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An Ensemble of Weight of Evidence and Logistic Regression for Gully Erosion Susceptibility Mapping in the Kakia-Esamburmbur Catchment, Kenya

Lorraine K. Nkonge ¹, John M. Gathenya ², Jeremiah K. Kiptala ³, Charles K. Cheruiyot ³ and Andrea Petroselli ^{4,*}

¹ Civil Engineering (Environment, Arid and Semi-Arid Lands), The Pan African University Institute for Basic Sciences, Technology and Innovation (PAUSTI), Jomo Kenyatta University of Agriculture and Technology, Nairobi P.O. Box 62000-00200, Kenya

² Soil, Water and Environmental Engineering Department, Jomo Kenyatta University of Agriculture and Technology, Nairobi P.O. Box 62000-00200, Kenya

³ Department of Civil, Construction and Environmental Engineering, Jomo Kenyatta University of Agriculture and Technology, Nairobi P.O. Box 62000-00200, Kenya

⁴ Department of Economics, Engineering, Society and Business Organization (DEIM), Tuscia University, 01100 Viterbo, Italy

* Correspondence: petro@unitus.it

Abstract: Gully erosion is the most intensive type of water erosion and it leads to land degradation across the world. Therefore, analyzing the spatial occurrence of this phenomenon is crucial for land management. The objective of this research was to predict gully erosion susceptibility in the Kakia-Esamburmbur catchment in Narok, Kenya, which is badly affected by gully erosion. GIS and ensemble techniques using weight of evidence (WoE) and logistic regression (LR) models were used to map the susceptibility to gully erosion. First, 130 gullies were detected in the study area and portioned out 70:30 for training and validation, respectively. Nine gully erosion conditioning factors were selected as predictors. The relationships between the gully locations and the factors were identified and quantified using WoE, LR and WoE–LR ensemble models. The results show that land use/cover, distance to road, sediment transport index (STI) and topographic wetness index (TWI) are the factors that have the most influence on gully occurrence in the catchment. Additionally, the WoE–LR model performed better than the WoE and LR models, producing an AUC value of 0.88, which was higher than that of the WoE model, 0.62 and the LR model, 0.63. Therefore, the WoE–LR ensemble model is useful in gully erosion susceptibility mapping and is of help to decision makers in land-use planning.

Keywords: gully susceptibility; weight of evidence (WoE); logistic regression (LR); ensemble; soil loss; Kakia-Esamburmbur; Narok

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1. Introduction

Soil erosion caused by water is considered to be one of the primary causes of land degradation worldwide [1]. Soil erosion, which is a natural process that entails detachment, transportation and deposition of soil particles, can be exacerbated by anthropogenic activities [2]. Water induced soil erosion is usually caused by deforestation, climate change, intensification of agriculture, urbanization and tectonic activities, all of which threaten land and water resources sustainability [3]. Soil erosion leads to reservoir siltation [4]; loss of fertile topsoil [5]; flooding and decline in species [6,7]; and eutrophication in streams, reservoirs and lakes [8]. Furthermore, there has been an increase in soil erosion rates over the years [9], for instance soil erosion is responsible for soil loss in most landscapes in Ethiopia and Kenya [10].

Water erosion occurs in various forms including splash, interrill (sheet), rill, stream bank and gully erosion [11]. Gully erosion is the most complex type of erosion amongst these, as it is triggered and accelerated by heavy rainfall and land use change [12]. Studies conducted around the world have shown that gully erosion can contribute between 10% and 94% of the total catchment erosion [13]. Gullies decrease soil productivity through the incision of agricultural lands, and cause restrictions on roads, land use and structures [14].

A gully is defined as an erosion channel with steep side walls and head-cut that is actively eroding due to the surface flows that remove and transport soil particles [15]. It can be defined as having a cross-sectional area greater than 929 cm² [13], and is too big to be removed by ordinary tillage practices [16]. Gully erosion is a threshold process and therefore several studies have put emphasis on defining the topographic as well as hydraulic conditions to predict gully erosion susceptibility [16,17].

In contrast to the significant contribution of gullies to total erosion on watersheds, few models have been developed for quantifying the effects of this phenomenon [18]. There are few physically based models that can assess gully erosion. They include CREAMS (chemicals, runoff and erosion from agricultural management systems), EGEM (ephemeral gully erosion mode) and WEPP (Water Erosion Prediction Project), which have been applied in the Loess Plateau [19,20]. However, the above models need a lot of geophysical and geochemical input data. Furthermore, the physical methods cannot assess the spatial distribution of gullies, which is important in visualizing the exposure of an area to gullying [21]. In regions where there is data scarcity, statistical and data mining methods can be successfully used.

Natural hazards have been assessed using a variety of data mining, bivariate and multivariate statistical methods. Some of these have been used to assess the susceptibility to gully erosion. Logistic regression (LR) [14,22]; weight of evidence (WoE) [23]; maximum entropy (ME) [24]; stochastic gradient tree boost (SGT) [16]; frequency ratio (FR) [25]; random forest (RF) [26]; multivariate adaptive regression splines (MARS) [17,27]; index of entropy (IoE) [28]; certainty factor (CF) [29] and support vector machine (SVM) [30].

All the aforementioned techniques have some drawbacks in the effectiveness of their predicted results, despite being able to determine gully erosion susceptibility. These disadvantages can be reduced through ensemble modeling. Recently, ensemble modeling has received significant attention in the spatial prediction of natural hazards such as landslides [31], groundwaters [32], droughts [33] and floods [34] due to improved prediction performance and the ability to deal with complex data [11]. Ensemble methods are techniques in which a prediction model is formed from a combination of various base classifiers [35].

WoE and LR have been used in particular in gully erosion susceptibility mapping, nonetheless, they have their own weaknesses. The main advantage of WoE is that it calculates the weight of the factors through statistical methods and thus avoids subjective weighting. In addition, input maps with missing data can be accommodated and have no significant impact on the result [23]. However, it neglects the correlation between the factors, which is important in gully erosion susceptibility because the conditioning factors should not be correlated. LR is able to evaluate the association between conditioning factors but it cannot analyze the influence of different classes within a conditioning factor [36]. Hence, their drawbacks can be solved and performance improved through their integration.

Starting from such premises, the main objectives of this study were to: (i) determine the level of influence of environmental conditioning factors causing the occurrence of gully erosion in the study area and (ii) assess the capability of WoE–LR to predict gully erosion susceptibility.

2. Materials and Methods

2.1. Study Area

The study area is composed of Kakia and Esamburmbur sub-catchments, which are 30.5 km² and 15.7 km², respectively (Figure 1), and are located in Narok County, South-West of Kenya. It lies between longitudes 35.83°E and 35.93°E and between latitudes 1.00°S and 1.10°S. The region's elevation ranges from 1828 to 2147 m above sea level [37]. The main drainage channel is the permanent Enkare Narok River, which rises from the Mau Forest and flows through Narok town. The Enkare Narok has two tributaries, which are the seasonal Esamburmbur and Kakia streams that flow through Narok town and converge a few meters before draining into it [38]. The catchment experiences bimodal rainfall in a year [36]. The long rainy season is usually between the months of March and May, while the short rainy season occurs between October and December. The mean annual rainfall for the area is 750 mm while the temperature range for the area is between 8 °C and 28 °C [39]. The main land use/cover in the catchment includes cropland, forests, built-up areas and shrubs. Cropland, which is the main land use, is made up of crops such as maize and wheat [38].

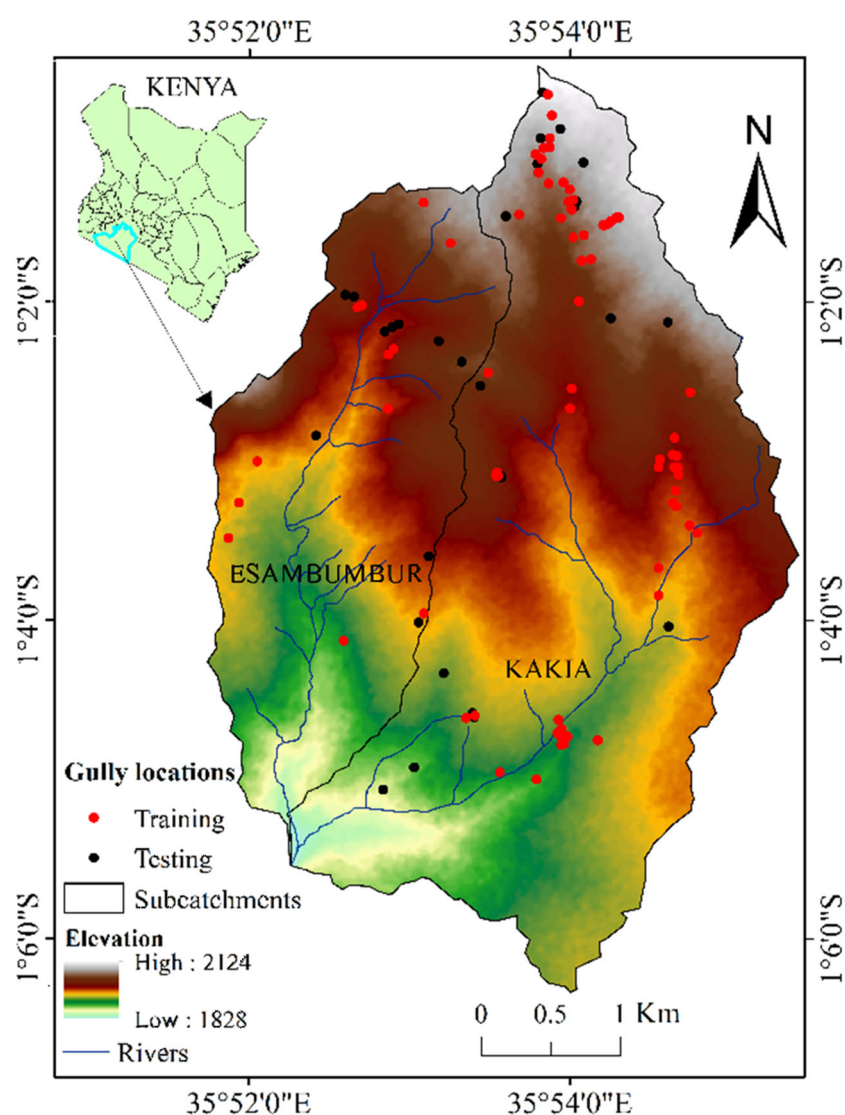


Figure 1. Map of Kakia-Esamburmbur catchment showing the training and testing datasets for modeling.

2.2. Methodology

Gully erosion susceptibility was carried out in four steps including: (1) preparation of a gully inventory which contains locations of gullies in the catchment; (2) preparation of the gully conditioning factors; (3) gully erosion susceptibility modeling using WoE and WoE-LR; and (4) model evaluation by constructing the receiver operating characteristic (ROC) curve and calculating the area under the ROC curve (AUC). Figure 2 is a flow diagram indicating the methodology used in this study.

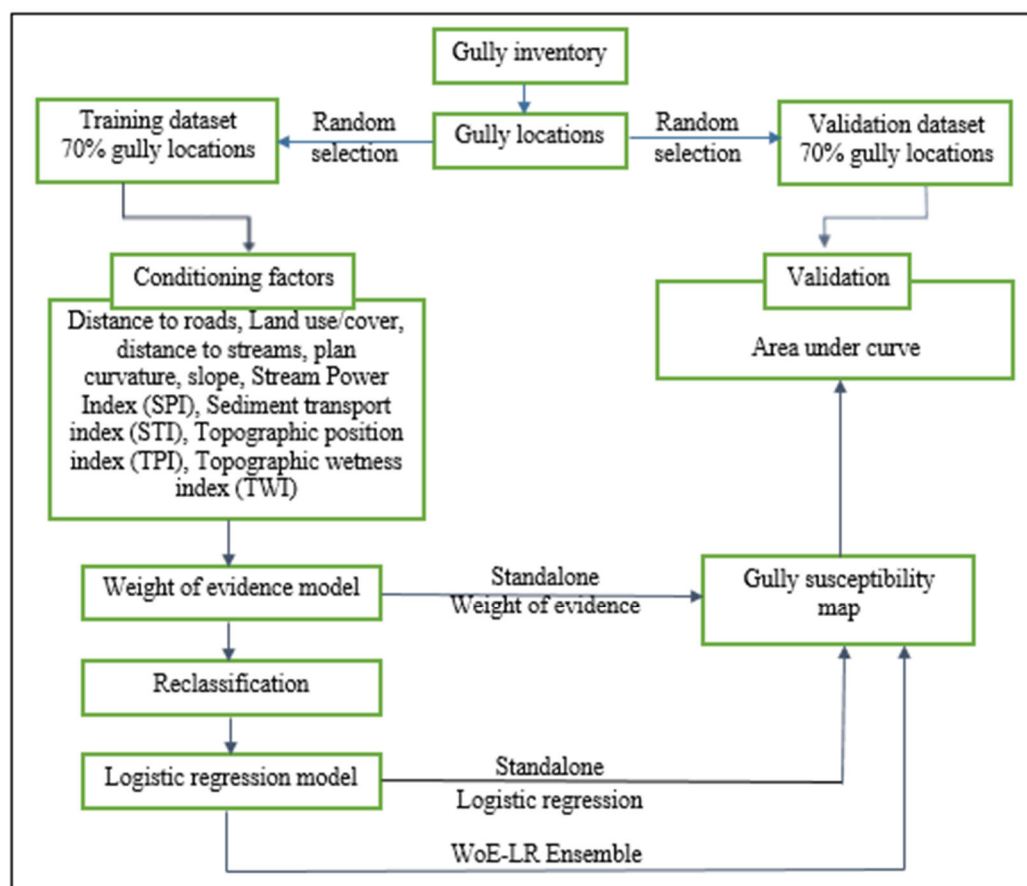


Figure 2. Flowchart for the research methodology on gully erosion susceptibility mapping in Kakia-Esamburmbur catchment, Narok.

2.2.1. Gully Erosion Inventory

Gully erosion mapping in the Kakia-Esamburmbur catchment was performed through field survey using GPS and Google Earth satellite images. Figure 3 shows some of the gully erosion in the study area. Eventually, a reliable and detailed inventory map with a total of 130 gullies was created. The gully locations were randomly divided into two groups which include the training (70%) and the validation (30%) sets, and which were differentiated from one another using a random dividing algorithm [40]. Both the training and validation sets were merged with an equal number of randomly selected locations that represent absence of gully erosion [24]. The absence dataset was created in ArcGIS by using the random-point tool [24].

2.2.2. Conditioning Factors

There are various environmental factors that control the critical conditions for gully development and these are mainly related to rainfall, topography, soil and land use [18]. In order to recognize the susceptible areas, good knowledge of the main gully erosion-

related factors is needed. Therefore, conditioning factors were chosen from previous studies [21,41]. In this study, ArcGIS, QGIS and a system for automated geoscientific analyses (SAGA) were used to generate and exhibit such a data grid. The conditioning factors that were used in this study are (1) slope, (2) plan curvature, (3) topographic wetness index (TWI), (4) distance to streams (m), (5) distance to roads (m), (6) topographic position index (TPI), (7) stream power index (SPI), (8) sediment transport index (STI) and (9) land use/land cover.

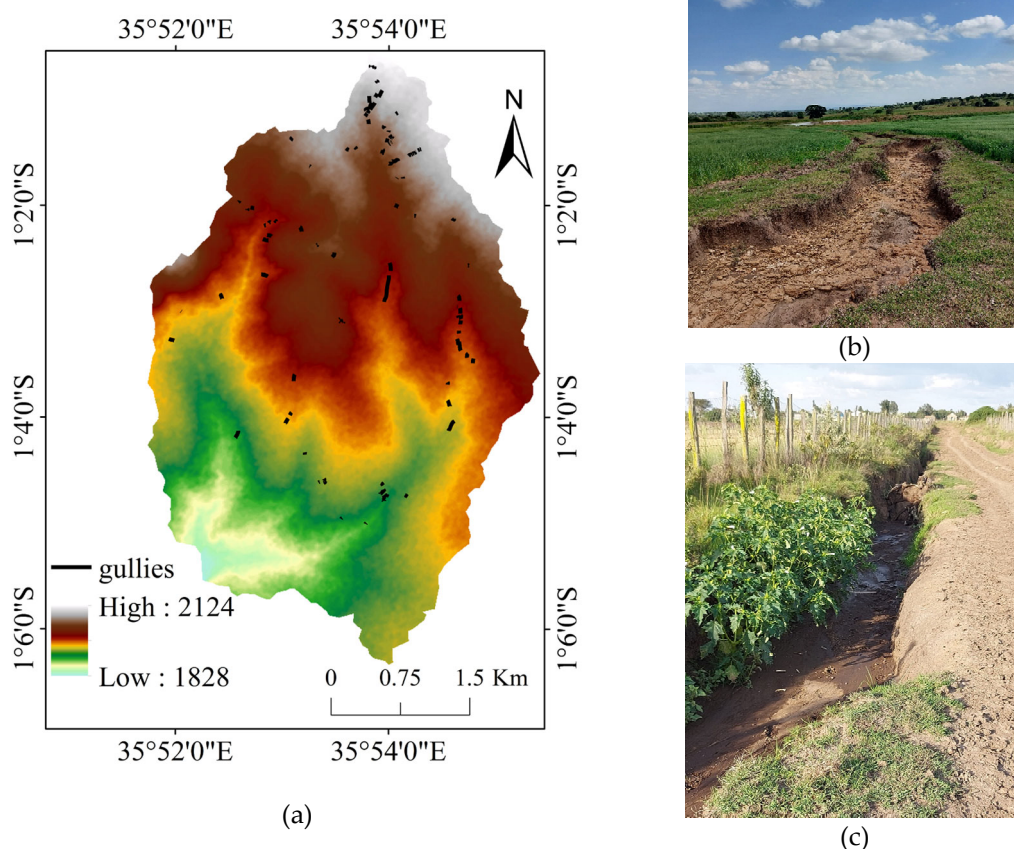


Figure 3. Map of the observed gullies (a) and pictures of some of the gullies identified in the Kakia-Esamburmbur catchment (b, c).

Slope controls the velocity and volume of concentrated flow thus affecting surface erosion and soil erosion [18]. Slope was derived from a 12.5 m resolution DEM from ALOS PALSAR[42] using ArcGIS and ranges from 0% to 42.19% (Figure 4a). Curvature assessment is important for inferring suitable geomorphological data. Plan curvature influences slope erosion processes through the convergence and divergence of water fluxes downhill. In this research, the plan curvature was derived from the DEM with a spatial resolution of 12.5 m in ArcGIS. The plan curvature values range from −3.2 to 3.2 (Figure 4b). Plan curvature can be classified into three classes: concave (positive curvature), flat (zero curvature) and convex (negative curvature) conditions, which were used in this study [36].

Topographic wetness index (TWI) is a secondary topographic factor that is used to evaluate the hydrological features of a region and is a crucial gully erosion determining factor. It represents the spatial distribution of wetness conditions [43]. It was calculated using Equation (1). The ArcGIS software was used for TWI mapping and the values range from 3.6 to 18.6 (Figure 4c).

$$TWI = \ln \left(\frac{A_c}{\tan \beta} \right) \quad (1)$$

where

A_c = upstream contributing area (m²) and

β = slope gradient (°).

Distance to streams is important in evaluating the role of runoff in gully erosion [44]. Road construction has an adverse influence on hill sustainability at which flow may be suitable for gullies [18]. They were both calculated in ArcGIS using the Euclidean distance tool, which will give the distance (m) from each raster cell to the closest stream/road section [45]. The distance ranged from 0 to 2530 m for streams (Figure 4d) and 0 to 1674 m for roads (Figure 5a).

Topographic position index (TPI) is a widely used approach for evaluating topographic slope location. It is the difference between the elevation of a cell and the average of the surrounding cells [17]. It was calculated for each cell using the algorithm [46] denoted by Equation (2) in QGIS using SAGA-GIS. The TPI values for the study area range between −6.7 and 7 and were divided into five classes (Figure 5b).

$$TPI = Z_0 - Z \quad (2)$$

where

Z_0 = elevation at the central point and

Z = average elevation around it within a predetermined radius (R).

The stream power index (SPI) has direct proportionality to stream power, which is the time rate of energy being used, and therefore can be used to estimate the overland flow erosive power. The SPI reflects the discharge and flow erosive power, which influences gully erosion susceptibility [47]. A higher value of SPI indicates that the stream has a much more powerful erosion on the slope surface [35]. The SPI value was calculated from the DEM in ArcGIS using the Equation (3).

$$SPI = (A_c \times \tan \beta) \quad (3)$$

where A_c is the upstream contributing area (m²) and β is slope gradient (°). The SPI values of the study area range between 0 and 13,639 (Figure 5c).

The sediment transport index (STI) has been used to analyze erosion and deposition processes and topographic effects on soil loss. It was calculated using Equation (4) [28] in ArcGIS.

$$STI = \left(\frac{A_c}{22.13} \right)^{0.6} \left(\frac{\sin \beta}{0.0896} \right)^{1.3} \quad (4)$$

where A_c is the upstream contributing area (m²) and β is slope gradient (°). The STI values in the study range from 0 to 246 and were classified into five classes (Figure 5d).

Land use/land cover (LULC) has a significant influence on hydrological and geomorphological pathways due to its direct or indirect effect on infiltration, evapotranspiration, runoff and sediment dynamics [48]. It also influences nutrients, structure and soil properties [45]. Vegetation protects the soil against erosion and surface runoff. Roots offer reinforcement thus increasing shear strength of the soil [45]. The land use/land cover map was acquired from Sentinel-2[49] and prepared in ArcGIS. It has seven classes, i.e., trees, shrubs, grassland, cropland, vegetation aquatic/regularly flooded, bare and built-up areas (Figure 6).

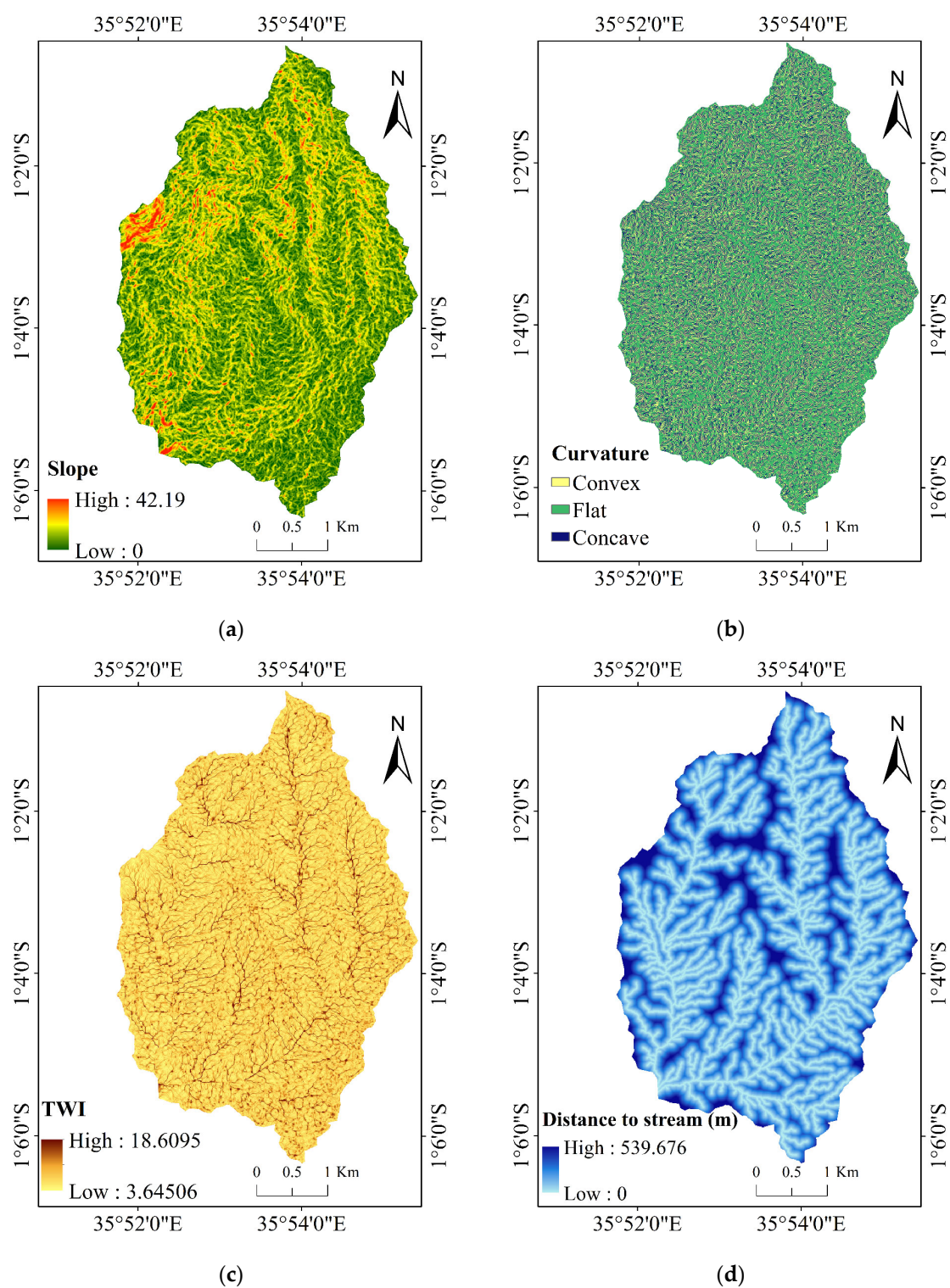


Figure 4. Gully erosion conditioning factors: (a) slope (percent), (b) curvature, (c) topographic wetness index (TWI) and (d) distance to stream/channel.

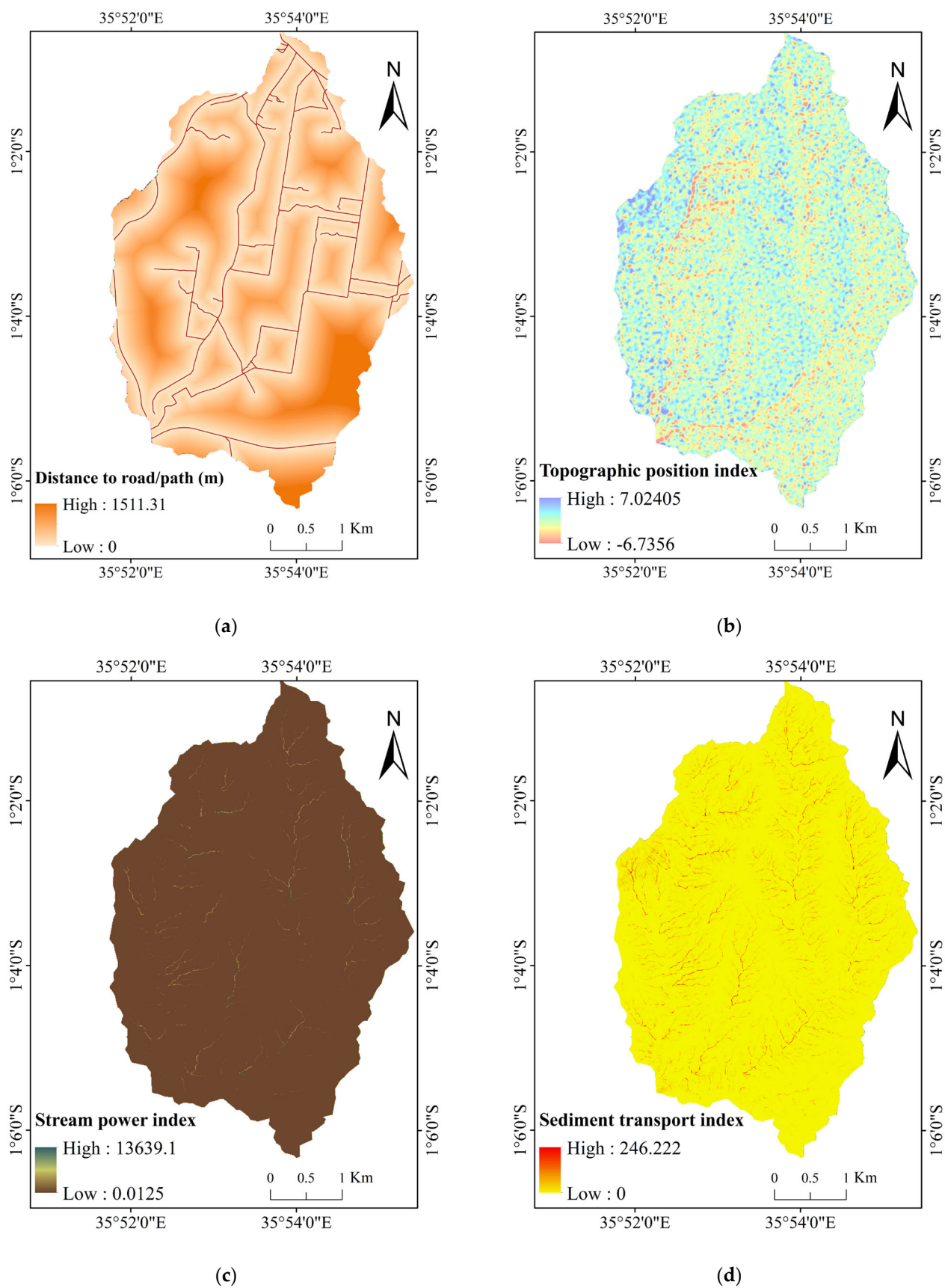


Figure 5. Gully erosion conditioning factors: (a) distance to road, (b) topographic position index (TPI), (c) stream power index (SPI) and (d) sediment transport index (STI).

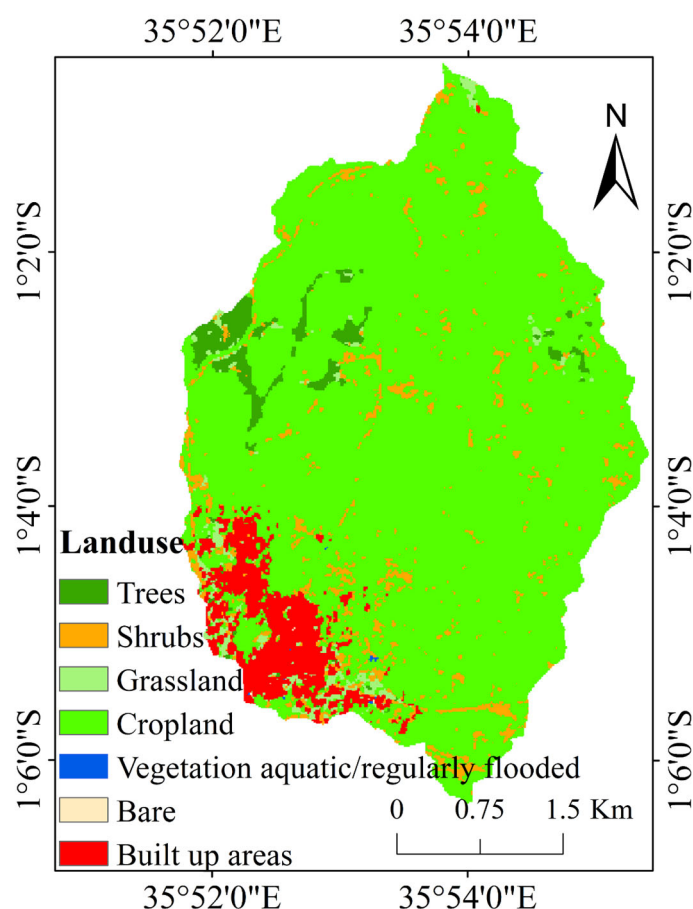


Figure 6. Gully erosion conditioning factors: land use/cover.

2.3. Multi-Collinearity Test

As the independent variable, the above-mentioned conditioning factors were used to examine the effect of correlation among them. It is a problem in the modeling process if both predictor variables are strongly related. The problem is known as collinearity. Tolerance and the VIF (variance inflation factor) are both significant measures of multi-collinearity identification. Tolerance is the inverse of VIF [50]. The test was carried out in the R software.

2.4. Weight of Evidence Model

The weight of evidence (WoE) is a probabilistic approach model based on a log linear form of Bayes' theorem of conditional probability [51]. It has been used for flood susceptibility mapping [37] and landslide susceptibility mapping [52]. By overlaying gully locations with each conditioning factor, their statistical relationship can be identified and assessed to establish whether and how significantly the conditioning factor is responsible for gully occurrence. WoE is expressed as shown in Equation (5)

$$P(A|B) = P(B|A) \times \frac{P(A)}{P(B)} \quad (5)$$

where A represents the presence of a gully and B represents the presence of the gully conditioning factor. Conditional independence is a very important aspect that should be considered in the WoE method. Positive, W^+ and negative, W^- weights are used to calculate the WoE model. The weight for each B is calculated based on the presence or absence of A as shown in Equations (6) and (7).

$$W^+ = \ln \frac{P(B|A)}{P(B|\bar{A})} \quad (6)$$

$$W^- = \ln \frac{p(\bar{B}|A)}{p(\bar{B}|\bar{A})} \quad (7)$$

where P denotes the probability and $\ln$ denotes the natural log function. A and $\bar{A}$ indicate the presence and absence of a gully, respectively. The presence of a gully conditioning factor is represented by B , and the absence of a gully conditioning factor is represented by $\bar{B}$. A positive (W^+) weight explains the presence of the conditioning factor at the gully location and its value indicates the correlation between the gullies and the gully conditioning factor [53]. A negative (W^-) weight explains the gully conditioning factor's absence and indicates the degree of negative correlation [41]. The final weight, $W_{\text{final}} = W^+ - W^-$ will be used to quantify and indicate the spatial relationship between the effective gully conditioning factors and gully occurrence. If W_{final} is positive, it indicates a positive spatial relationship and if it is negative, it indicates a negative spatial relationship [40]. After applying the WoE model, the weights of the factors W_{final} were summed to produce a map of gully erosion susceptibility based on the Equation (8) [54].

$$\text{GESI} = \sum W_{\text{final}} \quad (8)$$

where GESI is the gully erosion susceptibility index.

2.5. Logistic Regression Model

Logistic regression (LR) is a multivariate statistical technique used in the development of predictive models from either discrete or continuous explanatory variables [18]. LR allows the development of a multivariate regression association linking a dependent variable and explanatory variables, which are important in predicting presence or absence of an outcome based on values of a set of explanatory variables [51]. In this case, the outcome is the presence of gullies and the LR is applied to predict variable (Y) that can be equal to presence of gully (1) or absence of gully (0). The LR uses a logistic function to assess the association linking the dependent variable and the explanatory variables. The logistic function is expressed as Equation (9) [52].

$$P = \frac{1}{1 + e^{-l}} \quad (9)$$

where P is the probability of gully erosion occurrence, which varies from 0 to 1 and l is the linear logistic factor, whose value varies from $-\infty$ to $+\infty$ and is defined by Equation (10).

$$l = \text{intercept} + b_1x_1 + b_2x_2 + \dots + b_kx_k \quad (10)$$

where x_1 , x_2 and x_k are the explanatory variables and b_1 , b_2 and b_k are the coefficients of the LR model. In this study, LR was performed using the R software and ArcGIS, adopting forward stepwise regression to select the explanatory variables.

For the LR–WoE ensemble model, the determined class values of the WoE model were used to create the input for the LR model. The LR model requires a numerical rather than a categorical dependent variable. In order to address this issue, the weights of the classes of the conditioning factors were determined using the WoE model. The weights were then employed to transform the categorical variables into numerical variables. Therefore, all the classes of the conditioning factors were converted to numerical variables

as shown in Tables 1 and 2. Finally, using the natural break method, the gully susceptibility map was reclassified into very low, low, moderate, high and very high classes after applying the LR–WoE model [22].

Table 1. Multicollinearity test statistics of gully conditioning factors.

Parameter	Collinearity statistics	
	Tolerance	VIF
Curvature	0.85	1.17
Distance to road	0.83	1.20
Distance to stream	0.92	1.09
Landcover	0.94	1.06
Slope	0.88	1.14
SPI	0.96	1.04
STI	0.41	2.41
TPI	0.88	1.14
TWI	0.40	2.49

Table 2. Weights of conditioning factors Slope, Curvature, TWI, Distance to stream and Distance to road as analyzed using WoE method.

Factors	Class	W ⁺	W [−]	W _{final}
Slope (%)	0–4.4	−0.8852	0.0099	−0.8951
	4.5–8.1	−0.5559	0.0441	−0.6000
	8.2–11.2	−0.3376	0.0359	−0.3735
	11.3–16.0	−0.2115	0.1523	−0.3638
	16.1–42.1	0.4138	−0.3441	0.7579
Curvature	Concave	−0.1319	0.0420	−0.1739
	flat	0.1961	−0.2273	0.4233
	convex	−0.3327	0.0938	−0.4266
TWI	3–6.1	−0.4293	0.2090	−0.6383
	6.1–7.7	−0.1982	0.0832	−0.2814
	7.7–9.6	0.0501	−0.0105	0.0606
	9.6–11.8	0.4188	−0.0441	0.4629
	11.8–18.7	1.8308	−0.1672	1.9979
Distance to stream (m)	0–38	−0.2149	0.2410	−0.4559
	38–89	−0.6371	0.1579	−0.7949
	89–150	1.3807	−0.3503	1.7310
	150–224	−0.7861	0.0261	−0.8122
	224–539	−0.5384	0.0051	−0.5434
Distance to road (m)	0–204	3.8957	−0.2429	4.1387
	204–434	0.5204	−0.0521	0.5725
	434–683	−0.7537	0.1270	−0.8807
	683–959	−0.9306	0.2262	−1.1568
	959–1511	0.0563	−0.0442	0.1005

Note: W⁺ is positive weight, W[−] is negative weight, W_{final} is W⁺ − W[−].

2.6. Model Evaluation

The model performance was evaluated by drawing the receiver operating characteristic (ROC) and calculating the area under the curve (AUC). It was generated by plotting the sensitivity, also known as true positive rate (TPR), on the *y*-axis, Equation (11) against the 1-specificity, which is the false positive rate (FPR), on the *x*-axis using Equation (12)

[52]. A ROC of 1 indicates perfect prediction. The model sensitivity is the percentage of existing gully pixels correctly predicted using the model, while the 1-specificity is the percentage of predicted gully pixels over the total study area.

$$y\text{-axis} = \text{TPR} = \left(\frac{\text{TP}}{\text{TP} + \text{FN}} \right) \quad (11)$$

$$x\text{-axis} = \text{FPR} = 1 - \left(\frac{\text{TN}}{\text{TN} + \text{FP}} \right) \quad (12)$$

where TP stands for true positive, TN stands for true negative, FP stands for false positive and FN stands for false negative. The TP and TN are the proportions of gully cells that are correctly classified as gully and non-gully, while the FP and FN are the proportions of gully cells that are incorrectly classified as gully and non-gully [11]. The AUC is a common method for assessing models used in prediction of natural hazards [55,56]. The AUC is calculated using the Equation (13).

$$\text{AUC} = \left(\sum \text{TP} + \sum \text{TN} \right) / (P + N) \quad (13)$$

where P denotes the total number of gullies and N denotes the total number of non-gullies.

3. Results

3.1. Conditioning Factor's Effect

3.1.1. Multicollinearity Test

The VIF ranges from 1.04 to 2.49, according to the multicollinearity test, while the TOL, which is the reciprocal of the VIF, ranges from 0.40 to 0.96. (Table 1). VIF values greater than five, with corresponding TOL values less than 0.2, indicate significant multicollinearity among factors [57]. The results indicate that there is no multi-collinearity between the conditioning factors.

3.1.2. Weight of Evidence Model

It is observed that there is a higher chance of gully occurrence at the high slope range of 16.1–42.1 while the lower slope classes have a low possibility of gully occurrence, which means the relationship is positive as seen from Table 2. The convex curvature had the highest W_{final} value, indicating that such areas in the study area are most vulnerable to gully erosion. From the results it can be seen that higher values of TWI indicate a higher chance of gully erosion occurrence while lower values indicate lower chances of gully erosion occurrence, thus there is a positive association. This can be attributed to the fact that at low TWI, less runoff is generated and at higher TWI, gully development is encouraged [54].

The results in Table 2 show that there is a higher possibility of gully occurrence near a road network. This can be seen through the high positive value of the final weight for the least distance from the roads ($W_{\text{final}} = 4.1$). This can be explained by the fact that the development of roads leads to soil disturbance which exacerbates gully formation [47].

TPI has a negative relationship with gully erosion. The lowest values of TPI had the highest W_{final} values while the highest TPI values had the lowest W_{final} values. Table 3 shows that higher values of SPI are associated with higher chances of experiencing gully erosion and vice versa.

This shows that gully occurrence increases with an increase in SPI. This can be attributed to the fact that SPI is a product of slope and catchment area. It is used in showing areas of concentrated runoff and thus higher values of SPI indicate higher chances of experiencing gully erosion. The results also agree with a study carried out by [58].

Lower STI values have lower W_{final} values while higher STI values have higher W_{final} values. There is a positive association between STI and gully erosion. It indicates that gully

occurrence increases with an increase in STI. This can be attributed to the fact that STI accounts for topographic effect on erosion. Similar results were also found in research carried out by [23].

The main land coverages which were identified in the catchment are: trees, shrubs, grassland, cropland, vegetation aquatic/regularly flooded, bare and built-up areas. The built-up area is mostly around Narok town at the outlet of the catchment. The bare land cover class has a high positive final weight ($W_{\text{final}} = 4.0$) while the built-up area has the highest negative final weight ($W_{\text{final}} = -2.2$).

These results show that there is a positive association between gully erosion occurrence and bare land while there is a strong positive association between the occurrence of gullies and built-up areas. From the above results, there is an implication that change in land cover/use from forest to agriculture, which increases the presence of bare soil, leads to gully development in the study area.

These findings agree with [59] who found that there is an association between gully erosion formation with the change in land cover/use from forest to cropland. Land use change has occurred in the Kakia-Esamburmbur catchment where forest cover has declined by 39% and agriculture has increased by 55.4% [39]. These findings are in agreement with the knowledge that forested areas experience less erosion in the form of gullies than barren land or wastelands [60].

3.1.3. Logistic Regression Model

The result for the LR model is given by Equation (14).

$$\begin{aligned} Z = & -23.4199 + (5.519 \times \text{slope}) + (-1.890 \times \text{curvature}) + (7.590 \times \text{SPI}) + \\ & (1.183 \times \text{Distance to road}) + (-5.323 \times \text{STI}) + \\ & (0.639 \times \text{Distance to stream}) + (2.211 \times \text{TPI}) + \\ & (4.154 \times \text{LULC}) + (5.994 \times \text{TWI}) \end{aligned} \quad (14)$$

3.1.4. LR–WoE Ensemble Model

The LR–WoE ensemble model developed for prediction of gully erosion susceptibility in the study area at 10% significance level is given by Equation (15). The significance of the conditioning factors is shown in Table 4.

$$Z = -7.026 + (0.061 \times \text{TWI}) + (0.03 \times \text{Distance to stream}) + (0.007 \times \text{Distance to road}) - (0.023 \times \text{STI}) + (0.008 \times \text{LULC}) \quad (15)$$

From Equation (15) it is obvious that TWI, distance to stream, distance to road and LULC have positive coefficients.

This means that these factors are related to the occurrence of gullies in a positive way. The coefficient of STI, on the other hand, is negative, indicating a negative relationship with the occurrence of gullies in the study area.

Table 3. Weights of conditioning factors TPI, SPI, STI, LULC as analyzed using WoE method.

Factors	Class	W ⁺	W ⁻	W _{final}
TPI	−6.8–−1.5	0.4019	−0.0427	0.4446
	−1.5–−0.5	0.2975	−0.1021	0.3996
	−0.5–0.5	0.0118	−0.0067	0.0185
	0.5–1.6	−0.3065	0.0890	−0.3955
	1.6–7.1	−0.8978	0.0529	−0.9507
SPI	0–160	−0.1122	1.3792	−1.4915
	160–750	−1.3833	0.0208	−1.4041
	750–1925	2.1774	−0.0437	2.2211
	1925–4120	3.9965	−0.0769	4.0735
	4120–13640	2.9584	−0.0065	2.9649
STI	0–4	−0.1340	0.6750	−0.8090
	4–11	0.2549	−0.0254	0.2803
	11–27	1.0322	−0.0511	1.0834
	27–60	1.7170	−0.0346	1.7516
	60–247	1.7125	−0.0056	1.7181
LULC	Trees	−1.3375	0.0196	−1.3570
	Shrubs	−0.9576	0.0343	−0.9918
	Grassland	−0.8827	0.0098	−0.8925
	Cropland	0.1143	−1.0517	1.1660
	Vegetation aquatic/regularly flooded	3.1360	−0.0066	3.1425
	Bare	4.0024	−0.0067	4.0091
	Built-up areas	−2.1744	0.0553	−2.2296

Note: W⁺ is positive weight, and W⁻ is negative weight, W_{final} is W⁺ − W⁻

Table 4. Significance levels of the conditioning factors.

	Estimate	Standard Error	Z Value	Pr (> z)	
(Intercept)	−7.025994	741.6681	−0.009	0.99244	
Curvature	−0.003545	0.002803	−1.265	0.20593	
Distance to road	0.00677	0.001605	4.218	2.46 × 10 ^{−5}	***
Distance to stream	0.002653	0.001544	1.719	0.08569	.
Land use/cover	0.007804	0.003642	2.143	0.03214	*
Slope	0.004048	0.00634	0.639	0.52313	
SPI	0.008114	0.030244	0.268	0.78847	
STI	−0.023267	0.006674	−3.486	0.00049	***
TPI	−0.00194	0.002445	−0.793	0.42765	
TWI	0.061095	0.014213	4.299	1.72 × 10 ^{−5}	***

Note: Significance codes: '***' 0.001 '**' 0.05 '.' 0.1.

3.2. Gully Erosion Hazard

3.2.1. Weight of Evidence Model

The total weight, which is a result of summing the final weight (W_{final}) values presented in Tables 2 and 3, is shown in Figure 7. The total weighted map was converted into five classes: very low, low, moderate, high and very high hazard. It can be seen from the map that the areas around the forests have very low susceptibility levels. This implies that increasing forest cover in the Kakia-Esamburmbur catchment can be carried out in order to reduce soil erosion. The majority of the catchment that has moderate to high susceptibility levels is agricultural land.

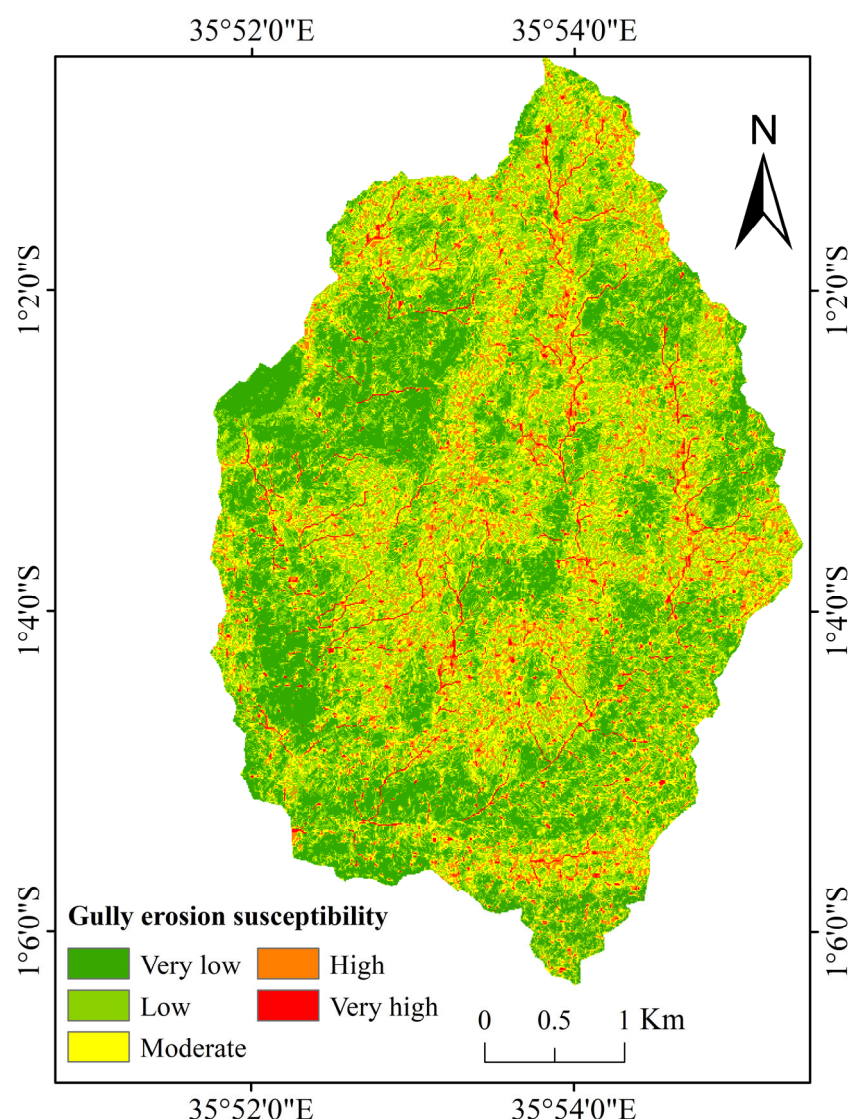


Figure 7. Map of gully erosion susceptibility of Kakia-Esamburmbur catchment using WoE.

3.2.2. LR Model and WoE–LR Ensemble Model

A gully erosion susceptibility map was created with the LR (Figure 8) and WoE–LR ensemble (Figure 9) using Equations (14) and (15), respectively, in ArcGIS interface and using the Jenks natural breaks classification method, reclassified into five classes (very low, low, moderate, high and very high) for visual interpretation.

3.3. Model Validation

The model performance was evaluated by drawing the receiver operating characteristic (ROC) curve. A ROC of 1 indicates perfect prediction. The following is a classification of the relationship between prediction accuracy and AUC: 0.9–1 equals excellent; 0.8–0.9 equals very good; 0.7–0.8 equals good; 0.6–0.7 equals average; and 0.5–0.6 equals poor [55]. It was found that the WoE model has an accuracy of 62% during training and a validation accuracy of 67% as shown in Figure 10. This accuracy level is average but lower than that obtained by [5] of 79.5% and by [23] of 67.8%. The LR model has an accuracy of 63% and 67% during training and validation, respectively, as shown in Figure 11. The

WoE-LR ensemble performed much better and had an accuracy of 88% during training and a validation accuracy of 78% as shown in Figure 12.

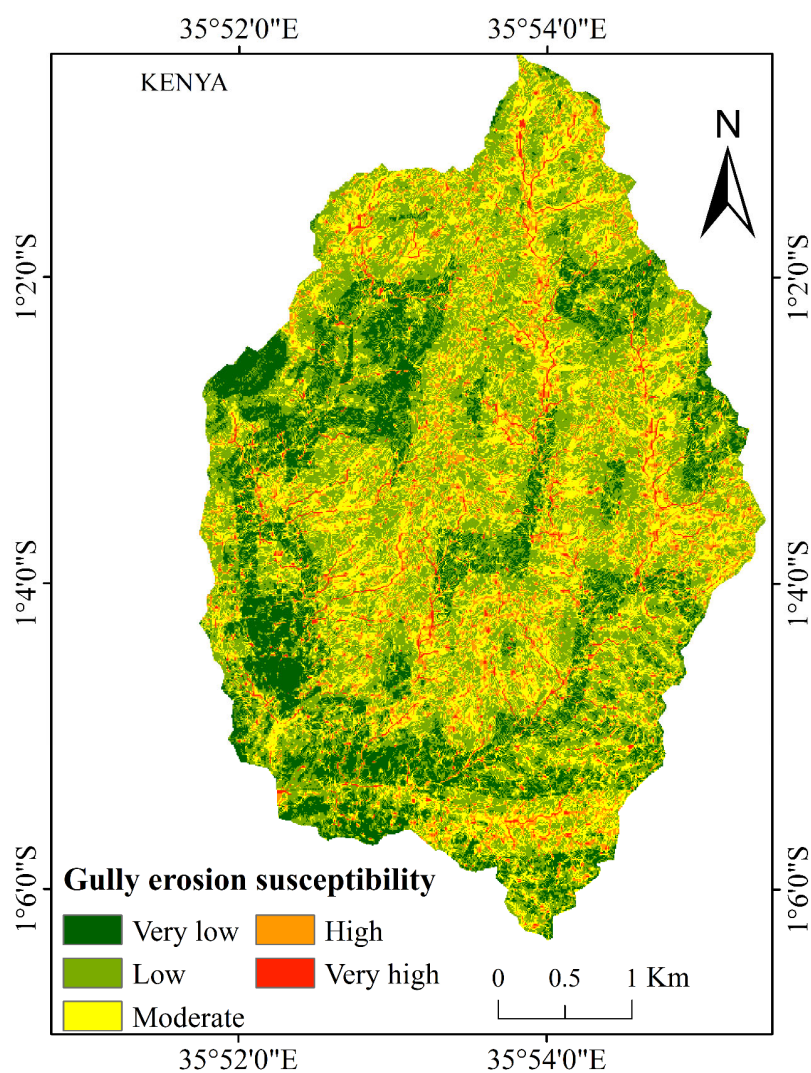


Figure 8. Map of gully erosion susceptibility of Kakia-Esamburmbur catchment using LR.

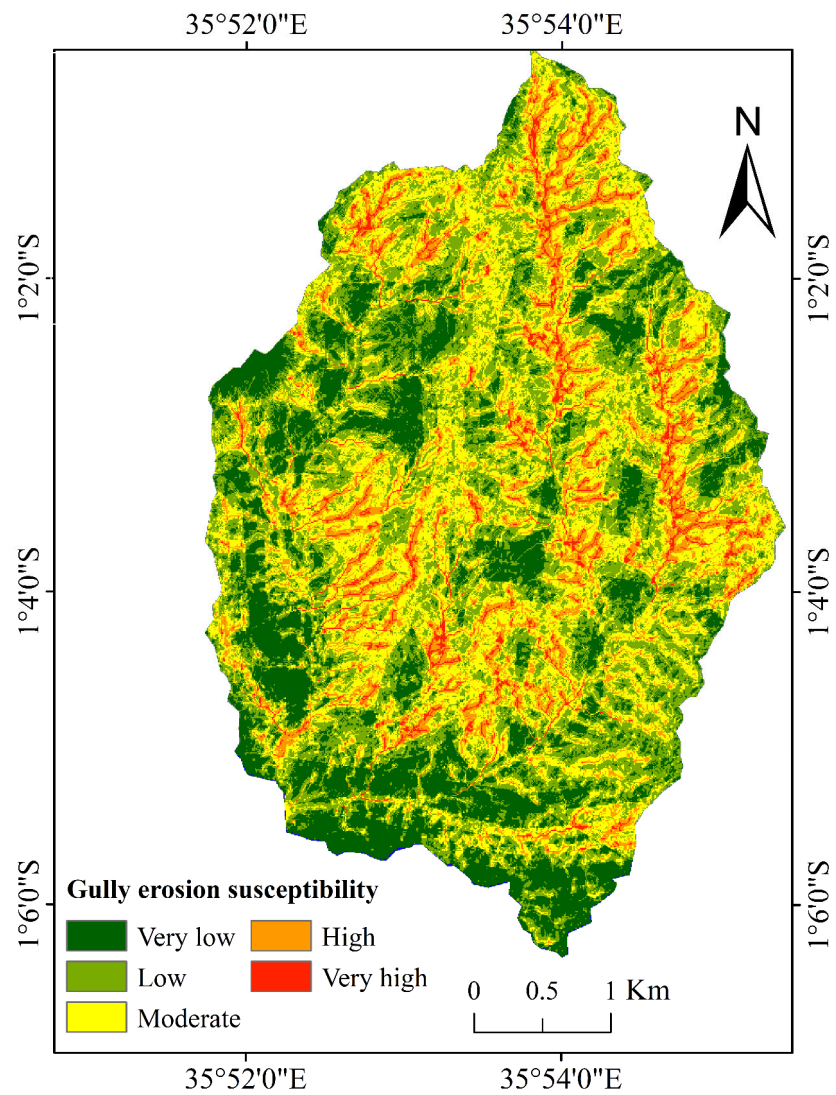


Figure 9. Map of gully erosion susceptibility of Kakia-Esamburmbur catchment using WoE-LR.

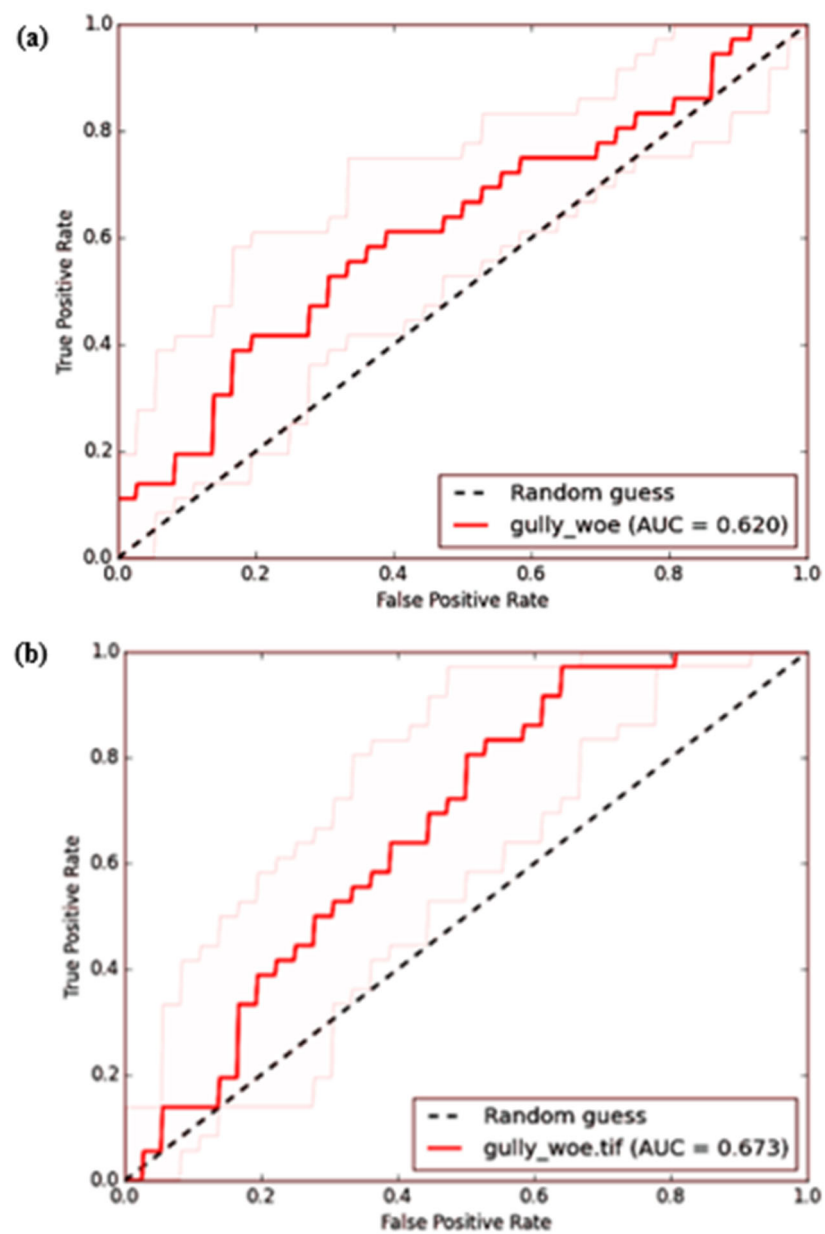


Figure 10. Prediction rate curve for gully erosion susceptibility map using WoE in Kakkia-Esamburmbur catchment: (a) training and (b) validation.

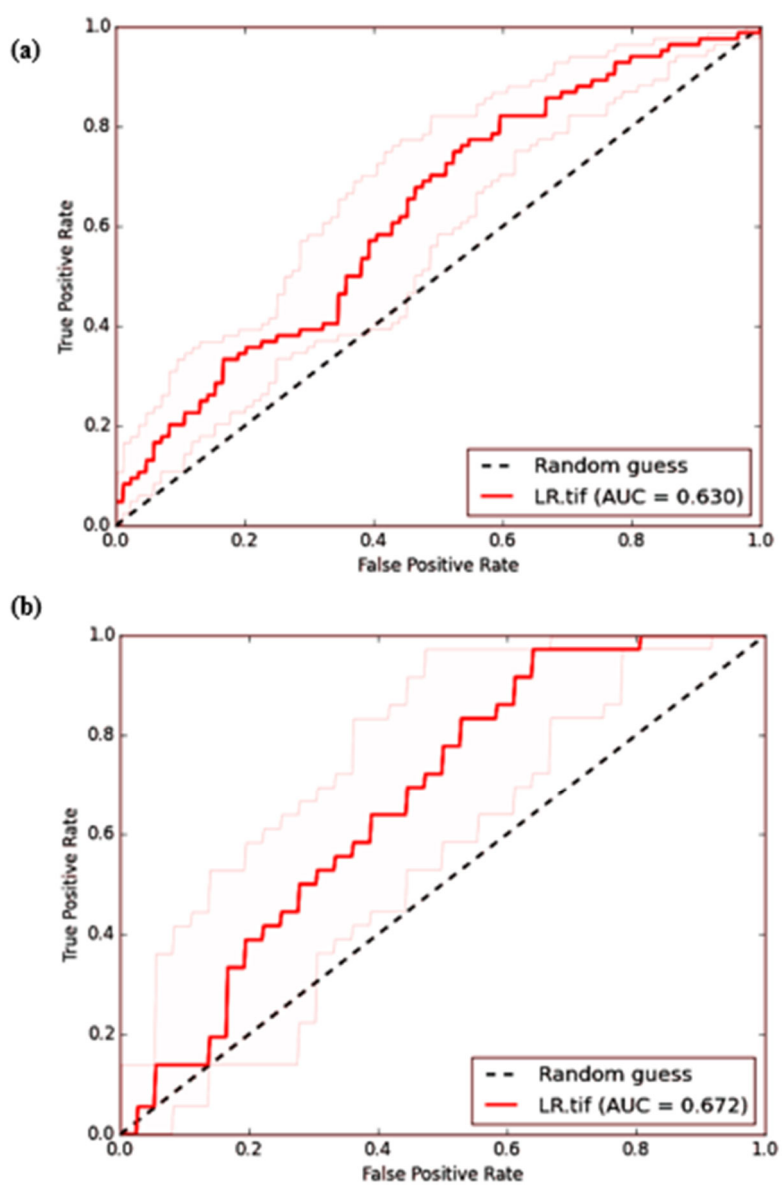


Figure 11. Prediction rate curve for gully erosion susceptibility map using LR in Kakia-Esamburmbur catchment: (a) training and (b) validation.

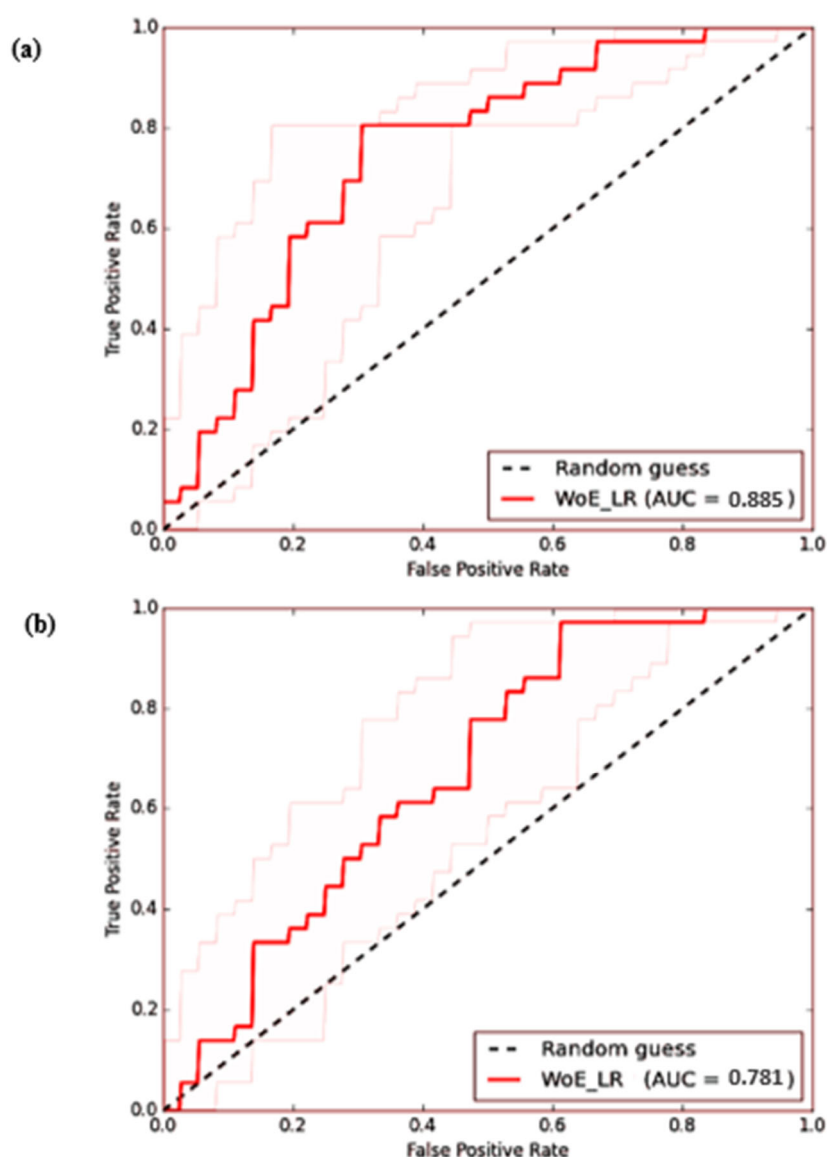


Figure 12. Prediction rate curve for gully erosion susceptibility map using WoE-LR in Kakia-Esamburbur catchment: (a) training and (b) validation.

4. Discussion

Gully erosion has a two-fold impact on the environment: first, it degrades the surface and subsurface horizons of the soil, increasing the production of sediment, and second, it increases surface runoff and decreases groundwater recharge [61,62]. The first step in managing gully erosion is through gully erosion risk assessment that is conducted using gully erosion susceptibility models. Susceptibility maps can be helpful to government institutions, particularly since they can facilitate mitigation decisions for gully erosion [63]. In this research, three approaches along with the GIS technique were used for gully erosion susceptibility mapping: (1) using weight of evidence, (2) logistic regression and (3) their ensemble model. Using ROC curves and AUC values, the overall accuracy of the gully erosion susceptibility models was assessed.

In gully erosion investigations, it is critical to assess the significance of conditioning factors in gully susceptibility mapping. The results of the current study also showed that distance to roads, distance to streams, land use, TWI and STI are the most influential factors on gully occurrence. The output of the models reveals different gullying susceptibility value ranges. The results show that gully formation is more likely to develop in regions

that are closer to roads and streams, have sparser vegetation and have higher drainage densities than other areas. These results are consistent with [17].

Maps showing gully erosion susceptibility classified areas of the basin with low slopes and close proximity to roads/paths as having high and extremely high susceptibility. In contrast, forest regions with steep slopes showed low susceptibility to gully erosion. In the forest, roughness due to vegetation cover may result in medium runoff factors in this area as well, resulting in a low concentrated flow force of degradation [63]. The outcomes further showed that the LR model's prediction accuracy was improved by combining the WoE method with the LR approach. Therefore, rather than employing a single model that is tailored to each study area, it is crucial to assess the efficacy of a combination/ensemble of multiple models.

5. Conclusions and Recommendations

Gully erosion can lead to damage to the environment and agriculture lands thus leading to migration and less agricultural productivity. Many methods have recently been used to assess gully erosion susceptibility. In this paper, the WoE model and a proposed WoE–LR model were used to produce a gully erosion susceptibility map.

Nine conditioning factors were used including: slope, plan curvature, distance to streams (m), distance to roads (m), topographic position index (TPI), topographic wetness index (TWI), stream power index (SPI), sediment transport index (STI) and land use/land cover. Using the natural break method, the susceptibility maps were classified into five susceptibility classes (very low, low, moderate, high and very high). The WoE technique produced a map of areas susceptible to gully erosion with a prediction accuracy of 62% while the LR model and the WoE–LR ensemble had an accuracy of 63% and 88%, respectively.

These results show that an ensemble model performs better than an individual model. Amongst the conditioning factors, it was found that STI, land use/cover, TWI, distance to stream and distance to road had the most influence on the occurrence of gullies. The areas that were found to have low susceptibility include the forested areas and also near the already developed Narok town. The areas where agriculture is practiced and next to the roads were found to more susceptible to gully erosion.

The Kakia-Esamburmbur faces major land degradation due to loss of top fertile soil caused by water erosion. The susceptibility map can be used as a basic rule of thumb reference for land management in the Kakia-Esamburmbur catchment. The proposed ensemble model and gully erosion susceptibility map should be helpful to environmentalists and engineers for future planning and management.

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Data Availability Statement: The data presented in this study are available on request from the corresponding author. The data are not publicly available due to privacy restrictions.

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