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Mapping and Quantifying Integrated Land Degradation Status of Goa Using Geostatistical Approach and Remote Sensing Data

V. G. Prabhu Gaonkar*, F. M. Nadaf† and Vikas Kapale*****
*Department of Geoinformatics, Goa University, Parvatibai Chowgule College, Margao, Goa, India
**Department of Geography, DPM's Shree Mallikarjun & Shri Chetan Manju Desai College, Canacona, Goa, India
***Indian Institute of Technology, Kanpur, India
†Corresponding author: F. M. Nadaf; fmnadaf@gmail.com

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ABSTRACT

Globally, land degradation is becoming a grave concern. Over the years, conditions such as drought, extreme weather events, pollution, changes in land use land cover, and desertification have intensified and led to land degradation, affecting both ecological and economic processes. Equally, during the last two centuries, population and urbanization have amplified manifold and increased the demand for additional food and shelter, resulting in alteration in land use land cover, over-grazing, and over-cultivation, loss of nutrient-rich surface soil, greater runoff from the more impermeable subsoil, and reduced water availability. Geographically, Goa is a highly diversified state. It is sandwiched between the West Coast and the Western Ghats. The state is blessed with beaches, mangroves, backwaters, wetlands, wildlife sanctuaries, evergreen forests, barren lands, and other vital ecosystems. The State of Goa, on average, receives more than 3000 millimeters of rainfall annually with high surface runoff. Using both primary and secondary data, this study sought to investigate and quantify the state's land degradation. Secondary data came from satellites and other sources, while primary data came from field observation and ground truthing. Land degradation factors related to soil loss and the spatial pattern of soil erosion are predicted and evaluated using the Revised Universal Soil Loss Equation (RUSLE) method. Landsat-8 OLI-TIRS images were utilized to decide land use and cover (C factor), while DEM information was utilized to assess (LS factor). A soil map and rainfall data were collected to acquire a better understanding of soil erodibility (K factor) and rainfall erosivity (R factor). The kriging interpolation technique was used to gain a deeper comprehension of land degradation.The purpose of this paper is to comprehend the concept of integrated land degradation and how it affects the environment of Goa. Using remote sensing data and geostatistical methods, the study creates a comprehensive map of land degradation in the region by identifying and analyzing the various forms of land degradation in Goa. The paper also looks at how rainfall and the amount of land cover affect the rate of soil erosion in Goa. According to the findings, intense rainfall makes the eastern part of Goa particularly susceptible to soil erosion, and bare soil has a greater potential for erosion than vegetated land. The paper concludes that comprehensive land degradation mapping can be a useful tool for developing efficient land management strategies to preserve soil and encourage sustainable development in the region.

INTRODUCTION

Land debasement is the crumbling of land's quality and ability to support human and ecological frameworks. Over the years, it has become a critical environmental problem affecting the quality of soil, water, and air and threatens food security and economic development (El-Gammal et al. 2015, Ewunetu et al. 2021, Flores-Renteria et al. 2016, Kawy & Darwish 2019, Nkonya et al. 2016, Balasubramani et al. 2015, Odorico et al. 2011, Taylor & Millar 2009, Ravi et al. 2009). Land degradation arises from various factors, including human activities, climate change, erosion, and deforestation (Yolanda & Mart 2021).

The phenomenon of Integrated Land Degradation is intricate and results from a blend of natural and anthropogenic variables. In recent times, there has been growing apprehension regarding the scale and intensity of land degradation and its repercussions on both ecological systems and human welfare (Prabhu Gaonkar et al. 2022). Land degradation affects billions of people worldwide, directly or indirectly. It can potentially harm rural livelihoods, reduce ecosystem productivity, alter vegetation composition, and overuse soil resources (D'Odorico & Ravi 2023).

Land degradation, desertification, and soil erosion pose a significant threat to sustainable development, particularly in regions with low rainfall, low soil fertility, and high poverty rates (IPCC 2019). Based on global land degradation patterns, roughly 24% of the world's land area experiences moderate to high levels of degradation. The most severe levels of degradation are observed in Africa and Asia (Bai et al. 2008). India is the most severely affected by land degradation (Obalum et al. 2012, Almouctar et al. 2021).

The United Nations Environment Programme (UNEP) emphasizes the significance of an integrated land degradation assessment to tackle the various causes and consequences of land degradation in a methodical and comprehensive approach, which considers the social, economic, and environmental dimensions of the problem (Vi & World 1950). Integrated Land Degradation is a complex and multifaceted issue that requires a holistic and integrated approach to address

Since the 1930s, scientists have employed land degradation assessment to forecast and identify control erosion methods (Allafta & Opp 2021, Ayalew 2015, Dutta et al. 2015). At various levels, including global, regional, and local, numerous approaches have been employed to quantify land degradation (Allafta & Opp, 2021, Auerswald 1992, Ayalew 2015, Dutta et al. 2015, Jarašiunas et al. 2020, Quiquampoix 2008, Thapa 2020, Wagari & Tamiru 2021). Numerous models have been created to estimate rates of soil loss to enhance comprehension (Amiya et al. 2019, Poesen et al. 2003).

Several methodologies and equations for risk assessment or predictive evaluation of soil degradation are prevalent (Angima et al. 2003, Hoyos 2005, Peng & Shao 2009, Prasannakumar et al. 2011, Quarishi 2014, Zhao et al. 2012). Using old field-based approaches, meticulously mapping and monitoring the spatial distribution of soil loss across enormously large zones is a difficult, costly, and time-consuming task (Allafta & Opp 2021, Prasannakumar et al. 2011). On the contrary, at the regional scales, erosion models, such as USLE/RUSLE, SEMMED, WEPP, ANSWERS, EUROSEM, LISEM, SWAT, AGNPS, and SWRRB, have distinct characteristics and different applications (Blackley et al. 2015, Boggs et al. 2001, Dabral et al. 2008, Golijanin et al. 2022, Ismail & Ravichandran 2008, Jazouli et al. 2019, Lu & Li 2004).

Remote sensing technology linked with Geographic Information System (GIS) is widely used and recognized as a remarkable and effective method for analyzing land degradation (Anand et al. 2018, Ara et al. 2021, Chen et al. 2021, Jazouli et al. 2019, Selvakumar 2018). Various models were developed to study land degradation, such as the Erosion potential method, the Modified Universal Soil Loss Equation, and the Revised Soil Loss Equation Model (Golijanin et al. 2022). Numerous current works and research studies have employed the RUSLE approach in conjunction with GIS (Tosic et al. 2011, Blackley et al. 2015, Kouli & Soupios 2009, Lanorte et al. 2019, Milentijević et al. 2021, Polykretis et al. 2020, Prasannakumar et al. 2011a, Swarnkar et al. 2017, Yuksel et al. 2008, Golijanin et al. 2022).

The Revised Universal Soil Loss Equation (RUSLE) is a widely used model in Geographical Information Systems (GIS) for predicting soil erosion and assessing the impact of land use activities on soil loss (NSW 2021). The RUSLE model considers multiple factors that contribute to soil erosion, including slope gradient, soil type, land cover, climate, and land management practices. The model uses a set of algorithms to calculate the erosion risk for each cell in a given geographic area.

Land degradation is a growing concern in the small coastal state of Goa in India. Goa is a global tourist destination that has been rapidly expanding in recent years, putting immense pressure on the land. In recent years, Goa has been facing multiple forms of land degradation that are threatening not only its environment but also its social and economic well-being. Urbanization, changes in land use, land cover, deforestation, and mining activities have led to soil erosion, loss of soil fertility, and depletion of groundwater resources. Hence, this chapter attempts to examine the extent of land degradation that has occurred in the State of Goa using the RUSLE model.

OBJECTIVES

The key objectives of this study include

1. To understand the concept of integrated land degradation and its impact on Goa's environment.
2. To identify and analyze the different types of land degradation occurring in Goa using remote sensing data.
3. To apply geostatistical techniques to create a comprehensive map of land degradation in Goa.
4. To quantify the extent of land degradation in Goa and determine the spatial distribution of different types of land degradation.

AREA OF INVESTIGATION

Goa is a small coastal state located on the west coast of India. Goa is known for its natural beauty, vibrant culture, and tourism industry. The eco-geography of Goa is unique, with a diverse range of ecosystems, flora, and fauna. The

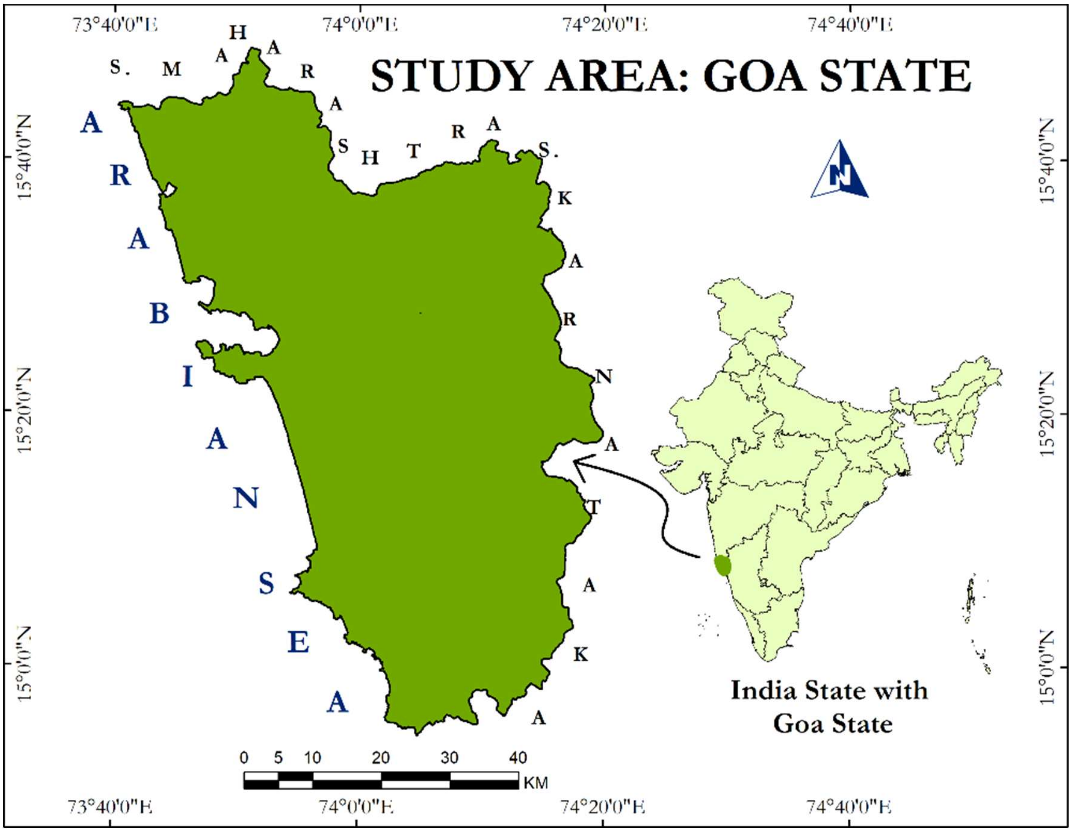

Fig. 1: Map of the study area: Goa.

state is blessed with numerous hills, sandy beaches, rocky cliffs, rivers, waterfalls, estuaries, mangroves, forests, and that attract millions of visitors from all over the world.

Mathematically, Goa extends amidst the parallels of 1400‘45°” to 1559‘47°” North latitudes and 7354‘40°” to 7411‘20°” east of meridians (Prabhu Gaonkar et al. 2022) (Fig. 1). It covers a geographical expanse of 3702 sq. km. It tolerates pressure of 1,458,545 persons (2011, Census). The State of Goa is 105 km long and 65 km wide. To the north, Goa is bordered by Maharashtra, while to the south lies Karnataka, and on the western side, it is surrounded by the blue waters of the Arabian Sea.

Goa’s territory has been classified into four physiographic divisions by the Geological Survey of India, which are:

1. Western Ghats Region (700-1000 Meters above Sea Level)

2. Foot Hill Region of Western Ghats (300-700 Meters above Sea Level)

3. Undulating Terrain (10-300 Meters above Sea Level)

4. Coastal Plains (0-10 Meters above Sea Level)

The eco-geography of Goa is under threat from various human activities, including mining, deforestation, urbanization, and tourism. Mining activities in the state have led to soil erosion, water pollution, and loss of biodiversity. Deforestation, primarily for commercial purposes, has led to soil degradation and loss of forest cover. Urbanization, particularly in the coastal areas, has led to the destruction of natural habitats and the loss of biodiversity. The tourism industry, which is a major source of revenue for the state, has also put pressure on the state’s natural resources, including water, land, and forests.

MATERIALS AND METHODS

This study is the result of primary and secondary data sources. Primary data were collected from field observations and ground-truthing, while the secondary data were derived from the following sources (Table 1).

There are several steps involved in the RUSLE model implementation methodology. The creation of the input parameter database is the first step. Using measurements taken in the field of the rates of soil erosion, the second step is to calibrate the model. The third step involves applying the equations to the database’s input parameters to determine the

Table 1: Databased used for RUSLE model.

Sr. No.	Data Type	Description	Sources
1.	Satellite Data	https://earthexplorer.usgs.gov_	LANSAT OLI for the year 2021 was grouped into 7 classes
2.	Digital elevation model	https://earthexplorer.usgs.gov	SRTM with 30m resolution
3.	Rainfall Data	Indian Meteorological Department, Goa-India	Rainfall data from 12 rain gauge stations for 30 years
4.	Soil Data	Directorate of Mines and Geology, Goa-India	The study area's soil map is categorized into seven classes based on the texture of the soil.

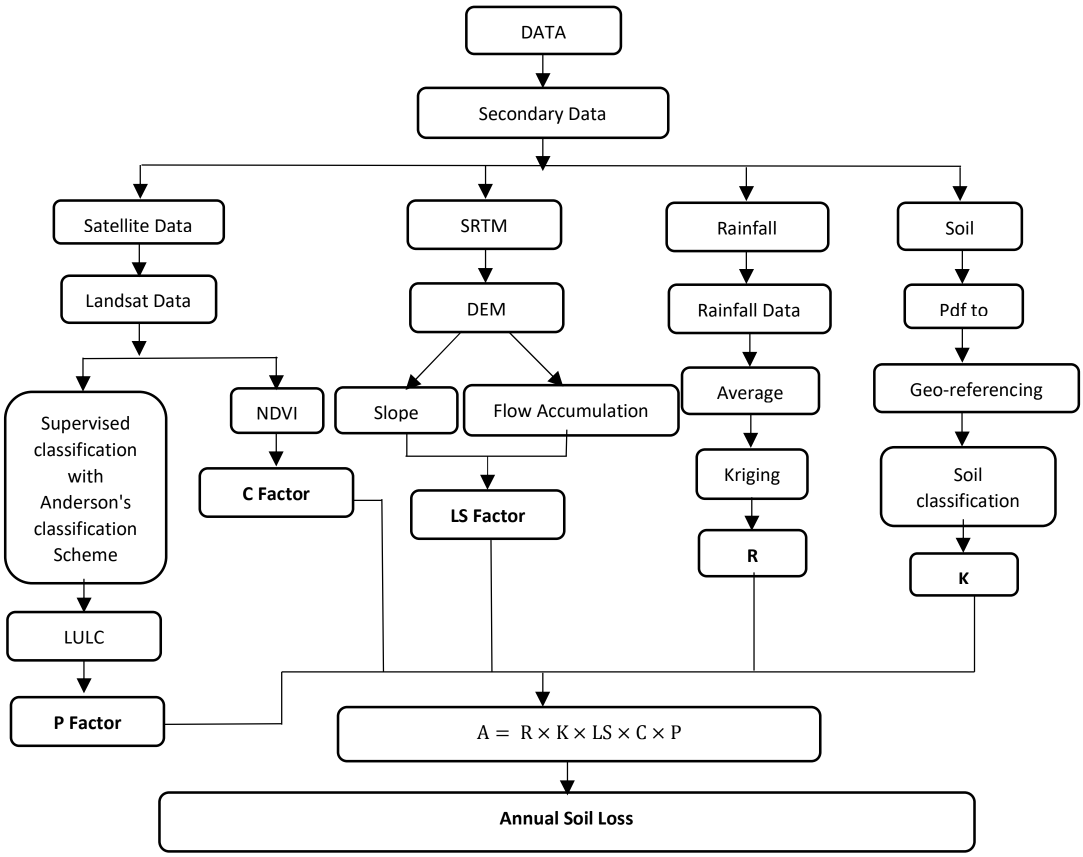

Fig. 2: Methodology chart.

risk of soil erosion for each cell. The fourth step is to look over the results and figure out where soil erosion is most likely. The development of management plans to lessen the likelihood of soil erosion in these locations is the final step (Fig. 2).

The RUSLE model employs a set of algorithms to calculate the erosion risk of each cell within a specific geographical area. By utilizing a GIS environment, the output of the RUSLE model can be showcased to exhibit the risk of soil erosion across a given landscape (Jarašiunas et al. 2020, Terranova et al. 2009). The RUSLE model uses five parameters to determine the average yearly soil loss measured in tons per hectare (Benavidez et al. 2018, Ganasri & Ramesh 2016, Ghosh et al. 2022, Kulimushi et al. 2021, Negese et al. 2021, Tayebi et al. 2019, Terranova et al. 2009, Thomas et al. 2018a).

$$A = R \times K \times LS \times C \times P \qquad \ldots(1)$$

Where A signifies the average soil loss, R stands for rainfall-runoff erosivity, K for soil erodibility, LS for slope length and slope steepness, C for cover management, and P for conservation practices (Abdul Rahaman et al. 2015, Prasannakumar et al. 2012, Thomas et al. 2018b). Dimensionless parameters include LS, C, and P factors (Prasannakumar et al. 2011b). The data inputs for the RUSLE model used in this study were obtained from various sources. Rainfall data was sourced from the Indian Meteorological Department, while soil data was acquired from the Directorate of Mines and Geology in Goa. Landsat-8 OLI-TIRS data and elevation data were retrieved from the GLOVIS website to determine slope length, slope steepness, and conservation practices. To create a soil erosional map, the raster outputs of all parameters were processed using the "Raster Calculator" tool, found within the "Spatial Analyst tools" in the ArcGIS 10.8 edition. By incorporating information on rainfall, elevation, soil, and land use/land cover, the study was able to estimate soil loss within the state of Goa.

RESULTS AND DISCUSSION

Rainfall-Runoff Erosivity (R Factor)

A thorough evaluation of rainfall erosivity is essential to comprehend hydrological and geomorphological processes as it denotes the potential of rainfall to erode soil (Yassoglou et al. 2017). The computation of the R-factor is a challenging undertaking that heavily depends on multiple factors, including the length, volume, intensity, energy, and size of raindrops, as well as the precipitation pattern and ensuing runoff rates (Farhan & Nawaiseh 2015, Jarašiunas et al. 2020). Rainfall probability can be determined using rainfall

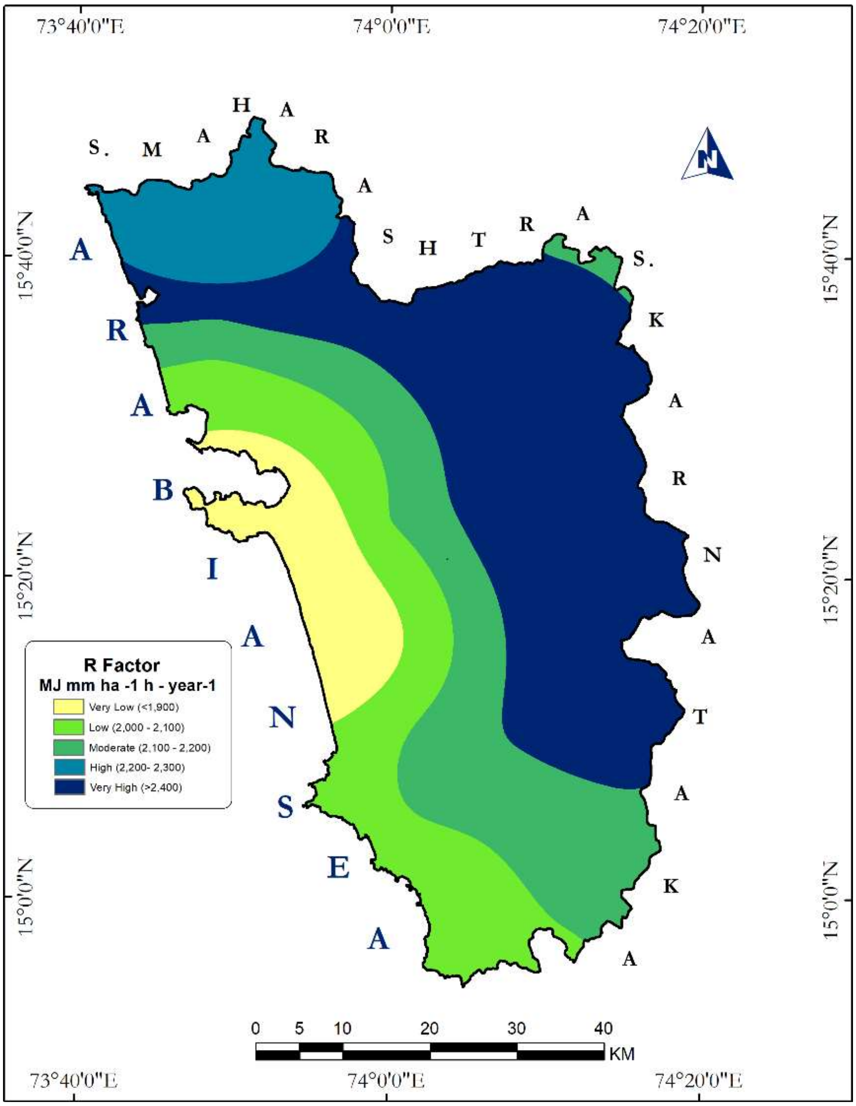

Fig. 3: The study area map depicting R- Factor: Rainfall erosivity.

Table 2: Taluka-wise rainfall distribution, Goa.

Station	Average of 1971-2020	Actual Rainfall in 2021	Station	Average of 1971-2020	Actual Rainfall in 2021
Tiswadi (Panaji)	2904.6	3935.7	Sanguem (Sanguem)	3687.9	4438.5
Bardez (Mapusa)	2990	4041.2	Dharbandora (Dharbandora)	NA	NA
Pernem (Pernem)	NA	5247.6	Ponda (Ponda)	3453.3	4361.6
Bicholim (Sanquelim)	NA	4304.3	Canacona (Canacona)	NA	3836.6
Sattari (Valpoi)	4160.9	4499.3	Quepem (Quepem)	3617.1	4457.8
			Salcete (Margao)	3040	3242.8
			Mormugao (Mormugao)	2719.6	3206.6
North Goa	3351.8	4252.1	South Goa	3212.55	3768.2
			Goa	3277.8	3995.1

Source: Indian Meteorological Department, Goa

intensity (Amellah & el Morabiti, 2021). Multiple research papers have employed the average annual precipitation data to calculate the R-factor in the study area using the same methodology (Abdul Rahaman et al. 2015, Prasannakumar et al. 2011a, 2011b, Swarnkar et al. 2017, Taylor 2009, Thomas et al. 2018a).

$$R = P * 0.5 \qquad \ldots(2)$$

The symbol R represents yearly precipitation data. To determine the precipitation levels for the year 2021, data was obtained from the Indian Meteorological Department, drawing from average data from 12 different locations. This data was subsequently converted into raster format using “multi-dimensional tools” and “Make NetCDF Raster layer” in ArcGIS 10.8. The modified raster layer was then transformed into points using “Conversion Tools.” Finally, a rainfall map of the study area was produced using the statistical tool “Kriging” found within the “Spatial Analyst Tools” in ArcGIS 10.8, utilizing the collected points (Allafta & Opp 2021, Jarašiunas et al. 2020).

The coastal region of western India receives a significant amount of rainfall, making it one of the highest precipitation-receiving areas in the country. During the monsoon season from June to September, over 90% of the annual rainfall is concentrated in this region (Nandargi & Gupta, 2018, Patwardhan & Asnani 2000). Study shows that there is a swift surge in precipitation along the Arabian Sea coast in close proximity to the Western Ghats’ maximum elevation line (Patwardhan & Asnani 2000). Our study also reveals the same (Fig. 3 & Table 3).

The average annual rainfall in Goa is more than 3200 mm, with some variations depending on the region (Table 2). It is an observed fact that rainfall can have a significant impact on erosion. When it rains, water runs off the ground, causing soil erosion as it carries away topsoil, sediments, and other materials. The more intense the rainfall, the greater the potential for soil erosion.

The R factor for Goa varies depending on the location and the season. Though the western parts of Goa, including the coastal areas, receive less rainfall than the eastern parts of the state, it experiences cyclones and intense storms during the monsoon season, which can increase the erosive power of rainfall.

Rainfall erosivity is a critical factor in determining the potential for soil erosion. High rainfall erosivity leads to increased soil erosion rates, which can have negative impacts on soil fertility, water quality, and ecological health. As per the data presented in (Table 3), it is clear that almost half of

Table 3: Area of R- R-Factor: Rainfall erosivity.

Sr. No	Intensity	Area in Sq. Km.	Area in %
1.	Very Low	327.70	8.85
2.	Low	710.77	19.20
3.	Moderate	839.20	22.66
4.	High	323.83	8.74
5.	Very High	1501.39	40.55
	Total	3702.00	100.00

Goa's total geographical area (i.e., 50%) is categorized as having high and very high rainfall erosivity indicating that a significant portion of Eastern Goa is vulnerable to high levels of soil erosion due to intense rainfall. Additionally, around 22.66% of the total area of Central Goa is under moderate erosivity, which experiences moderate rainfall, indicating moderate soil erosion, while roughly 28% of the area falls under the category of very low-to-low rainfall erosivity. This suggests that western Goa experiences less intense rainfall, resulting in lower levels of soil erosion.

Cover Management (C Factor)

The C-factors are critical parameters for crop management, as they are closely linked to land-use types and reduction factors in soil erosion (Jazouli et al. 2019, Nigel & Rughooputh 2010, Rabia 2016). However, the majority of Indian crops lack C-factors, necessitating the use of values discovered by previous research (Almagro et al. 2019, Karaburun 2010, Solanky et al. 2018, Zhou 2009) to evaluate the impact of cropping and management strategies on soil erosion rates in agricultural regions. The C-factor is a dimensionless factor ranging from 0 to 1, with 0 indicating completely non-erodible conditions in areas with high green vegetation cover, while 1 indicates greater soil loss due to extensive tillage, leaving a smooth surface that generates significant runoff and makes the soil susceptible to erosion. NDVI spectral indices are calculated using the following equation:

$$\mathrm{NDVI} = \frac{NIR-RED}{NIR+RED} \qquad \ldots(3)$$

Where band 5 of OLI is the reflectance of near-infrared, while Red is the reflectance of the visible red band that is band 4 of OLI. The equation was used to compute the geographical distribution of the C factor (Chinthaparthi & Student 2007, Fathizad et al. 2014, Ganasri & Ramesh 2015, UNCCD 2017, Wischmeier 1959).

$$C = exp\left[-\propto \frac{NDVI}{\beta - NDVI}\right] \qquad \ldots(4)$$

Land Use Land Cover (LULC) influences soil erosion rates. Different land cover types have varying soil erodibility. For example, a field with bare soil has a higher C factor than a field with vegetation cover because bare soil is more susceptible to erosion. The study area consists of five main

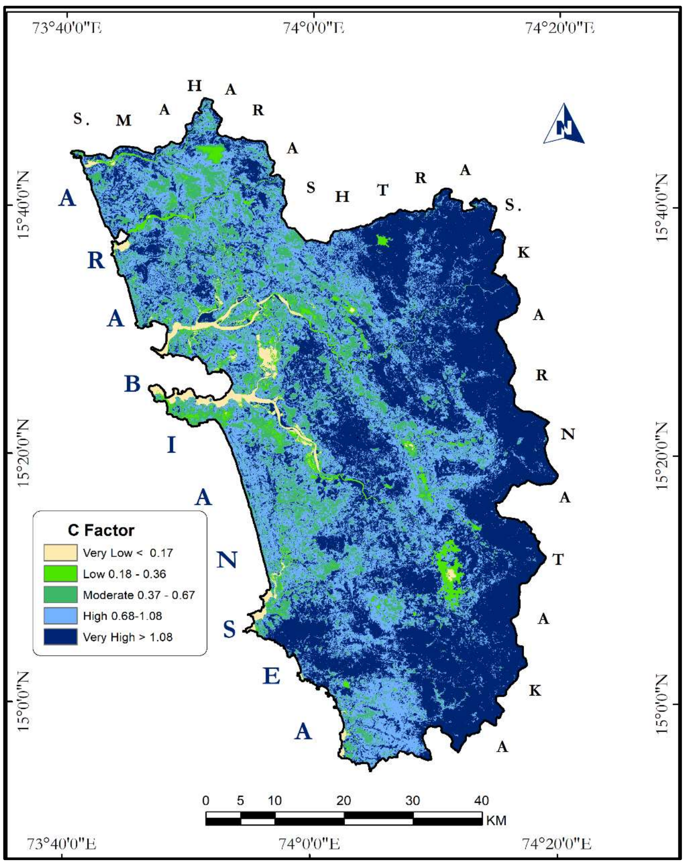

Fig. 4: The study area map depicting C- Factor: Cover Management.

Table 4: Area of C- Factor: Cover Management.

Classes	Area in Sq. Km.	Area in %
Very Low	1734.75	46.86
Low	1263.83	34.13
Moderate	524.68	14.17
High	101.38	2.73
Very High	77.36	2.09
Total	3702.00	100.00

LULC types, namely Vegetation, Flooded Vegetation, Agriculture, Built-up, and Barren land. Previous literature was consulted to determine the appropriate C factor values for each of these classes. The C factor values ranged from the lowest value of 0 assigned to the waterbody class to the highest value of 1 assigned to the Vegetation, Flooded Vegetation, Built-up, and Barren land classes. The Agriculture class was assigned a C factor value of 0.5.

It is evident from (Table 4) that the largest C factor class is "Very Low," covering almost half (46.86%) of the study area, followed by "Low" at 34.13%. These two classes indicate that the majority of the study area has a low susceptibility to soil erosion, which is a positive indication

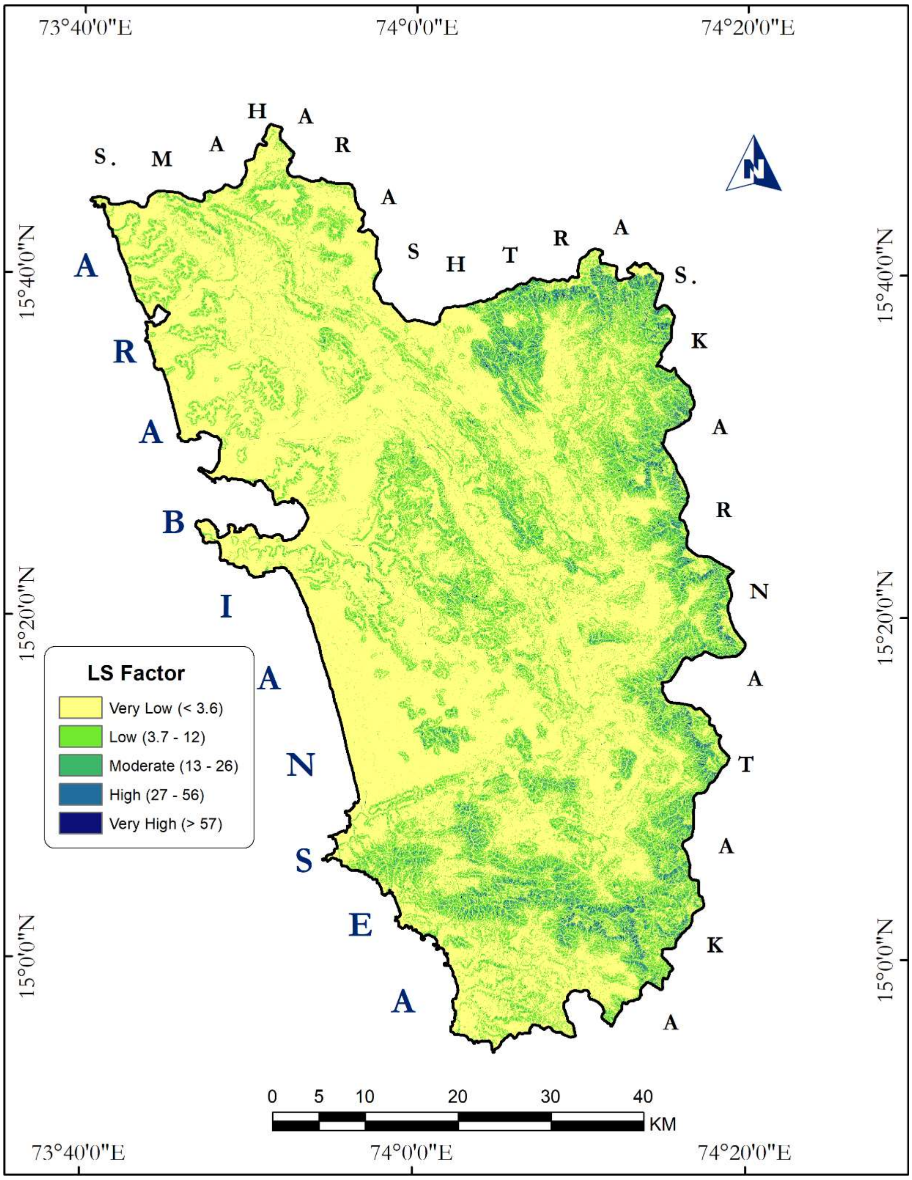

Fig. 5: The study area map depicting LS- Factor: Soil slope length.

for sustainable land management practices.

The “Moderate” class covers a smaller area of 14.17%, suggesting that some parts of the study area have moderate susceptibility to soil erosion. Meanwhile, the “High” and “Very High” classes have a combined area of only 4.82%, indicating that the study area has a relatively low susceptibility to severe soil erosion.

Slope Steepness and Slope Length (LS Factor)

The LS factor was computed in ArcGIS using a Digital Elevation Model (DEM) (Jarašiunas et al. 2020, Jazouli et al. 2019). It combines the effects of slope length (L) and steepness (S) on soil erosion in RUSLE. Steeper and longer slopes generate higher overland flow velocities, leading to greater runoff and increased potential for soil loss (Wagari & Tamiru 2021). The LS parameter, which is the product of L and S, quantifies the terrain’s impact on erosion (Jarašiunas et al. 2020, Lastoria et al. 2008). As the slope steepness increases, the runoff velocity and erosivity also increase. The values for L and S were obtained using ArcGIS Spatial Analyst tools. Other studies computed the LS factor using the same method by collecting 30 M SRTM datasets (Fayas et al. 2019, Moore & Burch 1986, Prasannakumar et al. 2011, UNCCD 2017). This approach was also followed for the study region.

$$LS = (Flow\ accumulation \times Cell\ size/22.13)^{0.4} \times (Sin\ slope/0.0896)^{1.3} \quad \ldots(5)$$

The LS factor plays a crucial role in the RUSLE Model since it accounts for the impact of topography on soil erosion. By incorporating slope length and steepness, the LS factor can effectively pinpoint areas that are more susceptible to soil loss and prioritize conservation measures to mitigate erosion.

In the study area, the “Very Low” and “Low” LS-factor classes dominate, covering almost 70% and 21.67% of the area, respectively. These classes indicate that the majority of the study area comprises gentle slopes and short slope lengths, which are less prone to soil erosion.

The “Moderate” LS-factor class covers a relatively smaller area of 6.29%, suggesting that some parts of the study area have moderate slope steepness and length, which may increase the risk of soil erosion. Meanwhile, the “High” and “Very High” classes combined only occupy 2.25% of the study area, indicating that the number of steep and long slopes highly vulnerable to soil erosion is limited.

Overall, the distribution of LS-factor classes suggests that the study area is relatively less susceptible to soil erosion due to the preponderance of gentle slopes and short slope lengths. However, it is important to note that certain parts of the area with moderate slope steepness and length may still be at risk and require conservation measures to reduce soil loss.

Soil Erodibility (K Factor)

Soil erodibility (K) is a metric that indicates the vulnerability of soil or surface material to erosion, sediment transportability, and the volume and speed of runoff for a given amount of rainfall under typical conditions (Zhao et al. 2012). The K factor is determined based on the inherent characteristics of soil, including physical, chemical, and mineralogical properties, which all contribute to soil erosion (Franzluebbers 2010, Fu et al. 2006, Pal & Chakrabortty 2019, Phinzi & Ngetar 2019). For instance, soils with a loamy texture, which are medium-grained and have a tendency to disintegrate and runoff, often exhibit high K values (Yuksel et al. 2008).

The K factor map was generated using the soil texture map obtained from the Directorate of Mines and Geology, Goa. The area of investigation was divided into six primary textural classifications of soils, and the corresponding K values were determined from different sources (Abdul Rahaman et al. 2015, Polykretis et al. 2020, Wagari & Tamiru 2021).

The K value of soil is dependent on its location and texture. Clayey soil has low K values due to its high resistance to separation, while sandy soil, which is coarse-grained, also has low K values and low runoff potentials. Conversely, loamy, fine loamy type, and fine mixed soils have high K values, as they are more prone to disintegration

Table 5: Area of LS- Factor: Soil Slope Length.

Classes	Area in sq. km	Area in %
Very Low	2584.06	69.80
Low	802.04	21.66
Moderate	232.8	6.28
High	59.55	1.60
Very High	23.55	0.63
Total	3702.00	100.00

Table 6: Depicting K values.

Sr.No.	Soil Texture Type	K Values
1.	Clayey	0.0402
2.	Loamy	0.26
3.	Fine Loamy	0.07
4.	Fine Loamy Typic	0.39
5.	Fine Mixed	0.43
6.	Sandy	0.20

Table 7: Showing the area of K- Factor: Soil Erodibility.

Classes	Area in sq. km	Area in %
Very Low	102.41	2.76
Low	2101.15	56.75
Moderate	325.47	8.79
High	54.20	1.46
Very High	1118.76	30.22
Total	3702.00	100

and generate more runoff. In the study area, six major soil texture classes were identified, including clayey, loamy, fine loamy, fine loamy type, fine mixed, and sandy.

The lowest K value is < 0.01, which is for the waterbody, while the highest K value (> 0.2) is located near the coastal belt to the mid-region of the study area. The fine mixed soil, which has a K value of 0.43 (Table 6), is classified as a very high class and is located in the eastern part of the state of Goa.

Table 7 indicates that the majority of the study area falls under the "Low" K factor class, covering 56.76% of the total area. The "Very High" K factor class covers 30.22% of the study area, indicating that a significant portion of the area is prone to soil erosion due to its soil texture. The "Moderate" and "High" K factor classes cover relatively smaller areas, indicating that only a few parts of the study area have soil textures that are more susceptible to soil erosion.

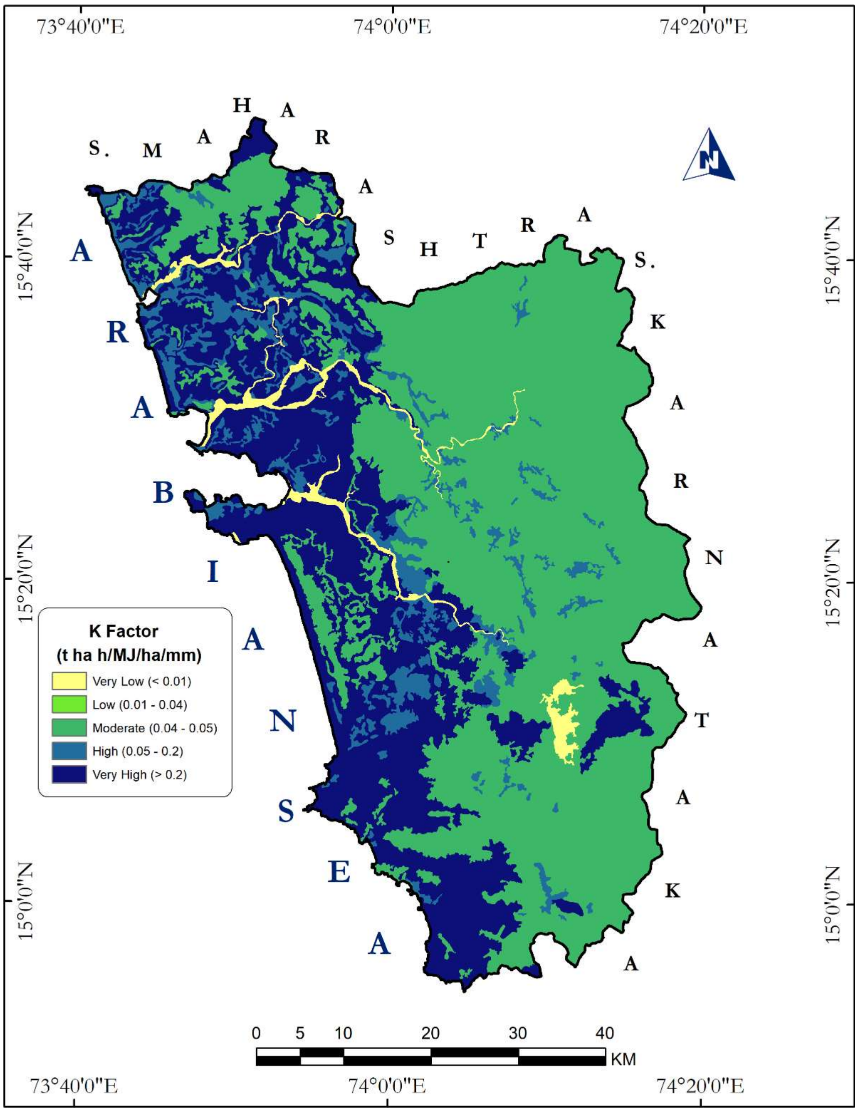

Fig. 6: The study area map depicting K- Factor: Soil erodibility.

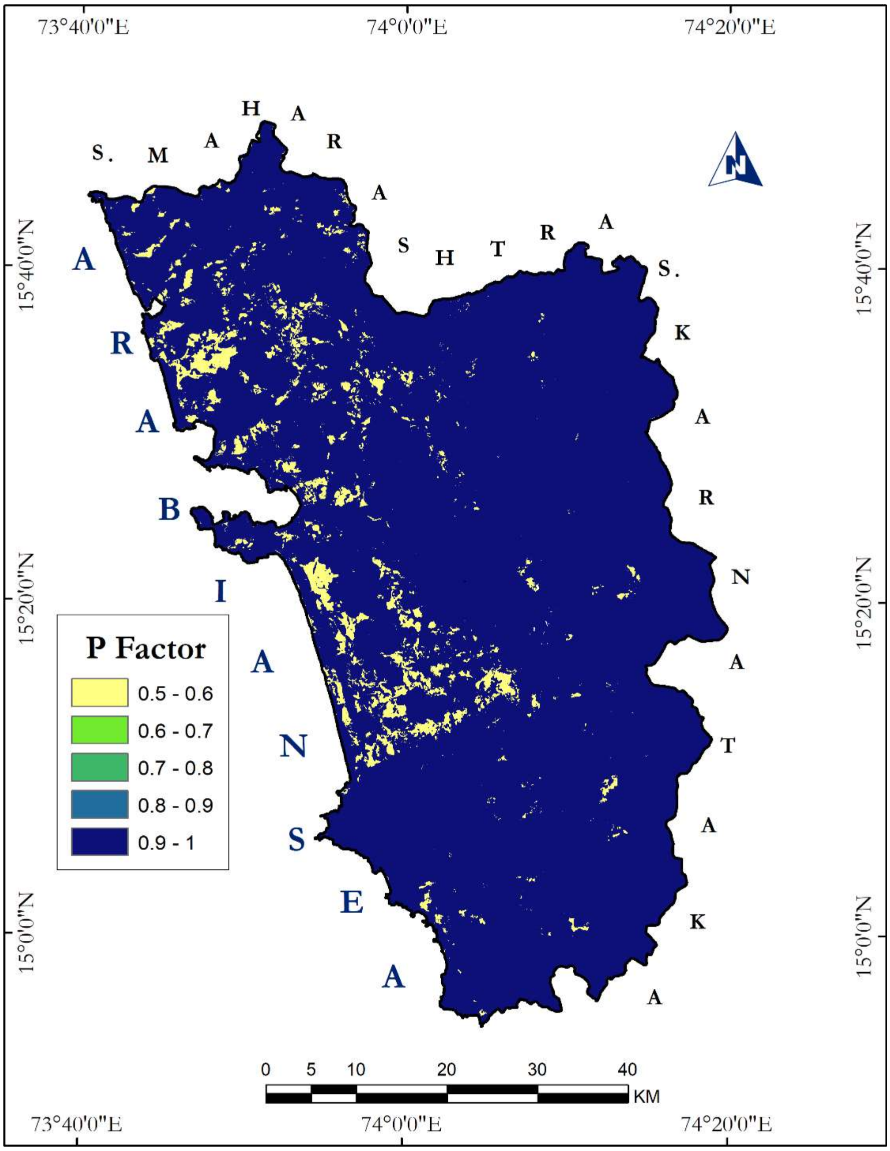

Fig. 7: The study area map depicting P- Factor: Conservation practice.

Conservation Practice (P Factor)

Erosion control measures, represented by the P factor (Naqvi et al. 2012), have an impact on the yearly soil loss in the research area. The support practice factor (Boggs et al. 2001, Karydas & Sekuloska 2009, Lee 2004, Yassoglou et al. 2017) indicates the effectiveness of measures that reduce water runoff volume and pace, as well as soil erosion. The P factor ranges from 0 to 1, with values close to 0 indicating good conservation practices and values close to 1 indicating poor conservation practices (Mohan & Kumaraswamy 2015, Periyasamy 2017). Land-use land-cover classes are used to determine the P factor, and the same process was used to determine the study area's P factor. No conservation activities receive the highest values, while the most effective conservation practices receive the lowest values.

The P factor is influenced by the terrain slope, with values ranging from 0 to 1. A value close to 0 indicates strong conservation behavior, while a value close to 1

Table 8: The area of P- Factor: Conservation practice.

Sr. No.	Area in sq. km	Area in %
1.	204.52	5.52
2.	3497.48	94.47
Total	3702.00	100.00

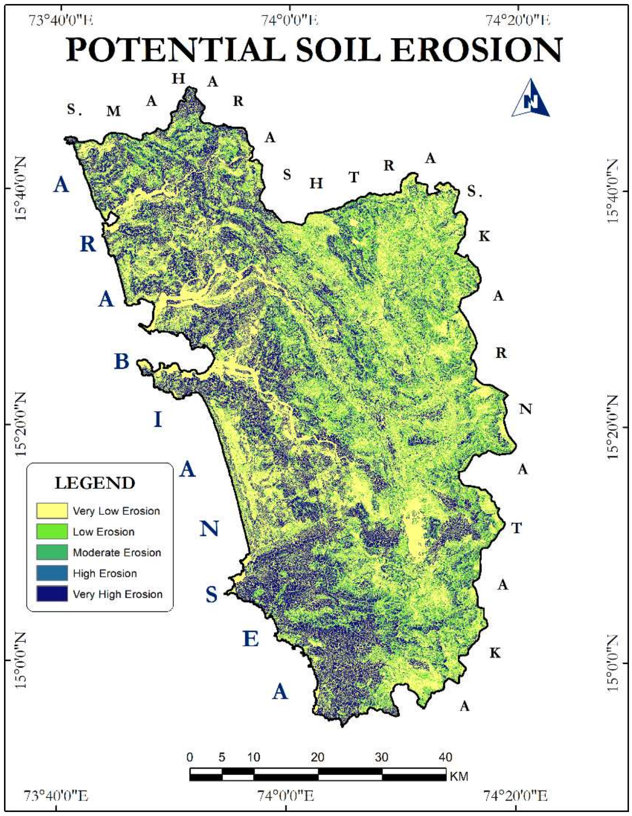

Fig. 8: RUSLE-based soil erosion rate estimated for the state of Goa.

indicates poor conservation practice. Within the study area, a P factor value of 0.5 pertains solely to a limited number of patches distinguished by the yellow color, indicating good conservation practices. Conversely, patches marked in blue represent bad conservation practices. Only 5.524% of the area is classified as being under the good conservation category, while the remaining 94.475% falls under the bad conservation category (Table 8).

RUSLE-based Soil Erosion Rate Estimation

The study area's potential soil erosion was evaluated using five key parameters, namely Rainfall Erosivity (R factor), Slope Steepness and Slope Length (LS factor), Soil Erodibility (K factor), Conservation Practice (P factor), and Cover Management (C factor). Figs. 3 to 7 illustrate the outputs of each parameter. The R factor indicates that higher rainfall intensity corresponds to higher erosion potential. The LS factor helps to understand slope steepness, where steeper slopes result in higher runoff and erosion. The C factor helps us understand the effects of Land Use Land Cover (LULC) on soil loss rates. The K factor describes soil's vulnerability to the rate of runoff and erosion, with soils that generate large runoff having the highest K values.

Based on the RUSLE-based soil erosion rate estimated for the state of Goa (Fig. 8), the entire State is classified into five categories based on its erosion risk such as very low, low, moderate, high, and very high.

The largest area falls under the "very low" erosion risk category, which comprises 48.03 percent (1778.20 sq. km) of the total area. This is followed by the "very high" erosion risk category, which comprises 24.35 percent (901.69 sq. km) of the total area (Table 9).

The "low" and "moderate" erosion risk categories each comprise a smaller proportion of the total area, with 14.68 percent (543.61 sq. km) and 8.81 percent (326.27 sq. km), respectively. The "high" erosion risk category is the smallest, comprising only 4.11 percent (152.20 sq. km) of the total area (Table 9).

CONCLUSION

Overall, the findings of this study provide valuable insights into the potential soil erosion in the state of Goa, which can be used to develop effective soil conservation strategies. By identifying the areas with the highest erosion

Table 9: The area of potential soil erosion.

Classes	Area in sq. km	Area in %
Very Low	1778.20	48.03
Low	543.61	14.68
Moderate	326.27	8.81
High	152.20	4.11
Very High	901.69	24.35
Total	3702	100

risk, policymakers can prioritize the implementation of conservation practices and cover management strategies to reduce soil loss rates. Additionally, these results can be used to inform land use planning decisions and ensure sustainable land use practices in the region.

It is important to note that the study's results are based on modeling and estimation techniques and are subject to some degree of uncertainty. Therefore, further research is needed to validate these findings and assess the effectiveness of soil conservation measures in mitigating erosion rates. Nonetheless, the study provides a solid foundation for understanding the potential soil erosion in the state of Goa. It highlights the importance of sustainable land use practices to protect the region's soil resources.

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ORCID DETAILS OF THE AUTHORS

V. G. Prabhu Gaonkar: https://orcid.org/0000-0002-2252-8274
F M Nadaf: https://orcid.org/0000-0002-5846-4591
Vikas Kapale: https://orcid.org/0000-0002-3069-6542