ISSN: 2148-9173 **Vol: 9 Issue:4 December 2022**

International Journal of Environment and Geoinformatics (IJEGEO) is an international, multidisciplinary, peer reviewed, open access journal.

Evaluation of land suitability for crop production in Northern Ghana using GIS and AHP based techniques

Eliasu SALIFU, Wilson AGYEİ AGYARE, Abdul ABDUL-GANİYU

Abstracting and Indexing: TR DIZIN, DOAJ, Index Copernicus, OAJI, Scientific Indexing Services, International Scientific Indexing, Journal Factor, Google Scholar, Ulrich's Periodicals Directory, WorldCat, DRJI, ResearchBib, SOBIAD

International Journal of Environment and Geoinformatics 9(4):046-056 (2022)

Research Article

Evaluation of land suitability for crop production in Northern Ghana using GIS and AHP based techniques

Eliasu Salifu[1*], **Wilson Agyei Agyare**[2], **Abdul-Ganiyu Shaibu**[1]

[1]Department of Agricultural Engineering, University for Development Studies, Tamale, GHANA;
[2]Department of Agricultural and Biosystems Engineering, Kwame Nkrumah University of Science and Technology, Kumasi, GHANA

* Corresponding author: E. Salifu
* E-mail: esalifu@uds.edu.gh

Received 25.11.2021
Accepted 16.04.2022

How to cite: Salifu et al., (2022). Evaluation of land suitability for crop production in Northern Ghana using GIS and AHP based techniques, *International Journal of Environment and Geoinformatics (IJEGEO)*, 9(4): 046-056. doi. 10.30897/ijegeo.1022275

Abstract

In this study, a land suitability index for crop production in three northern regions of Ghana is spatially generated using a land suitability analysis through the integration of AHP and GIS. The study further exploited actual maize and groundnut yield obtained by farmers in the study area by integrating it with the land suitability index to spatially generate potential maize and ground yield. The actual and potential maize and groundnut yields were overlayed in GIS to produce potential yield losses for maize and groundnuts. Factors of precipitation, slope of land, LULC, soil erosion, OM and the soil types were identified through expert opinion in literature, and assigned weights through AHP for the land suitability analysis. Results obtained from the land suitability index indicate about 19.2 % of land in the three regions is highly suitable for crop production, about 20.8 % is moderately suitable, about 27.0 % is less suitable and about 33 % unsuitable due to settlements and depleted lands. Potential yield loss due to difference in actual and potential maize and groundnuts yields were 70 % and 63 % for maize and groundnuts respectively for the Northern Region, 83 % and 66 % for maize and groundnuts respectively for the North-East Region, and then 66 % and 59 % for maize and groundnuts respectively for the Savannah Region. The AHP and GIS-based land suitability analysis techniques are potentials and effective tools for determining the suitability of land for crop production thereby enhancing sustainable agricultural development through enhancing food security and creation of new jobs.

Keywords: Multi-Criteria Decision-Making, Potential Yield, Yield Loss, Maize, Groundnuts

Introduction

The suitability of land for sustainable food production is vital for the survival of humanity (Mueller et al., 2010) and a prerequisite for the optimum utilization of land resources (Mann et al., 1977). To achieve optimum utilization of available land resource for agricultural production, land suitability analysis is a recommended requirement (Van Ranst et al., 1996; Kumar et al., 2018). Land suitability refers to the useability of a given type of land for a specific purpose. The process of land suitability analysis involves the evaluation and grouping of specific areas of land in terms of their suitability for a defined purpose. Performing land suitability evaluation and generating maps of land suitability for agricultural or non-agricultural uses facilitates the attainment of sustainable agriculture (Vargahan et al., 2011; Rabia and Terribile, 2013; Vaghela et al., 2018).

Land suitability analysis involves the integration of various criteria, which can be well achieved by multi-criteria decision-making (MCDM) techniques (Malczewski, 2006; Ying et al., 2007; Cinelli et al., 2014; Savun-Hekimoğlu et al., 2021). The aim of the MCDM process is mostly predicting the potential of the land for different applications (Maddahi et al., 2017). Theoretically, the potential of land suitability for agricultural use is estimated through an evaluation process which uses criteria such as climate, soil, water resources, topography, components of the environment, and understanding the local environment (Ceballos-Silva and Ľopez-Blanko, 2003; Pourkhabbaz et al., 2014; Mihiretie., 2022). In MCDM process, it is extremely difficult to assign relative weights to the different criteria involved in making a decision on suitability of land for a defined purpose. Hence, the Analytical Hierarchy Process (AHP) is adopted to estimate and assign weights in MCDM process.

The AHP is a commonly used MCDM technique to resolve complex decision-making processes which include multiple criteria, scenarios, and factors. The AHP involves structuring multiple choice criteria into a hierarchy, assessing the relative importance of these criteria, comparing alternatives for each criterion, and determining an overall ranking of the alternatives. AHP completely aggregates various facets of the decision problem into a single objective function (Saaty, 2001; Ulukavak, and Miman, 2021).

The integration of MCDM analysis in Geographic Information System (GIS) provides a powerful spatial decision support system which offers the opportunity to efficiently produce land suitability maps. The AHP is a MCDM method for assessing the land use suitability based on GIS (Satty, 1980; Malczewski, 2004; Hansen, 2005) and is one of the popular methods widely used to resolve MCDM problems (Chang et al., 2007). AHP and GIS based land suitability analysis has widely been applied to numerous land suitability assessment problems in the last few decades (Feizizadehab and Blaschkeb, 2013; Ullah and Mansourian, 2015).

The aim of this research is to develop a map of land suitability index for crop production in the northern parts of Ghana by combining AHP and GIS techniques. The research also sought to generate potential yield maps based on the land suitability index and actual crop yield obtained by farmers in the study regions. To achieve this objective, data of maize (Zea mays) and groundnuts (Arachis hypogaea) yield were obtained from farmers to facilitate the analysis. Maize and groundnuts were selected for the study because they are Ghana's most commonly grown cereals and legumes respectively (Kombiok et al., 2012).

Materials and Methods

Description of study area

The Northern, North-East and Savannah Regions of Ghana where this study was conducted, were until recently together as one region known as the Northern Region of Ghana. For this reason, the three regions share similar ecological, demographical, and socio-cultural characteristics. The regions belong to the Guinea and Sudan Savannah Agro-ecological zones which is mainly characterized by shorth grasses and trees such as Dawadawa (Parkia biglobosa) and Shea (Vitellaria paradoxa) in isolations. Rainfall in these regions is erratic and averages between 800 - 1000 mmy-1 from May to October of the calendar year (Ghana Meteorological Service, 201). The regions are above sea level at about 180 m and spatially located on latitudes 10° 38' N and 08° 0.8' N and longitudes 0° 48' W and 1° 7.2' W (Figure 1).

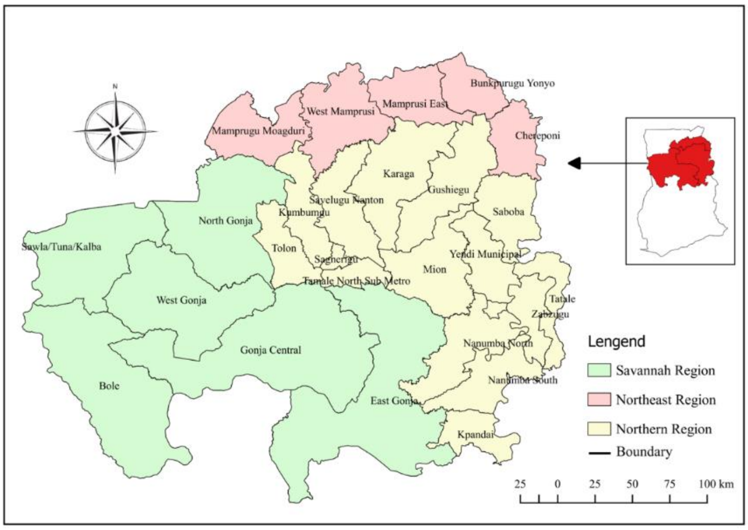

Fig. 1: Map of study regions

Land suitability analysis

A land suitability analysis was carried out to determine the suitability of the study regions for crop production. The land suitability analysis was achieved by incorporating factors that are known to influence crop production, to generate a spatial land suitability index. The spatial land suitability index is a relative indicator of land suitability for crop production. The suitability index spatially shows areas of potentially higher suitability and areas of potentially lower suitability for crop production in relative terms. The factors for the land suitability analysis were identified and assigned weights through the Analytic Hierarchy Process (AHP).

Implementation of the AHP

The AHP was used to identify and assign weights to the factors used in the land suitability analysis. The AHP is a multi-criteria method widely used to resolve multi-criteria decision-making (MCDM) problems. The theory of the AHP assessment is based on a pairwise comparison (Parry *et al.*, 2018), that works with the basic assumption that, assessment of two elements is derived from their relative importance. The AHP was used for assessing the land use suitability with GIS.

Criteria (factor) evaluation

This is the process where the factors that are considered to effectively influence crop production are evaluated. The most important and effective factors identified for the land suitability analysis were precipitation, slope of land, land-use/landcover (LULC), soil erosion, organic matter (OM) and the soil type. These factors were considered based on literature and expert opinions on the most effective factors to determine the suitability of land for different uses (Makhdoum, 2000; Mahfoozi *et al*,. 2001; Jafari and Onagh, 2005).

Weighting criteria (factors)

A comparison matrix based on the nine-point weighting scale of Saaty (1977) was used to determine the relative importance of the factors (Table 1). In the AHP, the identified factors were all compared with each other in a pairwise comparison matrix, which indicates the measure of the relative preference between the factors on a scale of comparison (Saaty, 1977), which consists of a

Table 1: Analytic hierarchy process scale for pair wise comparison

Expressions of importance	**Index**	**Reciprocal Index**
Equally important	1	1/1
Equally or slightly more important	2	1/2
Slightly more important	3	1/3
Slightly to much important	4	1/4
Much more important	5	1/5
Much to far more important	6	1/6
Far more important	7	1/7
Far more important to extremely more important	8	1/8
Extremely more important	9	1/9

Table 2: Random index (RI)

N	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**
R	0	0	0.58	0.9	1.12	1.24	1.32	1.41	1.45	1.49	1.51

range of values from 1 – 9. The value '1' expresses equal importance among factors and the '9' expresses a factor having an extreme importance over the other.

Computation of pairwise comparison matrix

The matrix of the pairwise comparison is a technique involving a comparison of pairs of alternatives, pairs of factors and sub-factors. AHP utilizes a nine-point fundamental measurement scale to define individual judgements or preferences (Saaty, 1980; Bozdağ *et al.,* 2016). This generates a pairwise comparison matrix that allows the contribution of each of the factors, to be independently evaluated, hence, making the decision-making process easier and simple (Rezaei-Moghaddam and Karami, 2008). The format of the pairwise comparisons matrix describes $A = [a_{ij}]_{n\times n}$ as shown in Equation (1).

$$A = \begin{pmatrix} a_{11} & a_{12} & a_{1n} \\ a_{21} & a_{22} & a_{2n} \\ a_{n1} & a_{n2} & a_{nn} \end{pmatrix} \quad \text{(Eq.1)}$$

Where *i* and *j* = 1, 2, 3…..*n.*

It is necessary for all *i* and *j*, that $a_{ii} = 1$ and $a_{ij} = 1/a_{ij}$

The vector of weights $w = [w_1, w_2, w_3, \dots w_n]$ is formed after all the matrices of the pairwise comparison, based on Saaty's eigen-vector method.

The eigen-vector is normalized by the expression in Equation (2) and the weights computed by the expression in Equation (3).

$$a_{ij} = \frac{a_{ij}}{\sum_{j=1}^{n} a_{ij}} \quad \text{(Eq.2)}$$

$$w_{ij} = \frac{\sum_{j=1}^{n} a_{ij}}{n} \quad \text{(Eq.3)}$$

Where *i* and *j* = 1, 2, 3,…..*n.*

The *n* represents the number of factor comparisons, which is determined by Equation (4).

$$Number\ of\ comparison = n(\frac{1-n}{2}) \quad \text{(Eq.4)}$$

Consistency ratio (CR)

The CR is a weight of priority importance that is obtained from the AHP technique comparison matrix. It enables incompatible relationships and at the same moment offers a degree of validity measure for the robustness of the AHP (Chen *et al.,* 2010; Feizizadehab and Blaschkeb, 2013). After the pairwise comparisons process, some few inconsistencies may arise in the AHP. The consistency level of the weight values in the AHP is controlled with the CR, which is given by the expression in Equation (5).

$$CR = \frac{CI}{RI} \quad \text{(Eq.5)}$$

Where *CI* = Consistency Index
RI = Random Index

Equation (6) gives the Consistency Index (*CI*)

$$CI = \frac{\lambda_{max} - n}{n-1} \quad \text{(Eq.6)}$$

Where; λmax = Principal Eigen-value of the pairwise comparison matrix

n = number of the factors

The *RI* represents a consistency index of a pairwise matrix that is produced by random inconsistency ratings (Ying *et al.*, 2007) (Table 2).

The matrix is consistent if CR < 10 % (0.10), hence, indicating a reasonable consistency level. If the CR > 10 % (0.10) however, then the judgments are inconsistent (Saaty, 1980; Chakraborty and Banik, 2006; Chen *et al.*, 2010). The input data sources and flowchart for the land suitability analysis are presented in Table 3 and Figure 2 respectively.

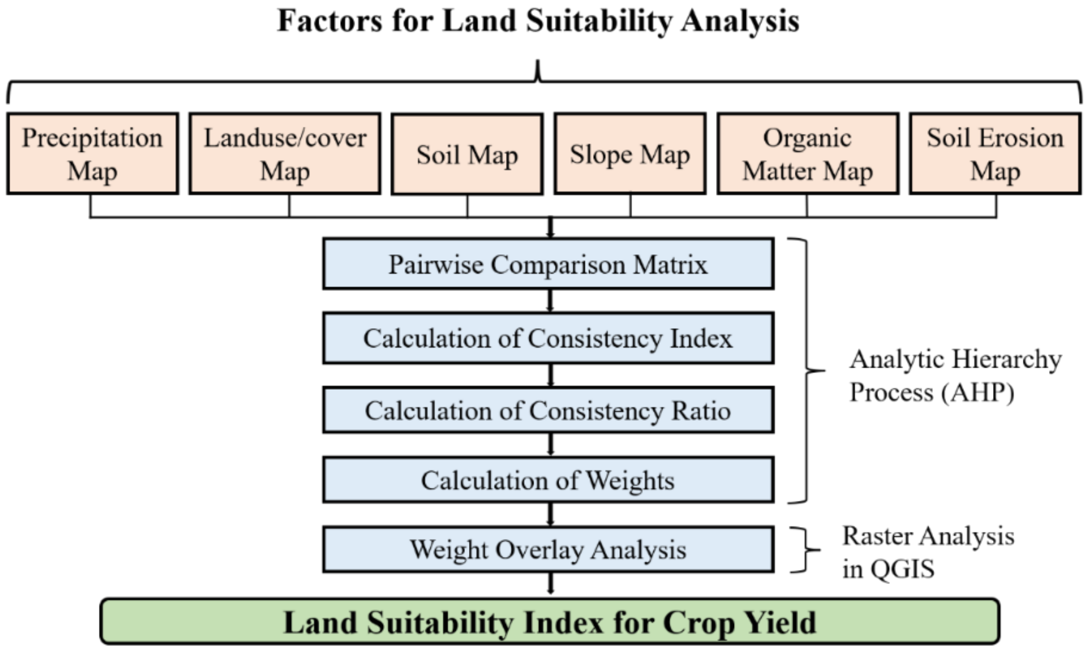

Fig. 2: Flowchart of procedure for determining land suitability index for crop production

Actual maize and groundnut yield data

Actual maize and groundnut yield were collected from about four hundred farmers from the study regions for the 2017 and 2018 farming seasons. The yields were georeferenced and the average yields were spatially interpolated to generate a spatial map of actual maize and groundnut yield for the study regions. The interpolation was accomplished by the Inverse Distance Weighing (IDW) method in GIS. The IDW method Equation (7) uses values of known points, to estimates unknown values by specifying search distances, closest points, power settings and barriers.

$$Z_p = \frac{\sum_{i=1}^{n}(\frac{z_i}{d_i^p})}{\sum_{i=1}^{n}(\frac{1}{d_i^p})} \quad \text{(Eq.7)}$$

Where Z is the estimated value for prediction point, *Zi* is the measured value for sample point, *di* is the Euclidean distance between sample and prediction points, *p* is a power parameter, and *n* represents the number of sample points. A main factor affecting IDW interpolation result is the *p* value. When the *p* value increases, the smoothness of IDW output surface increases.

Potential yield and potential yield loss

Potential yield maps for maize and groundnuts were spatially generated through an overlay process in GIS by integrating the actual yield maps with the land suitability index map of the study regions. The potential yield loss for maize and groundnuts were determined and generated spatially to show areas of higher yield losses and areas of lower yield losses. The spatial potential yield loss was obtained directly by spatially subtracting the actual yield (t ha^{-1}) from the potential yield (t ha^{-1}) in GIS for both the maize and groundnuts.

Model performance evaluations

In evaluating the results of the suitability analysis, the Willmott d-index and the Root Mean Square Error (RMSE) were used. The *d*-value of Willmott varies between zero (0) and one (1). One shows an ideal model, whereas zero shows bad output (Wilmott, 1981). The least the RMSE value, the stronger the performance of the model and an RMSE value of zero indicates a perfect model-performance. In Equation (8) and (9), the Willmott d-index and RMSE are presented respectively.

$$d\text{-value} = 1 - \frac{\sum_{i=1}^{n}(Observed_i - Simulated_i)}{\sum_{i=1}^{n}(Simulated_i - Mean_{observed}) + (Observed_i - Mean_{observed})} \quad \text{(Eq. 8)}$$

$$\text{RMSE} = [\frac{1}{n}\sum(yield_{simulated} - yield_{observed})^2]^{0.5} \quad \text{(Eq.9).}$$

Table 3: Analytic Hierarchy Process (AHP) pairwise comparison matrix for the factors

	Precipitation	Cover	Soil	Slope	OM	Erosion
Precipitation	1.00	5.00	2.00	3.00	3.00	4.00
LULC	0.20	1.00	0.33	0.50	0.50	0.50
Soil	0.50	3.00	1.00	2.00	2.00	3.00
Slope	0.33	2.00	0.50	1.00	2.00	2.00
OM	0.33	2.00	0.50	0.50	1.00	2.00
Erosion	0.25	2.00	0.33	0.50	0.50	1.00
Sum	2.62	15.00	4.67	7.50	9.00	12.50

Table 4: Calculated coefficient matrix of priorities for factors of land suitability analysis

	Precipitation	Cover	Soil	Slope	OM	Erosion	Sum
Precipitation	0.38	0.33	0.43	0.40	0.33	0.32	2.20
LULC	0.08	0.07	0.07	0.07	0.06	0.04	0.38
Soil	0.19	0.20	0.21	0.27	0.22	0.24	1.33
Slope	0.13	0.13	0.11	0.13	0.22	0.16	0.88
OM	0.13	0.13	0.11	0.07	0.11	0.16	0.71
Erosion	0.10	0.13	0.07	0.07	0.06	0.08	0.50

Table 5: Weight ratio of the factors of land suitability analysis

Factor	Normalized weights
Precipitation	0.3710
LULC	0.0573
Soil	0.2194
Slope	0.1453
Organic Matter (OM)	0.1156
Erosion	0.0913

Input data sources and processing

The precipitation data for the study was acquired from the Ghana Meteorological Service. The precipitation data for the past 30 years (1990 - 2020) was interpolated into a raster file for the study area. The digital elevation model (DEM) for the study was acquired from Advanced Spaceborne Thermal Emission and Reflection Radiometer (ASTER) - Global Digital Elevation Map (GDEM). The DEM was used to generate the slope (slope length and steepness) map for the study. The LULC map for the study was acquired from Global Land Cover by National Mapping Organizations (GLCNMO) which provided accurate mapping of different LULC categories due to its high spatial resolution. The soil map for the study was acquired from the International Soil Reference and Information Centre (ISRIC). whilst the map for organic matter was acquired from Moderate Resolution Imaging Spectro-radiometer (MODIS). Finally, the soil erosion map was obtained from Salifu et al., which was generated through the Revised Universal Soil Loss Equation (RUSLE). See Fig. 3 for the various input factors.

GIS process and analysis

The Quantum Geographical Information System (QGIS) version 2.6.1 was used for the GIS analysis due to its relative stability. The QGIS is an open-source GIS program, fully featured with geospatial algorithms, integrated with established geo-computation platforms such as Geographic Resource Analysis Support System (GRASS) and System for Automated Geoscientific Analyses (SAGA) (Dumedah *et al.*, 2019). Each input factor was clipped to the spatial extent of the study area and the pixel dimension resampled to 250 m resolution (due to the scale of the study area) and geo-referenced in the Universal Transverse Mercator (UTM) coordinate system (EPSG: 32630, WGS 84 / UTM zone 30N) for compatibility. The input factors were reclassified into suitability levels (unsuitable, less suitable, moderately suitable and highly suitable) in terms crop production. The raster calculator, (A key feature of QGIS) which allows the geoprocessing of input raster data, was used to process and generate the land suitability map from the input factors, and to integrate the land suitability map with the yield data to generate maps of actual and potential maize and groundnut yields in absolute terms. The raster-layer statistic tool, which is a geo-algorithm, within the processing toolbox, was used to determine the statistics of the factors and results.

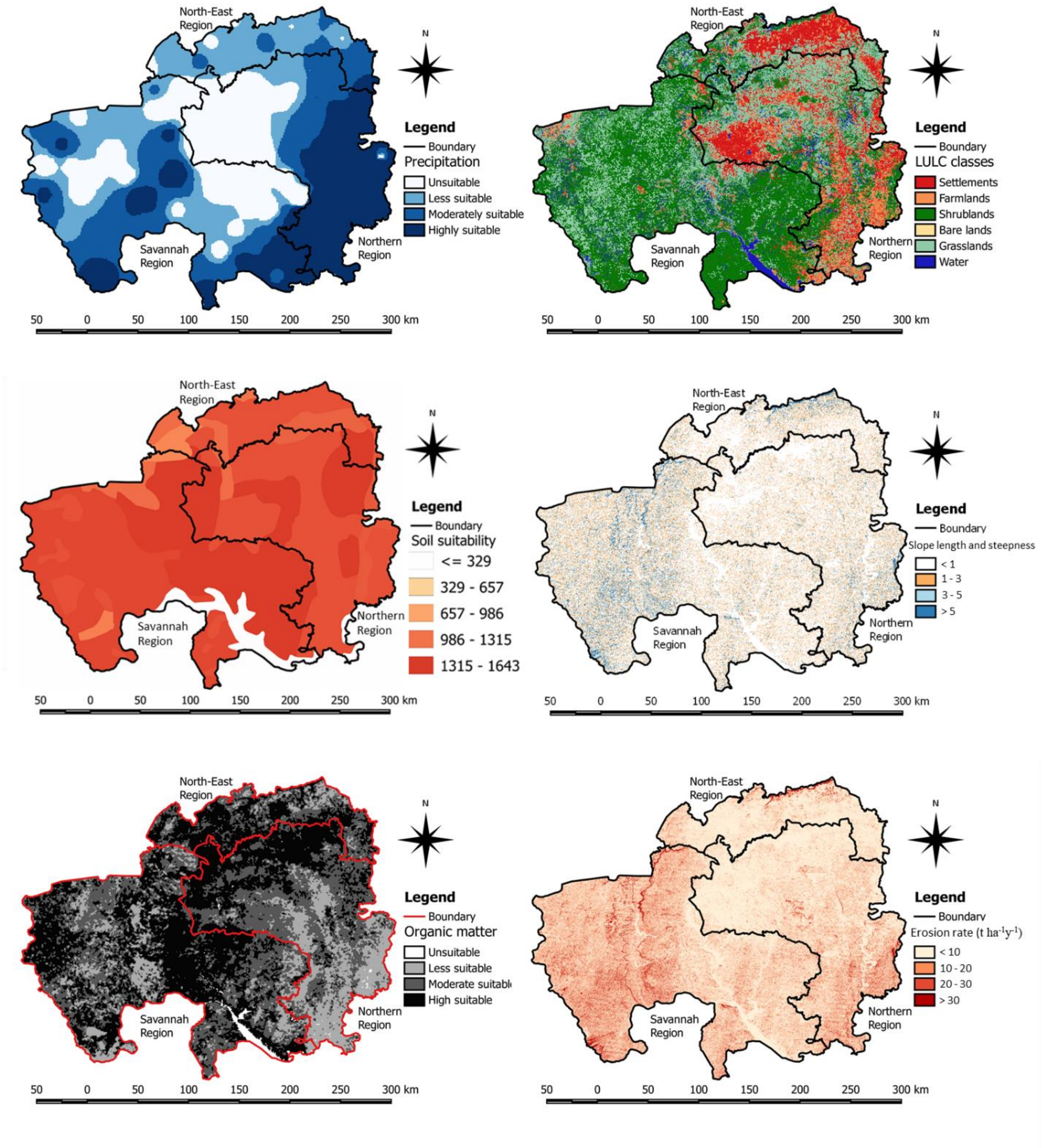

Fig. 3: Spatial distribution of factors for crop-yield suitability index – (A) precipitation, (B) LULC, (C) soil, (D) slope length and steepness (E) organic matter and (F) soil erosion.

Results and Discussions

Factors of land suitability analysis

The primary aim of the AHP-based analyses is to identify areas of high suitability for crop production (Bozdağ *et al.*, 2016), mainly maize and groundnuts. Table 4 shows the pairwise comparison matrix for the factors of the land suitability analysis. The values in the pairwise comparison matrix show the importance of compared factors in terms of influence on crop production. Table 5 shows the calculated coefficient matrix of priorities for the factors based on a standardized eigen-vector, extracted from each comparison matrix, allowing for the assignment of weights to factors. The results indicated the highest weight (0.3710) for precipitation while, the lowest weight (0.0573) was assigned to the land LULC as shown in Table 6.

Factors of the land suitability index for crop production were spatially generated by resampling the factor maps based on their respectively assigned weights (Figure 3).

The weighted factors were Precipitation, LULC, Soil, Slope, OM and Erosion. The factor maps show areas of high suitability for crop production to areas of low suitability for crop production.

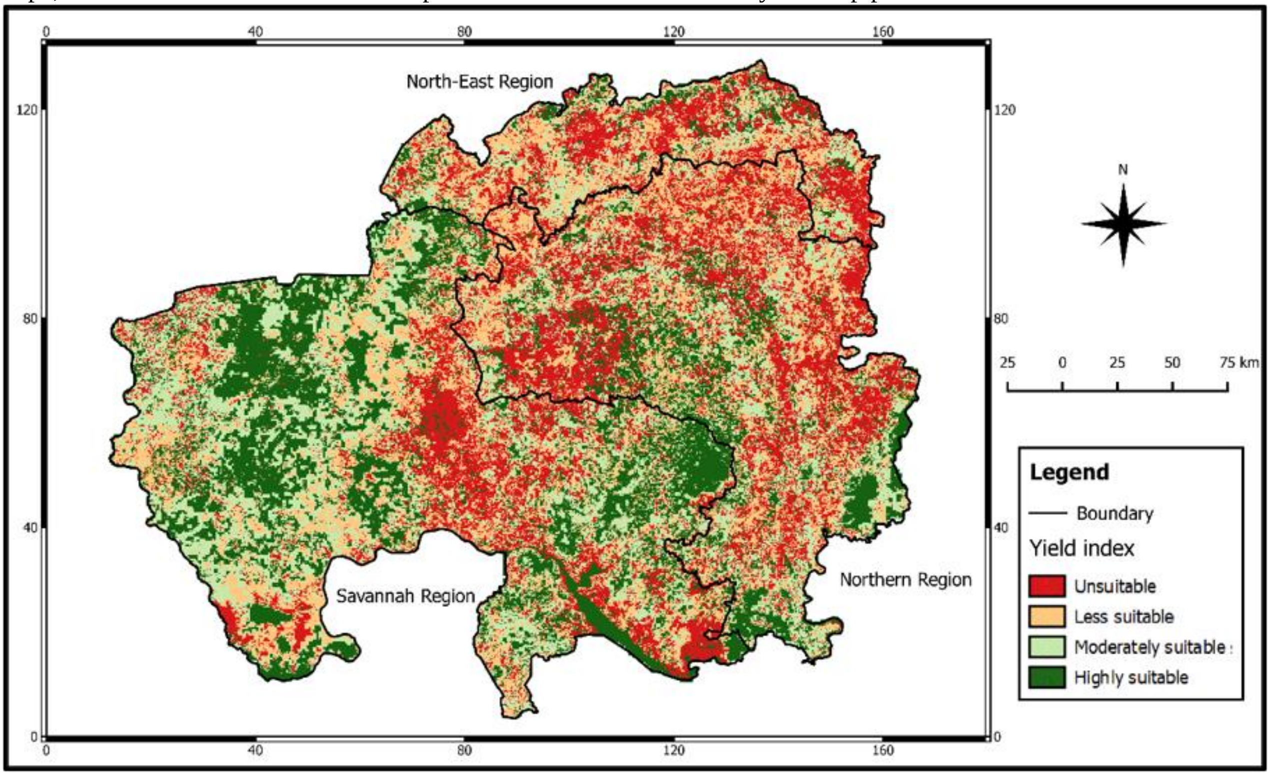

Fig. 4: Spatial distribution of land suitability index for maize and groundnuts production

Table 6: Land suitability index for crop production

Land suitability (%)	Northern Region	North-Eastern Region	Savannah Region	Total (Average)
Unsuitable	36.7	41.4	20.8	33.0
less suitable	25.5	32.1	23.5	27.0
Moderate suitable	19.2	13.2	30.1	20.8
Highly suitable	18.6	13.3	25.6	19.2

Land suitability index for maize and groundnut production

The resultant land suitability index for crop production based on the input factors is shown in Figure 4. The map shows areas of high potential for increased agriculture productivity. The map indicates higher yield potential for maize and groundnut production in the Savannah region compared to the Northern and the Northeastern Regions. This phenomenon may be due to relatively favourable crop production factors (Precipitation, OM, soil composition and LULC) in the Savannah Region. The land suitability index further indicates that, about 63.3 % of the Northern Region can be considered suitable for crop production. For the North-Eastern Region, 58.6 % of the land is considered suitable for crop production. Whilst the Savannah Region has 79.2 % of the land considered suitable for crop production. The results are summarized in Table 7. The unsuitable portions of the land are mainly due to settlements and land degradation.

Actual and potential maize yield

The spatial distribution of the actual and potential maize yield is presented in Figure 5. The actual maize yield map was generated by interpolating actual yield data obtained from farmers in the study regions. However, the potential maize yield map was obtained by integrating the actual maize yield with the land suitability index. The actual average maize yield obtained by the farmers in the study regions were 1.2 t ha^{-1} for the Northern Region, 0.9 t ha^{-1} for the North-East Region and 1.4 t ha^{-1} for the Savannah Region. The potential maize yield obtained by the simulation process for the study regions were 3.6 t ha^{-1} for the Northern Region, 3.3 t ha^{-1} for the North-East Region and 4.1 t ha^{-1} for the Savannah Region. These actual and potential maize yields are in line with MoFA (2017) that reported a national average maize yield and potential yield of 1.9 t ha^{-1} and 5.5 t ha^{-1} respectively. Table 8 presents detail for the actual and potential maize yield for the study regions.

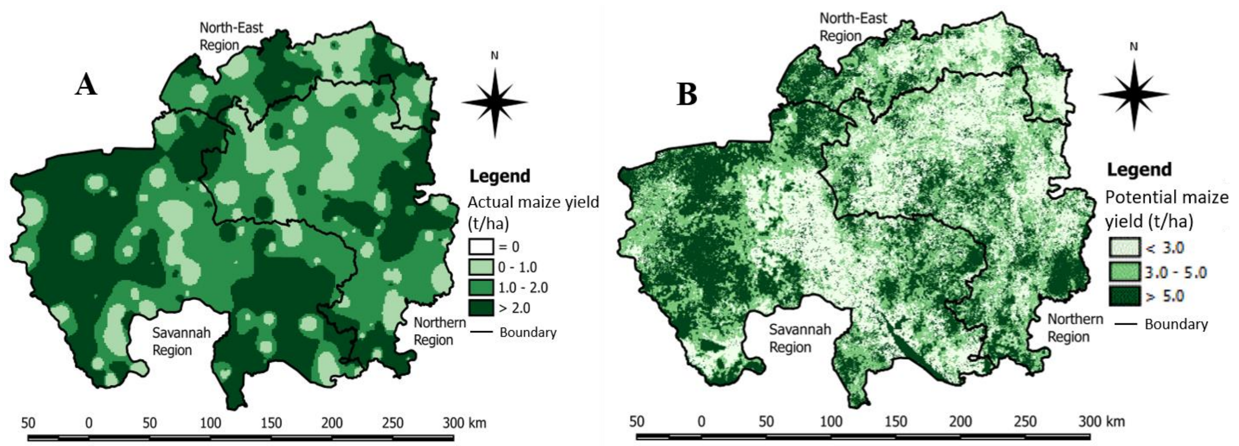

Fig. 5: Spatial distribution of (A) actual maize yield (B) potential maize yield

Table 7: Actual and potential maize yield

Maize Yield ($t\ ha^{-1}$)	Northern Region		North-East Region		Savannah Region	
	Actual	Potential	Actual	Potential	Actual	Potential
Min.	0.4	0.8	0.5	0.6	0.3	1.2
Max.	3.9	5.8	3.6	5.4	4.6	6.3
Mean	1.2	3.6	0.9	3.3	1.4	4.1
SD	1	2.4	1.1	2.1	1.2	2.2

Actual and potential groundnuts yield

The map of actual groundnuts yield was similarly obtained by interpolating yield obtained from farmers in the study regions whilst the potential yield was generated by integrating the map of the land suitability index and that of the actual groundnuts yield (Figure 6). The actual average groundnuts yield obtained by the farmers in the study regions were 2.4 $t\ ha^{-1}$ for the Northern Region, 2.8 $t\ ha^{-1}$ for the North-East Region and 2.5 $t\ ha^{-1}$ for the Savannah Region. The potential groundnuts yield obtained by the simulation process for the study regions were 3.7 $t\ ha^{-1}$ for the Northern Region, 3.7 $t\ ha^{-1}$ for the North-East Region and 3.8 $t\ ha^{-1}$ for the Savannah Region. These actual and potential groundnuts yields are in line with MoFA (2017) that reported a national average groundnut yield and potential yield of 1.2 $t\ ha^{-1}$ and 3.5 $t\ ha^{-1}$ respectively. A summary is presented in Table 9.

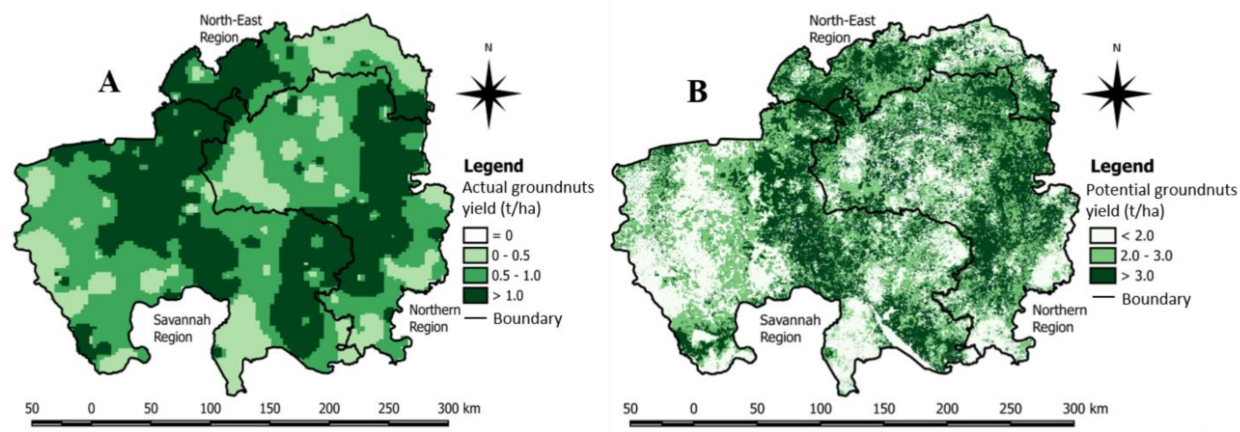

Figure 6: Spatial distribution of (A) actual groundnuts yield (B) potential groundnuts yield

Table 8: Actual and potential groundnuts yield

Groundnuts Yield ($t\ ha^{-1}$)	Northern Region		North-East Region		Savannah Region	
	Actual	Potential	Actual	Potential	Actual	Potential
Min.	0.2	0.6	0.2	0.5	0.2	0.5
Max.	0.4	2.2	0.4	2.3	0.5	2.1
Mean	2.4	3.7	2.8	3.7	2.5	3.8
SD	0.5	1.1	0.5	1.0	0.5	1.2

Potential yield loss

The map of potential yield loss for maize and groundnuts was done by spatially subtracting the actual yield from the potential yield in GIS. Figure 7 shows the spatial distribution of potential yield loss in percentage terms for maize and groundnuts in the study regions. Table 10 provides a summary of the potential yield loss. The average potential yield loss of maize in percentage terms were 70 % for the Northern Region, 83 % for the North-East Region and 66 % for the Savannah Region. For groundnuts, the average potential yield losses were 63 % for the Northern Region; 66 % for the North-East and 59 % for the Savannah Region. The significance of the potential yield loss is that, it brings to bear the gap between the actual yield obtained by farmers and the yield they could potentially gain under favourable climatic and ecological factors in the study regions.

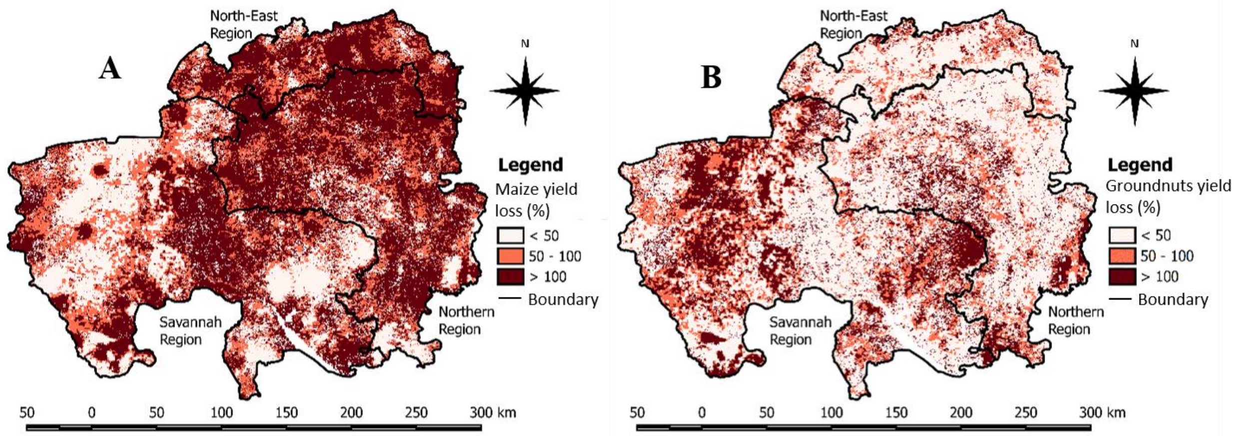

Figure 7: Spatial distribution of potential yield loss for maize (A) and groundnuts (B)

Table 9: Maize and groundnut potential yield losses

	Northern Region		North-East Region		Savannah Region	
Potential yield loss (%)	Maize	Groundnuts	Maize	Groundnuts	Maize	Groundnuts
Minimum	27	21	23	23	21	24
Maximum	133	167	141	173	145	158
Mean	70	63	83	66	66	59
SD	77	56	73	61	56	59

SD: Standard Deviation.

Model performance evaluation

The evaluation of the potential maize and groundnut yield simulations with the root mean square error (RMSE) gave 3.4 d and 2.7 d respectively. Whilst the Willmott's *d*-index evaluation gave potential maize and groundnut yield predictions at 0.87 and 0.83 respectively.

Conclusion and Recommendations

This study intends to determine the suitability of lands in three northern regions of Ghana for crop production using GIS and AHP based techniques. For this purpose, six factors (Precipitation, LULC, Soil, Slope, OM and Erosion) were identified through expert opinion in literature and assigned weights through AHP for the land suitability analysis for crop production.

The results of the land suitability analysis show 63.3 % (1,626,683 km^2), 58.6 % (553,770 km^2) and 79.2 % (2,929,370 km^2) of the Northern, North-Eastern and Savannah Regions can respectively be considered suitable for crop production. The unsuitable portions are made up of settlements degraded lands, and water bodies. The results further indicate a potential maize yield loss of 70 %, 83 % and 66 % for the Northern North-East and Savannah Regions respectively. That for the groundnuts yield were 63 %, 66 % and 59 % for the Northern North-East and Savannah Regions respectively.

The AHP and GIS based land suitability analysis has the potential to bolster decision making for sustainable agricultural production in Northern Ghana and offers an opportunity to enhance agricultural planning by providing the much required spatial information for farmers and agricultural planners. Consequently, the resultant land suitability map for crop production will provides stakeholders as well as local and international investors with an idea of the agricultural potential of the northern parts of Ghana. This will reassure and heighten investments in the agricultural sector for sustainable development through the creation of new jobs and food security.

References

Bozdağ, A., Yavuz, F. and Günay, A.S. (2016). AHP and GIS based land suitability analysis for Cihanbeyli (Turkey) County. Environ. Earth Sci., 75(9). doi: 10.1007/s12665-016-5558-9.

Ceballos-Silva, A. and Ľopez-Blanco, J. (2003). Delineation of suitable areas for crops using a Multi

Criteria Evaluation approach and land use/cover mapping: a case study in Central Mexico. Agric. Syst., 77: 117–36.

Chakraborty, S. and Banik, D. (2006). Design of a material handling equipment selection model using analytic hierarchy process. Int J Adv Manuf Technol, 28: 1237 – 1245.

Chang, N., Parvathinathan, G. and Jeff, B.B. (2007): Combining GIS with fuzzy multi criteria decision-making for landfill siting in a fast-growing urban region. J. Environ. Manage., 87: 139–153.

Chen, Y. Yu, J. Khan, S. (2010). Spatial sensitivity analysis of multi-criteria weights in GIS-based land suitability evaluation. Environ Model Softw, 25(12): 1582 – 1591.

Cinelli, M., Coles, S.R. and Kirwan, K. (2014). Analysis of the potentials of multi criteria decision analysis methods to conduct sustainability assessment. Ecol., 46: 138-148.

Feizizadehab, B. and Blaschkeb, T. (2013). Land suitability analysis for Tabriz County, Iran: a multi-criteria evaluation approach using GIS. J. Environ. Plan. Manag., 56(1): 1–23.

Ghana Meteorological Service, (2012). Ghana Meteorological Service, Ghana.

Hansen, H.S. (2005). GIS-based multi-criteria analysis of wind farm development. In: Proc. 10th Scandinavian Research Conf. Geographical Information Science. Stock- holm, Royal Institute of Technology: 75–87.

Jafari, H. and Onagh, A. (2005). Zoning the protected area of Geno in GIS, J. Environ. Stud., 38: 39-46.

Kombiok, J.M., Buah S.S.J., Dzomeku I.K. and Abdulai, H. (2012). Sources of pod yield losses in groundnut in the northern savanna zone of Ghana. West Afr. J. Appl. Ecol., 20(2): 53-63.

Kumar, N., Singh, S.K., Mishra, V.N., Obi Reddy, G.P., Bajpai, R.K. and Saxena, R.R. (2018). Soil suitability evaluation for cotton using analytical hierarchic process. Int. J. Chem. Stud., 6(4): 1570-1576.

Maddahi, Z., Jalalian, A., Kheirkhah Zarkesh, M.M. And Honarjo, N. (2017). Land Suitability Analysis for Rice Cultivation Using a GIS-based Fuzzy Multi-criteria Decision-Making Approach: Central Part of Amol District, Iran. Soil & Water Res. 12(1): 29–38. doi: 10.17221/1/2016-SWR.

Mahfoozi, M., Darvishsefat, A. and Makhdoom, F. (2001). Watershed land use planning of Dadghan-Tafresh with Geographic information system. J. Environ. Stud., 27: 99-108.

Makhdoum, M.F. (2000). Fundamental of land use the planning. Tehran University publication, 8th edition.

Malczewski, J. (2004). GIS-based land-use suitability analysis: a critical overview. Prog Plan, 62(1): 3–65.

Malczewski, J. (2006). GIS based multi criteria decision analysis: a survey of the literature. Int. J. Geogr. Inf. Syst., 20: 703-726.

Mann, H.S., Malhotra, S.P. and Shankarnarayan, K.A. (1977). Land and resource utilisation in the arid zone. Desertif. Control, 89-101.

Mihiretie, A. (2022). Assessment of Malaria Risk Using GIS and Multi Criteria: The Case Study of East Gojjam Zone, Ethiopia. *International Journal of Environment and Geoinformatics*, 9(1), 74-78, doi. 10.30897/ijegeo.781219.

MoFA. (2007). *Food and Agriculture Sector Development Policy (FASDEP II).* Ministry of Food and Agriculture, Accra, Ghana.

Mueller, L., Schindler, U., Mirschel, W., Shepherd, T.G., Ball, B.C., Helming, K., Rogasik, J., Eulenstein, F. and Wiggering, H. (2010). Assessing the productivity function of soils. A review. Agron Sustain Dev, 30: 601-614.

Parry, J.A., Ganaie, S.A. and Sultan-Bhat, M. (2018). GIS based land suitability analysis using AHP model for urban services planning in Srinagar and Jammu urban centres of J and K, India. J. Urban Manag. Elsevier B.V., 7(2): 46–56. doi: 10.1016/j.jum.2018.05.002.

Pourkhabbaz, H.R., Javanmardi, S., Faraji Sabokbar, H.A. (2014). Suitability analysis for determining potential agricultural land use by the multi-criteria decision-making models SAW and VIKOR-AHP (Case study: Takestan- Qazvin Plain). J. Agric. Sci. Technol., 16: 1005–1016.

Rabia, H.A. and Terribile, F. (2013). Introducing a new parametric concept for land suitability assessment. Int. J. Environ. Sci. Dev., 4(1): 15-19.

Rezaei-Moghaddam, K. and Karami, E. (2008). A multiple criteria evaluation of sustainable agricultural development models using AHP. Environ Dev Sustain, 10(4): 407-426.

Saaty, T.L. (1977). A scaling method for priorities in hierarchical structures. J. Math. Psychol., 15: 234 - 281.

Saaty, T.L. (1980). The analytical hierarchy process. McGraw Hill, New York.

Saaty, T.L. (2001). Decision Making with Dependence and Feedback: The Analytic Network Process, 2nd edition, PRWS Publications, Pittsburgh PA.

Salifu. E., Agyare, W.A., Kyei-Baffour, N. and Dumedah, G. (2021). Estimation of Soil Erosion in Three Northern Regions of Ghana Using RUSLE in GIS Environment. *International Journal of Applied Geospatial Research, IGI Global. 12:2, pp 1-19. DOI: 10.4018/IJAGR.2021040101.*

Savun-Hekimoğlu, B., Erbay, B., Burak, Z. S., Gazioğlu, C. (2021). A Comparative MCDM Analysis of Potential Short-Term Measures for Dealing with Mucilage Problem in the Sea of Marmara. *International Journal of Environment and Geoinformatics*, 8(4), 572-580, doi.10.30897 /ijegeo.1026107.

Ullah, K.M. and Mansourian, A. (2015). Evaluation of land suitability for urban land-use planning: case study Dhaka City. Trans GIS. doi:10.1111/tgis.12137.

Ulukavak, M., Miman, M. (2021). Selection of The Most Proper Unmanned Aerial Vehicle for Transportation in Emergency Operations by Using Analytic Hierarchy Process. *International Journal of Environment and Geoinformatics*, 8(1), 78-91, doi. 10.30897/ijegeo.760758

Vaghela, B. N., Parmar, M. G., Solanki, H. A., Kansara, B. B., Prajapati, S. K., Kalubarme, M. H. (2018). Multi Criteria Decision Making (MCDM) Approach for Mangrove Health Assessment using Geo-informatics Technology, *International Journal of Environment and Geoinformatics*, 5(2) , 114-131, doi.10.30897/ijegeo.412511

Van Ranst, E., Tang, H., Groenemans, R. and Sinthurahat, S. (1996). Application of fuzzy logic to land suitability for rubber production in peninsular Thailand. Geoderma., 70: 1-19.

Vargahan, B., Shahbazi, F. and Hajrasouli, M. (2011). Quantitative and qualitative land suitability evaluation for maize cultivation in ghobadlou region, Iran. Asian J. Appl. Sci., 4(1): 91-104.

Willmott, C.J. (1981). On the validation of models. Phys. Geogr., 2: 184 - 194.

Ying, X., Guang-Ming, Z., Gui-Qiua, C., Lin, T., Ke-Linc, W. and Dao-Youc, H. (2007). Combining AHP with GIS in synthetic evaluation of eco-environment quality-A case study of Hunan Province, China. Ecol Modell., 209: 97-109.