is usually accompanied by heavy rainfall which portend great risk for soils, while the wettest months of June and July or even September are often characterized by light shower of rainfall which may not necessarily have so much storm energy. In addition, the fact that the area is characterized by double maxima of rainfall means that using the two wettest months may not bring out the risk associated with rainfall and in view of this; the rainfall obtained during the entire rainy season (March-November) was used. In using this model, the R factor was derived from monthly rainfall measurement obtained in 34 locations within the area of study for the year 2006. The average rainfall obtained over these nine months period was used to derive the index. This computation was done for the entire 34 locations and the value obtained was divided by the total annual rainfall for that year. The average and total annual rainfall were converted to grid data and the latter was used to divide the former and this result in rainfall erosivity grid data. The result provides an indicative measure of rainfall intensity pattern (Figure 2).

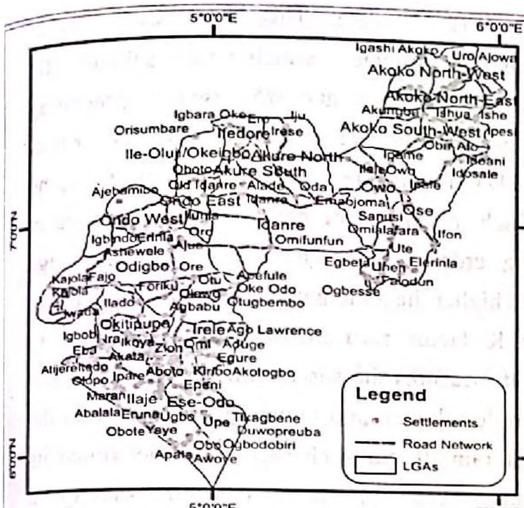

Figure 1: Administraive Map of Ondo State

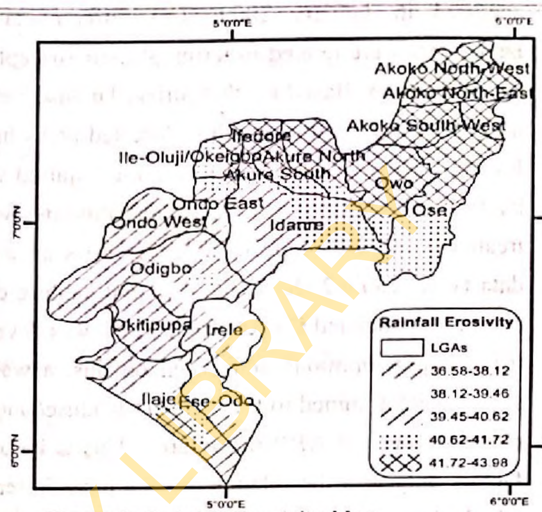

Figure 2: Rainfall Erosivity Map

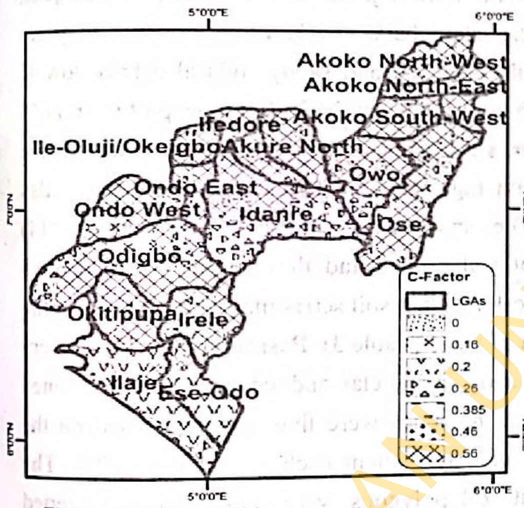

Figure 3: C-Factor Map

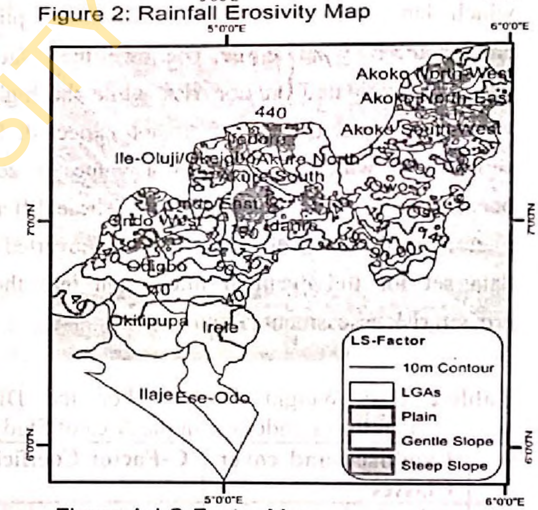

Figure 4: LS-Factor Map

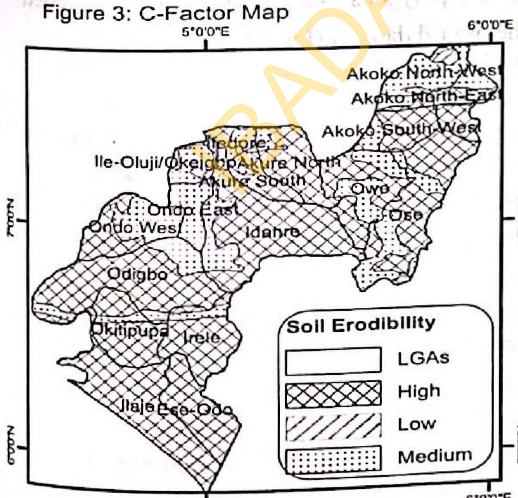

Figure 5: Soil Erodibility Map

0 15 30 60 90 120 Kilometers

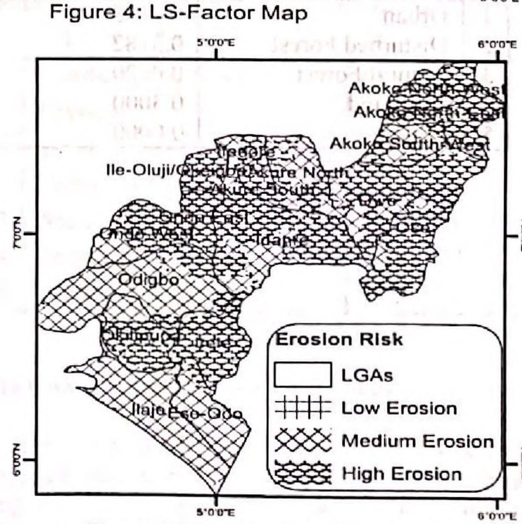

Figure 7: Erosion Risk Potential Map

The C-Factor which is popularly referred to as crop management factor was derived from the landuse/landcover map produced from Landsat ETM acquired in January 2009. The different landuse/ landcovers were ranked in terms of their susceptibility to soil erosion. Based on this, urban landuse recorded the highest susceptibility while forested areas had the lowest. AHP was used in deriving the required weight based on the opinion of experts and this involves the treatment of each landuse/landcover class as separate data layer. Table 2 shows the different landuse classes and their associated C coefficient which was developed using expert opinions and based on this, a weighted scores were assigned to the different landuse/landcover classes using the AHP procedures. This is because C factors only need be relative to each other in terms of which landcovers are more or less susceptible to erosion and by what degree. The lower the C-factor the less the anticipated erosion risk while the higher the value, the higher the rate of erosion expected. Table 2 shows that water is assigned a value of zero (0) because no erosion takes place on it. These different C-Factor coefficients were subsequently converted to grid data set for the eventual integration into the final erosion risk assessment (Figure 3).

Table 2 AHP Weight Derived For the Different Landuse/Landcover in the Area of Study.

	Landuse/Land cover Classes	**C-Factor Coefficient**
1	Urban	0.3198
2	Disturbed Forest	0.3182
3	Natural Forest	0.0620
4	Farmland	0.3000
5	Water	0.0000

L-factor which examines the role of topographical variable in the overall process of soil erosion was derived from the Shuttle Radar Topographical Mapping (SRTM) data. This data has a spatial resolution of 90meter which was subsequently resampled to 30meters and was used in generating slope information in percentage. Therefore, rather than using the DTM which describes height of positions, the slope which relates to gravitational force was used in modelling erosion risk. The higher the percentage slope, the higher the anticipated erosion risk (Figure 4).

The K factor is a measure of soil erodibility because it measures the susceptibility of different soil groups to detachment and transport resulting from the impact of rainfall. Soils characteristics determine its rate and speed of removal and subsequent transportation from place to place [23]. It has been noted that clays have low K values because they are not easily detached and sandy soils also have low K values because they are difficult to transport via runoff, however, silt loam soils have medium K values while soils with high silt content have high K values also [23]. The study area comprises of fourteen (14) different soil groups and these groups were derived from the 1:1million soil series map of Nigeria covering the area of study (Table 3). Basically, the soils are very rich in sand, silt and clay and mostly deep well drained soils. The K-values were thus assigned based on the amount of clay content each soil contains [24]. The different soil polygons were subsequently converted into K-factor grid data set (Figure 5).

Table 3 Soil K-Factor or Erodibility Index

	Soil Description	Soil Code	K-Factor Coefficient
1	Very deep, poorly moderately well drained soils; sandy, sandy loam or sandy clay loam surfaces over sand, sandy loam to sandy clay loam subsoils.	1a	0.02
2	Deep to moderately deep poorly drained soils; loam to loamy sand, sandy loam, silt or silty loam surfaces over fine sandy loam, silt loam, silty clay loam or sandy clay subsoils.	2c	0.05
3	Very deep well drained soils; sandy, loamy sand, or loamy surfaces over loamy, sandy loam or sandy clay.	5c	0.24
4	Very deep to deep and moderately deep well drained and few imperfectly drained soils; sand, sandy loam or loamy sand surfaces over sandy loam, sandy clay loam or gravelly sandy clay loam subsoils.	5d	0.14
5	Very deep well drained soils; loamy sand to sandy loam surfaces over sandy clay loam to sandy clay subsoils.	6a	0.24
6	Very deep well drained soils; sandy loam, loam over clay loam, sandy clay loam or sandy clay subsoils.	7b	0.24
7	Very deep well drained and very deep poorly drained soils; sandy loam, sandy loam, sandy clay loam or loamy sandy surfaces over gravelly sandy clay loam or sandy clay, clay loam or loamy sand subsoils	7c	0.02
8	Very deep and deep well drained soils; loam, loamy sandy or sandy loam surfaces over gravelly or stony sandy clay, sandy clay loam or clay loam subsoils.	8a	0.24
9	Deep and very deep well drained soils; sandy clay or sandy loam surfaces over gravelly or stony sandy clay loam, sandy clay or clayey subsoils	8b	0.20
7	Deep well drained soils; sandy loam, loamy sand, sometimes gravelly surfaces over gravelly sandy clay loam, sandy clay or clay loam, sometimes mottled subsoils.	11a	0.24
9	Deep well drained and shallow well drained soils; sandy loam surfaces over stony sandy clay subsoils or bedrock.	13a	0.16
10	Very deep well drained soils; sandy loam surfaces sometimes gravelly over sandy clay loam to sandy clay and sometimes gravelly subsoils.	15g	0.24
11	Generally deep well drained with few poorly drained soils; loamy sand surfaces over sandy loam to sandy clay loam and sometimes gravelly subsoils.	18d	0.04
12	Very shallow to shallow and deep well drained soils; loamy sand to sandy loam surfaces, sometimes gravelly and over bedrock, over sandy clay loam subsoils, sometimes gravelly.	24b	0.10

The P-factor assesses and ranked the various landuse/landcover conservation strategies employed to protect land. It is the human attempt at land and soils conservation and management. Since the focus is on land management, the methods of land conservation for the different landuse/landcover classes derived from the Landsat imageries were examined. Based on the observation made during the field survey, little or no methods of land conservation is in place in the study area. Table 4 shows the Boolean weight assigned to the different landuse/landcover. The higher the C-factor the less the rate of erosion expected while the lower the C-factor the higher the erosion risk anticipated. Based on this, it was only the natural forest that has a natural protection against the agents of erosion; hence the impact of P was assumed to be less important because even for the natural forest, there is no human method of protection.

Table 4 Boolean Weight Assigned to the Different Landuse/Landcover.

	Landuse/Landcover Classes	C-Factor Coefficient
1	Urban	0
2	Disturbed Forest	0
3	Natural Forest	1
4	Farmland	0
5	Water	0

Data Conversion and Standardization

The five data layers identified above were converted from vector to their grid (raster) equivalent using ArcGIS and Idrisi32 Software. The initial data capture were carried out using ArcGIS software while Idrisi32 was used in the standardization and data modeling including the AHP analysis that was carried out. To determine areas that are susceptible to soil erosion, the various data layers were standardized using a fuzzy set standardization approach. Fuzzy set theory finds application in systems where human judgment, perceptions and emotions play a central role [25]. It is a body of concepts and techniques aimed at providing a systematic framework for dealing with the vagueness and imprecision inherent in human thought processes [26,27,12]. The theory extends the classical Boolean logic (true and false) of set membership towards a third region which is between true and false [28]. It represents sets without sharp boundaries because it is characterized by a fuzzy membership grade or possibility that ranges from 0.0 to 1.0, indicating a continuous increase from non-membership to complete membership [3,25]. A Fuzzy Set membership evaluates the possibility that each pixel belongs to a fuzzy set by evaluating any of a series of fuzzy set membership functions such as Sigmoidal, J-shaped and Linear functions which are controlled by four points ordered from low to high on the measurement scale. These functions serve to define the shape of the fuzzy set membership curve and the resultant output may be scaled from 0-1 or from 0-255.The latter is necessary because the factor images are in different measurement units (e.g., kilometers and percentage slope) and on very different scales. Data standardization helps to brings all the factors to a common measurement unit (suitability, vulnerability, etc.) and scale (0-255). The standardized factors were then aggregated. With respect to the standardization of the rainfall erosivity index using the fuzzy set membership function, the initial climate index which ranges between 17.29mm-20.43mm was stretched to between 0-255 using a monotonically increasing linear function. This function ensures that the initial values are rescaled to between 0-255 and that areas having high rainfall index are giving greater value. The slope map, the K-map, and the C-map were equally stretched to between 0-255 using the same monotonically increasing linear function. This was done in order to facilitate easy comparison of the risk value arising from the incorporation of each data layer used in the soil erosion risk modelling. The variables were subsequently weighted using an AHP methodology.

Analytical Hierarchy Process (AHP) was used in defining weights assigned for each of the fuzzy map representing each of the erosion factors through a pairwise comparison process of the different factors considered. The weight development involves the compilation of pairwise comparison of the lower half of a symmetric matrix. Only the lower-left triangular half was evaluated since the upper right is symmetrically identical [8]. To rate each pairwise comparison and to fill in the matrix cells, the relative importance of the row variable to its corresponding column variable was rated according to the typical AHP 9-point rating scale. The relative importance is ascertained by calculating the eigenvector of the matrix. A square matrix is formed when every two criteria are compared. The matrix has the property that the element aij = 1/aji (if item i is 2 times as important as item j, then item j is 1/2 as important as item i). The relative importance is given as a normalized eigenvector of the pairwise comparison matrix, ensuring that the sum of relative importance of siblings always equals one. It should however be noted that since the diagonal of the matrix represents the comparison of each variable with itself, these cells automatically contain a 1 and if two variables were equally of great importance they receive a rating of 1 just as would two variables that were equally of little importance. The Consistency Ratio of the matrix was generated and it indicates the probability that the ratings were randomly assigned or otherwise. Values less than 0.10 indicate good consistency while values higher than 0.10 indicate inconsistency in factor rating by the decision makers [8]. The consistency matrix shows how the individual ratings would have to be changed if they were to be perfectly consistent with the best fit weightings achieved.

Results and Discussion

Rainfall erosivity data shows a discernable north-south alignment. The north eastern part has higher erosivity compared to the south western segment with lower value. The middle part of the state as well as the south eastern extreme has low index and this corresponds to areas with low rainfall regime. Generally, 34.15% of the study area can be classified as low erosivity index area, while 35.86% belong to medium erosivity index and the remaining 29.99% were classified as high erosivity index area. The C-factor data shows that 73.2% of the entire area can be classified as having high C-factor index, while 22.6% is classified medium and the remaining 5.1% as low. The higher the C-factor, the more susceptible the land is to soil erosion. It should however be noted that unlike erosivity index, there is no discernable pattern in C-factor distribution. The L-factor also did not show any defined pattern after converting its data into grid format. However, 89.6% has high L-factor which implies that most part of the study area had higher elevation while the remaining 10.1% have relatively low elevation. It is assumed that the higher the elevation; the more the erosion risk. In addition, the K-factor shows that 84% of the area under consideration has high erodibility based on soils textural characteristics, while 8% have low erodibility and the remaining 7% have medium erodibility. Most of the southern part was classified as medium erodibility area because of the predominant soil textural characteristic in the area. Areas with low K-factor are expected to have low erosion risk. The P-factor shows that 93.7% of the area does not have any conservation strategy, while only the isolated portion particularly area dominated by forest that have some form of natural conservation. Areas with lower coefficient are expected to have high susceptibility to soil erosion.

The experts were asked to ranking these five factors in order of priority in precipitating soil erosion. The ranking was subsequently weighted using AHP method. The resultant weight provided the basis for prioritization of each of these five parameters in the erosion risk assessment model. The pairwise comparison matrix used based on expert ranking of each of the factors that could precipitate soil erosion is contained in Table 5. The table shows the relative rating of the variables. The table shows that landuse is strongly more important than slope in initiating soil erosion, while soil k-factor is less extremely important than rainfall erosivity in initiating soil erosion.

Table 5 Pairwise Comparison of Erosion Risk Factors

	Erosivity	Slope	Landuse	Soil-K
Erosivity	1			
Slope	1/5	1		
Landuse	1	3	1	
Soil-K	1/5	3	1/3	1

Table 6 shows the eigenvector of the assigned weights derived from the use of the AHP and it shows that based on expert opinions and ranking, rainfall erosivity has the greatest impacts in causing erosion and this was followed by the landuse practices. The third most important factor that affects soil erosion is slope and this was also followed by the amount of clay content in the soil. The consistency ratio which is an indication of the cross validation of the various factors shows that the expert opinion ranking is consistent (0.07). These weights were then used in prioritizing erosion risk using a weighted linear combination (WLC) approach.

Table 6 The Eigenvector of Weights of Erosion Risk Factors Used.

S/N	Factors	Erosivity
1	Erosivity	0.4439
2	Landuse	0.3414
3	Slope	0.0779
4	Soil-K	0.1368
	Consistency Ratio	**0.07**

Figure 6 shows the number of pixels in each of the data range from 0-255 in a graphical format. The graph shows that fewer pixels are located in the lower data range while the clusters of pixel are found particularly between 90-200 categories. Since the data was standardized before using the WLC, and based on this, only a small area within the state has low erosion risk potential, while majority of the areas have between medium and high erosion risk potential.

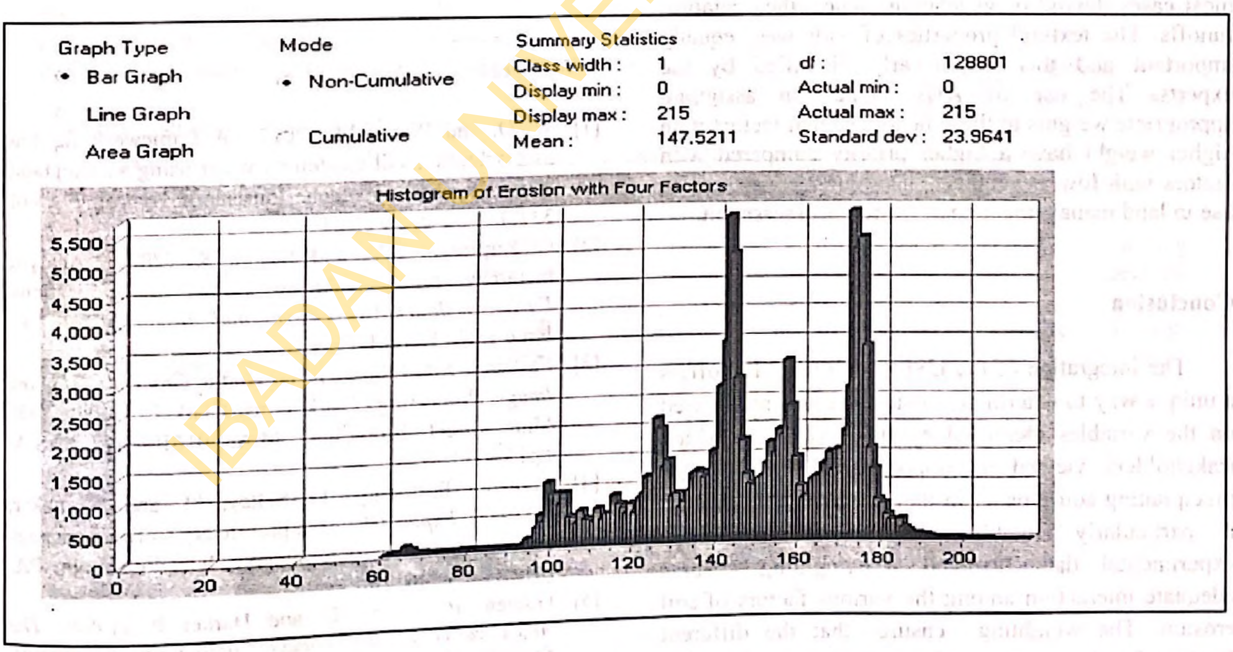

Figure 6 Bar Graph Showing the Number of Data Pixel within Each Class

Figure 7 is the erosion risk potential map and it shows that erosion risk varies across the study area based on the five factors identified. The southern part experience medium erosion risk, while the northern part has high erosion risk potential. In order to estimate the amount of land under different erosion risk scenario, the area under different erosion risk was calculated. Table 7 shows the percentage area under different erosion risk scenarios.

Table 7 State Wide Erosion Risk Assessment

Erosion Risks	Area	% Area
Low Erosion Potential Area	0.1220	0.0902
Medium Erosion Potential Area	55.6762	42.1298
High Erosion Potential Area	76.4969	57.7800
Total	132.1853	100.0000

The role of the rainfall in causing soil erosion was clearly revealed in this study. The model identified rainfall erosivity as the most important factor in initiating soil erosion while landuse practices was identified as the second most important factors. The increasing urbanization of cities and villages is exposing much of the land areas to the impact of soil erosion. The percentage of impervious surface has consistently being on the increase and this has implication for the runoff and subsequent soil erosion. Topographical factor was considered the third most important because without the impact of the first two factors, soil erosion will not likely occur even if the topography is steep. However, it is major factor to consider once the first two factors are present. The study area is characteristically hill with extensive inselbergs in more than 20% of the area. These inselbergs act as impervious surface since they are in most cases devoid of vegetation, hence, they catalyze runoffs. The textural properties of soils were equally important and this was clearly identified by the experts. The use of AHP helped in assigning appropriate weights to these factors so that factors with higher weight have a higher priority compared with factors with lower weights. The resultant map can be use in land management apart from risk assessment.

Conclusion

The integration of the USLE with the AHP offers a unique way to determine erosion risk potential based on the variables identified by the USLE and which stakeholders viewed as important in initiating or precipitating soil erosion in their domain. The method is particularly suitable when there are limited experimental data [2] and it weighting ensures adequate interaction among the various factors of soil erosion. The weighting ensures that the different factors of soil erosion were integrated into soil erosion risk modelling based on their perceived importance because several alternatives exist that will satisfy the objectives of a given problem to varying degrees [29]. The AHP procedure allows full trade off among all factors, while weighing of attributes and scoring of options leads to useful data about concerns and preferences for factors. The amount any single factor can compensate for another is, however, determined by its factor weight. In this study, a high suitability score in rainfall erosivity can easily compensate for a low suitability score in landuse for the same location. In the reverse scenario, a high suitability score in landuse can only weakly compensate for a low score in rainfall erosivity. It can trade off, but the degree to which it will impact the final result would be severely limited by the low factor weight of landuse. The decision-maker has to choose the best alternative without having alternative knowledge of the effect of each alternative on the objectives. The method therefore offers a comprehensively easy approach to combine the strengths of fuzzy set theory and the AHP for erosion risk assessment and quantification even at the smallest administrative unit. Hence, it provides a useful framework for the evaluation of environmental policies aimed at addressing specific environmental problem. The implementation of this model within a GIS environment ensures a greater sense of control over the model, than the AHP implemented in isolation, by providing immediate access to underlying maps and decision zone information. Structuring a problem as a hierarchy is a useful aid to understanding problems and driving discussions about them because the process helps to reveal issues which have not previously been explicitly stated.

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