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Abstract

The urban watershed of Guwahati, Assam, has witnessed a rapid urbanization in recent years, making it to one of the most deteriorated cities in terms of environmental issues. Therefore, this work focused on finding the most suitable soil-water conservation areas at a micro-scale using coupling coordination mechanism. Principal component analysis (PCA) was used to create a priority model for sub-watershed basin based on nineteen morphometric parameters. We then quantified the soil erosion using the revised universal soil loss equation (RUSLE) for current and future scenarios based on the representative concentration pathway (RCP) 2.6 and 8.5 models (RCP2.6 and 8.5). In addition, we proposed the fuzzy logic and analytical hierarchy process (AHP) model-based soil-water conservation suitability (SWPC) model for current and future scenarios. Finally, the most suitable soil-water conservation areas for current and future scenarios were identified using coupling coordination degree model (CCD). To the author's knowledge, this is the first in-depth study that identifies the most suitable conservation areas by analyzing the watershed prioritization, soil erosion, and topographic, hydrologic, land cover, and climatic parameters-based soil-water conservation suitability models. Sub-watersheds comprising Silsako, Bharalu, Deepor Beel, and North Guwahati have been identified as high-priority sub-watersheds. According to the current RUSLE model, soil erosion in the study area varies from 140 to 181.64 tonnes per hectare per year. In contrast, soil erosion would continue to increase in the future as per the RCP8.5 model, which varies from 305 to 332 tonnes per hectare per year. The current SWPC model predicted 46.92 km^2 area as high and 54.40 km^2 area as very high suitable zones. However, under the RCP 2.6 and RCP 8.5 models, the high and very high SWPC zones will experience extended areas in the future due to increased soil erosion intensity. According to the CCDM results, Bharalu, Deepor Beel, and North-Guwahati sub-watersheds have observed a very high to medium coupling degrees, which are considered the most suitable areas for conservation. The findings of this study will significantly help stakeholders and experts in long-term land-water resource management and effectively address environmental degradation issues in urban watersheds around the world.

Keywords: Watershed priority zone; artificial intelligence; soft computing; soil erosion; soil conservation; revised universal soil loss equation; coupling mechanism; fuzzy logic

1. Introduction

River erosion, land use change, and incompetent management contribute to the loss of tons of soil per year, causing permanent damage in agricultural and mountain areas (Kulimushi et al., 2021, Kebede et al., 2021). Many countries have developed river basin management plans that prioritize watersheds based on their drainage and ecological importance (Patle et al., 2020; Arefin et al., 2020; Rodrigues et al., 2022). The drainage system of an area and the characteristics of the watershed are crucial to the long-term development, management and restoration of soil-water process, as they allow accurate estimation of water flow, soil loss, and management alternatives (Naqvi et al., 2019; Hembram and Saha, 2020). Recently, numerous studies have used remote sensing (RS) coupled with geographic information systems (GIS) to reliably calculate morphological features and analyze basin attributes (Resmi et al., 2019; Bogale, 2021). In recent years, experts and researchers worldwide have developed methods for automatic extraction of drainage networks and their properties utilizing remote sensing and GIS (Arubalaji and Padmalal, 2020; Hibi et al., 2021; Ahad et al., 2022). Furthermore, several scholars have reported about the application of GIS for morphometric analysis with interaction of drainage morphometric features of various watersheds of India (Kumar et al., 2021: Shekar et al., 2022). Therefore, RS can be considered a valuable technique for morphometric analysis, and prioritizing watersheds, which are crucial indicators to adopt any different relevant conservation actions. However, prioritization of watershed and landscape planning are often considered for developing and implementing robust management and restoration strategies (Sharda et al., 2021). Prioritization is key to identifying areas that need attention (Yu et al., 2021; Abdeta et al., 2020). Due to time and cost constraints, it is challenging to undertake restoration and soil and water conservation work at all sites simultaneously in a watershed management program. Therefore, watershed prioritization for robust soil-water conservation can be a feasible approach to solve the mentioned issues (Zhang et al., 2021; Meshram et al., 2022). Although soil erosion (SE) can occur naturally, human activities such as land use change, agriculture, livestock grazing, and deforestation have worsened erosion and soil deterioration (Gong et al., 2022). As a result, SE is seen as a natural and human-caused issue with severe economic and environmental consequences in many cultures. Despite the significant impacts of SE on soil sustainability, there is a scarcity of data on existing and future situations. The lack of this data is because of the complexity of erosion processes, making SE estimates costly, time-consuming, and challenging (Cunha at al., 2022; Ferreira et al., 2022). Because of this difficulty, several models and techniques have been developed to simplify SE modelling and better our knowledge of the pattern and processes of SE. Previous researchers have found that RUSLE model outperformed other models in terms of accuracy and simplicity to estimate the potential soil erosion (Mengie at al., 2022; Somasiri et al., 2022). Therefore, in the present study, we used the RUSLE model to estimate the potential soil erosion for current and future scenarios.

However, previous researchers have developed future soil erosion scenarios by considering the R factor (erosive factor) for current and future times (Pal et al., 2022). They have computed R factor from future rainfall datasets. The Intergovernmental Panel on Climate Change (IPCC) has released the Representative Concentration Pathways (RCPs), which comprises four future scenarios for earth's greenhouse gas (GHG) emission (2.6, 4.5, 6, and 8.5), for future climatic variables. The RCP2.6 model simulates low GHG emissions, whereas the RCP4.5 and RCP6 models represent stability scenarios, and the RCP8.5 model simulates high GHG emissions. Using several

CMIP5-RCP scenarios, research has been undertaken to forecast the influence of future climate on soil erosion; however, relatively few studies have been conducted on the Indian subcontinent (Choudhury et al., 2022; Raj et al., 2022). In this research, we considered minimum and maximum RCP scenarios to compute the R factor for future rainfall scenarios. The soil erosion estimation using RUSLE model is very common, not the future soil erosion models, but the research on the conservation strategies for reducing soil erosion and its impact is very rare. Also, it is very challenging to identify the areas to be conserved and monitored for soil erosion based on limited resources. However, to do so, several parameters related to soil erosion are required under the framework of multi-criteria decision making (MCDM) process. Therefore, this research aimed to predict robust suitable soil-water conservation zone, not only for current situation, but also for future soil erosion scenarios, under the MCDM framework. Previous researchers have already applied several MCDM techniques to find the flood, landslide susceptible zones, wetland habitat zone, urban surface ecological health condition zones (Rehman et al., 2022; Craciun et al., 2022). Few popular MCDM techniques are analytical hierarchy process (AHP) (Kumar et al., 2022; Roshani et al., 2022), analytical network process (ANP) (Dahri et al., 2022; Abedini et al., 2022), weights of evidence (WOE) (Bopche & Rege, 2022; Behera & Panigrahi, 2022), evidential belief function (EBF) (Ramesh & Iqbal, 2020; Zhao et al., 2022) etc. However, the MCDM techniques have suffered from biasness due to subjective weights, time consuming and slow computational process. To prevent these drawbacks, the fuzzy logic model, a semi machine learning algorithm, has been emerged and frequently used for solving several environmental issues (Aghaloo and Chiu, 2020; Baharvand et al., 2020; Jha et al., 2020; Noori et al., 2019). Because of its capacity to handle linguistic data efficiently, Vema et al. (2019) employed a fuzzy inference system (FIS) for the selection of sites concerning the facilities related to harvesting of water (e.g., ponds, check dams, and tanks). Similarly, Kumar and Anbalagan (2015) and Ramesh and Anbazhagan (2015) identified landslide prone regions using landslide frequency ratio and fuzzy logic based on GIS. According to the conclusions of these investigations, the fuzzy logic technique exceeds the other methods in terms of accuracy. Literature review also validates fuzzy-based work for groundwater as well as land suitability analysis (Bikdeli, 2020; Moonjun et al., 2020; Tafreshi et al., 2018). Therefore, based on previous literature, we used advanced fuzzy logic and conventional AHP model to prepared SWPC model for current and future scenarios. Furthermore, the association between watershed prioritizing and soil-water appropriateness is a new and emerging idea (Melaku et al., 2018). The current study links these two systems to comprehend the influence of physical and drainage features on soil and water resources in a location. Coupling coordination theory can explain the degree to which two or more subsystems interact. The degree of coupling describes the strength of the contact between two subsystems, whereas the degree of coordination indicates the intensity of cooperative growth between them (Lai et al., 2020). We selected the coupling coordination theory because of its capacity to provide a complete assessment system and its intuitiveness, but it has not been frequently employed in empirical applications. Only a few researchers have recently applied the coupling coordination theory to investigate the coordination between two or more parameters (Ye et al., 2021; He et al., 2021; Dong et al., 2021). Yuan et al. (2021) for example, investigated the coordination among the regional environment, economy, and tourism in western Hunan Province, China, using a coordinated development model. In addition, Yang et al. (2021) employed the CCDM (coupling coordination model) and GIS spatial methodologies to examine the correlation, coupling, and coordination degrees between the geo-ecological environment and urbanization in Chongqing Municipality.Guwahati Metropolitan Area is one of the most urbanized areas in India, on the bank of the Brahmaputra River. Therefore, because of the urbanization, this river has experienced flow of domestic waste or sewages and industrial debris from the city, such as hazardous, chemical, industrial solid, and solid waste generated by municipalities (Pondari et al., 2020; Tsering et al., 2020). Little work has been done so far in the urban watershed of Guwahati, focusing on soil-water conservation modelling. Therefore, to fill the research gaps, this study proposed a robust way to find the soil-water conservation zones by considering PCA-NDVI based watershed prioritization, RUSLE based soil erosion and fuzzy logic and AHP based-soil water potential conservation (SWPC) zones under current and future scenarios at RCP2.6 and 8.5. The novelty of the present study is to identify the highly accurate areas to be conserved or monitored in order to reduce the area coverage and impact of soil erosion for current and future scenarios through a coupling coordination mechanism in the Guwahati watershed To the author's knowledge, this has been the first study that considered different aspects for mitigating soil erosion by identifying the conservation areas. In this study, we provide an alternate method for watershed prioritization in the six sub-watersheds of the Guwahati Metropolitan Area, Assam, such as Deepor Beel, Bharalu, Silsako, North Guwahati, Foreshore, and Kalmoni, by leveraging factors with strong influence (as determined by PCA) on soil degradation in each of these micro-watersheds. Furthermore, for the first time, the coupling coordination evaluation model (CCD) has been used to examine the degree of coupling and coordination among watershed prioritized model, soil erosion model, and soil-water suitability model. The present research will provide scientific support and insights for mitigating the severity of soil erosion by identifying accurate conservation areas for current and future scenarios (2040). The main objectives of the present study are:

1. to provide an alternative method for watershed prioritization by effectively utilizing factors that have a strong influence (as determined by PCA) on soil degradation in the urban watershed of Guwahati,
2. to estimate soil erosion using RUSLE model for current and future scenarios (2040) at RCP2.6 and 8.5,
3. to develop the sub-watershed zones-wise soil-water conservation suitability model (SWPC) in the study area for current and future scenarios (2040) at RCP2.6 and 8.5,
4. to identify the highly suitable soil-water conservation areas through the coupling degree and degree of coordination among the priority, soil erosion and SWPC models for current and future scenarios (2040) at RCP2.6 and 8.5.

2. Material and Methodology

2.1 Study Area

The urban watershed of Guwahati was chosen as the study area as it is the fastest-growing city in Northeast India. Guwahati is located in Assam's Kamrup (Metro) district. Guwahati's urban watershed, known as the Guwahati Metropolitan Region, includes the Guwahati Municipal Corporation (GMC) area, the North Guwahati Town Committee (NGTC) area, the Amingaon Census Town (ACT), and 21 revenue villages (GMA). It has a total area of 340.67 km^2. Guwahati's overall population has grown from 500,000 in 1991 to 8, 14,575 in 2008, and 963,429 in 2011 (Census of India, 2001 & 2011). The study area is on an undulating plain with elevations ranging from 50 to

55 meters above mean sea level (MSL). Guwahati's urban watershed is further expanded in an east-west ward trend, spanning 45 kilometres between Narengi in the east and Lokpriya Gopinath Bordoloi (LGB) International Airport in the west, as well as both sides of the Brahmaputra River in the north and the slopes of the Shillong Plateau in the south. The urban watershed of Guwahati is divided into six sub-watersheds: Bharalu, Silsako, Kalmoni, Deepor Beel, Foreshore, and North Guwahati (Fig. 1). In recent years, all the basins being part of the primary drainage route have been undergoing increasing urbanization. As a result, they have become the most degraded regions due to encroachment and dumping of solid and liquid wastes into these watersheds. Thus, watershed prioritization of these six micro-watersheds will considerably alleviate the problem of soil degradation and water management in the given area.

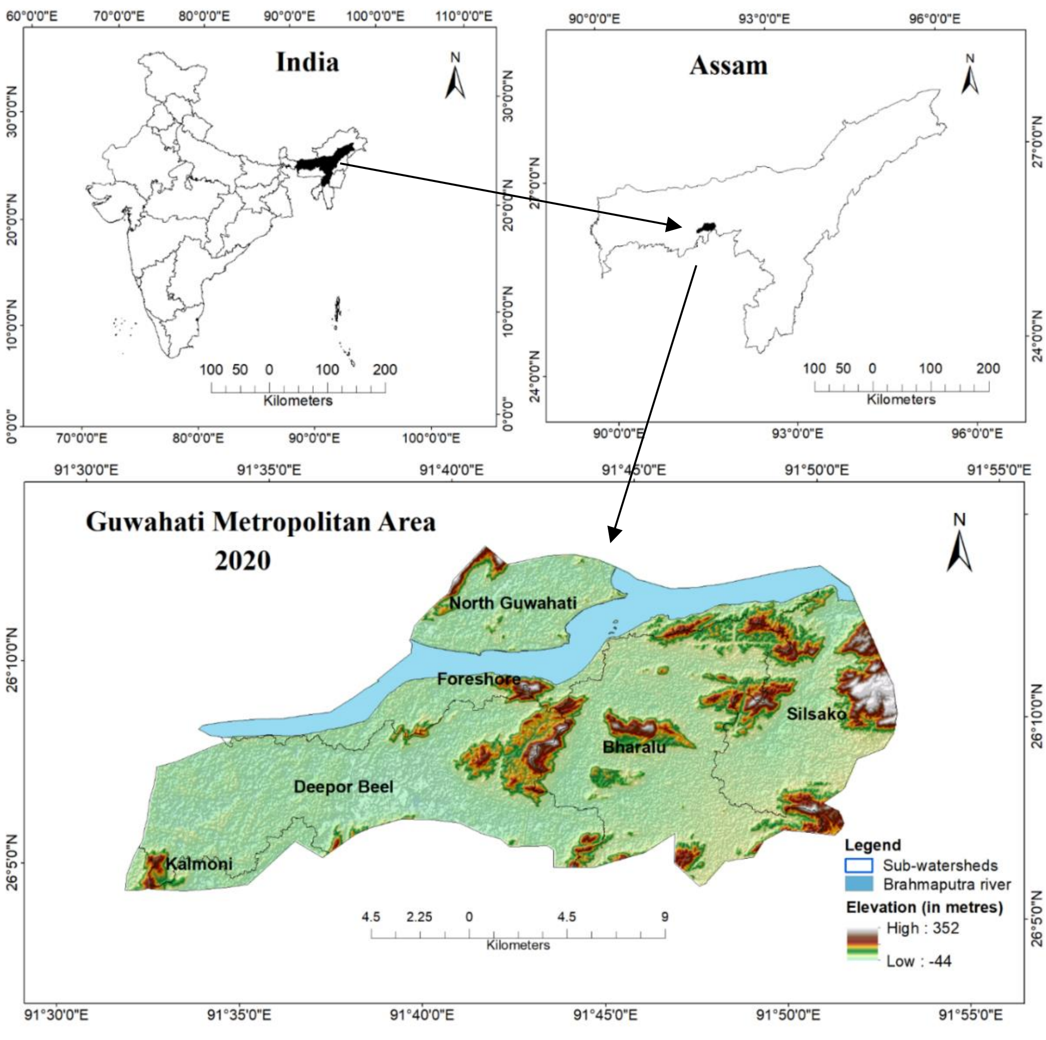

Figure 1 Location of the study area

2.2 Database

The morphometric analysis of the urban watershed of Guwahati was conducted using the 1:50,000 scale topographical maps collected from the Survey of India (SOI). Landsat 8 (OLI/TIRS) image acquired from the website of the United States Geological Survey (USGS). The analysis comprises delineating the study area into six sub-watersheds and then calculating nineteen morphometric parameters based on each watershed's areal, linear, and relief aspects (e.g., stream number, stream length ratio, elongation ratio, ruggedness number, bifurcation ratio, drainage density, etc.). In addition, the drainage network of the urban watershed of Guwahati was evaluated using Horton's (1945) and Strahler's (1945, 1964) methodologies. SoI topographic maps were georeferenced in ArcGIS desktop version 10.4 using the WGS84 datum and UTM zone 46 N. The SRTM digital elevation map (DEM) was downloaded from earth explorer of USGS. The rainfall map was collected from meteorological stations of IMD for the periods of 2000-2018. The road data was collected from DIVA GIS.

2.3 Method for morphometric analysis

A detailed description of the methodology is provided in the supplementary material and supplementary table 1.

2.3.1 Methods for watershed prioritization

The areal, linear, and relief morphometric parameters were designated as the significant aspects for prioritizing sub-watersheds (Kulimushi et al., 2021; Kale and Deshmukh, 2020). Soil erosion of an area directly relates to linear (e.g., stream number, stream order, etc.), as well as relief parameters (e.g., ruggedness number, relief ratio, etc.). As a result, higher ranks are assigned to a higher value of linear and relief factors. Areal parameters (e.g., basin area, drainage texture, elongation ratio) have opposite relationship with soil erodibility (Hema et al., 2021). Areal parameters with lower values have a more significant influence on the degradation of the soil of a watershed. Hence, the ranking of the erodibility of soil was computed through assigning priority ranks. In this research, we used three methods to prepare the watershed priority model i.e., compound factor, PCA, and NDVI. The theoretical background of these methods has been given below:

Compound Factor

For the final watershed prioritization map, three basic weighted sum ranking systems were used: compound parameter (CP), priority rank (NP), and priority degree (GP) (Chauhan et al. 2016; Prabhakar et al. 2019). At first, CP for each sub-watershed was determined through computing the mean of all morphological parameters. The second phase involves assigning NP. The sub-watershed with the lowest compound parameter was given the highest NP, and so on. Furthermore, the priority degree was calculated using eq. (1), (2), and (3), and they were categorized into high, medium, and low priority ranks.

$$GP_{High} = \left[CP_{MIN},\ CP_{MIN} + \left(\frac{CP_{MAX} - CP_{MIN}}{3}\right)\right] \quad [1]$$

$$GP_{Medium} = \left[CP_{MIN} + \left(\frac{CP_{MAX} - CP_{MIN}}{3}\right),\ CP_{MIN} \pm 2 * \left(\frac{CP_{MAX} - CP_{MIN}}{3}\right)\right] \quad [2]$$

$$GP_{Low} = \left[CP_{MIN} + 2 * \left(\frac{CP_{MAX} - CP_{MIN}}{3}\right),\ CP_{MAX}\right] \quad [3]$$

In the same way, the NDVI was calculated, and its values were classified according to the methods proposed by Gómez-Almonte (2005) and Merg et al. (2011) (Supplementary Table 2).

Principal Component Analysis

The PCA was primarily used in this study to reduce data and represent fundamental data properties with only a few principal components (Pourghasemi et al., 2021; Mohamed and Worku, 2021; Perez and Reynoso, 2021). Using PCA, we computed the correlation matrix, the principal component loading matrix, and the respective Eigenvalues (Singh et al. 2021; Patle et al., 2020; Meshram and Sharma, 2017)) based on nineteen morphometric parameters. Finally, we used PCA to assess the structural correlations of the morphometric characteristics and classify the basins based on component values.

Normalized difference vegetation index

Vegetation indices, which utilize the transformation of electromagnetic spectrum (EMS) reflected from the earth's surface to satellite sensors, are the most prevalent and widely studied remote sensing products. For example, the normalized differential vegetation index (NDVI) measures the difference between near-infrared and red bands to quantify vegetation (Tucker, 1979).

2.3.2 Method for current and future soil-water conservation model

In this research, to compute the current and future soil-water conservation model, we prepared several components, such as current and future rainfall, soil erosion model using RUSLE, fuzzy logic based SWPC model, and final robust SWPC model using CCD mechanism. The methods for these components have been presented below sections:

2.3.3 Method for estimation of current and future rainfall

The circulation patterns of the atmospheric and ocean currents have changed because of global warming. The geographical and temporal patterns of precipitation and temperature throughout the planet have altered because of this. As a result, rising groundwater depletion is linked to global warming (IPCC, 2011). Increased flooding risks in particular landscapes, which are entirely unfavorable for groundwater recharge, may be directly connected to a change in the pattern of extreme rainfall events (IPCC, 2011). Researchers have attempted to create these connections in a stochastic manner. Therefore, future climates may be forecasted using GCMs in conjunction with expected changes in land use to predict future SWPC models. To consider climate change in the research field, we extracted precipitation data of RCP 2.6 and 8.5 climate scenarios from CCSM-4 of the 4th IPCC Assessment Report based on AR5. These data are freely available from the NCAR GIS Initiative Climate Change Scenario portal (https: /gisclimatechange.ucar.edu) in vector format (Shapefile). Representative pathways of concentration (RPCs) show the concentrations of greenhouse gases (GHGs) in the atmosphere and the routes that may be taken to get there. The GHG emission will be 2.6 W/m^2 at RCP2.6 by 2100, followed by 4.5 W/m^2 at RCP4.5, 6.0 W/m^2 at RCP 6 and 8.5 W/m^2 at RCP8.5. In the present study, we produced rainfall data for the period of 2020-2040 based on minimum and maximum concentration of greenhouse in atmosphere (RCP2.6 and RCP8.5). In the present study, we prepared R-factor based on the rainfall obtained from RCP 2.6 and RCP 8.5 for the period of 2020-2040.

2.3.4 Method for potential soil erosion estimation for current and future scenario using RUSLE

This research uses the RUSLE to estimate the soil erosion in an urban watershed. It needs significant input variables, which can be readily obtained from accessible data sources. RUSLE measures the long-term erosion process of rills and inter-rills over a wide range of agricultural and forest catchments (Ostovari et al., 2021; Biswas and Pani 2015). It is modified version of USLE model, which has issues of sensitivity (Renard et al., 1997). The RUSLE model has widely been used for its accurate estimation of average annual soil erosion. RUSLE estimates the average annual soil loss in an area using equation 5.

$$SE = R \times K \times LS \times C \times P \qquad [5]$$

SE is the projected soil loss (t ha-1 year-1) in this equation, and R is the rainfall-erosivity index (MJ mm ha−1 h−1 year−1). K is the predicted soil erodibility factor (t h ha MJ−1 ha−1 mm−1). C is the land use-specific cover management component; P is the conservation support practice element that includes slope length and slope steepness. For a detailed explanation of the parameters used for RUSLE modeling, readers can follow Behera et al. (2020) and Teng et al. (2018).

2.3.5 Soil-water conservation suitability zone modeling for current and future scenario

To identify robust soil-water conservation areas, topographic, hydrologic, climatic, land cover, and artificial structure-related parameters are required. The application of fuzzy logic and AHP to create SWPC model has not been done so far in any study, so the approach used in this paper is novel. Physical as well as drainage parameters are strongly connected to soil and water conservational activities. DEM, Aspect, Slope, LULC, Topographic Wetness Index (TWI), drainage density (D_d), length of overland flow (L_g), basin relief (B_h), ruggedness number (R_n), and rainfall are all standard criteria for assessing soil-water suitability. The affluence, as well as the influence of these parameters, varies depending on the land characteristics. Also, the future conservation areas can be modelled using fuzzy logic as well as an analytical hierarchy process (AHP) under the scenario of climate change in terms of rainfall (2020-2040).

Fuzzy logic based SWPC modelling

The SWPC model was prepared by integrating eleven parameters using fuzzy logic and AHP methods. To implement fuzzy logic, the 'Membership function' and 'Fuzzy overlay' analysis were implemented in ArcGIS 10.4 environment. There are two important aspects related to selecting a membership function (MF): the midpoint and spread. Initially, it is possible to choose from several membership functions, such as linear and non-linear fuzzy MF, including large, small, Gaussian, and linear.

Non-linear membership function "MsSmall" (large membership values are assigned to a small input raster value), as well as "MsLarge" (small membership values are set to an enormous input raster value), were used to assess soil-water suitability for all the nine parameters. Furthermore, five distinct combinations of fuzzy operators are described in the literature (fuzzy OR, fuzzy AND, fuzzy Product, fuzzy Sum, and fuzzy Gamma). The fuzzy Gamma operator was used in this study because it is determined by all input layers' maximum and minimum membership values (Ki and Ray, 2014; Tafreshi et al., 2018).

Analytical Hierarchical Process (AHP) based modeling

Multi-criteria decision analysis, such as the Analytical Hierarchical Process (AHP), is a well-known method that analyzes different environmental parameters and involves ranking based on certain criteria to solve a very complex decision-making process (Saaty and Vargas, 2001). It is the most common method for delineating potential zones of various natural phenomena (Rahaman et al., 2022). The hierarchy of the parameters of SWPC was determined by its interdependence and interplay with other parameters, and the hierarchy was built from the top down. In the decision-making process, this strategy employs subjective and objective criteria (Baig et al., 2020). It also uses a pairwise comparison of a distinct parameter affecting the study area's soil and water. The pairwise comparison was done with the assistance of a parameter matrix and assigning weight to the parameter concerning their effect on other parameters stated in a numerical scale and consistency ratio (Saaty, 1980). Each parameter's weights were assigned using Saaty's scale (1-9) of relative relevance value.

Estimation of important variables using Random Forest

To calculate the importance of each soil erosion parameter for defining soil loss in the study area, the methodology of random forests (a classifier that combines many single decision trees) is used. In this study, we have used the two-variable importance measures of the RF algorithm: mean decrease in accuracy (MDA) and mean decrease in Gini (MDG). The Gini index measures node impurity; the mean decrease in Gini indicates an improvement in the splitting criterion, which measures the reduction in class impurity from partitioning the data set (Myles et al., 2004). At the same time, the mean decrease in accuracy is a permutation-based measure of variable importance derived from evaluating a variable's contribution to prediction accuracy. The mean decrease in Gini also measures of variable significance by permuting the values of each soil erosion controlling factor in the out-of-bag sample. The factors with the highest mean Gini importance in the model were primarily responsible for flood prediction in the study area.

2.3.6 Method for identification of precise soil-water conservation areas using coupling coordination mechanism

The coupling coordination degree model has been used to compute the agreement between two sub-systems through interaction and physical process. Therefore, in this research, the watershed prioritization, potential soil erosion, and soil-water conservation potential areas have been integrated using CCD model to find the agreement areas of all models. The application of CCD for identifying suitable model by considering three different system is totally new concept, also provides quite accurate results. The CCDM is derived using equation 5.

$$C = \sqrt{((SW \times WP)/(SW + WP)^2)} \text{ -----------------------Eq. (5)}$$

Where SW is the comprehensive index of soil-water conservation level, WP is the watershed prioritization index, and C is the coupling degree value of the coupled system of soil-water conservation and watershed prioritization. The CCDM degree value ranges from $0 \leq C \leq 1$, higher the value, more precise the soil-water conservation suitable zones and vice versa (Supplementary Table 3). The high priority watershed, areas with higher soil erosion rates, and areas with higher chances to be conserved potentiality can have the high value of coupling degree and coupling coordination degree. These areas should be monitored closely for implementing management plans. In this research, several sophisticated methods have been applied to identify different aspects for soil erosion conservation modeling. Therefore, to explain the methodology in a bird-eye-view, a hierarchical methodology chart has been given (Figure 2).

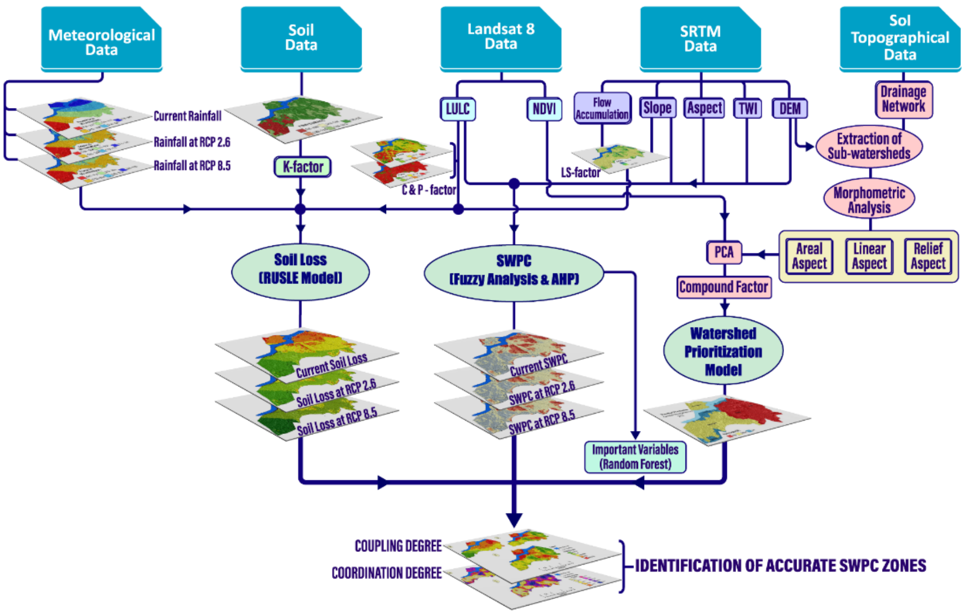

Figure 2 Hierarchical methodological framework of the study

3. Result

3.1 Watershed prioritization modeling

In the present study, the watershed prioritization has been done based on the parameters of areal aspect, linear aspect, and relief aspect. The parameters of these three morphometric aspects have been integrated at ArcGIS platform. The details of these aspects and computation of watershed priority model is given below:

3.1.1 Areal aspect of sub-watersheds

Morphometric analysis of the sub-watershed areal aspects reveals a dendritic drainage pattern strongly affected by the terrain of the study area. The urban watershed of Guwahati is divided into six sub-watersheds. The total drainage area of the watershed is 339.25 km^2, while the perimeter is 922.16 km^{2,} and the basin length is 42.81 km^2, respectively. Further, the total length (L_u) of the urban watershed is 316.58 km. Deepor Beel (98.14 km^2) is the largest sub-watershed of the 6, while Kalmoni was the smallest (8.75 km^2). The highest and lowest perimeters among the sub-watersheds were Deepor Beel, and North Guwahati are 90.40 km and 25.52 km, respectively. Supplementary Fig. 1 (a), (b) & (c) depicts the variations in the basin area, perimeter and length. The basin length corresponds to the total area of the drainage basin, with a maximum length of 10.50 km observed in Deepor Beel, followed by Foreshore (Supplementary Table 4). D_d ranges from 0.84 km/km^2 in North Guwahati to 1.43 km/km^2 in the Kalmoni sub-watershed in the study area, indicating abundant vegetation and permeable surface material (Supplementary Table 4). The study shows that higher F_s values are observed in the southern part of the Brahmaputra River (Supplementary Fig. 1 e), primarily in sub-watersheds Kalmoni (3.89) and Foreshore (2.33) (Supplementary Table 4). As per the result, the textures of all the sub-watersheds are classified as very coarse, indicating the presence of vegetation-protected massive and resistant rocks in the study area resulting in low soil degradation (Supplementary Fig. 1 f). The L_g value varies from 0.59 to 0.35, which indicates that L_g moves over longer distance before joining the respective channel in the study area. Such a situation arises primarily due to a gentle slope gradient, abundant vegetation, more infiltration, and reduced runoff (Supplementary Fig. 1g). The F_f ranges from 2.87 to 0.17 for all watersheds (Supplementary Table 4). The sub-watershed of Bharalu (2.87) and Silsako (1.48) have high F_f. These values represent a rounded basin quickly, followed by high peak flow resulting in soil degradation condition (Supplementary Table 4). The R_e value ranges from 0.47 to 1.11, with moderate to slightly steep slope, Kalmoni and Foreshore have the lowest R_e, which indicate that the basin is elongated and has less chance of erosion. In contrast, Deepor Beel, Bharalu, Silsako, and North Guwahati have high R_e values indicating a circular basin and will be more prone to flooding (Supplementary Fig. 1i).

3.1.2 Linear aspect of sub-watersheds

The study area is a fourth-order river based on Strahler's hierarchical ranking (Strahler, 1964). Silsako watershed is the only fourth-order (Supplementary Table 5), while most sub-watersheds are categorized into three orders. Out of the total stream in the watersheds, the 1st streams account for 59.4 percent (243 Nu), while the 2nd order accounts for 24.2 percent (99 Nu), the third-order accounts for 13.6 percent (56 Nu), and the fourth-order account for 2.68 percent (11 Nu) (Supplementary Fig.3a). Similarly, to stream number, first-order streams have accounted for 64.22 percent (212.8 km) of total length (Supplementary Fig. 2b). Supplementary table 5 clearly shows more information about the sub-watershed’s characteristics (e.g., area, perimeter, length, stream length, etc.). The L_{sm} of the sub-watersheds in the urban watershed of Guwahati ranges from 0.27 to 1.15. Supplementary Table 5 clearly shows that the L_{sm} of a given stream order is greater than the lower order but less than the next higher order. The R_l in the urban watershed of Guwahati is highest for the third-order and second-order streams. The highest R_l is from second to third-order streams (73.64) in the Kalmoni sub-watershed (Supplementary Table 5). A high R_l indicates an increased susceptibility to soil erosion in the study area. In the present study, the sub-watersheds of the urban watershed of Guwahati have high R_b values ranging from 0.72 to 5.4, indicating early hydrograph peaks, flash flood potential, and soil erosion susceptibility.

3.1.3 Relief aspects of sub-watersheds

The highest and the lowest maximum height of basin mouth (Z) is observed in the sub-watershed of Silsako (352 meters) and Kalmoni (166 meters), respectively. While the highest and lowest minimum height of basin mouth (z) is observed in Bharalu (0.00 meters), Silsako (0.00 meters), and Deepor Beel (-10.00 meters) above mean sea level, respectively (Supplementary Table 6). The more the basin mouth rises, the more vulnerable the area becomes to soil erosion. Supplementary Fig. 3 a & b shows the variation in relief across the sub-watersheds. The highest relief is observed in the sub-watershed of Silsako (352 meters), while the lowest is observed in Kalmoni (166 meters). R_h values in the urban watershed range from 28.17 to 83.33 (Supplementary Table 6). In the study area, sub-watersheds with high relief features and steep slope gradients have high R_h values and more susceptibility to soil degradation, while regions with low relief and a gentle to uniform slope have low R_h (Supplementary Fig. 3d). The R_n of the watersheds is shown in table11. R_n in this study ranged from 0.24 to 0.39. The ruggedness values were highest in the Silsako sub-watershed and lowest in the Kalmoni sub-watersheds (Supplementary Fig. 3e). It suggests that the Silsako sub-watershed (0.39) is more vulnerable to soil erosion than the others (Asfaw and Workineh, 2019; Tiwari and Kushwaha, 2021).

3.1.4 Computation of watershed prioritization

Supplementary Table 7 summarizes the Pearson correlation coefficient (r) between all the morphometric parameters. According to the findings, 19 parameters had very high positive correlations (with *r* greater than 0.70). In contrast, we discovered 17 negative correlations with a high significance level (at 0.05 level of significance level). In addition, it is observed that 14 parameters that have no significant correlation with each other (below 0.10). Furthermore, the analysis discovered that seven morphometric parameters, have significant correlations, four are associated with areal aspects (drainage density, drainage texture, stream frequency, length of overland flow), and three are associated with relief aspects (ruggedness number, basin relief, and height of basin mouth). Although these correlations permit for recognition of high and effective relationships amongst the parameters, they do not yet qualify for the grouping of specific parameters into components and the assignment of physical significance. PCA was used in the present study because there were many correlations among these morphometric parameters. PCA helped determine the morphometric parameters with a more significant influence on watershed behavior. Supplementary Table 8 depicts the various morphometric parameters analyzed by PCA methods that influence the soil erosion in the study area. According to the results, the first five principal components (PC01, PC02, PC03, PC04, and PC05) had a total variance of 100%. But alone, PC01, PC02, and PC03 account for 88% of the total variance (Supplementary Table 9). The result showed a high correlation of PC01, PC02 and PC03 with the parameters. The analysis also shows that PC01 is associated with linear parameters e.g. N_u (0.744 & 0.655), L_s (0.748 & 0.611), L_{sm} (0.854 & 0.085) and F_s (0.747 & 0.655). At the same time, PC02 has a high correlation with basin perimeter, D_d, and D_t, and moderately with L_s, basin area, and basin length, indicating that these parameters are associated with the continuous soil erosion process of the watershed over time. Also, it was observed that PC03 has a suitable correlation with R_e and F_f, along with a minimum height of basin mouth (Supplementary Table 8). The PCA determined that basin perimeter, D_d, F_s, D_t, L_g, F_f, R_e, and R_n were relevant variables to assess the watershed prioritization of the study area (Table 1). These variables were chosen due to their highest values correlated with the three principal components.

Table 1 Watershed prioritization based on morphometric parameter

Sub-watersheds	***Basin perimeter***	D_d	F_s	D_t	L_g	F_f	R_e	R_n	***CP***	***NP***	***GP***
Deepor Beel	1	3	6	4	3	4	4	2	3.375	3	Medium
Bharalu	3	2	5	3	4	1	1	3	2.75	1	High
Foreshore	2	5	2	6	2	5	5	5	4	5	Low
Silsako	4	4	3	1	5	2	2	1	2.75	2	High
Kalmoni	5	1	1	5	6	6	6	6	4.5	6	Low
North Guwahati	6	6	4	2	1	3	3	4	3.625	4	Medium

Where, Dd drainage density, Fs stream frequency, Dt drainage texture, Lg length of overland flow, Re elongation ratio, Rn Ruggedness number, CP compound parameter, NP priority rank and GP priority degree

Table 1 shows the sub-watersheds CP, NP, and GP based on basin perimeter, D_d, F_s, D_t, L_g, F_f, R_e, and R_n. Bharalu, Silsako, Deepor Beel, and North Guwahati have the highest and medium priority ranks. On the other hand, the priority rank of sub-watershed Foreshore increases due to the urban areas' presence and scarcity of vegetation cover (Supplementary Fig. 4). Supplementary table 10 shows the priority index of NDVI-estimated vegetation cover. The degradation of the sub-watersheds caused by concentrated flow channels and downslope flow of water is described by NDVI. Based on vegetation NDVI, the highest priority is allotted to North Guwahati and Foreshore due to the lowest vegetation cover in these sub-watersheds. However, the rank of Bharalu and North Guwahati has decreased when seen in the result of ranking based on morphometric parameters than that of NDVI ranking. The NDVI indicates that the vegetation cover in these sub-watersheds is at its peak. Finally, the watershed's final prioritization (GP_f) demonstrates that sub-watershed Silsako and Bharalu have very high susceptibility to soil degradation with NP_f 1 and 2, respectively. In contrast, Deepor Beel and North Guwahati have a high susceptibility to soil erosion with NP_f 3 and 4 (Table 2). Furthermore, table 2 shows the rank of priority and final priority for sub-watersheds as a component of morphometric parameters and NDVI values. The final priority (GP_f) analysis clearly states that the highest priority comprises Silsako and Bharalu, followed by Deepor Beel and North Guwahati (Fig. 3). The priority rank clearly shows the degradation condition of the sub-watersheds. The slopes are steeper in the sub-watersheds with high-priority ranks, and the profiles constitute deeper channels. With the descent of the slope degree of the sub-watersheds, the steepness, depth of the channel profile, and erodibility of the areas also reduce.

Table 2. Watershed prioritization based on final priority index

Sub-watersheds	***CP$_f$***	***NP$_f$***	***GP$_f$***
Deepor Beel	3.4375	4	Medium
Bharalu	3.25	2	High
Foreshore	3.75	5	Low
Silsako	3.125	1	High
Kalmoni	4.125	6	Low
North Guwahati	3.3125	3	Medium

Where, CP compound parameter, NP priority rank, GP priority degree, *f* mean morphometry, *NDVI* and final

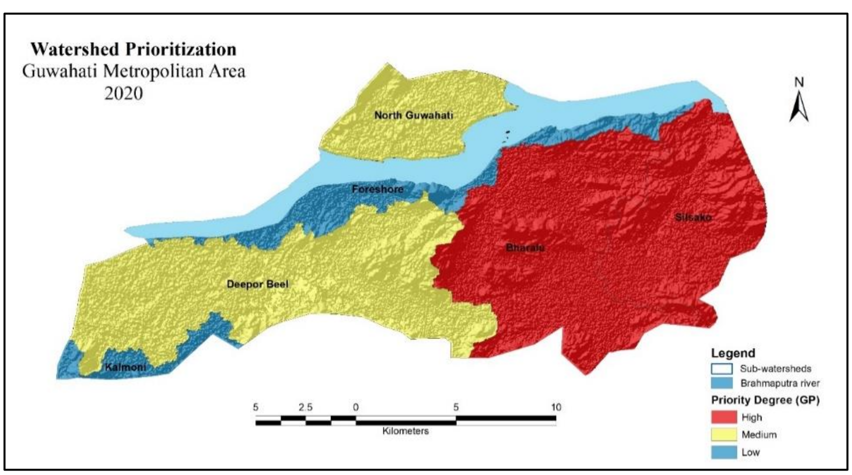

Figure 3 Watershed prioritization map of the urban watershed of Guwahati

3.2 Estimation of potential soil erosion with future insight

In the present study, we estimated potential soil erosion using the RUSLE model for the current scenario and under the climate change scenario for 2040. Therefore, to do so, we prepared future climatic change-related parameters, like rainfall for 2020-2040, under RCP2.6 and RCP8.5. Figure 4 shows the annual average rainfall data for the current time and 2040 for RCP2.6 and RCP8.5. The maximum rainfall for the present scenario (2000-2018) is 186.7 mm, and the minimum is 156 mm. but, maximum and minimum rainfall will increase by 42% and 27% in future (2040) if we consider both methods (RCP2.6 and RCP8.5) based on the minimum and maximum concentration of greenhouse gases (Figure 4b and 4c).

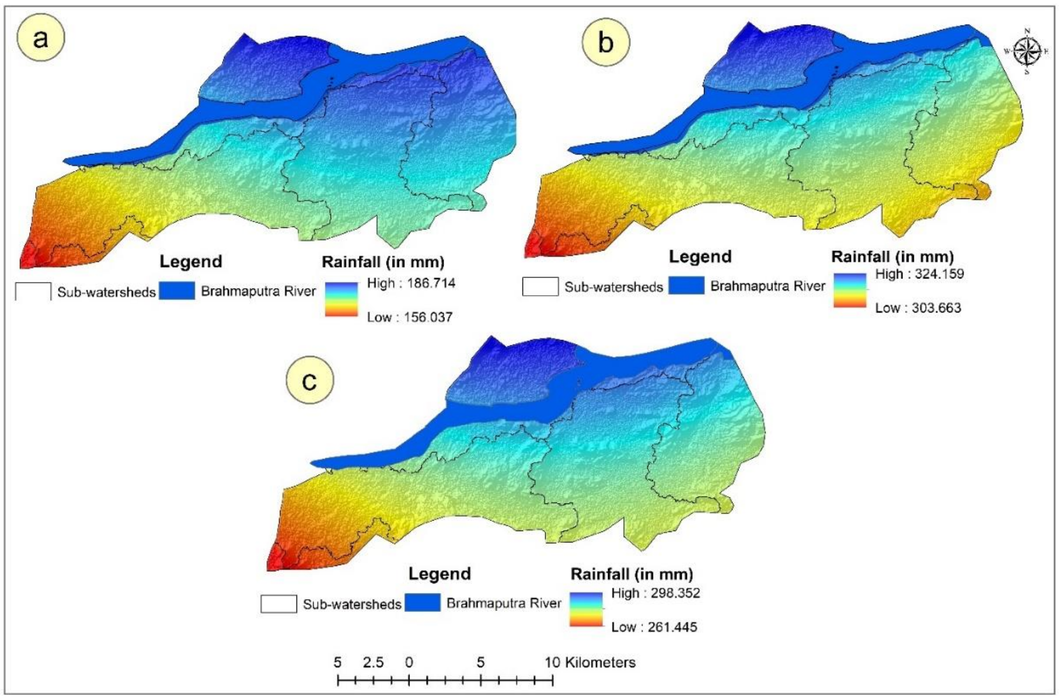

Fig. 4 Rainfall Modelling (a) Present rainfall (b) Rainfall 2.6, and (c) Rainfall 8.5

In the present study, we employed the RUSLE model to estimate soil erosion in the present and future scenarios using five factors (K, C, P, LS, and R) (Figure 5). Figure 5a shows that the K factors vary from 0.02 to 0.212 tons Ha $MJ^{-1}mm^{-1}$ across the watershed. High soil erodibility indicates the higher potentiality of soil erosion and vice versa. Also, the sub-watersheds like Silsako, Bharalu, North Guwahati, and Foreshore show very high to high K factors, as these regions have sand-dominated soil texture. On the other hand, Deepor Beel has very low K values, indicating lower soil erosion sensitivity. In the case of the LS factor, the value ranges from -0.61 to 46.23. High values indicate higher chances of eroding and vice versa (Figure 5b). The value of the P factor ranges from 0.5 to 1, while low values imply higher sensitivity to be eroded (Figure 5c). The value of the C factor ranges from 0.01 to 0.35, where a low value indicates a higher potentiality to be eroded by rainfall and runoff. Most of the Silsako and

Bharalu sub-watershed areas have been covered by low values of the C factor, which indicates that these regions are highly susceptible to soil erosion. The present study computed the R factor for current and future scenarios (2040) using RCP2.6 and RCP8.5. The R factor of the current scenario ranges from 25.84 to 34.49 MJ mm/ha/year. Higher R factor or rainfall erosivity can have higher erosional ability and vice versa. Very high and high values of the R factor have been observed in the Silsako, Bharalu, and Foreshore. Similarly, the R factor for 2040 (RCP8.5) will be increased at 42 MJ mm/ha/year, which can cause severe damage to the soil.

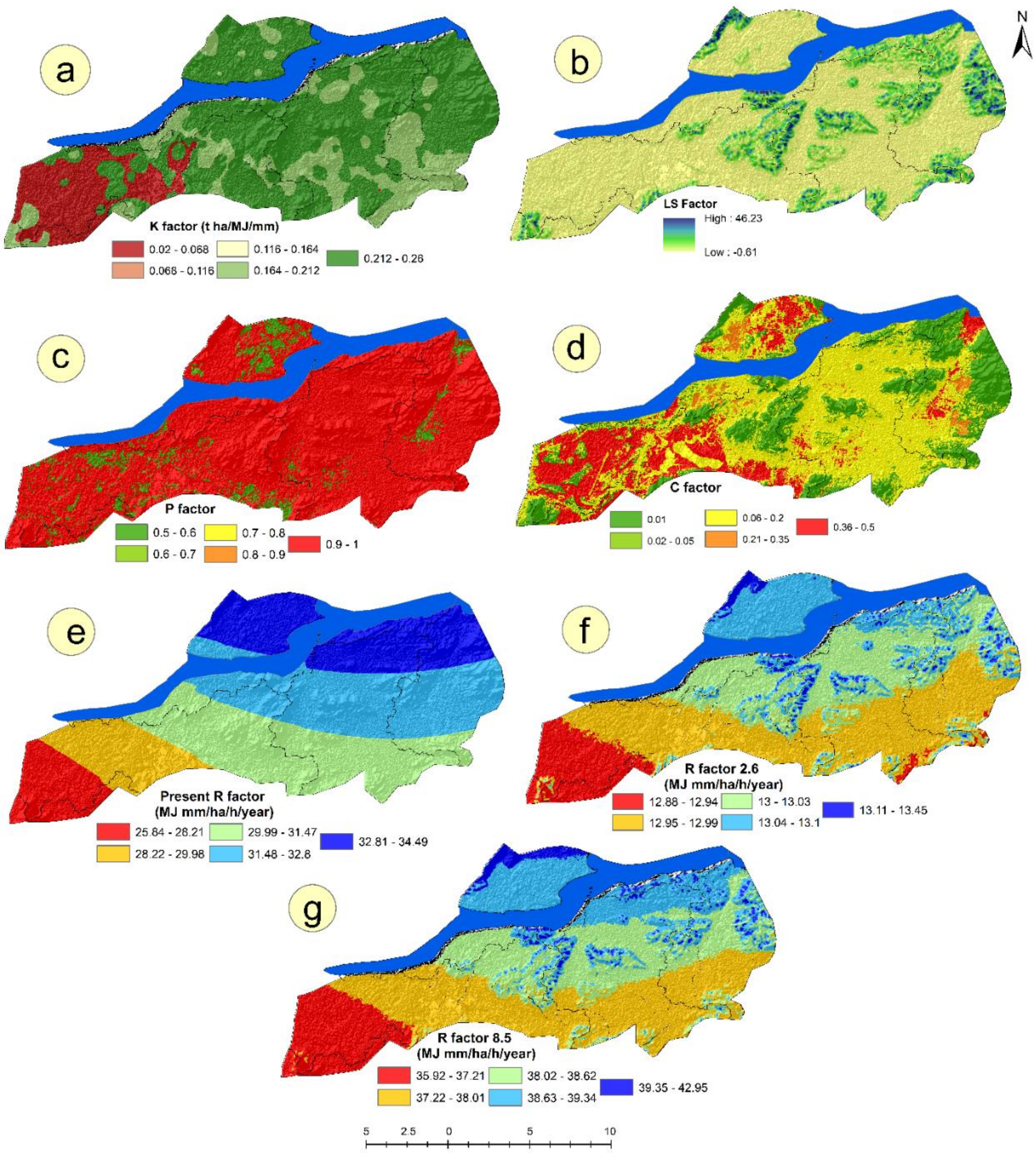

Figure 5 RUSLE parameters (a) K factor (b) LS factor (c) C factor (d) P factor (e) Present R factor (f) R factor at RCP2.6 (2040), and (g) R factor at RCP8.5 (2040)

The RUSLE models were created after integrating all the parameters in the raster calculator of ArcGIS (version 10.8) software. The final RUSLE models have been generated for three time periods to estimate soil erosion. The current RUSLE model shows that the soil erosion of the study area ranges from 140 to 181.64 tonnes hectare per year. The RUSLE model for 2040 (RCP8.5) estimates the soil erosion ranges from 305 to 332 tonnes hectare per year. While, the RUSLE model for 2042.0 (RCP2.6) estimates the soil erosion ranges from 267 to 302 tonnes hectare per year (Figure 6). Therefore, the models show that the soil erosion will be increased manifold in the future. After deriving the RUSLE soil erosion models, we classified the models using Jenk's natural break algorithms into five classes: very high, high, moderate, low, and very low. Very high and high soil erosion zones have been identified in Silsako, Bharalu, North Guwahati, and Foreshore. While very low soil erosion zone has identified in Kalmoni sub-watershed and some parts of Deepor Beel.

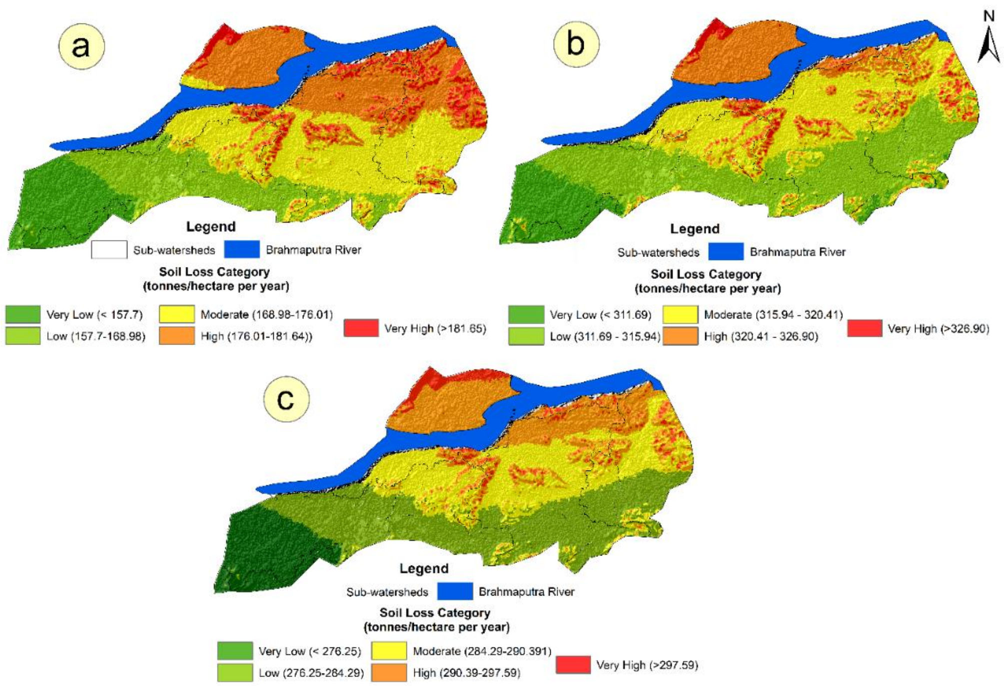

Figure 6 Estimation of soil erosion using RUSLE Models for (a) current scenario (b) future scenario (2040) (RCP2.6), and (c) future scenario (2040) (RCP8.5)

3.3 Proposing potential soil-water conservation models for current and future scenarios

Estimating and identifying the degree of soil erosion is insufficient and is just for quantification and visualization. As a result, the high priority region should be designated to avoid soil erosion. Hence, we also proposed a fuzzy logic and AHP-based model for detecting potential soil-water conservation zones for the present and the future (by 2040) under a climate change scenario to minimize future soil erosion. Topographical, hydrological, and land cover-related parameters were used to create the SWPC model (Supplementary Figures 5 and 6). Since each parameter has a distinct dimension and direction, all parameters were normalized before modelling.

As a result, among various membership functions, we used two fuzzy membership functions in this study: MsLarge (Large considers large values of the parameters, would have a low degree of membership with the destination (soil conservation), and MsSmall (small considers small value of the parameters, will have a high degree of membership with destination). After that, we used fuzzy operator, like GAMMA 0.9 to integrate all the fuzzified parameters to create fuzzy logic based SWPC model. The value of SWPC model ranges from 0 to 1, where close to 1 indicates highly suitable areas for conservation and vice versa. Then, we used Jenkin's natural break algorithm to classify the SWPC model into five classes, such as very high, high, moderate, low, and very low soil conservation zones.

Figure 7 shows the locations of the sites with the highest soil-water suitability using fuzzy logic and AHP. According to the fuzzy logic present SWPC, most of the study area is in a very poor soil-water conservation potential zone. Approximately 125.82 km^2 of the total SWPC area is in the moderate suitability zone, followed by the low suitability zone (73.51km^2). At the same time, high (46.92 km^2) and very high (54.40 km^2) suitability zones cover a sizable area (Figure. 7a). In RCP 2.6 (129.98 km^2) and RCP 8.5 (128.99 km^2), the area under the moderate SWPC increased (Fig. 7b-c). In terms of sub-watersheds, the three SWPC maps show that Deepor Beel, Kalmoni, and North-Guwahati have the lowest potential for soil-water conservation, followed by Kalmoni and North-Guwahati. On the other hand, the highest SWPC is found in the Bharalu and Silsako sub-watersheds, with nearly 80% of the area falling into the high and very high SWPC zones. Also, the three maps show that around 41% of the total area (Figure 7a-c) is suitable for moderate SWPC, while 33% of the watershed is compatible with high and very high SWC sites. When the final fuzzy models were compared to the watershed prioritization map (Fig. 3), it was obvious that the SWPC maps roughly corresponded to the prioritization map. For example, the sub-watersheds of Bharalu and Silsako had high priority values on the watershed prioritization map (Fig. 3), corresponding to higher values on the soil-water conservation maps (Fig. 7a). To compare the findings of fuzzy logic, we applied MCDM technique (AHP) to prepare SWPC models for current to future periods. We used twelve parameters to compute pairwise comparison matrix of AHP for generating weights of each parameter. We obtained weights for all parameters, such as drainage density (0.85), ruggedness number 0.75), basin relief (0.4), Lg (0.25), LULC (0.2), TWI (0.18), elevation (0.15) and so on. The CR value for this matrix was 0.08. Then, the weights have been assigned to the parameters in raster calculator to produce the SWPC models under current and future scenarios. The generated SWPC model for current scenario shows 81.2km^2 as low suitability zone, and 49km^2 as very high SWPC zones (Figure 7d). Similarly, the AHP based SWPC models under RCP2.6 and 8.5 scenarios showed quite similar results like fuzzy logic based SWPC models (Figure 7e & f).

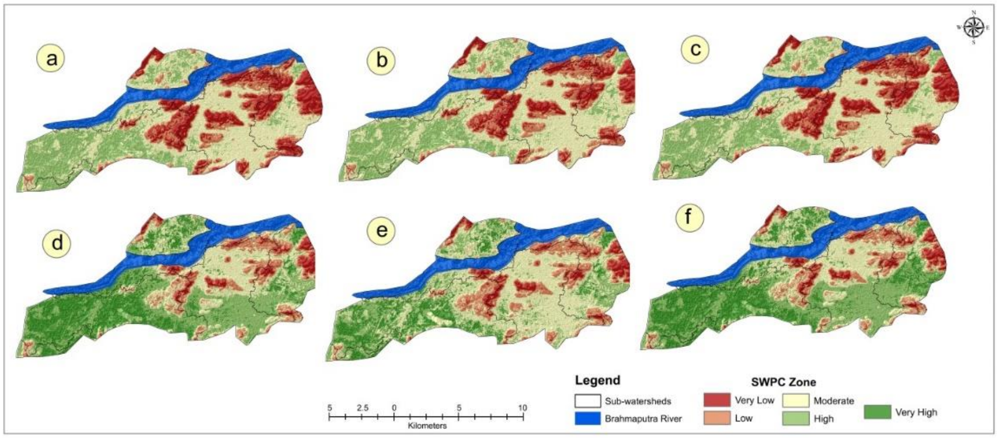

Figure 7 Soil-water suitability zones for (a, d) Present SWPC (b, e) SWPC in 2040 (RCP2.6), and (c, f) SWPC in 2040 (RCP8.5) using fuzzy logic and AHP

The variable importance for SWPC model needs to be assessed because the management plans should be carried out based on the important variables. Therefore, this study used random forest (RF) based sensitivity technique to compute the variable importance to the model (Figure 8). In the present study, we used this sensitivity technique on the fuzzy logic based SWPC model because we consider it as base model of this study. The figure shows that drainage density has highest influence to the model, followed by ruggedness number, aspect, TWI, basin relief, and elevation. Length of overland flow has lowest influence to the output, followed by LULC, and NDVI.

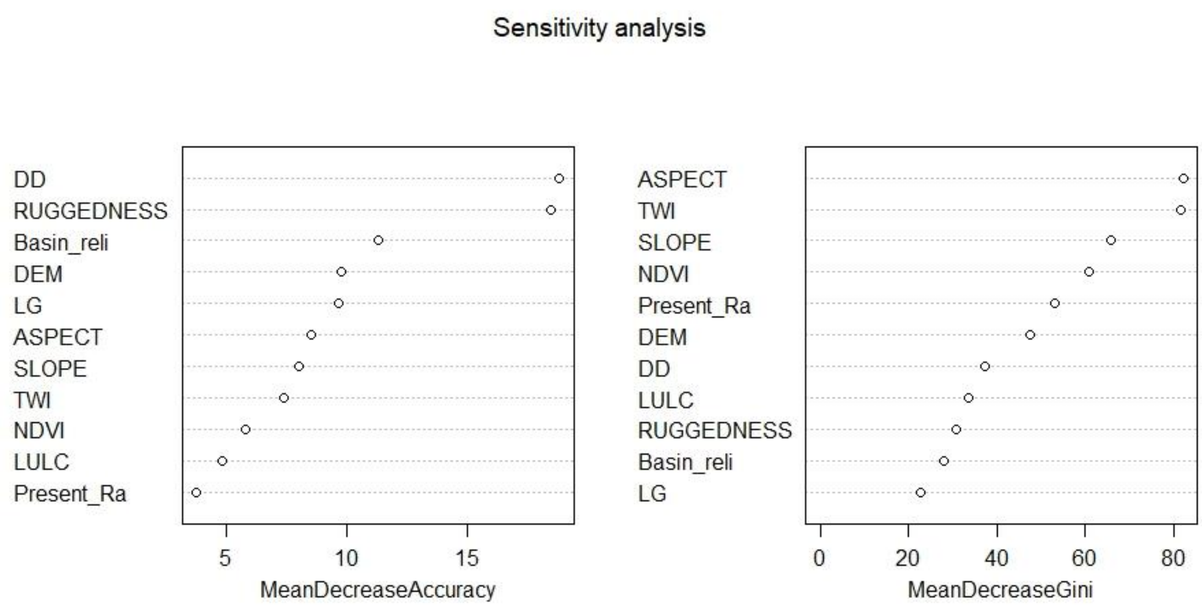

Figure 8 Computation of importance variable for current SWPC model using RF based MDA and MDG technique

3.4 Coupling coordination degree mechanism for identifying accurate soil-water conservation zone

Figures 9(a-c) and 10(a-c) depict the degree of coupling coordination between watershed prioritization, soil-water conservation and soil loss in the urban watershed of Guwahati. It identified the agreement areas among three sub-systems based on coupling interaction. Therefore, the agreement areas have been quantified in terms of coupling degree and coupling coordination degree model. Higher the agreement indicates high value of three sub-systems, which reflects the high priority zones and vice versa. In general, the coupling coordination degrees in the region are classified into very poor, poor, medium, high, and very high. Figure 9a shows that the high agreement value for coupling degree model under present scenario has been observed in the sub-watersheds of Bharalu and North-Guwahati. In comparison, the Deepor Beel and Kalmoni sub-watersheds have very low coupling degrees. However, RCP 2.6 projections for 2040 show a moderate coupling degree for Deepor Beel and a very poor coupling degree for Silsako (Figure 9b). Furthermore, the high agreement areas for coupling degree model under RCP 8.5 scenario has observed a slight difference from the mentioned two models (Figure 9c). Foreshore and North Guwahati have the highest coupling degree, as shown in Fig. 9c. The coupling models clearly show that the maximum extent of the urban watershed has very high to moderate coupling. The coupling degree for all the sub-watershed has varying agreement values in all three models (Figure 9a-c). Although, a very poor coupling degree is primarily observed in the sub-watershed of Deepor Beel and Kalmoni, indicating a serious imbalance between watershed prioritization, soil-water suitability and soil loss.

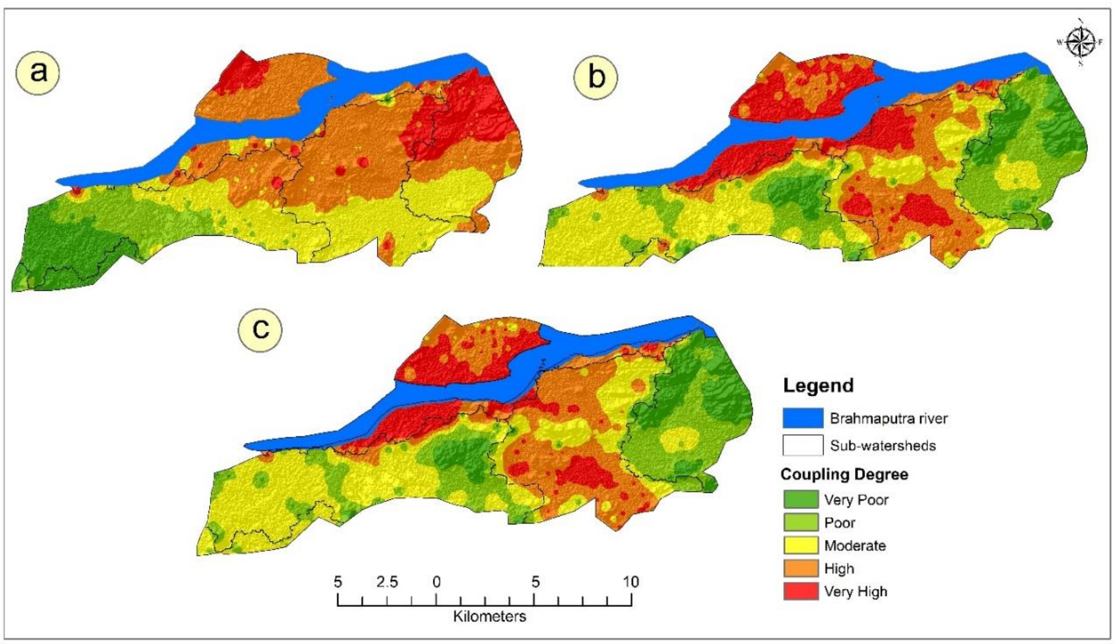

Figure 9 Coupling degree between watershed priority, SWPC and RUSLE model for (a) present scenario (b) future scenario at RCP 2.6 (2040), and (c) future scenario at RCP 8.5 (2040) of the urban watershed of Guwahati

Further analysis of the coordination degree is required to comprehend the coordinated relationship between subsystems. As a result, we calculated the coordination degrees of the six sub-watersheds based on the present RCP 2.6 and RCP 8.5 and classified the coordination degree values into ten classes, followed by Liu et al., (2018) (Figure

10a-c). The CCD value ranges from 0 to 1, suggesting the lowest to the highest level of coordination. Also, in the present coordination degree model, the highest coordination ($0.8 \leq C \leq 1$) is observed in three sub-watersheds: Silsako, North Guwahati, and some parts of Bharalu. Due to increased soil loss, these sub-watersheds also have high prioritization and are primarily suitable for soil-water conservation activities (Figure 9a-c). On the other hand, most parts of the Deepor Beel sub-watershed have the lowest coordination degree ($0 \leq C \leq 0.2$) in all three maps, indicating a severe imbalance in the study area between soil-water suitability, soil loss, and watershed prioritization. Figure 9a also depicts that the coordination of the variables stretched a higher degree to the northern, northeastern and central portions of the watershed due to extreme urbanization. Due to the existing vegetation and water resources, the southwestern region of the urban watershed exhibits a lower degree of coordination ($0 \leq C \leq 0.3$). Therefore, the areas with high coupling and coordination degrees should be monitored continuously. Also, appropriate soil-water conservation management plans should be proposed and implemented to mitigate soil erosion.

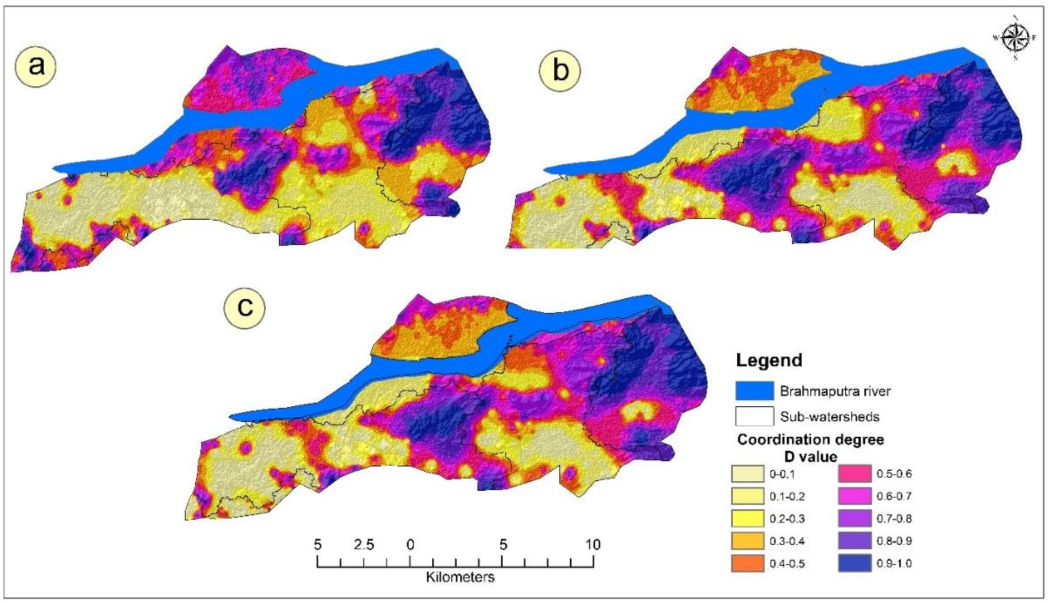

Figure 10 CCD model between watershed priority, SWPC and RUSLE model (a) Present (b) RCP 2.6 (2040), and (c) RCP 8.5 (2040) of the urban watershed of Guwahati

4. Discussion

In the present study, we intended to build a highly robust model of potential soil-water conservation, which can provide precise soil-water conservation areas. To do so, we first prioritized the sub-watersheds through advanced statistical techniques, then measured soil erosion using the RUSLE model for current and future scenarios based on RCP2.6 and RCP8.5, then proposed a fuzzy logic-based potential soil-water conservation zone. Finally, we introduced coupling coordination mechanism among watershed priority, soil erosion model, and potential soil-water conservation model for present and future scenarios to identify precise areas for soil-water conservation (Fig. 2). According to the author's knowledge, this is the first comprehensive analysis considering different dimensions and integrating all aspects through standard methods to identify the soil-water conservation areas. In this study, six sub-watersheds in the urban watershed of Guwahati, Assam, were delineated to prioritize watersheds based on morphometric parameters and NDVI values. The assessment of potential soil erosion vulnerability necessitates the consideration of several drainages and relief parameters. Morphometric properties significantly influence runoff and infiltration capacity (Pathare and Pathare, 2021; Hembram and Saha, 2020). The urban watershed of Guwahati covers a total area of 339.25 km^2. It has a perimeter of 42.81 km^2 km and is textured with 409 streams. First-order streams are approximately 243, accounting for 59.4 per cent of all streams, indicating the catchment's erosional risk. Nineteen morphometric indices (linear, areal, and relief parameters) (Supplementary Table 1) were encompassed to prioritize six sub-watersheds based on erodibility risk. Furthermore, the findings of this study state that the higher values of F_s are mostly found in the southern sub-watersheds of the Brahmaputra River, primarily in the sub-watersheds Kalmoni (3.89) and Foreshore (2.33), indicating soils prone to erosion and degradation (Supplementary Table 4). The Nilachal hills on the sub-watershed of Foreshore have massive landslides, soil erosion, and urban flash floods (Hussain and Goswami, 2016). Due to increased urbanization, dense vegetative cover, primarily in the hills of the Guwahati Metropolitan Area (GMA), has degraded at an alarming rate (Borthakur and Nath 2012; Patowary and Sarma, 2018). However, the linear aspects of an area directly correlate with soil erosion, with a higher value indicating greater erodibility. Similarly, the sub-watersheds of Guwahati's urban watershed have high R_b values ranging from 0.72 to 5.4. These high R_b values are connected to high peak flows, the potentiality of flash floods (Siddiqui et al., 2020), and susceptibility to soil erosion, all of which are influenced by geomorphological, as well as lithological conditions such as deformation forms, tectonism, as well as the mass movements (Kamberis et al., 2012). In the present study, PCA was very helpful in categorizing variables with physical relevance and differentiating morphometric aspects with little influence. The result shows that the first principal component (PC01) is linked to the linear parameters. In contrast, the second (PC02) is related to the watershed's areal aspects, and the third component (PC03) is directly correlated with the relief parameters. The values of PC01 and PC02 for the sub-watersheds suggest that soil erosion, as well as run-off, can be associated with linear features of morphometric study (e.g., N_u (0.744 & 0.655), L_s (0.748 & 0.611), L_{sm} (0.854 & 0.085), and F_s (0.747 & 0.655). Our result aligns with what Kamberis et al. (2012) found; components like soil characteristics, LULC, and geology are highly influenced by parameters such as D_d and F_s. Additionally, using these morphometric parameters combined with NDVI values improves the quality of watershed prioritization results. The morphometric parameters and the NDVI-estimated vegetation cover result are shown in supplementary table 10. The degradation of a watershed caused by concentrated water in channels and L_g on hillslopes is described by morphometry and NDVI, respectively. These sub-watersheds are very highly urbanized and often face scarcity of vegetation cover, leading to soil erosion susceptibility (Fig. 3). Hence, proper management of these sub-watersheds is necessary to safeguard against soil and water degradation in these areas. The present study results are also likely to help the local government and decision-makers identify the priority of the sub-watersheds that require prompt actions on soil degradation, management, and conservation practices in the study region.

Furthermore, based on the combined input fuzzy membership values, three SWPC maps are created based on present and future scenarios at RCP 2.6 and RCP 8.5. The final output shows the locations of the sites with the highest soil-water conservation suitability (Fig.7a-c). According to the three models, approximately 41% of the total area (Figure 7a-c) is suitable for moderate SWPC. In contrast, 33% of the watershed is compatible with high and very high SWC sites. According to the present SWPC, most of the study area is in a low soil-water conservation potential zone. The moderate suitability zone covers approximately 125.82 km^2 of the total SWPC area, followed by the low suitability zone (73.51km^2). Simultaneously, high (46.92 km^2) and very high (54.40 km^2) suitability zones also cover a large area (Fig. 7a). Moreover, the area covered by the moderate SWPC increased in RCP 2.6 (129.98 km^2) and RCP 8.5 (128.99 km^2). Deepor Beel, Kalmoni, and North-Guwahati have the lowest potential for soil-water conservation, according to the three SWPC maps, followed by Kalmoni and North-Guwahati, due to the existing vegetational resources and low urban development (Nath et al., 2021). The coupling maps also depicted that the SWPC maps roughly corresponded to the soil erosion and sub-watershed prioritization maps. The sub-watershed of Bharalu and Silsako had high priority values, which resembled higher values on the soil-water conservation maps and the soil loss models. The results suggest that the sub-watershed with the maximum likelihood of soil erosion is the zones that need the most attention in soil-water conservation practices. Moreover, the three-coupling coordination degree model (CCDM) as per the present, and RCP 2.6 and RCP 8.5 indicates that the coupling degree is most significant in the Bharalu and North-Guwahati sub-watersheds. Deepor Beel and Kalmoni sub-watersheds, on the other hand, have very low coupling degrees. On the other hand, RCP 2.6 projections for 2040 show a moderate coupling degree for Deepor Beel and a very poor coupling degree for Silsako. In addition, the coupling degree for RCP 8.5 has changed and depicts a high coupling degree in Foreshore and North Guwahati (Figure 8a-c). Deepor Beel, on the other hand, has the lowest coordination degree, indicating a severe imbalance in the study area between soil-water suitability, soil loss, and watershed prioritization. On the other hand, Deepor Beel's lowest coordination degree suggests a severe imbalance between soil-water suitability, soil loss and watershed prioritization in the study area. Figure 9a-c clearly shows that due to extreme urbanization, the coordination of the variables extended to a greater extent to the northern, northeastern, and central parts of the Guwahati urban watershed (Pawe and Saikia, 2017). On the other hand, a lower degree of coordination is observed in the southwestern region of the urban watershed. The findings reveal several notable characteristics in the analyzed relationships. Also, for future development, there is a need to promote the management of sub-watersheds and their soil-water resources at the sub-watershed level.

5. Conclusion

In this study an attempt has been made to identify precise and mathematically robust areas for potential soil-water conservation through coupling mechanisms in the urban watershed of Guwahati, Assam. To accomplish this, we used advanced statistical approaches to select the sub-watersheds, and then evaluated soil erosion using the RUSLE model for present and future scenarios based on RCP2.6 and RCP8.5, and lastly proposed a fuzzy logic-based perspective soil-water conservation zone. Finally, we established a coupling-coordination mechanism for present and future scenarios between watershed priority, soil erosion model, and potential soil-water conservation model to identify exact sites for soil-water conservation. The result shows that the sub-watersheds Silsako and Bharalu is highly susceptible to soil erosion, followed by Deepor Beel and North Guwahati. This is because these sub-watersheds are highly urbanized which led to decrease in vegetation cover, making the sub-watersheds vulnerable to soil erosion. Thereafter, we estimated the soil erosion using RUSLE model for current (2020) and future scenario i.e. 2040 (RCP2.6 and RCP8.5). According to present situation by applying RUSLE model, soil erosion in the study area varies from 140 to 181.64 tonnes per hectare per year but by 2040, the study predicts soil erosion to a tune of 267 to 302 and 305 to 332 tonnes per hectare per year by using RCP2.6 and RCP8.5 respectively. As a result, it is seen that that soil erosion will fast increase in future. Then, we proposed fuzzy logic-based soil-water conservation suitability zones based on topographic, hydrologic, land cover, and climatic variables for current and future scenarios (2040) at RCP2.6 and RCP8.5. The result signifies high soil-water potential zones in the sub-watersheds of Silsako, Bharalu, and North Guwahati. Whereas, Deepor Beel sub-watershed shows least potentiality for conservation due to high urban development in the region in recent decades. Finally, we identified the precise areas that need to be conserved for soil-water erosion for current and future scenarios (2040) at RCP2.6 and RCP8.5 based on coupling mechanism with the help of watershed priority model, soil erosion models, and soil-water conservation suitability models. Moreover, when the final SWPC and soil erosion models for current and future scenarios were compared to the watershed priority map with the CCDM model, extremely accurate conservation areas for current and future scenarios were determined. Lastly, the degree of coupling and coordination reflected the intensity of cooperative development in the study area. Appropriate measures to reduce soil erosion and activities are required in these sub-watersheds to safeguard the remaining fertile land. To the author's knowledge, this is the first comprehensive research that considers several dimensions and incorporates all elements using standard approaches to identify soil-water conservation zones. This research proposes a novel strategy for identifying sites with high-priority soil-water conservation in urban watersheds. The outcome of this may widen research areas as a reference for future studies on assessing soil erosion in urban watersheds with similar geographic conditions. The outcome may help decision-makers to prepare sustainable urban development plans and policies. Although this research provides several scientific insights, it has some limitations too, which need to be done in the future research. This research used moderate 30 m spatial resolution satellite imageries, but by using higher resolution images like 10 m Sentinel-2 data we may get micro level soil erosion zones. Further, the sensitivity analysis may be improved by employing deep learning-based sensitivity and uncertainty analysis.

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Conflict of Interest

The authors declare that they have no conflict of interest.

Data availability Statement

The datasets generated during and/or analyzed during the current study are available from the corresponding author on reasonable request.

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