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Assessment of Influencing Factors of Wayanad Landslides on July 30, 2024, India Using Geoinformatics

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Abstract
Landslides are a major natural hazard in Wayanad, Kerala, India, where steep terrain, intense monsoons, and human activities make the region highly vulnerable to landslides. Assessing the key factors influencing landslides is crucial for effective risk assessment and mitigation. This study employs geoinformatics, the Analytic Hierarchy Process (AHP), and spectral indices (NDVI, NDWI, BSI, NDMI) to analyze critical parameters, including slope, rainfall, elevation, rock type, and soil texture. By integrating remote sensing, GIS, and multi-criteria decision-making, the research determines the most influential factors contributing to landslides. The findings provide valuable insights for disaster preparedness, land-use planning, and risk reduction strategies in Wayanad.

Keywords
Landslides; Geoinformatics; AHP; Spectral Indices; Wayanad

Introduction

Landslides are a significant geo-environmental risk in mountainous terrain globally, frequently initiated by synergistic natural processes and anthropogenic activities. The Western Ghats, a UNESCO World Heritage site and one of the eight "hottest hotspots" of biodiversity, are extremely vulnerable to such catastrophes, particularly during the monsoon period (Sajinkumar et al., 2021; Ajin et al., 2022). In Kerala's Wayanad district, landslides have become common as a result of its irregular landscape, high rainfall, weak rock structures, and growing land-use changes. The July 30, 2024, landslide in Wayanad resulted in heavy damage to infrastructure, cropland, and natural habitats, highlighting the importance of conducting an in-depth analysis of its root causes (Rajaneesh et al., 2025; Sreenivas & Chauhan, 2025).

Conventional practices for constructing landslide susceptibility maps often struggle to integrate the diverse, interconnected factors that govern slope instability. Multi-criteria decision-making procedures, however, such as the Analytical Hierarchy Process (AHP), have been instrumental in this role. AHP enables the organized combination of varying landslide conditioning elements through pairwise comparisons and the application of weights based on subjective expert judgment (Saaty, 1980). When combined with Geographic Information Systems (GIS), AHP provides a powerful method for creating reproducible and spatially explicit landslide susceptibility maps (Mondal & Maiti, 2013; Kumar & Anbalagan, 2016).

This research combines the Analytical Hierarchy Process (AHP) with a set of remote sensing parameters and topographic factors to assess the major drivers that caused the 2024 Wayanad landslide. Of these, the Normalized Difference Vegetation Index (NDVI) is employed to analyze vegetation cover, as it plays an important role in ensuring slope stability. Healthy vegetation stabilizes the soil, decreases surface runoff, and reduces erosion, all of which are significant in forestalling the onset of landslides (Niraj et al., 2023; Pham et al., 2022). The Normalized Difference Moisture Index (NDMI) and Normalized Difference Water Index (NDWI) facilitate the identification of soil and plant moisture, as well as surface water, both of which are critical in inducing landslides under saturated conditions (Gao, 1996; McFeeters, 1996). The Bare Soil Index (BSI) determines areas of exposed soil that are susceptible to erosion and surface instability, thereby helping to determine areas prone to landslides (Polovina et al., 2024).

Moreover, terrain parameters like the Compound Topographic Index (CTI), Stream Power Index (SPI), and Standard Curvature are integrated to evaluate the hydrological and geomorphological processes of the terrain (Dar et al., 2019; Singh et al., 2023). These factors have been found to efficiently represent areas of high water accumulation, flow divergence, and slope curvature, favorable conditions for slope failure (Florinsky, 2016; Pourghasemi et al., 2012).

Through the integration of these indices and terrain characteristics through AHP in a GIS environment, this research seeks to assess the significance of landslide-influencing factors in Wayanad. The result not only elucidates the significance and spatial variation of certain landslide-causing factors but also serves as an essential decision-making tool for land-use planning, disaster mitigation, and sustainable development in other susceptible hilly regions.

Geographical location and geologic setting of the study area

The study area for this research is the Wayanad district, located in the northeastern part of Kerala, India. Geologically, Wayanad is part of the Deccan Plateau and is characterized by Precambrian rocks of ancient age, primarily granite-gneiss. These underlying rock units are overlaid by lateritic soils due to the intense tropical weathering processes prevalent in the region. The region is further traversed by numerous fault lines and fractures, making it particularly susceptible to tectonic activity and slope failure, especially during the monsoon season (GSI, 2020).

The geomorphology of Wayanad is characterized by its hill landscape, which comprises steep slopes, deep valleys, and rough terrain. The elevation varies from about 700 meters to 2,100 meters above sea level, with Chembra Peak being the highest in the district (District Survey Report, Wayanad, 2017). The northern section of the district is made up of a generally flat plateau, which is quite distinct from the escarpments of the steep southern and eastern edges. There are several rivers, such as the Kabini and its tributaries, which cut through the landscape, contributing to the geomorphic diversity and landslide risk.

The major land use and land cover (LULC) comprises agriculture. Plantation crops include tea, coffee, and pepper, while paddy is prevalent in valley bottoms (John et al., 2020). Although tropical evergreen and deciduous forests exist, especially within protected areas such as the Wayanad Wildlife Sanctuary, deforestation is becoming a growing concern. This is mainly fueled by increasing agricultural operations and increasing tourism-related development (Kerala Forest Department, 2018). Wayanad receives high annual rainfall, ranging from 2,500 mm to more than 4,000 mm, primarily due to the southwest monsoon. These heavy, short-duration rainfalls are one of the major initiators of landslides, especially in steep terrain areas with reduced vegetation cover (IMD, 2020).

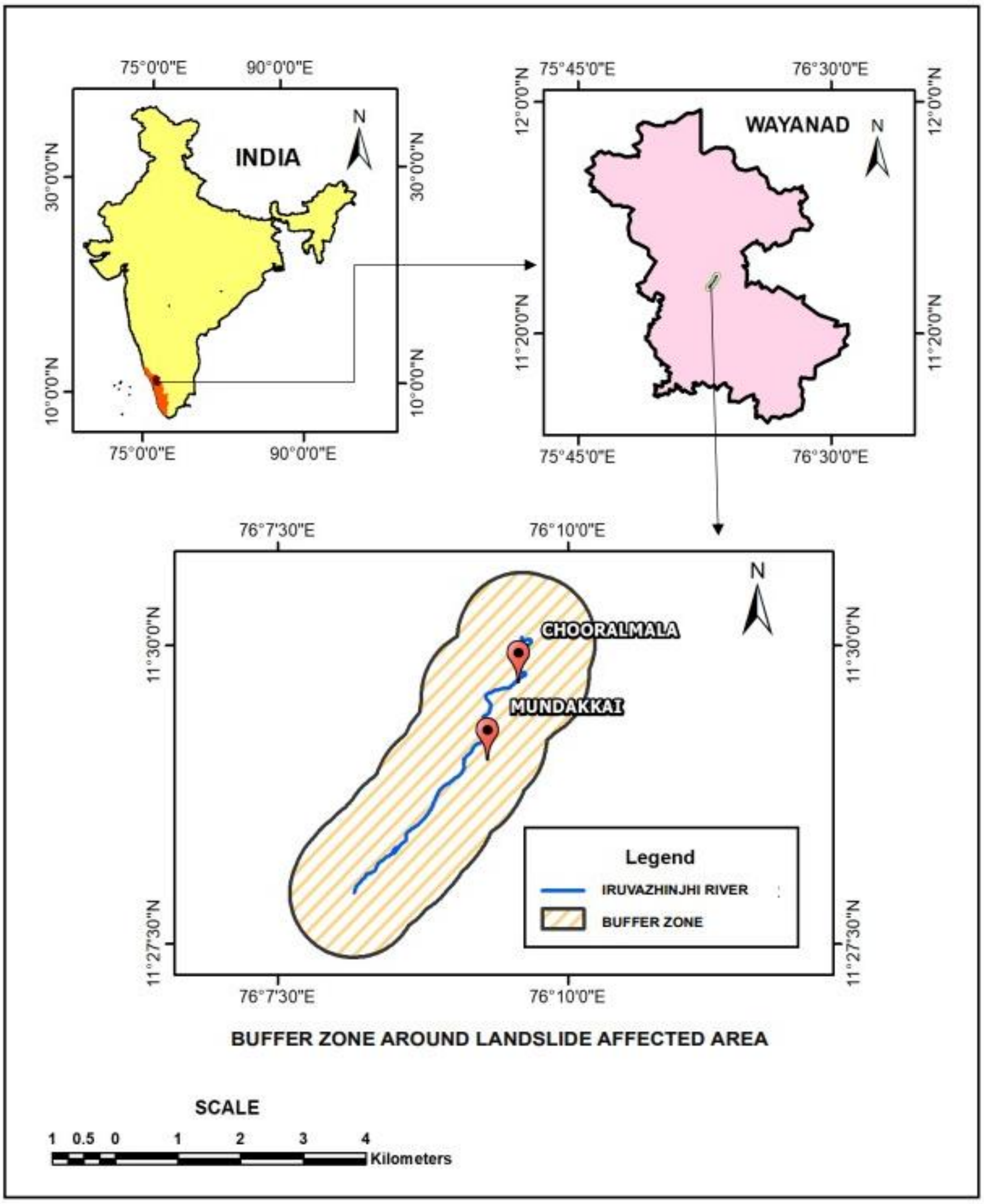

Fig. 1. Study Area

The district has a population of 817,420 according to the 2011 Census of India, with a density of 383 persons per square kilometer. The region is still rural-dominated, and the main source of livelihood is agriculture. The district is also inhabited by many tribal groups, and urbanization is restricted to the towns of Kalpetta, Sultan Bathery, and Mananthavady.

The susceptibility of Wayanad to landslides was highlighted during the 2019 monsoon season, when villages such as Mundakkai, Chooralmala, Attamala, and Kunhome were extensively damaged. Chooralmala received 572 mm of rain in the 48 hours preceding the landslides (Kerala State Disaster Management Authority, 2019), which led to the collapse of more than 236 structures and damage to over 400 others. The disaster killed at least 254 people, making it one of the most devastating landslide tragedies in Kerala in recent times (Gopinath et al., 2024).

Wayanad is a mountainous area with severe monsoons and fragile ecosystems. The Iruvazhinjhi River tends to swell during the monsoon, and the subsequent soil moisture, coupled with unstable slopes, exacerbates landslides. The landslide would most probably have occurred because of heavy rainfall, river erosion, and the slope's angle. Buffering the river aids in identifying areas vulnerable to landslides and in preparing steps to minimize their occurrence and effects. Consequently, a 1 km buffer area was established along the Iruvazhinjhi River to evaluate landslide-affected areas in Wayanad. It assists in identifying risk areas, identifying nearby communities and buildings, and evaluating factors such as erosion and slope failure. The buffer also assists in developing measures of protection, including reforestation and restricted construction, to avoid future destruction.

Data and Methodology

Data

The study utilized a combination of satellite imagery and open-source geospatial datasets to analyze the environmental and geographical characteristics of the study area. Landsat 9 OLI imagery (Scene ID: LC09_L2SP_145052_20240731_20240801_02_T2) was used to obtain high-resolution multispectral data for land surface analysis. The Digital Elevation Model (DEM) derived from the Shuttle Radar Topography Mission (SRTM) was employed to extract elevation and terrain-related parameters such as slope, which are crucial for geomorphological assessments.

Additionally, thematic layers from various reliable sources were integrated into the study, as shown below:

Tab. 1. Data Sources

Thematic layer data	Resolution	Source
LULC	10 m	Sentinel 2
RAI	~5.3 km	CHIRPS yearly rainfall dataset
Geomorphology	0.5 km	Bhukosh
Lineament	0.5 km	Bhukosh
Geology	0.5 km	Bhukosh
Drainage	~500 m	Hydroshades
Slope	30 m	Open topography
Soil	5 km	Bhuvan
Rainfall	~5.3 km	CHIRPS daily rainfall dataset

Methodology

The study focused on the Wayanad landslide of July 30, 2024, beginning with the definition of the study area, identification of landslide events, and setting of objectives. Relevant satellite, DEM, geological, and rainfall data were collected from primary and secondary sources. Using the Analytical Hierarchy Process (AHP), landslide conditioning factors were weighted and analyzed. Geospatial preprocessing involved image correction, DEM and LULC processing, and generation of indices (NDVI, NDWI, NDMI, BSI, CTI, SPI, Standard Curvature). All data were integrated into GIS for analysis. Based on accurate results, findings were documented, influencing factors interpreted, and conclusions drawn.

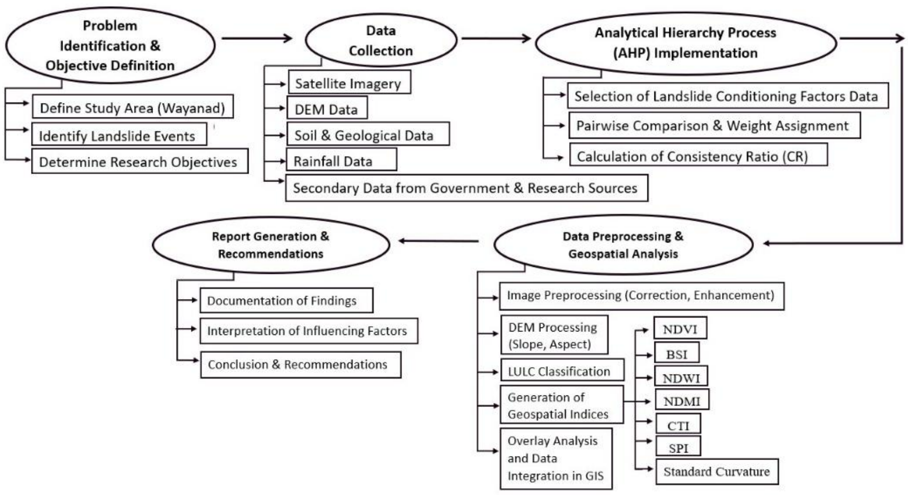

Fig. 2. Methodology Flowchart

Analytic Hierarchy Process (AHP)

The Analytic Hierarchy Process (AHP) is a decision-making technique that simplifies complex problems by breaking them down into more manageable components. It operates on three main principles: problem decomposition, comparative evaluation, and synthesis of relative priorities or rankings. In AHP, the problem is structured into a hierarchy of criteria, which are then evaluated through pairwise comparisons. These comparisons help determine the relative importance of each criterion. The rankings are calculated using the eigenvector method, and the consistency of the results is verified using the consistency ratio. Table 2 presents Saaty's scale for pairwise comparisons (Saaty, 1980).

Tab. 2. Saaty's scale of Analytic Hierarchy Process(AHP)

Degree of Preference	Definition	Explanation
1	Equally Important	The two criteria hold equal significance or exert the same level of influence on the occurrence of landslides
3	Moderately Important	One factor has a greater impact or influence than the other
5	Highly Important	One factor has a significantly greater impact than the other
7	Very Highly Important	One factor significantly outweighs the other in influence
9	Extremely Important	One factor has the greatest potential to influence landslide occurrence compared to the other
2,4,6,8	Intermediate Values	When a trade-off between two factors is necessary, intermediate values may be applied

The consistency of the relative importance weights assigned during the pairwise comparisons can be evaluated using the following equations (Eq. 1, Eq. 2) (Saaty, 1980).

$$\text{Consistency Index (CI)} = (\lambda max - n) / (n - 1) \quad (1)$$

Where, λmax represents the largest eigenvalue, and n denotes the size (order) of the matrix.

$$\text{Consistency Ratio (CR)} = CI / RI \quad (2)$$

Where CI stands for the Consistency Index, whereas RI refers to the Random Index.

The Random Index (RI) values, provided by Saaty, vary based on the value of n. These values are derived from extensive experiments conducted on a large dataset. Table 3 presents the RI corresponding to different values of n (Saaty, 1980). A Consistency Ratio (CR) of 0.1 (or 10%) or lower indicates that the pairwise comparison is consistent. If the CR exceeds 0.1, the results are deemed inconsistent, and the weights in the pairwise comparison matrix need to be revised. The weightage and CR of major causative factors and sub-factors are displayed in Tables 4 and 5, respectively.

Overlay Analysis

Overlay analysis with conditional statements is an effective method in geospatial analysis that can combine several raster layers to derive useful spatial patterns. The technique assesses the pixel-wise combination of classified input layers based on certain logical conditions to produce a resultant new output layer. Conditional statements function as rules of decision, determining output values as a function of input layer class combinations.

Using this method, intricate spatial relationships between different environmental or topographic parameters can be modeled systematically. This is particularly beneficial when dealing with multi-criteria data, as it allows the creation of composite indices or classifications that account for the combined impact of multiple factors. Conditional overlay operations were used in this research to combine various indices, such as spectral (e.g., NDVI, BSI, NDWI, NDMI) and topographic (for instance, CTI, SPI, Standard Curvature), to generate final output layers for various land surface or terrain classes. This rule-based approach provides a rational and uniform step for combining various geospatial data layers. Formulas for the indices from Table 6 were used to calculate them.

Results and Discussion

The results are categorized into two sections: 1. Analytic Hierarchy Process (AHP) and 2. Overlay analysis, which helped to investigate the factors causing landslides in Wayanad. AHP and overlay analysis are established GIS-based techniques that have been extensively studied and utilized in landslide susceptibility mapping for the last two decades. These methods are preferred for their simplicity and effectiveness in producing reliable predictive maps.

1. Analytic Hierarchy Process

In the present study, AHP has been applied using ten parameters associated with landslide susceptibility, namely, slope, rainfall, elevation, rock type, soil type, drainage length and curvature, geomorphological landforms, lineaments, and land use/land cover (LULC).

Tab. 3. Random Index (RI) Table

Number of Criteria	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
RI	0.0	0.0	0.58	0.9	1.12	1.24	1.32	1.41	1.45	1.49	1.51	1.53	1.56	1.57	1.59

Tab. 4. Weightage & CR of Major Causative Factors

Causative Factors	Slope	Rainfall	Elevation	Rock Type	Soil Texture	Drainage	Geomorphology	Lineament	LULC	Weightage	CI	CR
Slope	1	2	3	4	5	6	7	8	9	0.307	0.051	0.035
Rainfall	0.500	1	2	3	4	5	6	7	8	0.218		
Elevation	0.333	0.500	1	2	3	4	5	6	7	0.154		
Rock Type	0.250	0.333	0.500	1	2	3	4	5	6	0.109		
Soil Texture	0.200	0.250	0.333	0.500	1	2	3	4	5	0.076		
Drainage	0.167	0.200	0.250	0.333	0.500	1	2	3	4	0.053		
Geomorphology	0.143	0.167	0.200	0.250	0.333	0.500	1	2	3	0.037		
Lineament	0.125	0.143	0.167	0.200	0.250	0.333	0.500	1	2	0.026		
LULC	0.111	0.125	0.143	0.167	0.200	0.250	0.333	0.500	1	0.019		

Tab. 5. Weightage & CR of Major Causative Sub-Factors

Causative Sub-Factors										
		Low	Moderate	High	Very High			Weightage	CI	CR
Slope	Low	1	0.500	0.333	0.200			0.085	0.017	0.019
	Moderate	2	1	0.500	0.250			0.140		
	High	3	2	1	0.333			0.233		
	Very High	5	4	3	1			0.542		
		Very Low	Low	Moderate	High	Very High	Extremely High	Weightage	CI	CR
Elevation	Very Low	1	0.500	0.333	0.250	0.200	0.167	0.043	0.024	0.019
	Low	2	1	0.500	0.333	0.250	0.200	0.065		
	Moderate	3	2	1	0.500	0.333	0.250	0.102		
	High	4	3	2	1	0.500	0.333	0.160		
	Very High	5	4	3	2	1	0.500	0.249		
	Extremely High	6	5	4	3	2	1	0.379		
		Bare land	Built up	Crop land	Vegetation			Weightage	CI	CR
LULC	Bare land	1	2	3	4			0.466	0.010	0.011
	Built up	0.500	1	2	3			0.277		
	Crop land	0.333	0.500	1	2			0.161		
	Vegetation	0.250	0.333	0.500	1			0.096		

The AHP analysis conducted in this research yielded Consistency Ratio (CR) values of less than 0.1 (or 10%), which means that the pairwise comparisons are consistent. Thus, the obtained weights are reliable, and the AHP results are acceptable for further analysis.

To determine the integrated effect of the various surface and topographic characteristics concerning the occurrence of landslides, a multi-step overlay analysis was conducted based on four spectral indices: NDVI (Normalized Difference Vegetation Index), BSI (Bare Soil Index), NDWI (Normalized Difference Water Index), and NDMI (Normalized Difference Moisture Index). Each of these indices was first classified into two distinct classes based on appropriate threshold values that reflect vegetation cover, soil exposure, surface water presence, and moisture content, respectively.

Tab. 6. Spectral and Topographical Indices

Indices	Acronyms	Formula	Source
Normalized Difference Vegetation Index	NDVI	(NIR – Red) / (NIR + Red)	Huete and Jackson (1987)
Bare Soil Index	BSI	((Red + SWIR) – (NIR + Blue)) / ((Red + SWIR) + (NIR + Blue))	Rikimaru and Miyatake (2002)
Normalized Difference Water Index	NDWI	(Green – NIR) / (Green + NIR)	Gao (1996)
Normalized Difference Moisture Index	NDMI	(NIR – SWIR) / (NIR + SWIR)	Gao (1996)
Compound Topographic Index	CTI	$\ln(As / \tan\beta)$	Moore et al. (1993)
Stream Power Index	SPI	$\ln(As\tan\beta)$	Wilson and Gallant (2000)
Standard Curvature	Curvature	(profile curvature + planform curvature) / 2	Mitášová and Hofierka (1993)

Note: κ represents the total topographic curvature (measured in mm^{-1}), while β denotes the slope angle (expressed in degrees).

2. *Overlay Analysis*

The overlay analysis is performed in three parts. The first analysis is performed to quantify landslide-influencing parameters based on spectral indices, while the second analysis is conducted based on topographic indices. Finally, both spectral indices and topographic indices are spatially overlaid to determine the integrated effect of both on landslides.

2.1. Overlay Analysis Using Spectral Indices

The process begins with the classified NDVI (two classes, 10 and 20, where class 10 represents Low NDVI and class 20 represents High NDVI) and BSI (two classes, 1 and 2, where class 1 represents Low BSI and class 2 represents High BSI) layers. This initial overlay combined vegetation and bare soil information and resulted in a new output raster with four unique class combinations. These combinations represent the interactions between vegetated and non-vegetated surfaces, as well as the extent of bare soil exposure. The condition used to perform this overlay is mentioned below.

Con(("NDVI"==10)&("BSI"==1),1,Con(("NDVI"==10)&("BSI"==2),2,Con(("NDVI"==20)&("BSI"==1), 3,Con(("NDVI"==20)&("BSI"==2),4))))

Where class 1 indicates Low NDVI and Low BSI, class 2 indicates Low NDVI and High BSI, class 3 indicates High NDVI and Low BSI, and class 4 indicates High NDVI and High BSI, respectively.

The next step involved overlaying the 4-class NDVI-BSI output with the classified NDWI layer (two classes, 1 and 2, where class 1 represents Low NDWI and class 2 represents High NDWI). This overlay expanded the classification into eight possible combinations, capturing the joint characteristics of vegetation, soil exposure, and the presence of surface water. The condition used to perform this overlay is mentioned below.

Con(("NDVI_BSI"==1)&("NDWI"==1),1,Con(("NDVI_BSI"==1)&("NDWI"==2),2,Con(("NDVI_BSI"==2)&("NDWI"==1),3,Con(("NDVI_BSI"==2)&("NDWI"==2),4,Con(("NDVI_BSI"==3)&("NDWI"==1),5,Con(("NDVI_BSI"==3)&("NDWI"==2),6,Con(("NDVI_BSI"==4)&("NDWI"==1),7,Con(("NDVI_BSI"==4)&("NDWI"==2),8))))))))

Where, class 1 indicates Low NDVI, Low BSI, and Low NDWI, class 2 indicates Low NDVI, Low BSI, and High NDWI, class 3 indicates Low NDVI, High BSI, and Low NDWI, class 4 indicates Low NDVI, High BSI, and High NDWI, class 5 indicates High NDVI, Low BSI, and Low NDWI, class 6 indicates High NDVI, Low BSI, and High NDWI, class 7 indicates High NDVI, High BSI, and Low NDWI and class 8 indicates High NDVI, High BSI, and High NDWI, respectively

Finally, the 8-class output from the previous step was overlaid with the classified NDMI layer (two classes, 1 and 2, where class 1 represents Low NDMI and class 2 represents High NDMI). NDMI, being an indicator of vegetation moisture, added another dimension to the analysis. The condition used to perform this overlay is mentioned below.

Con(("NDVI_BSI_NDWI"==1)&("NDMI"==1),1,Con(("NDVI_BSI_NDWI"==1)&("NDMI"==2),2,Con(("NDVI_BSI_NDWI"==2)&("NDMI"==1),3,Con(("NDVI_BSI_NDWI"==2)&("NDMI"==2),4,Con(("NDVI_BSI_NDWI"==3)&("NDMI"==1),5,Con(("NDVI_BSI_NDWI"==3)&("NDMI"==2),6,Con(("NDVI_BSI_NDWI"==4)&("NDMI"==1),7,Con(("NDVI_BSI_NDWI"==4)&("NDMI"==2),8,Con(("NDVI_BSI_NDWI"==5)&("NDMI"==1),9,Con(("NDVI_BSI_NDWI"==5)&("NDMI"==2),10,Con(("NDVI_BSI_NDWI"==6)&("NDMI"==1),11,Con(("NDVI_BSI_NDWI"==6)&("NDMI"==2),12,Con(("NDVI_BSI_NDWI"==7)&("NDMI"==1),13, Con(("NDVI_BSI_NDWI"==7)&("NDMI"==2),14,Con(("NDVI_BSI_NDWI"==8)&("NDMI"==1),15,Con(("NDVI_BSI_NDWI"==8)&("NDMI"==2),16))))))))))))))))

Where, class 1 indicates Low NDVI, Low BSI, Low NDWI, and Low NDMI, 2 indicates Low NDVI, Low BSI, Low NDWI, and High NDMI, class 3 indicates Low NDVI, Low BSI, High NDWI, and Low NDMI, class 4 indicates Low NDVI, Low BSI, High NDWI, and High NDMI, class 5 indicates Low NDVI, High BSI, Low NDWI, and Low NDMI, class 6 indicates Low NDVI, High BSI, Low NDWI, and High NDMI, class 7 indicates Low NDVI, High BSI, High NDWI, and Low NDMI, class 8 indicates Low NDVI, High BSI, High NDWI, and High NDMI, class 9 indicates High NDVI, Low BSI, Low NDWI, and Low NDMI, class 10 indicates High NDVI, Low BSI, Low NDWI, and High NDMI, class 11 indicates High NDVI, Low BSI, High NDWI, and Low NDMI, class 12 indicates High NDVI, Low BSI, High NDWI, and High NDMI, class 13 indicates High NDVI, High BSI, Low NDWI, and Low NDMI, class 14 indicates High NDVI, High BSI, Low NDWI, and High NDMI, class 15 indicates High NDVI, High BSI, High NDWI, and Low NDMI and class 16 indicates High NDVI, High BSI, High NDWI, and High NDMI, respectively .

Although the theoretical outcome of this multi-layered overlay could yield sixteen unique classes, only fifteen were present in the study area due to the spatial distribution of the input variables.

Throughout this process, the above-mentioned conditional statements were applied at each stage to systematically assign output classes based on the combination of class values from the input layers. This approach enabled a spatially integrative classification of the land surface, depicting the combined influence of vegetation health, soil condition, water availability, and moisture content.

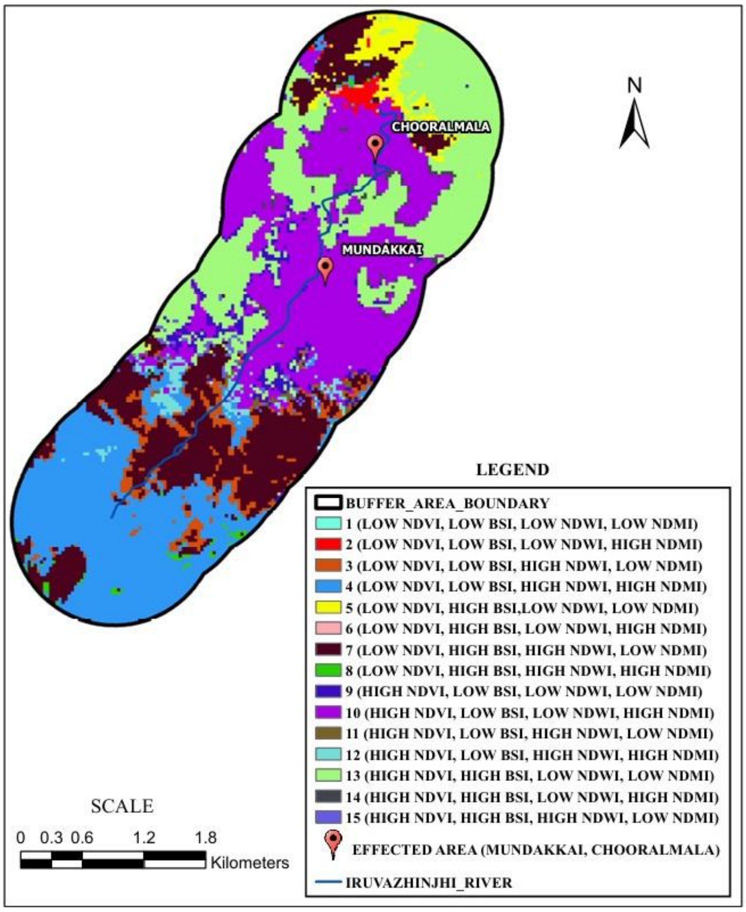

Fig. 3. Overlay Map of NDVI, BSI, NDWI, and NDMI

2.2. *Overlay Analysis Using Topographic Indices*

To evaluate the influence of topographic factors within the study area, a second overlay analysis was conducted using three terrain-based indices: the Compound Topographic Index (CTI), the Stream Power Index (SPI), and the Standard Curvature. Each of these indices was first processed and classified into two distinct classes. CTI was classified into two classes, such as low (class 10) and high topographic wetness (class 20). SPI was also classified into two stream power zones: low (class 1) and high (class 2), reflecting the potential erosive force of flowing water. Similarly, Standard Curvature was categorized into two classes, typically representing concave and convex slope features, which are essential in understanding water flow and slope behavior.

Following the individual classification, the first overlay was carried out between the CTI and SPI layers using conditional statements. This operation produced four unique class combinations, each representing an interaction between the potential for wetness and erosive power. The condition used to perform this overlay is mentioned below.

Con(("CTI"==10)&("SPI"==1),1,Con(("CTI"==10)&("SPI"==2),2,Con(("CTI"==20)&("SPI"==1),3,Con(("CTI"==20)&("SPI"==2),4))))

Where class 1 indicates Low CTI and Low SPI, class 2 indicates Low CTI and High SPI, class 3 indicates High CTI and Low SPI, and class 4 indicates High CTI and High SPI, respectively.

The intermediate output from this overlay, consisting of four classes, was further overlaid with the classified Standard Curvature layer (two classes, 1 and 2, where class 1 represents Low Curvature and class 2 represents High Curvature). This additional overlay operation involved applying conditional logic to integrate the curvature information with the previously obtained combinations of CTI and SPI. The condition used to perform this overlay is mentioned below. As a result, the final output yielded eight distinct classes, each representing a unique combination of wetness, stream power, and slope curvature characteristics.

```
Con(("CTI_SPI"==1)&("STANDARD_CURVATURE"==1),1,Con(("CTI_SPI"==1)&("STANDARD_CURVATURE"==2),2,Con(("CTI_SPI"==2)&("STANDARD_CURVATURE"==1),3,Con(("CTI_SPI"==2)&("STANDARD_CURVATURE"==2),4,Con(("CTI_SPI"==3)&("STANDARD_CURVATURE"==1),5,Con(("CTI_SPI"==3)&("STANDARD_CURVATURE"==2),6,Con(("CTI_SPI"==4)&("STANDARD_CURVATURE"==1),7,Con(("CTI_SPI"==4)&("STANDARD_CURVATURE"==2),8))))))))
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Where, class 1 indicates Low CTI, Low SPI, and Low Standard Curvature, class 2 indicates Low CTI, Low SPI, and High Standard Curvature, class 3 indicates Low CTI, High SPI, and Low Standard Curvature, class 4 indicates Low CTI, High SPI, and High Standard Curvature, class 5 indicates High CTI, Low SPI, and Low Standard Curvature, class 6 indicates High CTI, Low SPI, and High Standard Curvature, class 7 indicates High CTI, High SPI, and Low Standard Curvature and class 8 indicates High CTI, High SPI, and High Standard Curvature, respectively.

The overlay analysis of the terrain indices yielded a more detailed classification of the terrain, providing valuable insights into the topographic conditions that influence surface runoff, erosion susceptibility, and slope stability within the study area.

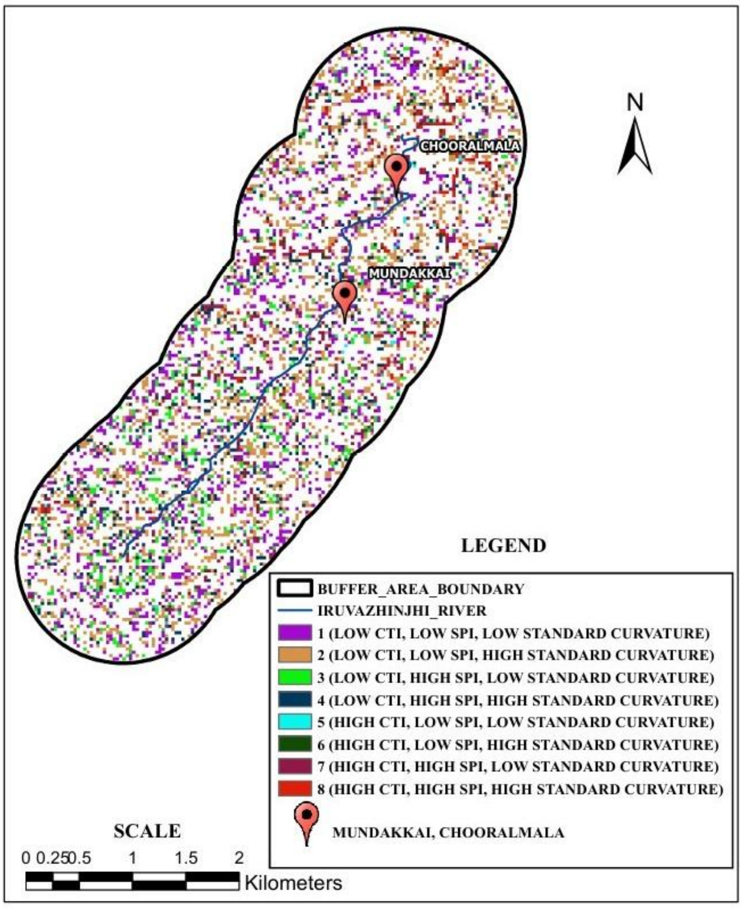

Fig. 4. Overlay Map of CTI, SPI, and Standard Curvature

As shown in Fig. 3, the landslide-affected area falls under Class 10, which is characterized by High NDVI, Low BSI, Low NDWI, and High NDMI. A high NDVI signifies abundant vegetation, implying that the area is likely covered with forests, grasslands, or well-grown crops. Low BSI indicates very little bare soil, suggesting minimal land degradation, deforestation, or exposed rock surfaces. Low NDWI indicates limited surface water, suggesting that water bodies, such as rivers, lakes, or wetlands, are scarce or dry. High NDMI shows high soil and crop moisture, suggesting recent rainfall, high humidity, or strong water retention in the soil. These conditions indicate that the area has a landscape dominated by dense, healthy-grown crops with moist soil but minimal surface water and bare soil exposure.

In Fig. 4, the landslide-affected area falls under Classes 2 and 4, which are characterized by Low CTI, Low and High SPI, and High Standard Curvature. Here, Low CTI suggests good drainage with minimal water accumulation, implying the area is less likely to have waterlogged soil and may be prone to rapid runoff. SPI values indicate varying erosion potential, where steeper areas experience stronger water flow and higher erosion, while gentler slopes have weaker water force. High Standard Curvature indicates the terrain has sharp ridges and deep valleys, which can influence water movement, soil stability, and erosion patterns. In brief, the results suggest that the area features well-drained, steep slopes, varying water flow intensities, and steep terrain characterized by pronounced ridges and valleys.

2.3. Overlay Analysis Using Spectral and Topographic Indices

To evaluate the combined influence of the spectral and topographic indices within the study area, an additional overlay analysis was conducted. In this analysis, class 10 from the spectral indices and classes 2 and 4 from the topographic parameters were selected to perform the conditional overlay. This approach enabled the assessment of the combined impact of both types of factors on the study area. The condition used to perform this overlay is mentioned below.

Con(("NDVI_BSI_NDWI_NDMI"==10)&("CTI_SPI_STANDARD_CURVATURE"==2),1,Con(("NDVI_BSI_NDWI_NDMI"==10)&("CTI_SPI_ STANDARD_CURVATURE"==4),2))

Where class 1 indicates High NDVI, Low BSI, Low NDWI, High NDMI, Low CTI, Low SPI, and High Standard Curvature, and class 2 indicates High NDVI, Low BSI, Low NDWI, High NDMI, Low CTI, High SPI, and High Standard Curvature.

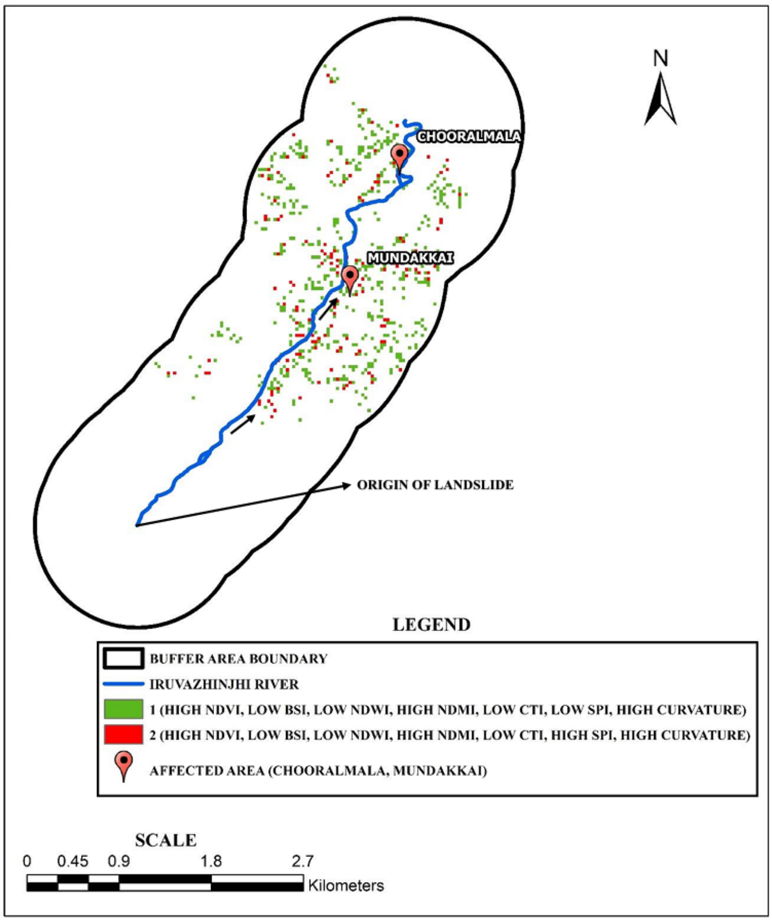

Fig. 5. Overlay Map of Spectral and Topographical Indices

Fig. 5 depicts that the landslide-affected areas (Chooralmala, Mundakkai) fall entirely within class 1. This suggests that the combination of these specific spectral and topographic conditions in Class 1, which is characterized by High NDVI, Low BSI, Low NDWI, High NDMI, Low CTI, Low SPI, and High Standard Curvature, has a stronger association with landslide occurrences in the region. These conditions reveal that the landslide-affected area has healthy crops or plants, with moist soil, but very little surface water or exposed bare soil. The land is steep and drains water well, with a low level of water flow and hilly terrain with sharp ridges and valleys.

Conclusion

The Wayanad region in Kerala state, India, experiences frequent landslides. Therefore, it becomes imperative to ascertain the influencing factors that could provide remedial strategies for alleviating the occurrence of landslides. Integrated analyses involving AHP and multiple spatial overlay analyses of the spectral and topographic indices revealed high NDVI, low BSI, low NDWI, and high NDMI, along with low CTI, moderate SPI, and high Standard Curvature as the vital factors triggering landslides in the study area. These conditions suggest that even regions with healthy vegetation cover (high NDVI) can be vulnerable to landslides when influenced by specific topographic and hydrological factors. The combined impact of moisture, soil exposure, and terrain curvature plays a critical role in slope instability.

While the current approach has provided meaningful insights, incorporating temporal data and machine learning techniques may also enhance the predictive capability of the model. Therefore, this multi-criteria approach not only offers a conceptual assessment of landslide-vulnerable zones but also lays a strong foundation for more advanced risk assessment and planning efforts in the Wayanad region.

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