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Abstract:

Soil erosion is a major environmental challenge that degrades agricultural land, reduces water quality, and threatens ecosystem sustainability, particularly in semi-arid regions. This study assessed soil erosion susceptibility in the Chittar River Basin, Tamil Nadu, by integrating the Revised Universal Soil Loss Equation (RUSLE), Geographic Information System (GIS), and machine learning (ML) techniques. The RUSLE factors rainfall erosivity (R), soil erodibility (K), slope length and steepness (LS), cover management (C), and support practice (P) were derived using IMD rainfall data, FAO soil datasets, SRTM Digital Elevation Model (DEM), and Landsat-based land use/land cover (LULC) data. Four machine learning models such as Random Forest (RF), Support Vector Machine (SVM), Classification and Regression Tree (CRT), and Boosted Regression Tree (BRT), were evaluated using Receiver Operating Characteristic (ROC) analysis to assess their predictive performance. the RF model achieved the highest accuracy with an Area Under the Curve (AUC) of 0.967, followed by SVM (0.925), CRT (0.870), and BRT (0.820). The estimated annual soil loss exhibited substantial spatial variability, with severe erosion primarily occurring in the steep upper catchments of the basin. The integrated RUSLE, GIS and ML framework effectively identified erosion-prone areas and demonstrated that the RF model provides a reliable and robust tool for soil erosion susceptibility mapping, supporting sustainable soil conservation planning and watershed management in the Chittar River Basin.

Keywords: Soil erosion; Revised Universal Soil Loss Equation (RUSLE); Geographic Information System (GIS); Machine learning; Random Forest; Soil erosion susceptibility; Watershed management.

Introduction:

Soil erosion is a leading driver of soil degradation worldwide, particularly in mountainous regions, and it poses a serious threat to environmental sustainability and global food security. (Rodrigo Comino et al., 2016). Increased soil erosion has negatively affected long-term environmental stability of soils in recent years, highlighting the continuing need to develop effective soil conservation practices and apply protective measures against various erosive

agents. (Telak et al., 2021). Water-induced erosion in tropical and subtropical regions has become a significant environmental problem owing to intense rainfall and seasonal climatic variability (Parveen et al., 2012). Identified as one of the most significant factors as one of the most influential factors controlling soil erosion, vegetation cover provides strong protection against various erosive forces. The existence of vegetation substantially leads to soil and water resource management by reducing rainfall impact and decreasing raindrop intensity, and regulating surface runoff (Zhang et al., 2014). The root, stems and leaves networks as natural regulating mechanisms for surface water flow, thereby reducing soil erosion and enhancing the conservation of soil and water assets (Stagnari et al., 2010). However, in recent decades, soil resources have been subjected to severe degradation and prone to water erosion due to rapid conversion of land use and land cover, primarily caused by intensive agricultural practices and deforestation. Furthermore urbanization and population growth have led to rapid vegetation reduction removal from the land surface, thereby intensifying soil displacement and erosion processes (Gong et al., 2022).

Runoff can detach and transport topsoil over long distances, leading to significant soil erosion and sediment accumulation across landscapes. The effects go beyond the depletion of fertile soil, as erosion also increases river and reservoir contamination and sediment buildup, clogs waterways, and harms fish and other aquatic life. In addition, degraded land retains less water, raising the risk of flooding (Hosseini and Khaleghi, 2020). Numerous studies have demonstrated the on-site and off-site impacts of soil erosion, deterioration of water quality, reduction in crop productivity and increased sediment accumulation in rivers, which collectively contribute to significant socio-economic challenges.

Accurate estimation of soil erosion and identification of key driving factors, and spatial mapping of soil erosion risk zone are essential for the effective design and implementation of sustainable soil and water management strategies. Many quantitative models have been proposed to estimate soil erosion. Physically based models include the Water Erosion Prediction Project (Nearing et al., 1989), European Soil Erosion Model and the Areal Nonpoint Source Watershed Environment Response Simulation (ANSWERS) (Beasley et al., 1980), the. Empirical approaches, such as the Universal Soil Loss Equation (USLE) (Wischmeier et al., 1978) and its revised form (RUSLE) (Avand et al., 2021), are also widely applied. Among these, RUSLE is the most commonly used due to its simplicity, reliability, and cost-effectiveness (Avand et al., 2022). RUSLE estimates soil loss by integrating key factors such as rainfall erosivity, vegetation cover, soil erodibility and land management practices (Bouchnak et al., 2009). Integrating RUSLE, geospatial data and Geographic Information Systems GIS enables efficient and economical analysis of soil erosion across regions arge watersheds. This combined approach has extensively used for mapping and analyzing soil erosion patterns (Borrelli et al., 2022).

The Revised Universal Soil Loss Equation (RUSLE) has been widely used for estimating soil erosion, but has only been developed as an empirical model and does not account for the complex nonlinear interactions between the topographic, climatic, soil and land use variables. To overcome these limitations, machine learning (ML) techniques such as Random Forest (RF), Support Vector Machine (SVM) have increasingly been adopted for soil erosion susceptibility mapping because of their ability to model nonlinear relationships, handle high-dimensional geospatial datasets, and achieve higher predictive accuracy than conventional methods (Nguyen et al., 2025)

In this study, the Revised Universal Soil Loss Equation was integrated with the Machine Learning algorithm such as Random Forest to enhance the spatial estimation accuracy of soil erosion susceptibility. Although RUSLE is effective in geospatial modeling of soil erosion susceptibility using environmental factors, its predictive capability is often constrained by the limited number of parameters considered, namely rainfall erosivity, soil erodibility, cover management, slope length and steepness, and conservation practice. To overcome these limitations, the present study incorporated additional environmental and terrain-related variables through the Random Forest model, thereby strengthening the reliability and robustness of soil erosion prediction. The performance of the developed model was analyzed using statistical validation metrics such as the Coefficient of Determination coefficient of regression determination (R^2) and the Area Under the Curve, which demonstrated the effectiveness and predictive capability of the integrated approach.

Materials and Data used:

The Chittar Basin forms a sub-basin of the Thamirabharani River system situated in southern Tamil Nadu, with a geographical extent between $8^{\circ}36' - 9^{\circ}17' N$ latitude and $77^{\circ}22' - 77^{\circ}57' E$ longitude and an area of about 2150 km^2 as shown in Fig.1. The climate of the basin is sub-humid and the topography varies from the hilly regions extending from the foothills of the Western Ghats to gently undulating terrain, downstream plains and is heterogeneous. The differences in altitude and gradient have a major influence on hydrological processes such as surface runoff generation, sediment transport, and soil erosion dynamics (Mohammed & Mesapam, 2026).

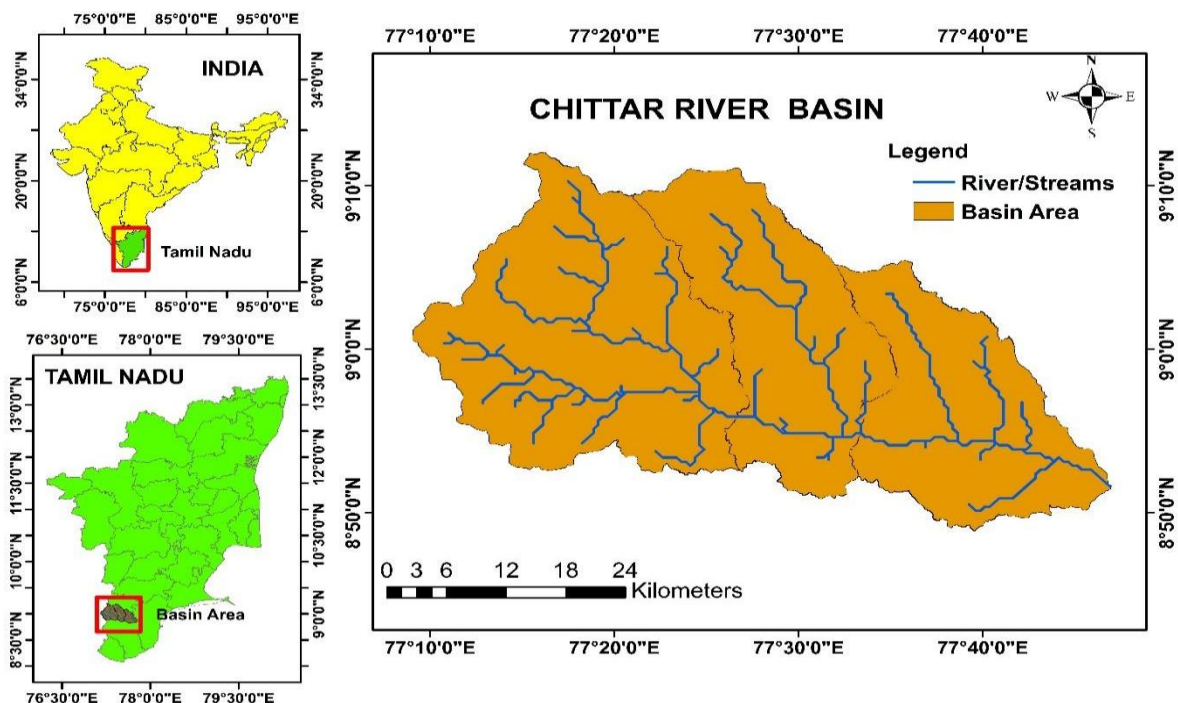


Fig.1 Study area map of the Chittar River Basin, Tamil Nadu, India.

The drainage pattern of the basin is primarily dendritic to sub-dendritic with a number of dendritic patterns and is dominated by the northeast monsoon rainy season. Overland flow

from the basin is significantly influenced by intense seasonal rainfall which also increases soil erosion. The basin also has a variety of land use and land cover types such as farming activities, forestry, urban development and scrub land that have a strong effect on runoff properties and erosion potential. Expansion of agriculture, deforestation and land management in some parts of the basin have also made it more susceptible to soil degradation.

The geology of the basin is predominantly hard crystalline geology which has a considerable impact on infiltration capacity, groundwater recharge, and surface hydrological responses within the basin. Upstream mountainous regions are subjected to more frequent high rainfall events, steep slopes, and consequently, higher erosion rates whereas the fertile alluvial plains in the downstream regions have intensive agricultural activities. In addition, the natural landscape has been modified due to increasing anthropogenic pressures, rapid population expansion and impacting the ecological stability and sustainability of soil and water resources in the basin.

The datasets utilized in this study include LULC, rainfall, river network, DEM, and soil data obtained from various national and global sources. These datasets were utilized for thematic layer preparation, terrain analysis, hydrological assessment, and soil characterization of the study area. Detailed information regarding dataset type, parameters, source, year, and format is presented in Table 1.

Table 1: Source Information of the Datasets

Dataset	Parameters	Year	Dataset information	Dataset source	Dataset Format
LULC map	Land Use/Land Cover classes such as Trees, Water, Cropland, Built-up Area, Bare Ground, Rangeland, Flooded Vegetation	2025	Global annual LULC dataset generated using Sentinel-2 imagery classification developed by Esri and Impact Observatory with 10 m spatial resolution	Esri Land Cover Explorer https://livingatlas.arcgis.com/landcoverexplorer/?utm_source=chatgpt.com	GeoTIFF
Rainfall	Rainfall Erosivity	2000 - 2025	0.25° × 0.25° spatial resolution (~25 km) daily gridded Precipitation dataset	India Meteorological Department (IMD-Pune) https://www.imdpune.gov.in/cmpg/Griddata/Rainfall_25_NetCDF.html	.NetCDF
River Map	Distance from the River		River map of the Thamirabarani River Basin	Hydro Sheds https://www.hydrosheds.org/hydrosheds-core-downloads	.shp
Digital Elevation Model	Slope, DEM Aspect, Topographic wetness index, drainage density terrain ruggedness index, Flow Accumulations, stream power index.	2014	SRTM 1 Arc-Second of 30 m	National remote sensing Centre https://earthexplorer.usgs.gov/	.tif
Soil map	Soil texture, soil depth, and organic carbon,	2012	Global soil database combining regional and national soil information for environmental and agricultural studies	HWSD Database https://www.fao.org/soils-portal/data-hub/soil-maps-and-databases/harmonized-world-soil-database-v12/en/?utm_source=chatgpt.com	.asc

Methodology:

The Methodology is combined with the RUSLE model and the Machine Learning algorithm. Some thematic layers were first developed such as rainfall erosivity, slope steepness, soil erodibility, support practice factor and overage management factor to estimate spatial soil erosion using the Revised Universal Soil Loss Equation. The RUSLE output was then used to extract severe erosion points, which were also cross-sectioned with topographic, hydro-climatic, anthropogenic, and soil-related factors to model erosion susceptibility. After that, the multi-collinearity analysis Random Forest (RF), Support Vector Machine (SVM), Classification and Regression Tree (CRT), and Boosted Regression Tree (BRT) were carried out, before proceeding to validate the results with the AUC, to derive the soil erosion assessment susceptibility map, as presented in Fig.2.

Revised Universal Soil Loss Equation

The rates of soil erosion were measured using the Revised Universal Soil Loss Equation. The equation to determine the average annual soil loss rate (A) across a large area using the following factors in Equation.1.

$$A = R * K * LS * C * P \quad (1)$$

A is the annual erosion rate (t/ha/yr); R is the erosivity factor of precipitation (MJ.mm/ha/h), K is soil erodibility factor (t ha h/ha MJ mm), L is the factor of slope length, S is the factor of slope inclination, C is Coverage Management factor and P is the support practices factor.

Rainfall Erosivity

Rainfall erosivity is used to quantify the erosive potential of the rainfall. Rainfall characteristics including volume and intensity are important factors affecting the detachment of particles and thus the erosivity (Mohammed & Mesapam, 2026). Monthly and annual rainfall data were used to estimate rainfall erosivity instead of hourly rainfall intensity data, due to limited availability of hourly rainfall intensity data. Equation.2 was used for the calculation of rainfall erosivity (Wischmeier and Smith et al., 1978)

$$R = \sum_{i=1}^{12} 1.735 \times 10^{(1.5 \log_{10} \left[\frac{P_i^2}{P} \right] - 0.08188)} \quad (2)$$

Where R is the rainfall erosivity factor (MJ.mm.ha⁻¹.yr⁻¹), P_i is the monthly rainfall (mm), and P is the annual rainfall (mm).

Soil Erodibility

Soil erodibility is influenced by soil characteristics such as sand, clay content and silt. composition, soil organic matter (SOM) content, permeability, and soil structure characteristics. (Wischmeier and Smith et al., 1978; Renard et al., 1997) and can be expressed in Equation. 3

$$K_{NOMO} = 0.1317 \{ 2.1M^{1.14} * 10\%^{-4} * (12 - SOM) + 3.25 (S - 2) + 2.5(p - 3) \} * 100 \quad (3)$$

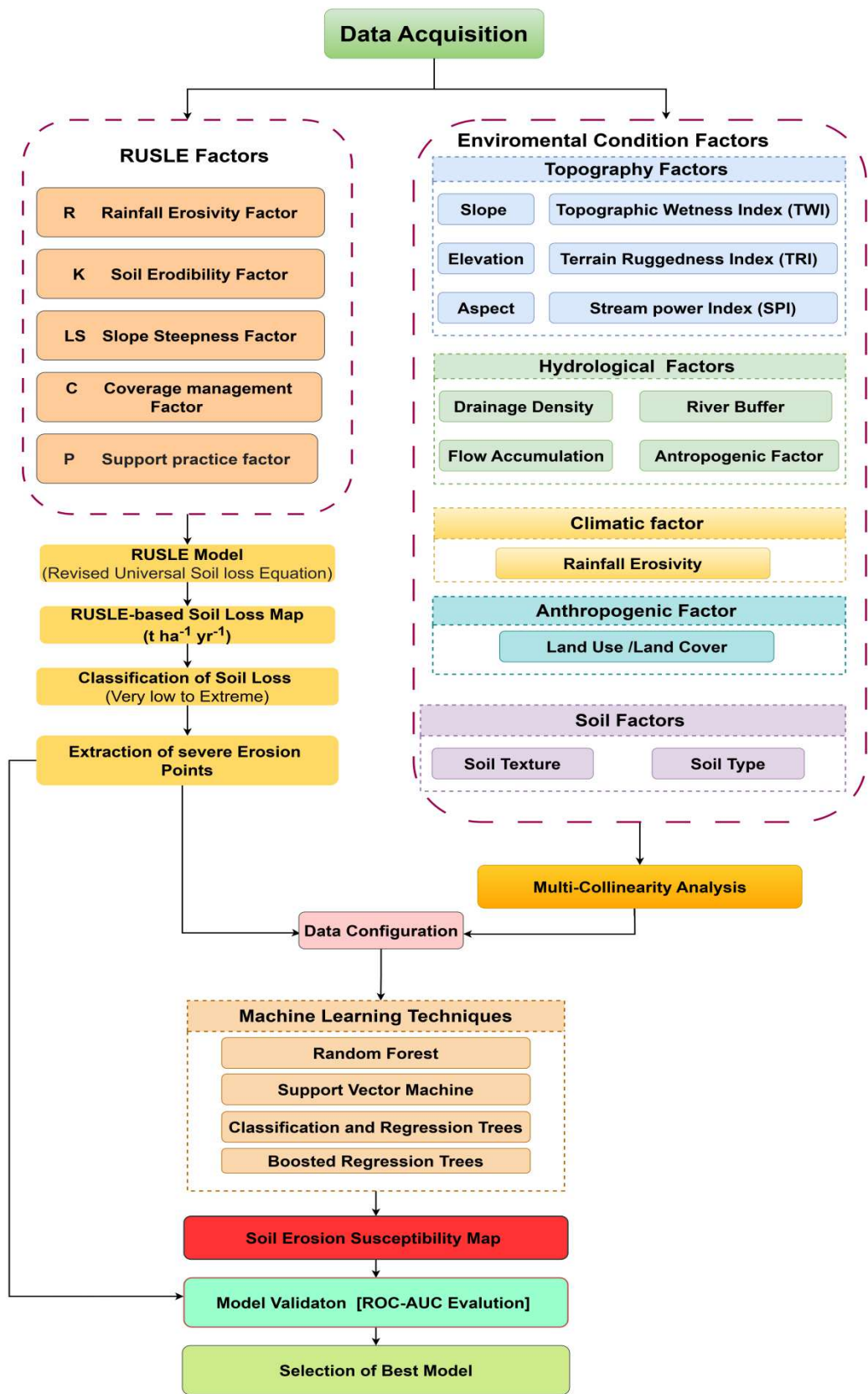
Where: K_{NOMO} = Soil erodibility factor estimated using the nomograph approach in t-ha-h/ha/MJ/mm.

M = {(100 - % of clay) * (% of silt + % of very fine sand)} = size of particle parameter.

SOM = soil organic matter content. s = soil structure classification.

168 p = permeability class code

169



170

171 **Fig.2** Methodology of the study.

Slope Steepness Factor:

The topographic factor, commonly referred to as slope length and slope steepness. (LS) factor, is one of the primary factors influencing water-induced soil erosion. Slope gradient plays a major effect on soil particle detachment, transport, and deposition. The LS factor represents the topographic characteristics of a region through two components: slope length (L) and slope steepness (S). These two parameters are commonly integrated into a single topographic index (LS) to evaluate the overall impact of terrain on soil erosion in Equation. 4.

$$LS = \left(Flow\ Accumulation * \frac{Revolution}{22.1} \right)^m * (0.065 + 0.045S + 0.065S^2) \quad (4)$$

With 'S' slope angle, 'm' is a slope class parameter (Wischmeier and Smith et al., 1978),

Cover management factor:

The cover management factor describes the influence of vegetation cover and land-use practices on soil loss due to rainfall and surface runoff. (Renard et al., 1997). Precipitation is absorbed by the land surface and vegetation cover. Land Use and Land Cover data were applied to estimate the C-factor (Kaffas et al., 2021). This study uses a high-resolution (1:250,000, ~54 m) LULC map used to assign C-factor values to every grid cell in India based on the literature (Kaffas et al., 2021; Ebabu et al., 2022). The values differ across different land use/land cover (LULC) classes, with values ranging from 0 to 0.45 are presented in Table 2.

Support Practice Factor:

The Support practice factor (P-factor) measures the effectiveness of the conservation practices by comparing the soil erosion from a practice relative to the standard upslope and downslope cultivation. It is an indication of the impacts of soil preservation techniques such as strip cropping, terracing, contour farming, and grassed waterways on runoff and soil erosion (Renard et al., 1997; Wischmeier and Smith et al., 1978). It plays a major role in the effective management of soil erosion by modifying surface flow patterns and causing less erosion by runoff and rainfall. The P factor is sometimes estimated depends on the Land Use and Land Cover data sets (Ebabu et al., 2022).

The P-factor values range from 0 to 0.8, with least p-factors reflecting improved soil conservation effectiveness. These vary based on the type of Land Use and Land Cover and the type of conservation measures applied and as shown in Table 2. This table is based on recommendations from previous studies (Kaffas et al., 2021; Ebabu et al., 2022; Maqsoom et al., 2020) as shown in Table 2.

Slope:

The infiltration intensity and infiltration amount. The flow has been determined by the infiltration, surface runoff patterns, and water accumulation, depending across regional slopes, which are subsequently affected by the erosion mechanism (Conforti et al., 2011).

210

211 Table 2. P-factor and C-factor values corresponding to Land Use/Land Cover (LULC) classes

S.No	LULC Classes	P factor	C factor
1	Build up land	0	0
2	Agricultural land	0.49	0.34
3	Fallow land	0.8	0.38
4	Plantation	0.6	0.18
5	Forest	1	0.03
6	Waste land	1	0.45
7	water bodies	0	0

212 **Aspect:**

213 The other aspect is slope instability, which depends on the slope direction and the direction of
 214 gravity. It affects the amount of solar radiation, vegetation cover, soil moisture, and
 215 weathering processes of various slope faces. Slopes that catch more sunlight tend to be drier,
 216 have fewer plants, and are more likely to be affected by erosion and less stable (Ohlmacher
 217 and Davis, 2003).

218 **Elevation:**

219 Elevation is among the main topographic determinants that affect the spatial distribution and
 220 occurrence of gully formations in a watershed. Changes in elevation influence runoff
 221 velocity, drainage pattern, slope characteristics, and sediment transport processes. Increased
 222 flow concentration and surface runoff along the surface will occur in higher elevation areas,
 223 potentially causing increased soil detachment and gully development.

224 **Topographic wetness index (TWI):**

225 The Topographic Wetness Index (TWI) is widely used to evaluate soil moisture conditions,
 226 identify saturated areas, and assess runoff generation (Ali et al., 2014; Samanta et al., 2018)
 227 as expressed in Equation. 5.

228
$$TWI = Ln \frac{\alpha}{\tan \beta + C} \quad (5)$$

229 where α represent flow accumulation, C is the constant value (i.e. 0.01), and β represent
 230 slope,

231 **Stream power index:**

232 The erosional capacity of a river and the corresponding surface runoff is measured using
 233 Stream Power Index (SPI) (Khosravi et al., 2019). SPI values indicate higher runoff intensity
 234 and enhanced erosion activity, whereas least SPI values represent reduced runoff and
 235 minimal erosion potential. SPI is widely used to delineate prone areas to severe soil erosion
 236 and gully formation within a watershed. SPI values were calculated using Equation 6.
 237 (Chowdhuri et al., 2020 b).

$$SPI = A_s \tan \beta \quad (6)$$

where A_s indicates the specific catchment area in square meters, and β indicates the slope angle in degrees.

Terrain ruggedness index (TRI):

The Terrain Ruggedness Index (TRI) is a terrain-based parameter used to quantify variations in elevation between neighboring cells in a Digital Elevation Model. TRI represents the land surface curvature characteristics, which significantly influences runoff concentration, soil detachment, and erosional activity. TRI was derived using Equation. 7. (Riley et al., 1999b).

$$TRI = \sqrt{|X|} (\max^2 - \min^2) \quad (7)$$

where X is represents the elevation of each neighboring cell surrounding a specific cell, while $\max$ and $\min$ denote the maximum and minimum elevations among the adjacent neighboring cells, respectively. These elevation variations are used to quantify terrain ruggedness and surface irregularity.

Drainage density

The hydrological behavior and associated DD have a major influence on the landforms of a catchment area. The drainage characteristics in tropical and subtropical regions are influenced by the erosional potential capacity. The Equation. 8 has been used to compute drainage pattern (Chowdhuri et al., 2020a).

$$DD = \frac{\sum_{i=1}^n S_i}{a} \quad (8)$$

where, $\sum_{i=1}^n S_i$ represent total length of the stream in kilometer and a is the total catchment area in sq. km.

Soil texture:

The properties of soil, particularly soil texture influence surface drainage pattern, the infiltration rate, and movement of water, thereby determining the susceptibility of soil to erosion. Different soil textures affect the dislodgement, transportation, and settling of soil particles, which directly control the intensity of erosional processes (Geissen et al., 2009).

Land use land cover

The LULC classes influence vegetation density, soil moisture retention, surface roughness, and human disturbances, which directly affect erosion intensity and sediment transport. Areas with dense vegetation generally reduce surface runoff and soil erosion, whereas barren land and built-up regions often increase runoff and slope instability (Bui et al., 2019).

271

272 **Multicollinearity analysis:**

273 Multicollinearity analysis was carried out to examine the correlation among the influencing
274 factors .High multicollinearity among independent variables may reduce the prediction
275 accuracy and reliability of the model by introducing redundancy among explanatory factors.
276 The Tolerance and Variance Inflation Factor methods were employed to determine
277 multicollinearity effects. Generally, VIF values less than 5 and TOL values greater than 0.1
278 indicate the absence of severe multicollinearity among variables. The obtained results
279 confirmed that all selected conditioning factors were statistically acceptable and suitable for
280 further modelling and spatial analysis (Aboutaib et al., 2023).

281 **Machine Learning Models**

282 The Random Forest (RF) algorithm is a machine learning technique widely used for
283 classification and prediction in environmental and geospatial studies because of its reliable
284 performance robustness, and ability to handle nonlinear and complex relationships. RF
285 creates of decision trees using randomly selected subsets of variables, training samples, and
286 predictors and the final process is obtained through majority voting among the trees. The
287 model effectively reduces over fitting and improves prediction performance compared to
288 single decision tree methods (Rodriguez-Galiano et al., 2012). The Random Forest model
289 was used to analyze the relationship between conditioning factors and erosion susceptibility.
290 Variable importance analysis was also conducted to determine the most influential factors to
291 controlling erosion occurrence (Wang et al., 2024; Behrouz et al., 2022).

292 Support Vector Machine (SVM) is a supervised machine learning algorithm for classification and
293 regression. It finds the hyperplane that best separates classes, thus making accurate predictions.
294 The SVM is capable to deal with both linear and nonlinear data by using its kernel function.
295 (Nguyen et al., 2025).

296 Classification and Regression Trees (CART) is a supervised machine learning algorithm that
297 uses a tree-based structure to classify or predict outcomes by recursively splitting data into
298 homogeneous groups (Marques Filho et al., 2024).

299 Boosted Regression Trees (BRT) is an ensemble machine learning algorithm that combines
300 regression trees with boosting to improve prediction accuracy. By sequentially correcting
301 errors from previous trees (Vu et al., 2020).

302 **Model Calibration and Validation**

303 The 30% of the soil erosion hotspot locations, which were not used to train the models, were
304 utilized to validate the model results. The predictive accuracy of the models was evaluated
305 using the receiver operating characteristic (ROC) curve to measure the sensitivity (true
306 positive rate) and specificity (true negative rate) of the test. The area under the curve (AUC)
307 associated with the ROC curve indicates the effectiveness of a model in predicting soil
308 erosion occurrence. The ROC curve is used to evaluate model performance, with AUC values
309 ranging from 0 to 1. An AUC value below 0.5 suggests that the model performs like random
310 guessing and lacks predictive capability, whereas values greater than 0.5 indicate that the
311 model possesses acceptable predictive ability.

The true skill score (TSS) was applied to evaluate the predictive accuracy of the models. TSS was determined using the following method: specificity statistics as expressed Equation.9,10,11.

$$TSS = Sensivity + specificity - 1 \quad (9)$$

$$Sensivity = \frac{TP}{(TP + FN)} \quad (10)$$

$$Specificity = \frac{TN}{(TN + FP)} \quad (11)$$

where True Positive and True Negative are the number of accurately identified pixels and FN (false false) are the options. The choices are negative and FP (false positive) are the numbers of pixels incorrectly classified.

Results and Discussion:

Factors of the Revised Universal Soil Loss Equation Model

The spatial pattern of major factors of Revised Universal Soil Loss Equation model used to evaluate soil erosion is presented in Fig.3.

The average annual precipitation map (Fig.3a) shows that the precipitation range was from 1050 to 1300 mm for the last 26 years (2000–2025). Relatively higher rainfall (1250 to 1300 mm) was received in the western zone of the basin, whereas lower rainfall (1050 to 1200 mm) was received in the eastern part of the basin.

The range for the rainfall erosivity factor (R-factor) shown in Fig.3b was from 950 to 1150 MJ mm ha⁻¹ h⁻¹ yr⁻¹. Erosivity values within the range of 1101–1150 MJ mm ha⁻¹ h⁻¹ yr⁻¹ were predominantly found in the west, where there was more rainfall intensity and therefore higher detachment potential of soil particles. Most of the basin experienced moderate erosivity (1000 to 1100 MJ mm ha⁻¹ h⁻¹ yr⁻¹).

The soil erodibility factor map in Fig.3c shows that the range of K-factor is 0.0205 to 0.0231 t ha h ha⁻¹ MJ⁻¹ mm⁻¹. The higher K values (0.0231) in the western region suggest higher erosion susceptibility, the lower K values (0.0205) in the eastern region suggest more stable soil conditions.

The LS-factor (topographic factor) shown in Fig.3d ranged from 0 to 178.115. The higher the LS-factor, the faster the flow of the runoff and the greater the transport of sediment, and the lower the LS-factor, the slower the flow of the runoff and the less sediment transported, with the steep slope and elevated terrain regions having the higher values, and the gentle slope and plain regions having the lower values.

The cover management factor (C-factor) in Fig.3e varied from between 0 and 0.8. Lower values of C close to 0 were correlated with dense vegetation and forest cover since they provide better protection against soil erosion. The higher values (close to 0.8) were

found predominantly in barren land and areas of agriculture which are more susceptible to erosion.

The conservation practice factor map shown in Fig.3f values ranged from 0 to 0.45. High p factor values represent areas where there are low levels of conservation practices and higher soil erosion potential while low p factor values represent areas in which there are effective conservation practices that minimize soil erosion and runoff.

The spatial variation of the RUSLE factors revealed that the processes of soil erosion are influenced by the combined effects of rainfall intensity, vegetation cover, topography and conservation practices.

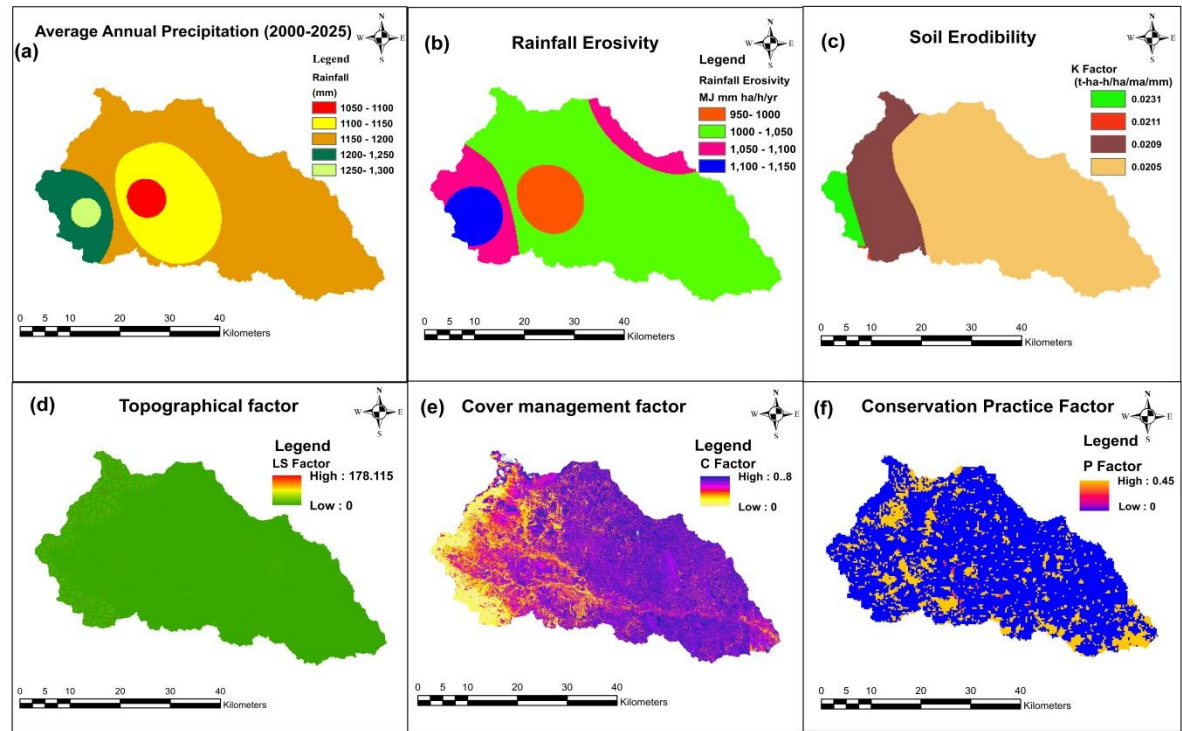


Fig.3 Spatial distribution of RUSLE model factors (a) average annual precipitation, (b) rainfall erosivity (R-factor), (c) soil erodibility, (d) topographic factor, (e) cover management factor and (f) conservation practice factor.

Soil Erosion Susceptibility Assessment in RUSLE:

The spatial pattern of soil erosion susceptibility obtained from Revised Universal Soil Loss Equation model is presented in Fig.4.

The results indicate that the area is predominantly classified under very low to moderate soil erosion susceptibility zones. Very low erosion zones ($0-5 \text{ t ha}^{-1} \text{ yr}^{-1}$) are found throughout the central and eastern portion of the basin, reflecting relatively high stability of the land surfaces, where the intensity of runoff is lower. Low and moderate erosion classes ($5-25 \text{ t ha}^{-1} \text{ yr}^{-1}$) are scattered across the basin and are mainly associated with agricultural lands and gently sloping terrain. The high to extreme erosion susceptibility zones ($>25 \text{ t ha}^{-1} \text{ yr}^{-1}$) were mainly found in the northwestern and steep slope areas of the basin.

Soil particle detachment and sediment transport are greatly enhanced in these areas, reflecting the strong influence of topographic conditions, rainfall intensity, low vegetation density and runoff flow processes. In particular, the areas of extreme erosion ($>100 \text{ t ha}^{-1} \text{ yr}^{-1}$) cover a relatively small proportion of the basin but are environmentally sensitive areas where immediate soil conservation action is required.

The spatial analysis shows that the susceptibility to soil erosion varies significantly in the study area, and is mostly influenced by rainfall erosivity, land cover, slope characteristics and condition, and conservation practices. The mapped susceptibility distribution may be a useful resource for sustainable land use and priority soil conservation planning.

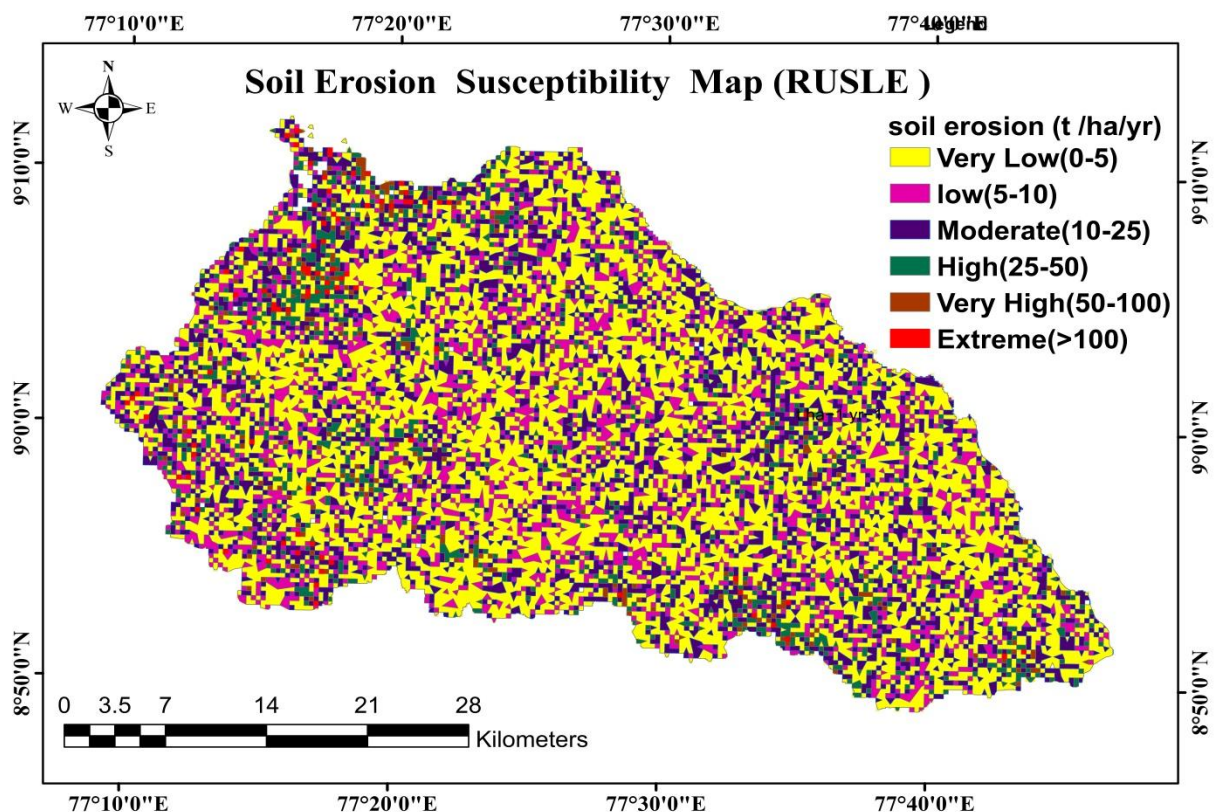


Fig.4. Spatial distribution of soil erosion susceptibility zones derived using the RUSLE model

Topographic Factors

Soil erosion susceptibility in relation to the spatial distribution of Topographic Factors is summarized in Fig.5. The parameters are important in regulating the generation of runoff, infiltration capacity, sediment transport, and slope instability in the basin.

The slope map (Fig.5a.) shows that the slope values ranged from 0 to 67.94. The western and northwestern region of the basin had a higher slope gradient, while the central part of the basin had a gentle slope. Slopes are generally steeper in the upstream areas than in the downstream areas, and tend to accelerate surface runoff and soil detachment and erosion processes.

The aspect map (Fig.5b) shows the direction of slopes, classified into classes of flat, northeast, north, east, south, southwest, southeast, northwest, west and north. Soil moisture, exposure to solar radiation, soil vegetation and evapotranspiration patterns, all of which are indirect controls on soil erosion susceptibility, can also be influenced by variations in slope aspect.

The elevation map (Fig.5c) indicates that the elevation ranged from 35.41 m to 1812.49 m above mean sea level. Higher elevation zones were predominantly situated in the western part of the basin while lower elevations were located towards the eastern part of the basin. Climatic variations, runoff parameters and geomorphological processes are strongly influenced by elevation.

The TWI map (Fig.5d) was found to vary from 2.50 to 19.29, which reflects spatial variation in soil moisture generation and concentration of runoff. The higher values of TWI correspond to regions of higher water accumulation potential and saturated soil conditions and the lower values to well-drained soil conditions.

The Stream Power Index map shown in Fig.5e varied from 0 to 1.27. Areas with higher SPI values are also the areas with higher erosive power of flowing water and sediment capacity. These areas are prone to channel erosion and concentrated surface runoff.

The range of the Terrain Ruggedness Index (TRI) found in Fig.5f was from 0.11 to 0.89, which are variations in the heterogeneity of the terrain and the surface roughness. Ruggedness and dissection were associated with greater TRI; smoothness and relative stability were associated with lower TRI.

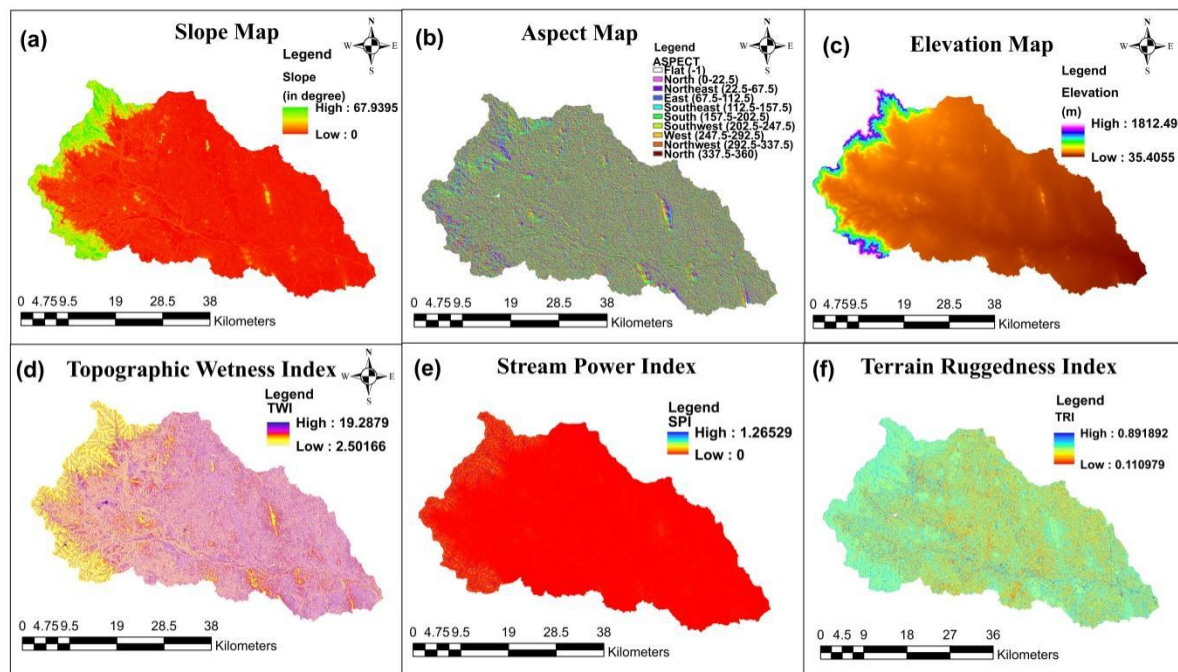


Fig.5 Spatial distribution of terrain and hydrological conditioning factors (a) slope, (b) aspect, (c) elevation, (d) Topographic Wetness Index, (e) Stream Power Index, and (f) Terrain Ruggedness Index.

Hydro-Climatic and Environmental Factors

The distribution of environmental and hydrological conditioning factors affecting soil erosion susceptibility is shown in Fig.6. All of these factors have a significant influence on the generation of runoff, infiltration capacity, sediment transport and erosion intensity in the basin.

The drainage density map (Fig.6a) is a representation of how dense drainage is in the study area. The drainage density is higher in these areas, meaning there is more surface runoff and less infiltration, and hence more susceptibility to soil erosion. Lower drainage density regions, however, are related to relatively stable hydrological conditions.

The stream buffer map (Fig.6b) shows the land areas that are near the stream network. Areas proximal to streams are more vulnerable to erosion because they experience processes of surface runoff that are concentrated and continuous fluvial action. Stream buffers are important to delineate environmentally sensitive areas that are susceptible to sediment transport and channel erosion.

The flow accumulation map (Fig.6c) shows the accumulation of surface runoff in the drainage system, ranging from 0 to 22,975. The areas with higher flow accumulation scores are those that receive a more focused flow from other upstream areas, thus having a higher likelihood of channel erosion and sediment deposition.

The rainfall erosivity factor map (Fig.6d) ranged from 949.61 to 1138 MJ mm ha⁻¹ h⁻¹ yr⁻¹ that reflects the erosive power of rainfall in the basin. Generally increased erosivity was observed in the western region which signifies higher intensity of rainfall and more soil particle detachment.

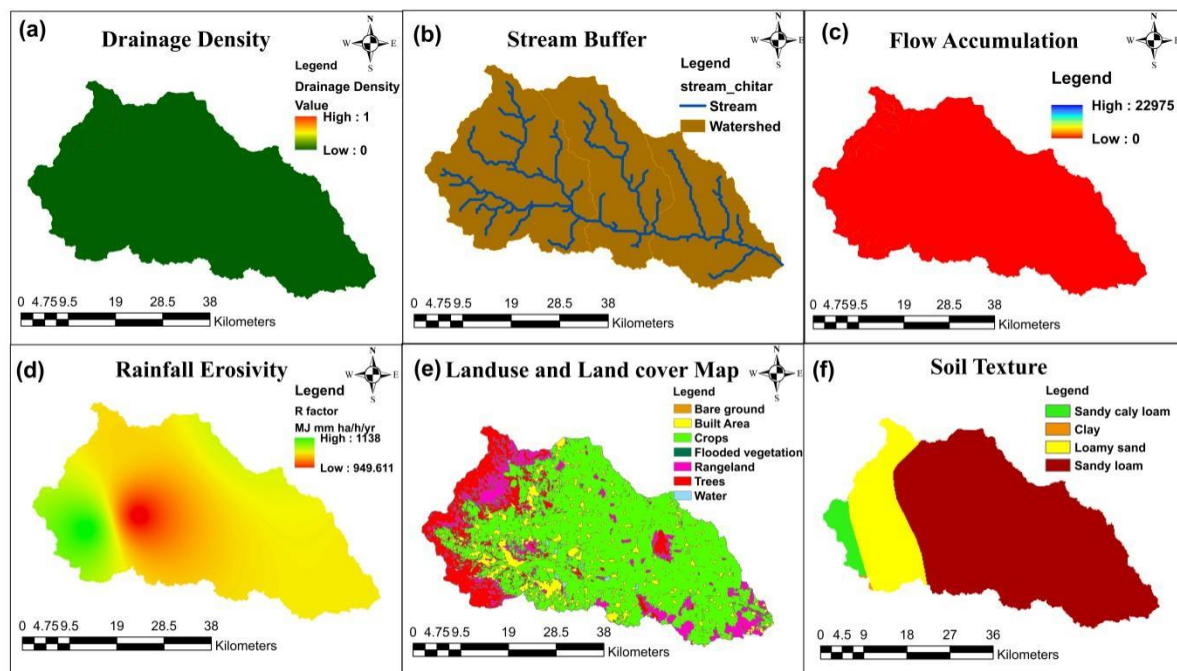


Fig.6 Spatial distribution of environmental and hydrological conditioning factors in the study area (a) drainage density, (b) stream buffer, (c) flow accumulation, (d) rainfall erosivity, (e) land use/land cover, and (f) soil texture.

The land use and land cover (LULC) map displayed in Fig.6e comprises of major classes such as bare ground, built-up area, croplands, rangeland, trees, and water bodies. Vegetated and forest-covered areas offer protection from erosion and are less susceptible to soil loss by direct rainfall impact and runoff, while areas that are bare and have low vegetative cover are more susceptible to soil loss because of direct rainfall impact and runoff.

The soil texture map Fig.6f shows the distribution of major soil types including sandy clay loam, clay, loamy sand and sandy loam. The infiltration rate, permeability, moisture holding capacity and erodibility characteristics of the soil are greatly affected by the texture. Soils that are not clay dominated are more vulnerable to detachment and transport processes than sandy loam and loamy sand soils.

The environmental and hydrological conditioning factors are generally highly variable in terms of space in the basin, and all of these factors affect the processes of soil erosion.

Multi-Collinearity Analysis

The factors which were highly redundant were eliminated through analyses. Correlated to others. Variables exhibiting very similar influences on the dependent variable may introduce multicollinearity; therefore, removing such variables can improve the predictive higher accuracy of the model. The Variance Inflation Factor (VIF) threshold value of 5 was adopted for variable elimination. The analysis indicated that all variables except TWI (VIF = 7.41) and TRI (VIF = 6.15) had VIF values less than 5 (Table 3). TWI and TRI were eliminated from the model.

Table 3. Multi-collinearity analysis of the conditioning factors

Number	Variable	VIF	TOL
1	Slope	1.18	0.98
2	Aspect	1.65	0.96
3	Elevation	3.12	0.4
4	TWI	7.41	0.15
5	SPI	2.67	0.89
6	TRI	6.15	0.10
7	Drainage Density	1.45	0.83
8	Stream Buffer	1.76	0.75
9	Flow Accumulation	2	0.62
10	Rainfall Erosivity	2.2	0.56
11	Land use	2.21	0.74
12	Soil Texture	1.87	0.82

Factor Importance Analysis

The significance of the conditioning factors in the Random Forest model .Among the selected conditioning factors, slope, elevation, Stream Power Index, aspect, Drainage density, flow accumulation, stream buffer, rainfall erosivity, land use/land cover, and soil texture significantly influenced soil erosion susceptibility. The analysis revealed that slope, land use/land cover, rainfall erosivity and elevation were the most influential factors controlling soil erosion processes in the Random Forest model. These findings correspond to the spatial

distribution analysis of erosion events, which demonstrated that multiple conditioning factors collectively contributed to soil erosion occurrence across different parts of the basin. However, variations were observed in the contribution and significance of conditioning factors among the different predictive models.

Soil Erosion Susceptibility Assessment Using Machine Learning Models

The soil erosion susceptibility maps generated using the Random Forest (RF), Support Vector Machine (SVM), Classification and Regression Trees (CART), and Boosted Regression Trees (BRT) models are presented in Fig.7. The RF model produced the most spatially coherent and balanced distribution of susceptibility classes, effectively identifying localized high-risk erosion zones while maintaining clear spatial continuity (Fig.7a). The SVM model exhibited a spatial pattern similar to that of RF but with relatively smoother transitions between susceptibility classes (Fig.7b). The CART model generated comparatively fragmented susceptibility patterns with greater pixel-level variability, resulting in less spatial consistency (Fig.7c). In contrast, the BRT model predominantly classified the basin into the Very Low and Low susceptibility classes, with relatively limited representation of the Moderate, High, Very High, and Extreme susceptibility zones (Fig.7d). Overall, the RF model provided the most realistic and spatially consistent representation of soil erosion susceptibility, indicating its superior capability to capture the complex interactions among topographic, climatic, soil, and land-use factors.

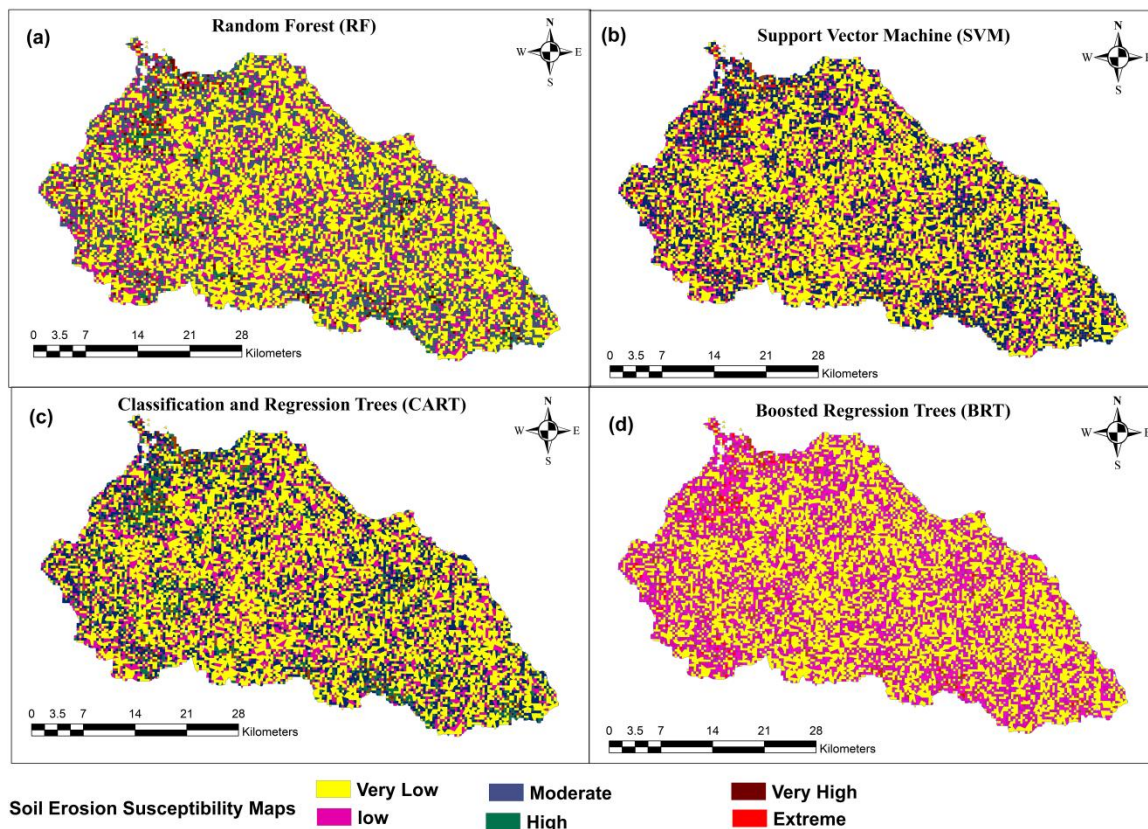


Fig.7 Spatial distribution of soil erosion susceptibility predicted using machine learning models: (a) Random Forest (RF), (b) Support Vector Machine (SVM), (c) Classification and Regression Trees (CART), and (d) Boosted Regression Trees (BRT).

Comparative Analysis of Model Prediction Accuracy

The prediction performance of the Random Forest (RF) model was evaluated during the validation stage using the Area Under the Curve metric (Fig.8). To objectively evaluate the predictive capability of the model, recent machine learning studies related to extreme events such as floods, soil erosion and landslides were also reviewed (Tang et al., 2020). The performance of the four machine learning models was assessed by Receiver Operating Characteristic (ROC) analysis (Fig.8). The Random Forest (RF) model was the best model with respect to classification performance with an Area Under the Curve (AUC) value of 0.967, which showed very good discrimination power in terms of the soil erosion susceptibility classes. The Support Vector Machine (SVM) model also showed good predictive ability (AUC=0.925) while the Classification and Regression Tree (CRT) model showed an AUC of 0.870. Boosted Regression Tree (BRT) model performed worse with AUC of 0.820 but they still achieved good predictive accuracy. In overall, the RF model showed the best performances among the other machine learning algorithms and is the most reliable model for soil erosion susceptibility assessment in the study area.

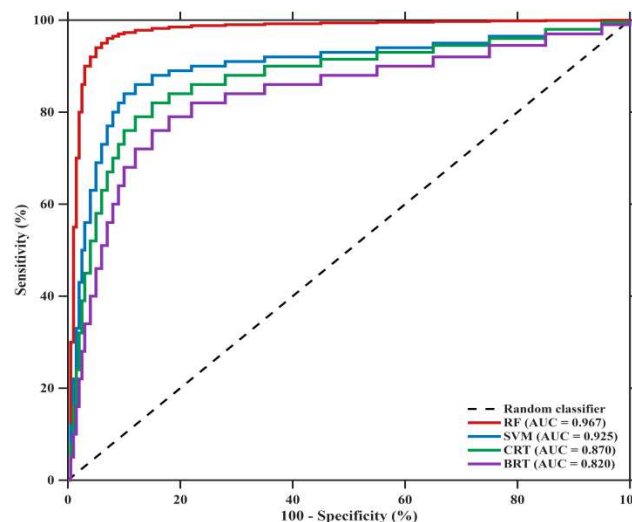


Fig.8 Bivariate comparison of model sensitivity and precision using validation data.

Discussion

Soil erosion susceptibility assessment in the Chittar River Basin was significantly enhanced by the incorporation of RUSLE model with machine learning. Random forest (RF) model was found to be most predictive model with AUC = 0.967, capable of capturing the complex nonlinear relationships between topographic, hydrological, climatic and environmental parameters. (Wang et al., 2024; Nguyen et al., 2025) reported similar results, in which RF was found as one of the most reliable algorithms for soil erosion susceptibility mapping. The spatial distribution of erosion also showed that the erosion was more serious in the northwest mountainous area, which is attributed to the steep slopes, high rainfall erosivity, low vegetation coverage and high concentration of rain runoff, while the central and eastern areas showed lower erosion which is attributed to the low rainfall erosivity, the vegetation cover, and low concentration of rain runoff. The observations are consistent with previous studies that found that soil erosion is the most prominent when the soil slope is steep, the rainfall erosivity is high, and land use/land cover is inappropriate (Borrelli et al., 2020; Ehabu et al., 2022 & Zhang et al., 2014).

The factor importance analysis also showed that slope, land use/land cover, rainfall erosivity and elevation were the most influential in explaining soil erosion susceptibility, supporting the results of (Aboutaib et al., 2023 & Marques Filho et al, 2024). This is because the RF model performed best in comparison to SVM, CART and BRT due to its ensemble-learning capability that reduces overfitting and is able to capture nonlinear interactions. In addition, a multicollinearity analysis was used to increase the reliability of the model by eliminating redundant variables before model development. The integrated RUSLE–GIS–RF approach is an efficient and effective technique for delineating areas vulnerable to erosion and managing the watersheds using the prioritization of conservation practices like afforestation, contour farming, terracing, and vegetative buffer strips in areas at high risk for erosion.

Conclusion:

This study integrated the Revised Universal Soil Loss Equation (RUSLE), Geographic Information System (GIS), and four machine learning algorithms, namely Random Forest (RF), Support Vector Machine (SVM), Classification and Regression Trees (CART), and Boosted Regression Trees (BRT), to assess soil erosion susceptibility in the Chittar River Basin, Tamil Nadu, India. The findings indicated that rainfall erosivity, slope, elevation, land use/land cover and hydrological conditions are major controlling factors of the soil erosion in the basin. The high to extreme erosion-prone areas were primarily found in the the northwestern and upper catchment areas of the catchment, where there is high surface runoff, low vegetation cover, and high intensity of rainfall with steep slopes.

The Receiver Operating Characteristic (ROC) analysis confirmed that the Random Forest (RF) model outperformed the other machine learning algorithms for soil erosion susceptibility mapping. The RF model achieved the highest predictive accuracy with an Area Under the Curve (AUC) value of 0.967, indicating excellent discrimination capability. The Support Vector Machine (SVM) also demonstrated strong performance with an AUC of 0.925, followed by the Classification and Regression Tree (CRT) model (AUC = 0.870). The Boosted Regression Tree (BRT) model showed comparatively lower performance (AUC = 0.820), although its predictive capability remained acceptable.

The integrated RUSLE–GIS–RF approach was found to be effective and reliable for identifying erosion-prone zones and ensuring sustainable watershed management and soil conservation planning. The results from this study might help policy and planning makers in prioritizing appropriate conservation actions for mitigating soil degradation and enhancing environmental sustainability in the basin.

This study was limited by the availability of high-resolution spatial datasets and the use of static conditioning factors, which may not fully represent the temporal variability of soil erosion processes. Although the Random Forest model achieved the highest predictive performance (AUC = 0.967), the developed models were validated only for the Chittar River Basin, and their applicability to other watersheds requires further investigation. Future research should integrate high-resolution remote sensing data, projected land use and climate change scenarios, and advanced machine learning algorithms to improve prediction accuracy and support more effective soil conservation and sustainable watershed management.

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Declarations

All authors have reviewed and complied with the “Ethical Responsibilities of Authors” provided in the Instructions for Authors.

Conflict of interest: The authors declare no conflict of interest.

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