Soil Erosion Assessment Using RUSLE & ANN Models and Identify Correlation by Landslide Frequency Ratio Method: A Case Study of Kalu River Catchment of Sri Lanka

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***Abstract*— Soil erosion is a significant environmental concern that can have adverse effects on agricultural productivity and natural resource sustainability. This research focuses on assessing soil erosion in the Kalu River catchment of Sri Lanka using the Revised Universal Soil Loss Equation (RUSLE) and Artificial Neural Network (ANN) models. The study aims to quantify yearly soil loss between 2000 and 2020 and identify the spatial pattern of soil erosion risk. The results of the study indicate that the K factor, LS factor, P factor, C factor, and R factor have varying levels of influence on soil erosion. An ANN model is used to accurately predict soil erosion, but the RUSLE model is found to be more effective in evaluating soil erosion susceptibility in the specific study area. The research also examines the variation in soil erosion among sub-catchments within the Kalu River catchment. Sub-catchment A10 exhibits the highest soil erosion value, while A4 has the lowest. The Landslide Frequency Ratio (LFR) is employed to establish a correlation between soil erosion hazard classes and landslide frequency. High-priority areas for soil conservation measures are identified based on LFR values, soil erosion rates, and land-use change. The findings underscore the importance of estimating soil erosion rates, creating soil erosion hazard zonation maps, and prioritizing areas for soil conservation practices and sustainable land management. Policymakers, land-use planners, and farmers can utilize this research to make informed decisions and promote sustainable land-use practices. The study contributes to the understanding of soil erosion factors and provides valuable insights for future research in other regions.*

***Keywords*— ANN Model, Landslide Frequency Ratio, RUSLE Model, Soil Erosion, Sri Lanka.**

I. INTRODUCTION

Soil erosion is a natural process that involves the removal and transportation of soil material, particularly water erosion. Water erosion can manifest in various forms, such as splash, sheet, rill, gully, or ravine erosion(Senanayake *et al.*, 2020). Gully erosion, in particular, refers to the accumulation of surface runoff in small channels, resulting in the removal of soil from deep layers(Rahmati *et al.*, 2016). The repercussions of soil erosion are detrimental to the sustainability of ecosystems and the long-term quality of productive landscapes. Consequently, there is a need for rapid assessment methods to select appropriate conservation measures and monitor their effectiveness(Somasiri, Hewawasam and Rambukkange, 2022). The consequences of soil erosion are detrimental to ecosystem sustainability and the long-term quality of productive landscapes. Rapid assessment methods are needed to select appropriate conservation measures and monitor their effectiveness. Field-based quantification techniques are employed to estimate soil erosion rates in the short term.

The Universal Soil Loss Equation (USLE), Modified Universal Soil Loss Equation (MUSLE), and Revised Universal Soil Loss Equation (RUSLE) are widely used prediction methods for erosion prediction and control(Panditharathne *et al.*, 2019; Somasiri, Hewawasam and Rambukkange, 2022). The U.S. Department of Agriculture's RUSLE decision support system is particularly employed in land use planning and soil conservation efforts.

Artificial Neural Network (ANN) models have become popular for predicting soil erosion due to their ability to handle complex, non-linear relationships(Gholami *et al.*, 2018). When integrated with Geographic Information Systems (GIS) data, ANN models improve prediction accuracy by considering spatial variability. Combining ANN with traditional methods like RUSLE offers a flexible and data-driven approach to soil erosion prediction, benefiting soil conservation and land use planning efforts, and enabling better management of erosion-prone areas.

This study combines the RUSLE Equation model and Artificial Neural Network (ANN) model with GIS to determine the impact of land use and land cover (LULC) conversion on the average annual soil loss in the Kalu watershed. Factors such as rainfall, runoff, soil erodibility, slope gradient and length, as well as crop and vegetation cover contribute to the magnitude and rate of soil erosion. Tillage practices, such as minimum till or no-till techniques, can minimize water erosion.

Monitoring and predicting soil erosion require the utilization of remote sensing and GIS technologies. However, accurate modeling is challenging due to the complex nature of erosion processes and the non-linear behavior of erosion models. Satellite images and digital elevation models are valuable tools for identifying areas with potential erosion risks(Fayas *et al.*, 2019; Senanayake *et al.*, 2020). Remote sensing data aids in identifying erosion zones and locations of sediment accumulation, enabling prompt documentation of erosion presence and severity, as well as predictions of their impact on topography, soils, agricultural lands, and landscape systems(Panditharathne *et al.*, 2019; Somasiri, Hewawasam and Rambukkange, 2022).

In Sri Lanka's agricultural development, soil erosion poses a significant challenge. This research aims to address inquiries concerning the benefits of monitoring soil erosion, suitable GIS and remote sensing methodologies, and the relationship between land-use change and landslide incidents. The primary objective of this study is to propose a methodology for assessing the vulnerability of soil erosion by integrating three approaches: evaluation of land-use changes, assessment of soil erosion severity, and the landslide frequency ratio method.

II. METHODOLOGY

A. Study area

The Kalu Ganga is a river in Sri Lanka, runs between 6.42° and 6.83°N and 80.00° to 80.67°E, and empties into the sea at Kalutara. Its primary water sources are mountainous forests in the Central Province and the Sinharaja Forest Reserve. The Kalu Ganga basin has a surface area of 2766 km^2 and is the second-largest river basin in Sri Lanka, with an average annual rainfall of 4000 mm and an annual flow of 4000 m^3 million. Figure 1 illustrates a map of the region.

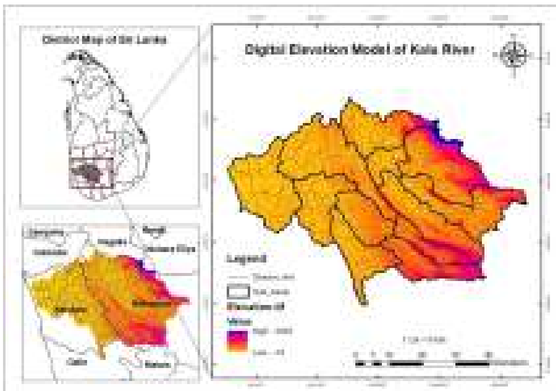


Figure 1. Geographical location and DEM of Kalu river basin

B. Image preprocessing

Google Earth Engine (GEE) was used to process Landsat imagery from 2000, 2005, 2010, 2015, and 2020. An object-based algorithm called Fmask was employed to select the best cloud-free pixel. Data normalization was performed to reduce noise and classification errors(Kouassi *et al.*, 2023). The USGS digital elevation model was used to differentiate elevation data in a watershed.

C. Land use land cover change

The process of analyzing satellite images to determine land use and land cover (LULC) is complex and multi-step, with two main types of image analysis algorithms: pixel-based image classifiers and object-based image classifiers. A mixed method was used to create false-color composites to identify different land cover types and classify the land into homogeneous groups. Five different land-use classes were defined based on prior knowledge and the LUPPD map of Sri Lanka. This study used a mixed method to classify the images and define five land-use classes using Google Earth Engine(Kouassi *et al.*, 2023). To ensure accuracy, an accuracy assessment was performed using 150 ground control points for each image. Google Maps and land-use maps were used to validate and verify the land-use classes generated from the Landsat satellite image dataset(Tian *et al.*, 2021; Kouassi *et al.*, 2023).

D. Factor generation

This study incorporated various factors, namely crop management (C-factor), soil erodibility (K-factor), slope length and steepness (LS-factor), conservation practices (P-factor), and rainfall erosivity (R-factor)(Al Rammahi and Khassaf, 2018; Saha *et al.*, 2019; Moisa *et al.*, 2021; Somasiri, Hewawasam and Rambukkange, 2022).

According to that, C-factor was determined from remote sensing information using the Normalized Difference Vegetation Index (NDVI) and Van der Knijff and colleagues (1999)'s CVK approach. Colman's (2018) approach was used to calculate the C-factor, which measures soil erosion potential. NDVI data was obtained using Landsat 7 (ETM+), Landsat 8 (OLI), and Landsat 5 (TM) surface reflectance imagery. A temporal analysis was conducted to investigate changes in the C-factor over time(Almagro *et al.*, 2019).

The K factor is a measure of how easily soil can be eroded by rainfall and runoff. It depends on soil properties like particle size, organic matter content, structure, and permeability. Researchers have developed equations to estimate the K factor, which is used in the RUSLE model to calculate soil erosion. Those equations are applied to soil data to determine the K factor values for a specific area(Pringle *et al.*, 2013; Mammadli and Gojamanov, 2021).

The slope length-gradient factor (LS factor) is a tool used to model soil erosion in hillslopes. To derive accurate LS factors for larger and more complex sites, a combined tool of Geographic Information Systems (GIS) and Remote Sensing (RS) can be utilized. Five methods were employed to determine the most effective approach for deriving the LS factor(Somasiri, Hewawasam and Rambukkange, 2022). A depressionless SRTM Digital Elevation Model (DEM) with a 30 m cell size was obtained from the USGS EarthExplorer website. Flow directions were generated to calculate the slope length factor (L) for the model. LS values were assigned to each 30-m cell of the grid surface of each catchment by multiplying L and S factors in the raster calculator of the ArcGIS environment.

The P-factor is a conservation practice that measures soil loss due to tillage practices. It ranges from 0 to 1, with higher values indicating a lack of conservation practices in steep areas and lower values indicating effective conservation in built-up and plantation areas. P-factor values were sourced from previous studies and assigned to different slope classes in a raster dataset created from a slope map derived from a digital elevation model(Tian *et al.*, 2021).

The Rainfall Erosivity (R-factor) measures the impact of rainfall on soil erosion. Eight rain-gauge stations were collected over a 20-year period and the mean annual precipitation was found in the Supplementary Material. The equation was used to calculate the R-factor, which was then converted to a raster surface using interpolation techniques(Senanayake *et al.*, 2020; Somasiri, Hewawasam and Rambukkange, 2022).

E. Multiple linear regression analysis

The research study used Multiple Linear Regression (MLR) to model the relationship between a dependent variable and two or more independent variables. The regression coefficients and weights for each predictor variable were displayed by the model code of MLR. A CSV dataset was loaded into the R programming language and a multiple regression model was fitted to the data. The regression coefficients and weights were extracted and stored in a variable named "coefficients". The model was summarized and a scatter plot was created to visualize the relationship between each factor and soil erosion.

F. Soil erosion assessment

This study compared two soil erosion models: the RUSLE model and an Artificial Neural Network (ANN) model. The RUSLE model used the factors of rainfall erosivity (R), soil erodibility (K), slope length and steepness (LS), crop management (C), and land management (P) to assess average annual soil loss rates. The model employed geo-informatics techniques and spatial data to classify and map soil erosion hazards. The ANN model aimed to predict soil erosion by analyzing the same variables. The analysis involved data exploration, normalization, splitting into training/testing/validation sets, building the ANN model, and evaluating its performance using metrics like RMSE, MSE, and R-squared(Gholami *et al.*, 2018).

G. Frequency ratio calculation

A landslide inventory map was created using GIS, incorporating data on 104 landslide incidents between 2000 and 2020. The severity of damages was considered. The purpose of this study was to assess the relationship between landslide incidents and soil erosion. The frequency ratio model was used to compute the landslide frequency ratio (LFR) for each land-use class and soil erosion hazard class. The average value of the landslide frequency ratio was found to be 1 for the occurrence of landslide incidents in a particular area. Landscape vulnerability was assessed and ranked based on the frequency ratio, soil erosion rates, and land-use change for soil conservation(Senanayake *et al.*, 2020). The LFR was computed using the number of landslide incidents in each RDZ, and the soil erosion hazard classes and land-use change together with LFR were used to rank the RDZs.

Figure 2 depicts the overall comprehensive methodology that was employed to achieve the research objectives.

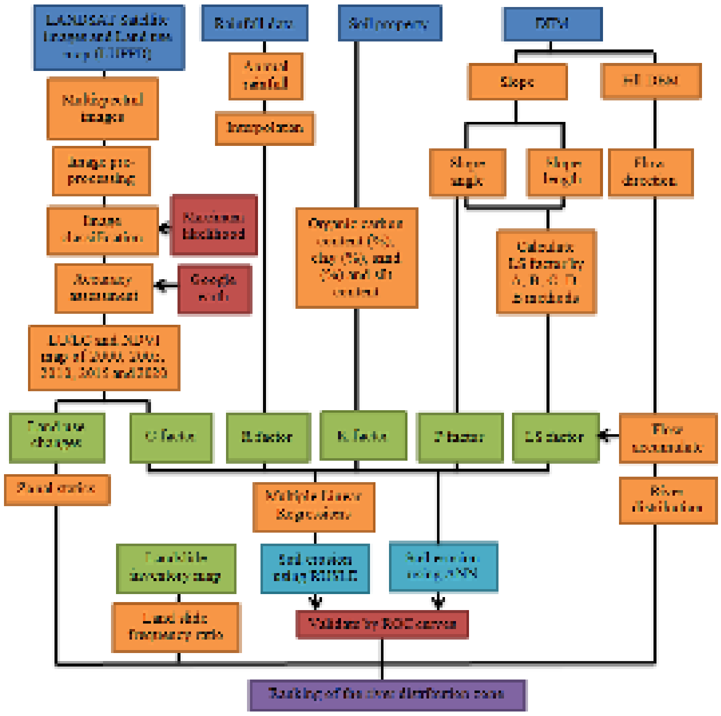


Figure 2. Methodology of the study

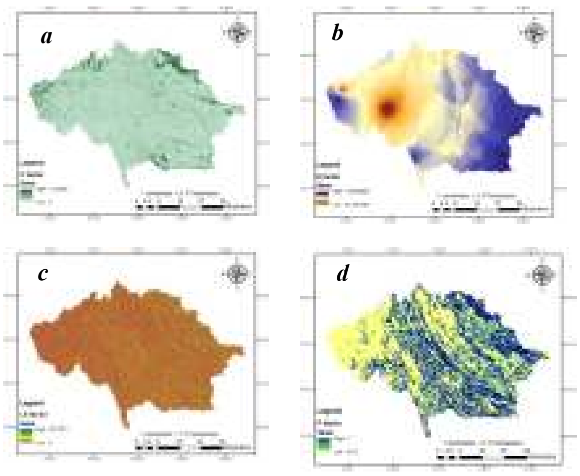
III. RESULTS AND DISCUSSION

A. Land use land cover change

A land-use analysis was conducted, classifying the land into five categories: water bodies, forest, agriculture, urban areas, and barren land. Processed maps for the years 2000, 2005, 2010, 2015, and 2020 were analyzed. The findings showed that agriculture areas, forest, and urban areas in the Kalu River basin increased by 7.88%, 2.13%, and 2.61% respectively from 2000 to 2020. In contrast, barren land decreased by 11.42% and 6.46% during the same period. These changes can be attributed to anthropogenic activities such as agricultural expansion, urban development, deforestation, and abandoned agricultural lands due to low productivity.

B. Factor generation

Figures 3a to 3e display important factors affecting soil erosion in the study area, including crop management (C-factor), soil erodibility (K-factor), slope length and steepness (LS-factor), conservation practices (P-factor) and rainfall erosivity (R-factor) over a 20-year period. These figures serve as formal and objective representations of the key elements influencing soil erosion in the region.



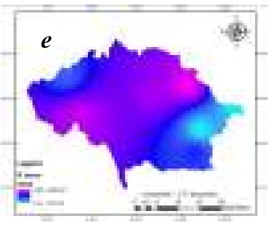


Figure 3. Factor maps: a C factor ; b K factor; c LS factor; d P factor; e R factor

C. Multiple linear regression analysis

A multiple linear regression model was used to estimate soil erosion based on five predictor variables: Kfactor, Cfactor, Pfactor, LSfactor, and Rfactor. The model was significant (p-value < 2.2e-16) with an adjusted R-squared value of 0.7028, indicating that 70.28% of the soil erosion variability could be explained by the included variables. LSfactor was found to be the most important predictor, followed by Cfactor, Pfactor, Rfactor, and Kfactor. The positive coefficients for Cfactor and Pfactor suggest that increased vegetation cover leads to higher soil erosion. Surprisingly, the coefficient for rainfall (Rfactor) was relatively low, possibly due to the study area's high rainfall intensity leading to soil compaction. Overall, the results highlight the significance of topography and soil factors in predicting soil erosion and can inform erosion control strategies and land management practices. Further research is needed to better understand the relationships between these factors and improve soil erosion models.

D. Soil erosion assessment

i) *RUSLE model:* According to the RUSLE model, the soil erosion hazard map for the Kalu river catchment indicates that approximately 0.04% of the total land area is highly vulnerable to soil erosion, with 0.03% in the high-erosion hazard category and 0.01% in the very-high category. Additionally, around 0.05% of the land area is moderately vulnerable to soil erosion. The findings also reveal that the average annual soil erosion in 2000 was 0.138, with a maximum annual soil erosion of 186.651. By the year 2020, the percentage of land area vulnerable to soil erosion increased to 0.02%.

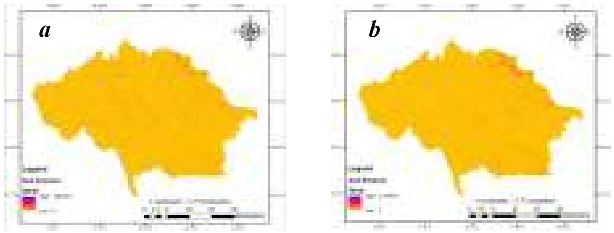


Figure 4. Soil erosion map from RUSLE model: a2020; b2000

ii) *ANN model:* A research study developed an Artificial Neural Network (ANN) model in Python to predict soil erosion using factors such as K-factor, C-factor, P-factor, LS-factor, and R-factor. The dataset had 625,000 observations with variables. Correlation analysis revealed a strong positive correlation between LS-factor and R-factor with soil erosion, while K-factor had a negative correlation. The dataset was normalized using the MinMaxScaler function from Scikit-learn. After normalization, the target variable (soil erosion) had a mean of 0.000723 and a standard deviation of 0.006464. The range of the target variable was between 0 and 1, with the 75th percentile at 0.000428 and the maximum value at 1. The dataset was split into training (75%), testing (15%), and validation (10%) sets. The model architecture consisted of three hidden layers with 30, 15, and 1 neurons, respectively. The model was trained, tested, and validated using the respective datasets. The model's performance was evaluated using R-squared values, MSE, and RMSE. The ANN model performed well on all datasets, with R-squared values of 0.73, 0.77, and 0.76 for the training, testing, and validation datasets, respectively. The MSE and RMSE values were both zero for all datasets, indicating accurate and precise predictions.

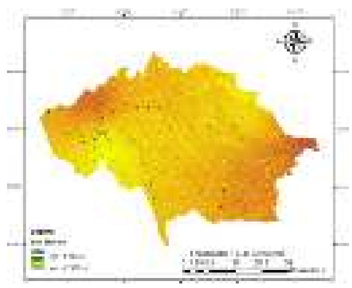
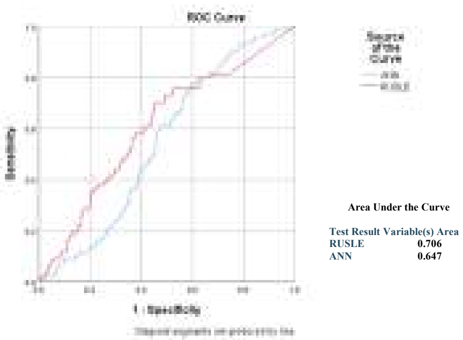


Figure 5. Soil erosion map from ANN for 2020

E. Validation by ROC Curve

The assessment of soil erosion prediction models involves a crucial step of validation. To validate the models, 104 landslide locations were utilized and the accuracy of the models was measured by the area under the curve (AUC) of the Receiver Operating Characteristic (ROC) curve. The results showed that the RUSLE model had an AUC of 0.706 (70%), while the ANN model had an AUC of 0.647. The AUC value of the RUSLE model was in the "satisfactory"" level of accuracy, while the ANN model was in the "poor" level. The RUSLE and ANN models have different strengths and weaknesses in predicting soil erosion susceptibility.

The RUSLE model is more accurate in areas where the physical characteristics of the soil are well understood, while the ANN model is more suitable for areas where the soil characteristics are complex and difficult to model using physical equations. Future studies may investigate hybrid models that combine the strengths of both models to improve the accuracy of soil erosion predictions.



F. Land-Use Change and its Correlation with Landslides

This research computed the Landslide Frequency Ratio (LFR) for various land-use categories in 2020. The results indicated that land-use categories pertaining to agriculture and urban areas exhibited higher LFR values (>1), suggesting a stronger association between these particular land-use categories and occurrences of landslides. The analysis revealed that RDZs A1, A2, A3, A8, A10, and A11 had LFR values greater than 1(Figure 6). These findings suggest that an increase in agricultural area may be linked to an increase in landslide occurrence in these RDZs. It is important to consider the impact of land-use change on landslide incidents in each RDZ to mitigate the risks associated with landslides.

Table 1 Landslide frequency ratio for each land-use

[illegible]	[illegible]	[illegible]	[illegible]	LFR	[illegible]
Water Bodies	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
Forest	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
Agriculture	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
Urban Area	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
Bare Land	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]

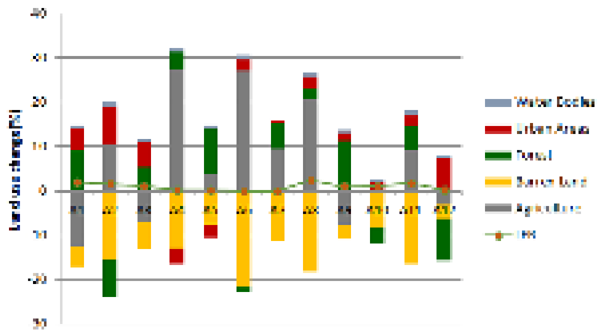


Figure 6. Land-use change and landslide frequency ratio (LFR) over the river distribution zones (RDZs)

G. Soil Erosion Hazard and Its Correlation with Landslide

To effectively implement soil conservation practices, it is crucial to identify and prioritize areas that are highly susceptible to soil erosion. A map of river distribution zones (RDZs) and an inventory of landslides(Figure 7) were used to assess and map the hazard of soil erosion(Figure 8). These maps were then overlaid, resulting in a map that shows the frequency of landslides in each RDZ based on different erosion hazard classes(Figure 9). This information can be utilized to prioritize the implementation of soil conservation practices in the areas that are most at risk.

Figure 7. River distribution zones with Landslide inventory map

Figure 8. Soil erosion hazard map with landslide locations

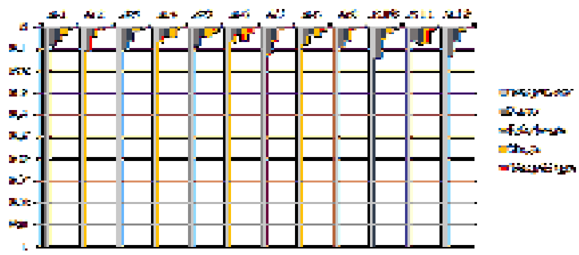


Figure 9. Area covered by soil erosion hazard classes of each RDZ

The correlation between soil erosion hazard classes and the Landslide Frequency Ratio (LFR) was analyzed using statistical methods to determine the LFR values for each RDZ as in table 2.

Table 2 Landslide frequency ratios of the RDZ

ID	Sub Catchment Name	Extent (km²)	Extent (%)	No of Landslides	Landslide Occurrence %
A1	[illegible]	[illegible]	[illegible]	18	18.947
A2	Ellawala Cum Kuru Ganga	249.35	8.52	13	13.68
A3	Kuruwita Ganga	[illegible]	[illegible]	4	4.21
A4	Kudu Ganga	224.97	7.693	1	1.05
A5	Kukule Ganga	177.49	6.08	1	1.05
A6	Lower Kalu Ganga	345.42	11.75		0
A7	Magura Ganga	209.84	7.18		0
A8	Middle Kalu Ganga, Malawala Cum Pannila Ganga	415.62	14.15	32	33.68
A9	Niriella Ganga, Hangamuwa Ganga	268.23	9.16	8	8.42
A10	Ra. Ganga, Denawak Ganga	356.39	12.17	12	12.63
A11	Upper Middle Kalu Ganga	90.19	3.08	5	5.26
A12	Wewa Ganga, Delmella Ganga	180.59	6.16	1	1.05

According to Table 2, RDZs A8 have the highest landslide frequency ratios, reaching a value of nearly 2. These RDZs are primarily used for agriculture. And the RDZs with the highest percentages of 'high' and 'very high' soil erosion categories are A11, A4, and A8.

Based on the LFR, average soil erosion rate, and land-use change values, RDZs A8 and A11 exhibit high to very high values for these parameters. Consequently, A8 and A11 are the highest priority RDZs for soil conservation in the Kalu River basin, as indicated in Table 3.

Table 3 Prioritization of RDZ

RDZ Code	[illegible]	Average Erosion Rate	[illegible]	Landslide Frequency	Priority
A1	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
A2	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
A3	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
A4	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
A5	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
A6	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
A7	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
A8	[illegible]	[illegible]	[illegible]	2.37	1
A9	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
A10	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
A11	[illegible]	[illegible]	[illegible]	[illegible]	1
A12	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]

IV. CONCLUSION

The research objective was to quantify and spatially map the amount of yearly soil loss in the Kalu river catchment and determine the spatial pattern of soil erosion risk between 2000 and 2020. The mean soil erosion in 2020 and 2000 was found to be 0.12149226324467t ha^{-1} year^{-1} and 0.13872407524966t ha^{-1} year^{-1}, respectively. Multiple linear regression analysis was used to determine the coefficients of the RUSLE model variables, namely K factor, R factor, P factor, C factor, and LS factor, and their impact on soil erosion. The highest coefficient value was observed for the K factor, followed by the LS factor, the P factor, the C factor and the R factor, indicating their respective levels of influence on soil erosion. The results of the study provide valuable insights into the factors affecting soil erosion and can be used to develop effective soil conservation strategies for sustainable land management.

An Artificial Neural Network (ANN) model was used to accurately predict soil erosion with a mean value of 0.9872220577728t ha^{-1} year^{-1}. Future research can expand on this study by exploring the use of other machine learning techniques to predict soil erosion and comparing their accuracy with the ANN model. The results of this The study's results indicate that the RUSLE model is a more effective tool for evaluating soil erosion susceptibility in the specific study area than the ANN model. The RUSLE model achieved an AUC of 0.706, indicating excellent predictive ability, while the ANN model achieved an AUC of 0.647. This comparison allowed for the identification of each model's strengths and weaknesses in prediction, providing valuable insights for decision-makers and stakeholders involved in soil conservation and management.

The research findings demonstrate that soil erosion has affected the sub-catchments differently, with sub-catchment A10 displaying the highest soil erosion value, whereas sub-catchment A4 displayed the lowest. Additionally, the landslide frequency ratio values varied significantly among the sub-catchments, with sub-catchment A8 recording the highest value of 2.37, while sub-catchment A6 showed no recorded landslides, indicating a value of 0. By categorizing the sub-catchments based on the severity of soil erosion, the research objective has been achieved, and these rankings can serve as a useful tool for selecting and implementing This study highlights the importance of estimating soil erosion rates and creating soil erosion hazard zonation maps to identify areas for soil conservation practices and land management. The Landslide Frequency Ratio (LFR) was used to establish a correlation between soil erosion hazard classes and the frequency of landslides. The research findings reveal that the Kalu River basin's RDZs A8 and A11 are high-priority areas for soil conservation measures due to their high to very high LFR, average soil erosion rate, and land-use change.

The research emphasizes the need for policymakers, land-use planners, and farmers to prioritize areas for soil conservation practices and manage land sustainably based on empirical data. The study also highlights the importance of monitoring soil erosion and understanding the factors that contribute to it. The research contributes to promoting sustainable land use practices and protecting the environment in the Kalu River basin and beyond.

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