Predicting soil erosion susceptibility associated with climate change scenarios in the Central Highlands of Sri Lanka

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Abstract

Soil erosion hazard is one of the prominent climate hazards that negatively impact countries' economies and livelihood. According to the global climate index, Sri Lanka is ranked among the first ten countries most threatened by climate change during the last three years (2018-2020). However, limited studies were conducted to simulate the impact of the soil erosion vulnerability based on climate scenarios. This study aims to assess and predict soil erosion susceptibility using climate change projected scenarios: Representative Concentration Pathways (RCP) in the Central Highlands of Sri Lanka. The potential of soil erosion susceptibility was predicted to 2040, depending on climate change scenarios, RCP 2.6 and RCP 8.5. Five models: revised universal soil loss (RUSLE), frequency ratio (FR), artificial neural networks (ANN), support vector machine (SVM) and adaptive network-based fuzzy inference system (ANFIS) were selected as widely applied for hazards assessments. Eight geo-environmental factors were selected as inputs to model the soil erosion susceptibility. Results of the five models demonstrate that soil erosion vulnerability (soil erosion rates) will increase 4% - 22% compared to the current soil erosion rate (2020). The predictions indicate average soil erosion will increase to 10.50 t/ha/yr and 12.4 t/ha/yr under the RCP 2.6 and RCP 8.5 climate scenario in 2040, respectively. The ANFIS and SVM model predictions showed the highest accuracy (89%) on soil erosion susceptibility for this study area. The soil erosion susceptibility maps provide a good understanding of future soil erosion vulnerability (spatial distribution) and can be utilized to develop climate resilience.

Keywords: Soil erosion susceptibility; GIS; Adaptive Neuro-Fuzzy Interface; Climate change scenarios; Sri Lanka

1. Introduction

Every year, a considerable number of natural disasters take place all over the world. Many countries have suffered from extreme weather events due to the impacts of climate change (Aryal et al., 2020). The global climate risk index indicates to what extent countries and regions have been affected by extreme climate events (floods, cyclones, heat waves etc.). The global climate index shows that Sri Lanka was ranked third, second, and sixth from 2018 to 2020, consecutively (Eckstein et al., 2019). Heavy rainfall, floods, droughts, and many landslide incidents were common in Sri Lanka (Alahacoon et al., 2018: Senanayake et al., 2020). Increasing rainfall and changes in rainfall patterns have been apparent during the past few decades (Nisansala et al., 2020). Due to these climate impacts, the country lost a substantial part of its productive land and millions of dollars in revenues.

The Intergovernmental Panel on Climate Change (IPCC) has reported, the global mean precipitation and the surface temperature have changed significantly during the past few decades and will continue to the next century (IPCC, 2015). The warming climates increase the frequency and extent of climate hazards such as droughts and floods. The IPCC's fifth assessment report (AR5) has focused on four future warming scenarios (RCP2.6, RCP4.6, RCP6 and RCP8.5), known as the Representative Concentration Pathway (RCP) scenarios. These scenarios predict how the climate might change from the present to 2100 and beyond. Based on the RCP climate projection, researchers are predicting environmental hazards to take mitigation actions to minimize future emissions (Chen et al., 2020; Magnan et al., 2021).

Many researchers have discussed the impacts of climate variation on water erosion (Nearing et al., 2005; Borrelli et al., 2020). However, early researchers mostly neglected climate scenario-based predictions on soil erosion (Mullan et al., 2012). Soil erosion hazard is one of the adverse events due to present climate variation that negatively impacts the environment, agricultural productivity, global food insecurity and livelihoods (Pandey et al. 2016; Lal 2014). Hence, investigating the impacts of climate variation on soil erosion hazards and predicting soil erosion vulnerability is important to introduce mitigating measures to protect precious natural resources. Identification of vulnerable hotspots is also a necessity to implement conservation strategies as well as to direct policy advice. Thereby, modelling the future potential rate of soil erosion is crucial to minimize the adverse impacts from climate variation.

Soil erosion prediction models have been employed to quantify and predict the risk of soil erosion (Karydas et al., 2014; Teng et al., 2018). Most of the traditional soil erosion risk assessment methods, such as the physical-based models, have used an exorbitant amount of data as well as the enormous computational cost involved (Teng et al., 2018; Gholami et al., 2021). Soil erosion assessment in large-scale field measurements may cause some disadvantages as cost wise, expensive, time-consuming, and nearly impossible due to limited resources (Batista et al., 2019; Gholami et al., 2021). In addition, soil erosion assessment is highly complex due to the various parameters are involved, and their interactions are highly non-linear (Pandey et al., 2016). Geo-informatics is useful for studying events bearing multi-dimensional behaviours, such as soil erosion, when considering modelling spatial and temporal aspects on the ground (Senanayake et al., 2020).

In the recent past, soft computing techniques have been widely applied in many fields, such as floods, drought and gully erosion (Janizadeh et al., 2021). Machine learning (ML) algorithms have been used to model complex non-linear datasets for accurate prediction. These models can identify complex changes or unpredictable situations. ML algorithms learn skills and continue to develop accuracy and performance(Luo et al., 2021). ML algorithms can analyze vast quantities of data, well suited for resolving multi-dimensional and multi-variety information. Most importantly, these models have performed well in a data scarcity environment. Chu et al. (2010) revealed that ML has better efficiency than other models when examining the impact of runoff due to climate change. Soil erosion hazards such as gully erosions were assessed using ML and deep learning models, such as an artificial neuron network (ANN), Support Vector Machine (SVM) and convolution neural network (CNN) (S. Saha et al., 2021), Boosted Tree (BT), Extreme Gradient Boosting (XGB), and Deep Boost (DB) (Chen et al., 2021)in recent years.

ML models have been frequently used by combining traditional-based models (Olden et al., 2008). ML modelling methods, such as ANN, SVM, and field data, have been used for soil erosion assessments (Gholami et al., 2021). Gholami et al. (2021) employed erosion pins and ANN to evaluate the spatial distribution of annual soil erosion rates. Combining soil erosion pins with an ANN-based model and obtaining GIS-based outputs was reliable (RMSE:0.1; R^2:0.9), low-cost, and easy-to-use approach for estimating the annual soil erosion. Zhang et al. (2009) performed soil erosion assessment using the Soil and Water Assessment Tool (SWAT), a physical-based soil erosion model with ANN and SVM models for soil erosion prediction. They found SVM model predicts better with approximating the SWAT model. A fuzzy interface system (FIS) has been widely used for time series prediction in uncertain situations. ANFIS is a hybrid method of ANN and FIS, which can execute the advantages of both these methods.

Modelling soil erosion for current and future climate scenarios is crucial for reducing potential environmental hazards and maintaining sustainable land resources (Panagos et al., 2021). Continuous observation and predictions are essential to detect vulnerability for soil erosion in climate variation (Li and Fang, 2016; Mullan et al., 2012). A proper understanding of the locations and magnitude of erosion for present and future situations is required to achieve the UN Sustainable Development Goals (SDGs) (Lal et al., 2021). However, limited knowledge is on soil erosion predictions over the climate scenarios. Hence, this study aims to develop a spatiotemporal process to predict soil erosion vulnerability using climate scenarios. This research employed five different models: empirical soil erosion model (RUSLE), statistical (FR), machine learning (ANN, SVM) and hybrid methods (ANFIS) to explore an accurate predicting model to find the vulnerability for soil erosion under two different climate scenarios. This research provides a novel approach by employing five different models and climate change scenarios using geoinformation tools. In addition, this research investigated the variation of satellite data and compared it with actual ground data. As per the authors' best of knowledge, no one has predicted the soil erosion susceptibility for the Sri Lankan context using climate scenarios. Therefore, the originality of this research is to predict soil erosion hazards vulnerability using RCP scenarios for the Central Highlands to minimize the impacts of climate change.

2. Materials and Method

2.1 Study area and data sets

The Central Highlands of Sri Lanka is located within 6° 12′ to 7° 42′ N latitudes and 80° 10′ to 81° 15′ E longitudes (Figure 1), the maximum and minimum elevations of 300m and 2565 m a.s.l., with an area of about 10,500 km^2. The natural landscape of the highlands mainly receives rainfall from two monsoons and two inter-monsoons. The average rainfall is above 2500 mm for the western side, and the eastern side receives above 1500mm throughout the year.

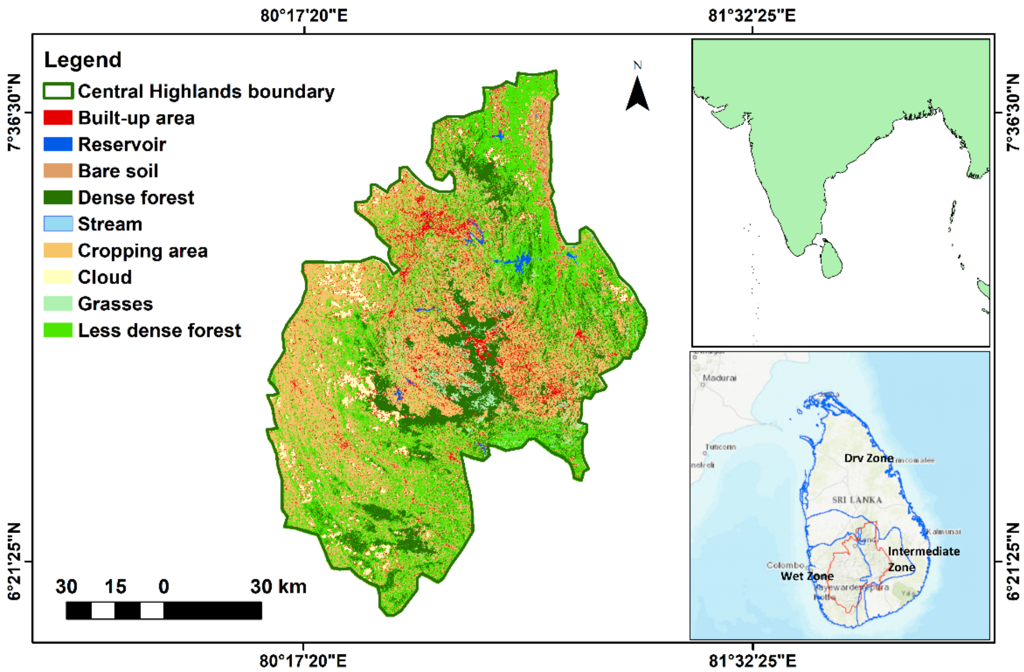

Figure 1. Location of the Study area: the Central Highlands of Sri Lanka.

Table 1. Summary of the data sources.

Data	Resolution	Source
Soil data	30m	Natural Resources Management Center (NRMC), Sri Lanka
Precipitation data from 1990 to 2019	30m	NRMC, Sri Lanka https://www.doa.gov.lk/NRMC/index.php/en/
Topographic data	30m	Survey Department of Sri Lanka
Past landslides incidences		UNISDR (United Nations International Strategy for Disaster Reduction) http://www.desinventar.lk:8081/DesInventar/index.jsp
Landsat images	30m	USGS earth explore https: earthexplorer.usgs.gov
Climate System Model (CCSM) projections National Center for Atmospheric Research (NCAR)		https://gisclimatechange. ucar.edu/ inspector https://gisclimate change.ucar.edu http://www. worldclim.org/

This study developed a spatiotemporal process to project the soil erosion vulnerability with future climate scenarios. This research employed a combined methodology by using: empirical soil erosion models, statistical, machine learning, and hybrid methods and techniques for modelling and projecting soil erosion under two different RCP climate scenarios. The study deployed a novel approach using five different models together for the projection of the soil erosion hazards using geoinformatics techniques and evaluating the best model performance for the projection. The overall methodology is illustrated in Figure 2.

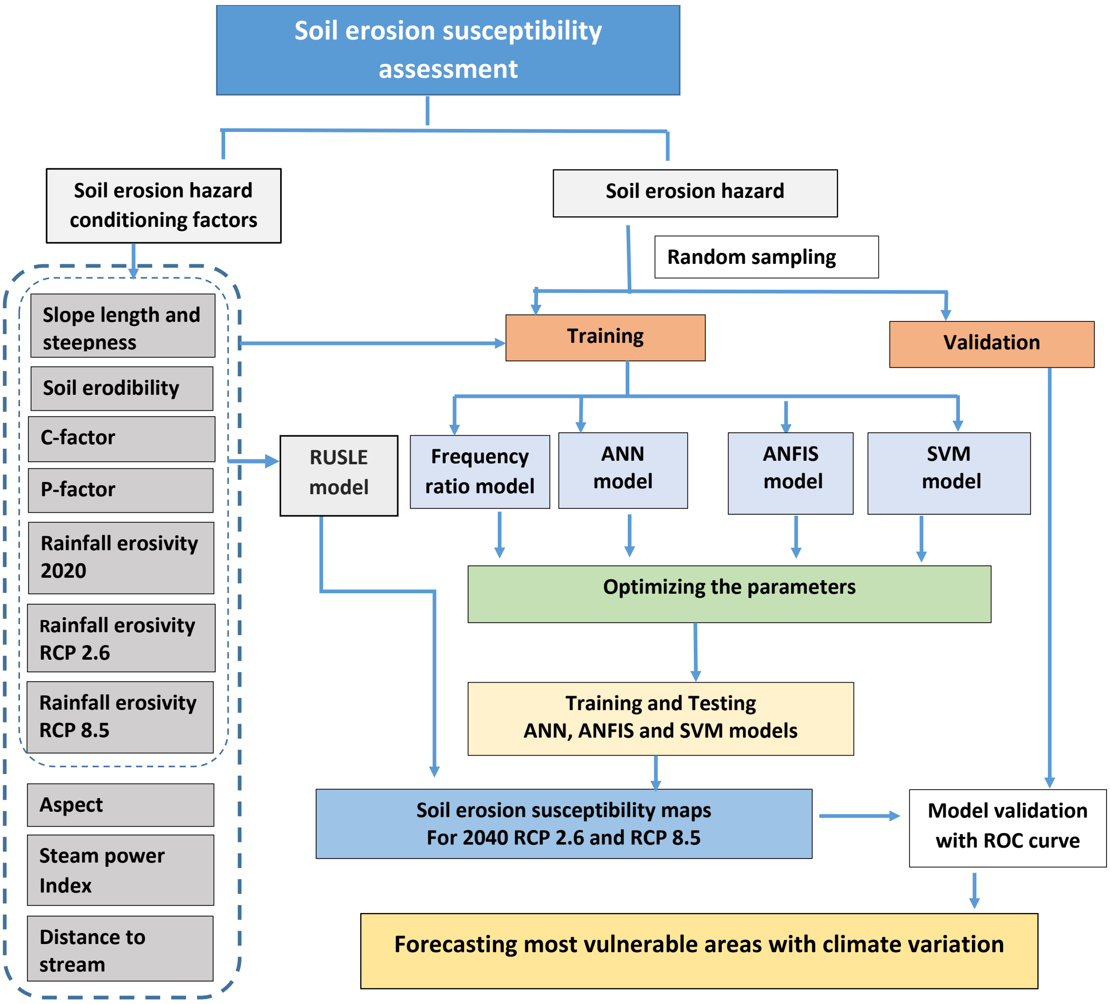

Figure 2. The overall workflow of the study.

2.2 Soil erosion susceptibility mapping using RUSLE

The soil erosion vulnerability over the Central Highlands was derived from using the RUSLE. The RUSLE model (Renard et al., 1997) has been commonly employed to estimate long-term soil erosion rates in agricultural watersheds, regional or country-level, in large-scale studies (Panagos and Katsoyiannis 2019; Panagos et al. 2015). Many researchers employed the RUSLE model to predict soil erosion (Teng et al., 2018; Panagos et al., 2021). Accordingly, the RUSLE model was employed in this study to assess and predict the average annual soil loss of the Central Highlands for 2020 and 2040 using the following equation (1):

$$A = R \times K \times L \times S \times C \times P \qquad (1)$$

The average annual rate of soil erosion (A) is provided in tons per hectare per year. The past 30 years of gauge rainfall data (1990-2019) and 20 years of satellite rainfall data from NCAR were collected to estimate the rainfall erosivity (R) factor (MJ mm ha^{-1} h^{-1} yr^{-1}). The RCP scenarios were developed based on statistically downscaled 1-degree precipitation data for 2040. The soil erodibility (K) factor (t ha^{-1} $MJ^{-1}mm^{-1}$), slope length and steepness (LS) factor (unitless), crop factor (C) (unitless) and management practices (P) factor (unitless) were executed from the data gathered from(Senanayake et al., 2020). Detail explanation of the analysis is given in (Senanayake et al., 2020).

Soil erosion in the Central Highlands was mainly driven by precipitation. The predicted rainfall raster layers for 2040 (R factors) with other erosion factors (K, LS, C, and P) were used to generate the vulnerability maps. The LS, R, K, C, and P-factor layers were generated in the GIS environment. These layers were multiplied using the raster calculator. The generated soil erosion vulnerability maps were classified into five classes according to the previous classifications of Senanayake et al. (2020).

2.3 Soil erosion susceptibility using frequency ratio

The frequency ratio (FR) model is a statistical-based bivariate approach, which can be employed to detect the spatial relationship among independent and dependent variables. This FR method has been employed to analyze the possibility of an event occurrence using probability mapping by Bonham-Carte (1994). FR can be computed using equation 2.

$$\mathrm{FR} = \frac{\mathrm{N}_{(\mathrm{LS}_i)}/\mathrm{N}_{(\mathrm{A}_i)}}{\sum \mathrm{N}_{(\mathrm{LS}_i)}/\sum \mathrm{N}_{(\mathrm{A}_i)}} \qquad (2)$$

where, $N_{(LSi)}$ is the number of hazard events in class (i), $N(A_i)$ is the total number of pixels in class (i). When the FR value is 1, an average possibility for occurrence, a value higher than 1, means a higher probability of occurrence, and a value lower than one means a low probability of hazard events (Senanayake et al., 2020).

2.3.1 Soil erosion hotspots

Landslides are one of the major natural disasters happening every year in the Central Highlands. A large amount of soil is delivered to streams due to landslides (Gunatilaka, 2007). The amount of sediments delivered to the reservoirs and tributaries is remarkably increased in recent years. Researchers highlighted it might be much larger than the flows of sediments supplied by other erosion processes.

Researchers have obtained more reliable soil erosion susceptibility results by introducing landslides incidents. The soil erosion conditioning factors have been used in landslide susceptibility prediction (Huang et al., 2020). Researchers found a correlation between soil erosion and landslide occurrences in several locations (Rozos et al., 2013). Although rainfall plays a leading role in landslide susceptibility in Sri Lanka, researchers found soil erosion may also contribute as one of the reasons for these incidences (Senanayake et al., 2020). Therefore, past landslides incidences were used as training and testing datasets. The locations of 279 soil erosion hot spots were selected, of which 70% and 30% were randomly divided for training and validation purposes. A total of 279 landslides locations (initiated during 2000 - 2019) were recorded from UNISDR (2021).

2.3.2 Soil erosion conditioning factors

The selection of suitable soil erosion conditioning factors is one of the prerequisites for soil erosion assessment and mapping. In the present study, the selection of the most suitable conditioning factors was drawn based on extensive literature reviews and expert advice. Soil erosion susceptibility was analyzed using eight conditioning factors, including rainfall erosivity under two climate scenarios RCP 2.6 for best and RCP 8.5 for the worst situation. Following soil erosion conditioning factors were used: soil erodibility, slope length and steepness, rainfall erosivity, land cover, aspect, distance to stream and steam power Index. The condition factors are explained in detail in the supplementary note S2 sections.

2.3.3 The variable importance

The variable importance (VI) was calculated to evaluate the importance of the soil erosion conditioning factors. The VI was calculated by using SPSS 27 package, according to the study of Termeh et al. (2018). The variable importance value is bounded by 0 and 1. The relative importance of each factor was obtained.

2.4 Artificial neural network methods

ANN has been applied for non-linear complex environmental applications. ANN is ML model that constructs soil erosion causative factors as inputs, and soil erosion can observe using output. The most popularized ANN model for prediction is multilayered perceptron (MLP). MLP with a three-layered interconnected neural network was performed using soil erosion causative factors as input notes. The weightage computations of the input data were used for hidden layer activation, and identity function was used for output layer activation. The weight component act as a coefficient to the inputs. The hidden layer computed the output through a non-linear activation function. The trial-and-error method was performed to determine the number of neurons for the hidden layer. The poor or excessive number of neurons in the hidden layers most likely cause the problems of bad generalization and overfitting (Orhan et al., 2011). A detailed explanation of the ANN model simulation was given in supplementary note S4.

2.5 The adaptive neuro-fuzzy inference system

The adaptive neuro-fuzzy inference system (ANFIS) is employed as a hybrid method by a combination of the fuzzy inference system and the ANN method. This method was developed by Jang (1993) using the Takagi–Sugeno rule format. This hybrid-learning algorithm is a combination of gradient descent and the least square method. ANFIS is a process of fuzzy logic and artificial neural network methods used to drive the fuzzy If-then rules into the artificial neural network with high computational power. Fuzzy rules are implemented along with suitable membership functions of training paired and further lead to an interface. The best possible combination of input parameters provides the best results with the highest accuracy (Islam et al., 2018). The main purpose of employing ANFIS prediction model is due to its rapid learning ability, automatic adaptation capability and capturing nonlinearity of a complex process such as soil erosion (Islam et al., 2018). Figure S2 shows the ANFIS architecture developed by this study.

2.6 Support vector machine algorithm

Support vector machine (SVM) is one of the most popular ML algorithms and is considered a high-performing technique. The SVM algorithm is a non-parametric supervised classification technique introduced by Vapnik proposed in 1995 (Cortes and Vapnik, 1995). Researchers revealed SVM is on statistical learning theory based on the principles of structural risk minimization. A detailed explanation of the SVM model simulation was given in supplementary note S3.

The ANN, ANFIS and SVM models were constructed using soil erosion conditioning factors as input. The resulting FR values were used as observed output or dependent variables using MATLAB software. The optimum value for each model was obtained from the trial-and-error method. Conditioning factor raster map layers (30m) were developed (Figure S1) using natural breaks. The soil erosion susceptibility maps were developed in GIS software.

2.7 The model validation using a statistical method

The models' performances were evaluated using mean-absolute-error (MAE) and root-mean-square-error (RMSE). Validation of soil erosion risk maps was done using ROC/AUC analysis. The ROC curve was obtained using SPSS software for the validation of soil erosion susceptibility maps. The AUC value is equal to 1 indicates the perfect model prediction. The ROC curves were established based on the false positive rate (1-specificity) and the true positive rate (sensitivity) with the various cutoff thresholds.

$$\mathrm{RMSE} = \sqrt{\frac{\sum_{i=1}^{N}[\bar{X} - X]^2}{N}} \qquad (8)$$

$$\mathrm{MAE} = \frac{1}{N}\sum_{i=1}^{N}[\bar{X} - X] \qquad (9)$$

where N is the sample size, $\bar{X}$ indicates predicted values, and X is observed values. Means absolute error is the sum of the deviation between predicted values of a variable and the real observed values. RMSE optimal value is zero (0), which indicates a higher model performance and prediction rate. However, the optimal value is close to zero is relative. Hence, previous studies revealed that RMSE with standard deviation (SD) of the observation values is appropriate for evaluating the acceptable model performance (Singh et al., 2005; Moriasi et al., 2007; Kastridis et al., 2020).

3. Results

3.1 Soil erosion susceptibility mapping and model performance

Predictions show average soil erosion rates will increase to 10.5 t/ha/yr under the RCP 2.6 and 12.4 t/ha/yr under the RCP 8.5 climate scenario in 2040. The results of RUSLE indicate the soil erosion rate in 2020 is 10.18 t/ha/yr with the satellite rainfall data. However, the ground-based gauge rainfall data indicate soil erosion rate is much higher than the results of satellite rainfall data (11.8 t/ha/yr). The average annual rainfall variation over the past 20 years derived from gauge and satellite data are illustrated in Figure 3.

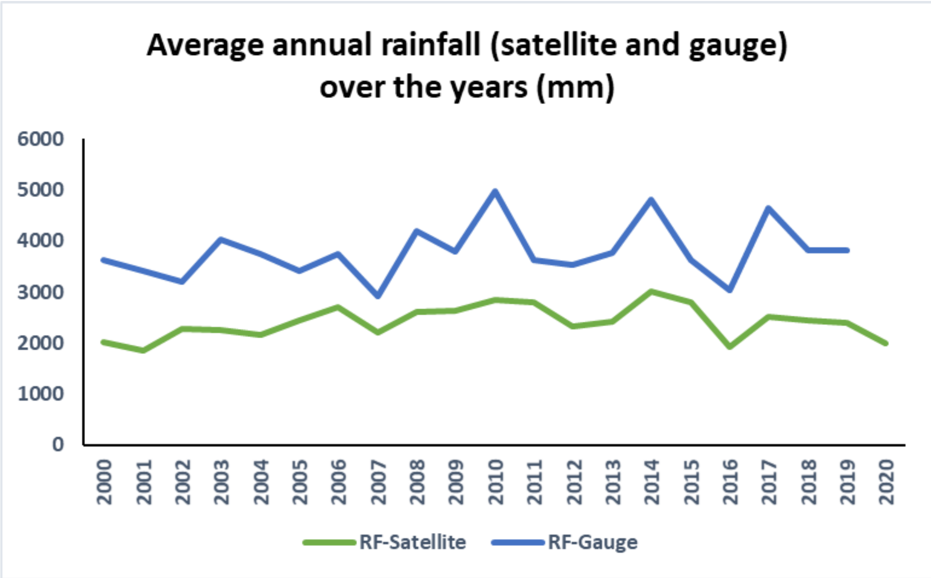

Figure 3: Average annual rainfall in Rathnapura area

The areas covered by soil erosion hazards high and very-high categories are increasing in 2040, with a projected RCP 8.5 scenario. The risk of soil erosion vulnerability in RCP 8.5 is greater than RCP 2.5. The respective soil erosion susceptibility maps and the area covered by each soil erosion category are illustrated in Figure S6 and Table 2.

Table 2. Area covered by the soil erosion category from the RUSLE model.

Class	Soil erosion rate	2020		2040	
		Gauge rainfall	Satellite rainfall	RCP2.6	RCP 8.5
Very Low	<5	5147.04	5228.71	5176.9	4845.05
Low	5-'10	1594.27	1630.48	1604.85	1396.54
Moderate	10 -' 20	1913.96	1927.82	1928.87	1961.01
High	20-50	1463.26	1383.80	1436.95	1765.93
Very High	50<	381.47	329.19	352.42	531.46
Area (km^2)		10500.00	10500.00	10500.00	10500.00

3.2 Frequency ratio method

Soil erosion susceptibility was analyzed with eight conditioning factors using the FR method (Figure S1). The results of the FR analysis and weight for each factor were given in Table S1. The soil erodibility, stream power index and slope length and steepness are obtained highest weights. The susceptibility maps of the frequency ratio method indicate the western side of the Central Highlands is more vulnerable to the projected RCP 8.5 scenario.

3.3 Artificial neural networks method

Figure 4 shows the results of the best validation performance curve. The results show that the best validation performance was achieved from seven epochs, the MSE = 1.31 and R values for training= 0.95, testing 0.84, validation = 0.85 and overall = 0.91. The best validation performance curve of the ANN model is given in Figure S5. The resulted weights are given in Table S3.

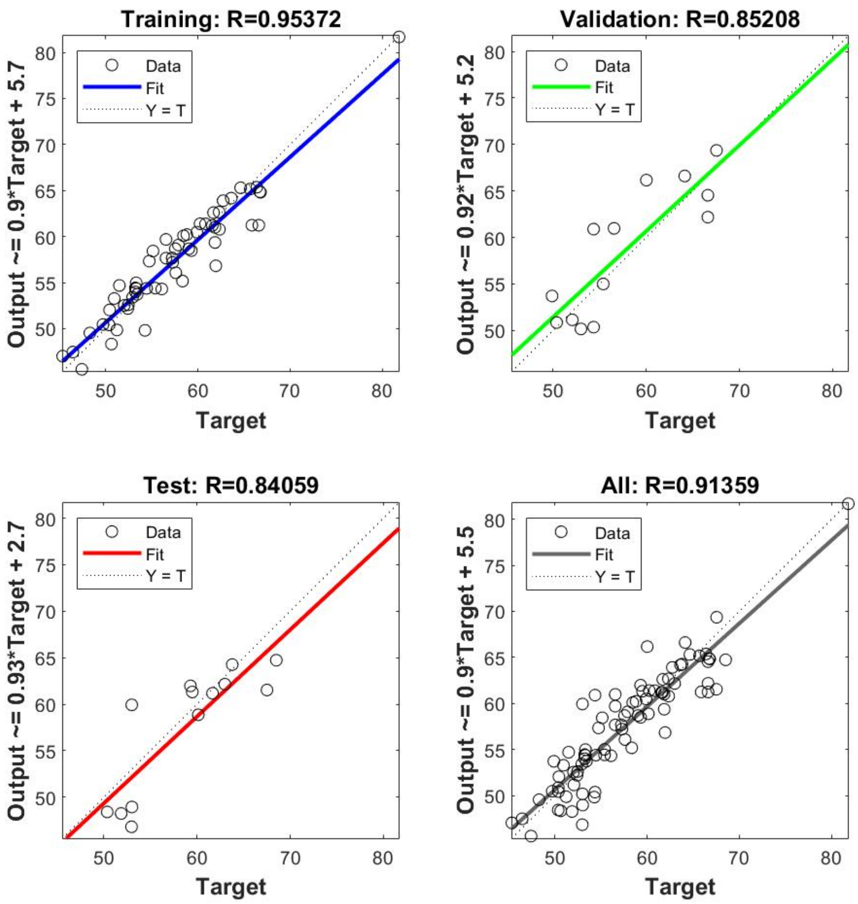

Figure 4. The performance curve of the ANN method.

3.4 Support vector machine learning method

This research employed SVM with eight predictors using Gaussian kernel function with optimization. The performance of SVM is RMSE = 2.29, SD = 4.2 and R^2= 0.70. The AUC indicates soil erosion susceptibility map from the SVM method was performed better than the ANN model (Figure 7). The RMSE value is 2.29, almost half of SD (4.2), indicating an acceptable model performance.

3.5 Adaptive neuro-fuzzy inference system method

The ANFIS model was applied in a trial-and-error method to obtain the best outputs in the training process. The best validation performance of the ANFIS model was obtained in RMSE = 0.001 from 2 epochs and $R^2 = 0.73$. The AUC results show ANFIS model performs better than the ANN model (Figure 7). Figure S8 illustrates a comparison of the ANFIS outcome and RUSLE outcome. The respective soil erosion susceptibility maps and the area covered by each soil erosion category are shown in Figure 5 and Table 3.

Table 3. Area covered by the soil erosion category from the ANFIS model.

	2020		**2040**	
Soil erosion Class	**Gauge RF**	**Satellite RF**	**RCP 2.6**	**RCP-8.5**
Very low	282.76	44.65	527.06	45.8
Low	1572.75	1835.24	1671.09	1658.6
Moderate	2719.98	1724.49	1605.08	1560.0
High	4116.70	3870.92	3772.82	3744.5
Very high	1807.81	3024.70	2923.95	3491.1
Area (km^2)	10500.00	10500.00	10500.00	10500.00

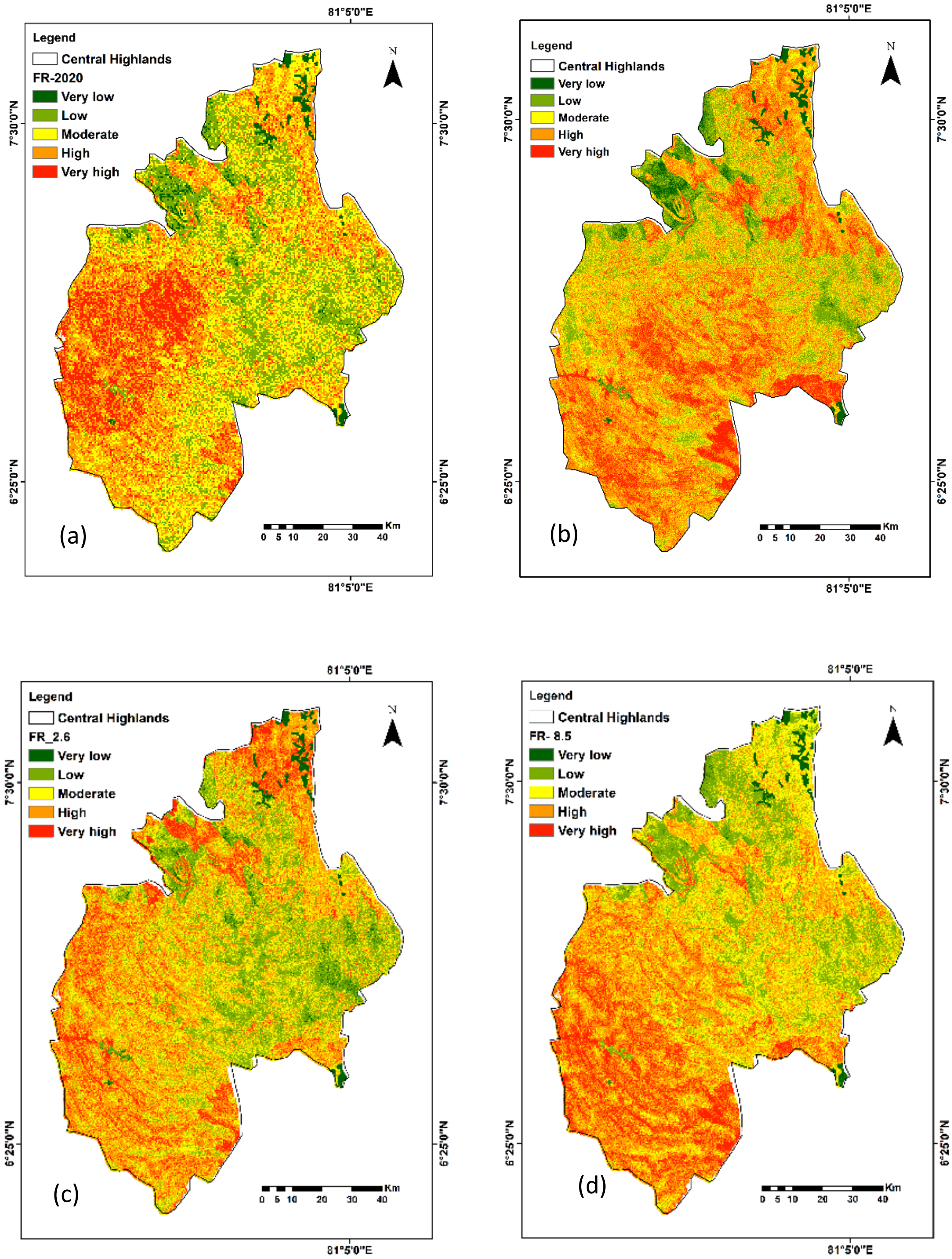

Figure 5. Soil erosion susceptibility map for (a) 2020 from gauged data, (b) 2020 from satellite data, (c) RCP 2.6, and (d) RCP 8.5 in 2040.

3.6 Relative importance of the soil erosion conditioning factors

The variable importance calculation method results indicate that rainfall, soil erodibility, slope length, and steepness are the most responsible factors for soil erosion susceptibility in this study area. Figure 6 illustrates the relative importance of soil erosion conditioning factors.

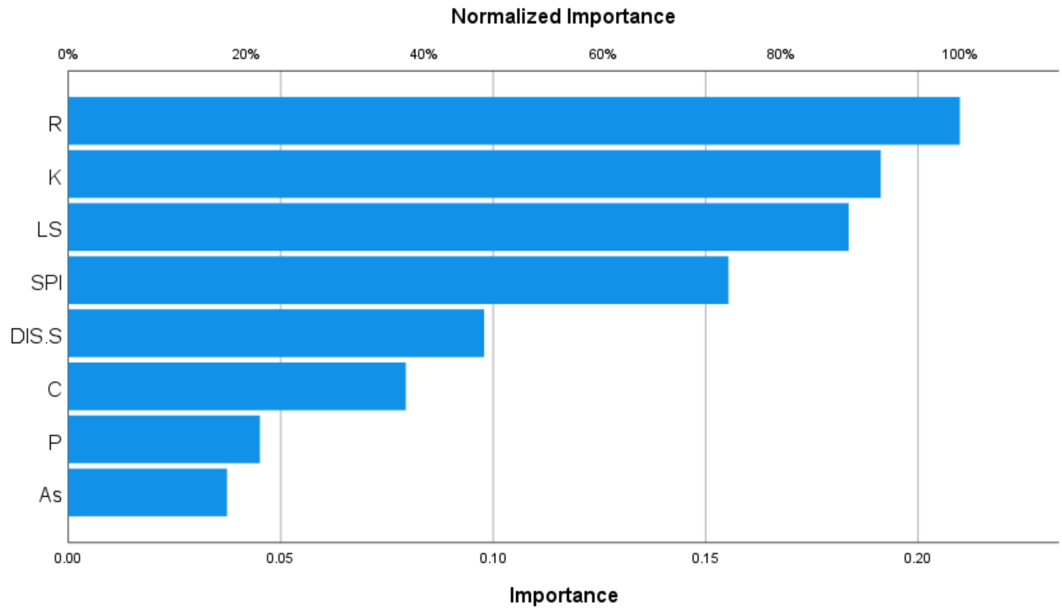

Figure 6. The relative importance of soil erosion conditioning factors.

3.7 Validation of susceptibility maps

Figure 7 and Table 4 indicate the model efficiency obtained from ROC and AUC analysis. Findings of the analyses revealed all five models employed in this study met the requirement of a threshold value of the ROC curve. The highest AUC values were obtained for ANFIS and SVM models. The ANN and FR methods received the lowest accuracy levels. A summary of the models AUC values shows in Table 4.

Table 4. The model performance using AUC

Test Result Variable(s)	Area under the curve	Std. Error[a]	Asymptotic Sig.[b]	Asymptotic 95% Confidence Interval	
				Lower Bound	Upper Bound
ANFIS_2020	.891	.089	.194	.716	1.000
ANFIS_RCP2.6	.957	.049	.129	.860	1.000
ANFIS_RCP8.5	.891	.102	.219	.670	1.000
SVM-SE2020	.891	.089	.194	.716	1.000
SVM-RCP2.6	.891	.089	.194	.716	1.000

SVM-RCP8.5	.891	.089	.194	.716	1.000
ANN_2020	.826	.126	.279	.579	1.000
ANN_RCP2.6	.870	.102	.219	.670	1.000
ANN_RCP8.5	.891	.089	.194	.716	1.000
FR_2020	.870	.089	.194	.716	1.000
FR_RCP2.6	.783	.150	.348	.489	1.000
FR_RCP8.5	.783	.150	.348	.489	1.000

a. Under the non-parametric assumption

b. Null hypothesis: true area = 0.5

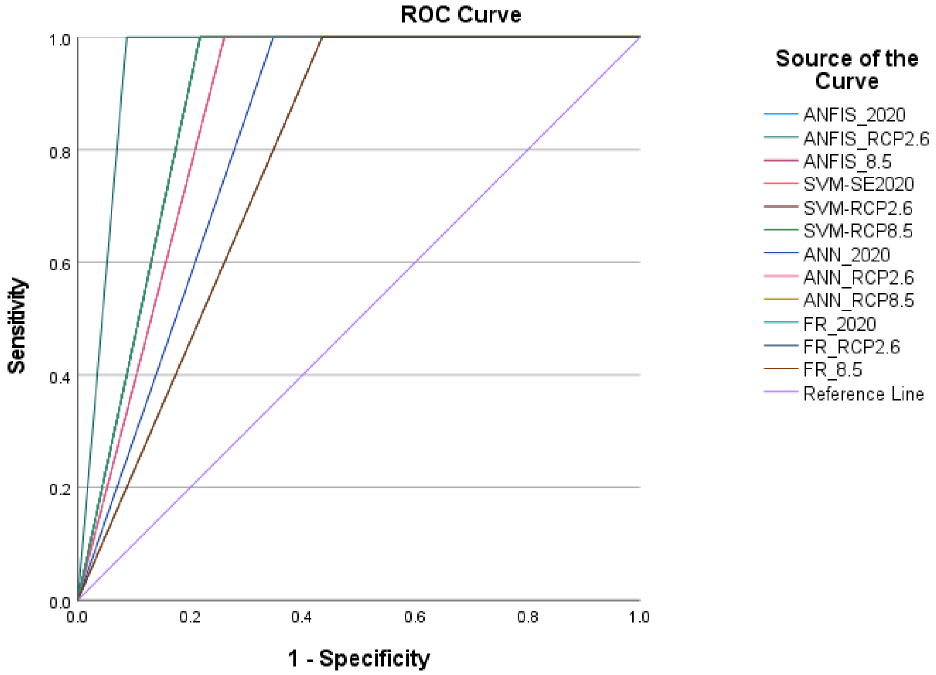

Figure 7. Model validation from ROC curve.

4.0 Discussion

The present study contributes by addressing a knowledge gap on a methodological approach for the spatiotemporal process to predict soil erosion susceptibility in the Central Highlands of Sri Lanka under different climate scenarios. In addition, this study introduces a methodological improvement by combining projected rainfall erosivity under RCP scenarios as conditioning factors for empirical equation, statistical, machine learning and hybrid machine learning techniques to predict soil erosion. This study suggests that SVM and ANFIS models accurately predict soil erosion vulnerability at two different climate scenarios.

This study identified that soil erosion rates will increase from 4% to 22% in 2040, compared to 2020, under the predicted climate scenarios. The results revealed the current soil erosion rate is 11.8 t/ha/yr (2020) in the Central Highlands. The satellite-based rainfall erosivity shows a relatively low value than gauged rainfall erosivity. That is primarily due to the low spatial resolution of the satellite images. However, satellite and gauge rainfall data have a better correlation (r=0.62, KEG's =0.41). Researchers have identified that tolerable soil erosion loss is around 1-2 t/ha/yr in the Central Highlands of Sri Lanka (Somasiri et al., 2021). According to the projected RCP8.5 scenario, all models employed in this study indicate soil erosion susceptibility and vulnerability are increasing. In other words, the risk of soil erosion will be high, specifically in western parts of the Central Highlands, by 2040. Although the areas covered by different soil erosion susceptibility classes are varied, one thing is prominent. The areas covered by very high and high susceptibility classes under projected RCP 8.5 are increasing in 2040 with all the models (Figure S7).

The above findings are in line with the study of Zheng et al. (2018). This estimated future climate and runoff projections across South Asia, including Sri Lanka, using a consistent method by 42 General circulation models (GCMs) in CMIP5. The modelling results indicate that projected runoff will increase throughout the region. The change of runoff is occurred due to the changes in precipitation. The median projection indicates the mean annual runoff increases by 20–30% in the Indian sub-continent by 2046–2075 relative to 1976–2005.

Researchers found that increasing rainfalls influence the soil erosion runoff in the western slopes of the Central Highlands. They have observed rainfall variation in terms of increasing rainfall intensity and average rainfall. Burt and Weerasinghe (2014) had investigated the main drivers of changes in daily precipitation in Sri Lanka. They found sea surface temperature of the Pacific and Indian ocean drives the atmospheric changes of regional climate change. Researchers observed that increasing one degree of Celsius in the global mean temperature increases water holding capacity in the atmosphere by 7%, resulting in intense rainfall and a vigorous hydrological cycle (Mullan et al., 2012). This study also identified rainfall and soil erodibility are the most important factors for soil erosion hazards in this study area. Hence, the areas with steep slopes and higher altitudes are more vulnerable to climate variability. Specifically western part of the Central Highlands will be more susceptible to soil erosion.

It is important to understand the risk of soil erosion in terms of physical, transitional, and human risk and their possible consequences for better preparedness. A recent study found that high intensive rainfall caused sudden and long-travelling landslides in the Central Highlands of Sri Lanka (Dang et al., 2019). Within three consecutive days, the above area received 446.5 mm heavy rainfall from May 14 to 17, 2017. Soil mass movement caused more significant damage in the Aranayake area by killing 127 people and demolishing 75 houses. In addition, almost all the houses in this area are still at risk of future landslides. Perera et al. (2018) have observed that 52% of household incomes were generated from agricultural activities, home-garden and plantation agriculture. The landslide has badly affected the social and economic aspects of the household, as well as the country's economy. This implies the possible risk of soil erosion hazards, which will enhance landslide incidences and damage to agricultural activities and livelihoods. It will also be threatening the lives of peoples and may possibility of peoples' migration to other areas. Hence, the potential risk of future environmental problems is important to reduce the negative consequences.

Hewawasam and Illangasinghe (2015) have identified the rate of soil erosion in the Central Highlands that significantly reduce the reservoirs' capacity. They have identified the major rivers and their tributaries transport a heavy load of sediments during the rainy seasons, which is a severe threat to the storage capacity of reservoirs that supply water for hydropower generation and agricultural production in the country. However, Diyabalanage et al. (2017) have researched to identify the impact of soil and water conservation measures on soil erosion rate and sediment yield. They have identified with this mitigation measures a five-fold reduction in the sediment load of the streams in the critical areas that successfully contributed to soil erosion reduction. Therefore, considerable attention should be paid to strengthening soil conservation measures over the highlands. The potential risk of soil erosion and changing rainfall patterns should be further studied.

Soil erodibility mainly depends on the chemical and physical structure of the soil (De Rouw and Rajot, 2004). The Central Highlands is covered by 73% of Red-Yellow Podzolic soils which have relatively high soil erodibility value. Increasingly, lands are exposed to poor agricultural practices, resulting in poor soil organic matter content. That implies a loss of soil structure (chemical and physical) and subsequently less stable aggregates (De Rouw and Rajot, 2004). Researchers found the agricultural land areas are increasing from 2000 to 2019 in the Central Highlands with increasing soil erosion rates (Senanayake et al., 2020). This indicates more attention should be paid to improving the soil condition by taking appropriate measures, such as increasing the organic matter content, especially in highly vulnerable areas for soil erosion. In addition, this research proposes to conduct research on soil erodibility assessment under different land uses. The results will indicate the critical soil organic matter content values in different land uses.

The findings of this study contribute to resilience development for future agricultural planning and management. Soil erosion susceptibility maps with the vulnerability assessment can be useful for land managers and policymakers with respect to agricultural strategic planning and environmental protection. Quantifying the impacts of climate variability and its effects on soil erosion over the study area is important to assist the land managers in adopting new techniques and conservation strategies to protect and minimize further damages or prevent the occurrence of disasters such as landslides. This research proposes further education and awareness programs on soil erosion and conservation strategies (Lal et al., 2021), integrated agro-meteorological advisory services, adaptation measures for climate resilience agriculture, social networking and community-based adaptation as long term - strategies for resilience development on soil conservation (Aryal et al., 2020). The projected increasing rainfall and runoff subsequently influence increasing runoff and gully erosion. Hence, improving the drainage system to remove excess water from the land may need to protect the soil from runoff. In addition, the construction of rain-shelters such as protected agriculture technology/ polytunnel may need to protect crops from intense or erratic rainfall.

The limitation of this study is socio-economic factors were not incorporated into this analysis. However, these factors may influence soil erosion over the next century. These projections could be achieved when the mitigation targets of RCPs are combined with the Shared Socioeconomic Pathways (SSPs) in the Coupled in Model Intercomparison Project Phase 6 (CMIP6). The SSP scenarios look at five different ways the world might evolve in the absence of climate policy or how different levels of climate change need mitigation. These projections include socio-economic factors such as population, economic growth, education, urbanization and the rate of technological development. Almazroui et al. (2020) researched the latest CMIP6 dataset to examine the projected changes in temperature and precipitation over six South Asian countries. The average annual precipitation is projected to increase by 25.1% in Sri Lanka under the SSP5-8.5 scenario by the end of the twenty-first century. The projected temperature increases by 1.2 °C, 2.1 °C, and 4.3 °C under the SSP1-2.6, SSP2-4.5, and SSP5-8.5 scenarios, respectively, over South Asia.

Lal et al. (2021) emphasized that sustainable soil management is key to achieving the SDGs. They have highlighted achieving SDGs: 2-zero hunger, 3-good health and well-being, 6- clean water and sanitation, 13- climate action, 15 - life on land and 17- partnership have a direct connection with the soil activities. This research contributes to addressing some of the decision-making challenges to achieve the SDGs in the 2030 UN agenda, such as identifying appropriate methods for risk assessment, understanding the location and magnitude of erosion, forecasting changes in soil erosion driven by water, land use, and climate change. Healthy soils maintain the eco-service activities in the farming systems and improve food security in a country.

5. Conclusion

The study focuses on five models: RUSLE, FR, ANN, SVM, and ANFIS, to predict and quantify soil erosion vulnerability in the Central Highlands of Sri Lanka. Soil erosion susceptibility was analyzed using eight conditioning factors to observe the soil erosion vulnerability for the present situation and 2040 under projected RCP 2.6 and RCP 8.5 climate scenarios. The results suggest the soil erosion rate in 2040 will increase to 10.5 t/ha/yr and 12.4 t/ha/y under RCP 2.6 and RCP 8.5, respectively, which increase the recommended threshold value in the country and tolerable soil loss value globally (10 t/ha/y). The frequency ratio method is the least accurate model for predicting soil erosion vulnerability. The probability maps of the ANFIS and SVM methods provide the highest accurate model predictions (accuracy 89%). The rainfall and soil erodibility are the most influential factors for hazards vulnerability. The results of these models' outputs indicate farming systems in the western slopes of the Central Highlands will be more vulnerable to soil erosion hazards under climate scenario RCP 8.5 in 2040. Findings suggest implementing soil conservation activities with short-and long-term strategies help to achieve the SGDs in the UN agenda 2030.

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