## ***Original Research Article***

# Geospatial Assessment of Landslide Risk Susceptibility Using Frequency Ratio and Remote Sensing in the Tropical River Basin of the Western Ghats


## ABSTRACT

Wayanad is prone to unexpected landslides due to human intervention~~s~~ and~~,~~ unusual geological and abundant rainfall, which cause loss of life and property damage. This study was conducted to construct a landslide susceptibility map of the Kabani River Basin area in the Southern Western Ghats region using a statistical method. For this, we used previously recorded landslide locations, and 11~~eleven~~ landslide factors were used for modelling:~~, namely~~ lithology, geomorphology, slope angle, soil texture, distance from streams, distance from roads, distance from landmarks, topographic wetness index (TWI), rainfall, land use/land cover, and slope curvature, which were extracted from the spatial database.

Initially, the study presented~~s~~ a very comprehensive approach by mapping landslide-prone areas using relative frequency and prediction rate, which generated~~s~~ a Landslide Prone Area Index (LSI) and a susceptibility map. Furthermore, the study revealed~~s~~ that the southwest part of the study area is prone to landslides because~~due~~ of~~to~~ the extensive influence of the 65° slope, intense rainfall, soil texture, topography moisture index, curvature, lithology, and geomorphology. It also includes the distances to roads, lines, and streams. The predicted pattern is highly similar to the area where landslides have occurred in the past, and it helps in future conservation planning and sustainable land use planning to mitigate landslide risk in the south-western ~~Western~~ Ghats.



**Keywords:** Landslide Susceptibility, Frequency Ratio (FR), Remote Sensing (RS), Western Ghats, Land Use/Land Cover (LULC)


**Commented [SA1]:** LSI stands for "Landslide Susceptibility Index".

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## 1. INTRODUCTION

A common but devastating natural disaster, a landslide, represents the downward and outward movement of slope-forming materials, such as rock, soil, and debris. (Gerrard 1994). Landslides occur when the stability of slopes is compromised by~~due to~~ natural and anthropogenic~~man-made~~ factors. The sheer force of a landslide can have~~cause~~ devastating consequences, including loss of life, damage to infrastructure, and significant economic losses. (A. Saha et al. 2023; Tien Bui et al. 2012; Nadim et al. 2006). The underlying causes of landslides are multifaceted, including seismic conditions, hydrological changes, seismic activity, and human intervention~~s~~, leading to natural imbalances. Mountainous areas around the world are prone to landslides, and as a measure, from 1995 to 2014, more than 3850 landslides were recorded, resulting in the loss of more than 11,500 human lives and the death of approximately 1,63,500 people. (Haque et al. 2019). It has been recorded that approximately 95% of landslide incidents occur in developed countries and cause damage of 0.05% of the country's annual income. (Glade et al. 2005). Therefore, it is necessary to take decisive and effective steps to adopt precautionary ~~measures~~ and mitigation measures related to landslides. Landslide hazard assessment and mapping are crucial processes for~~in~~ understanding and mitigating landslide-related risks. Sensitivity assessment of~~regarding~~ the spatial division of landslide-prone areas depends~~ing~~ on the topographic-ecological situation. (Merghadi et al.2020).

Growing awareness of landslide impacts and the need for urban development in challenging mountainous terrain ha~~ves~~ increased scientific interest in LSZ mapping. (Batar and Watanabe 2021; Chawla et al. 2019; Dikshit et al. 2020; Peethambaran et al. 2020; Pham et al. 2017). LSZ mapping methods have evolved by~~,~~ incorporating heuristic, semi-quantitative, statistical, or probabilistic approaches. (Shano et al. 2020). In the coming era~~, and still today~~, machine learning (ML) algorithms have gained importance as advanced tools for modelling complex relationships between geo-ecological components (Pham et al. 2016a, b; Pradhan, 2013a). Despite their many advantages, these algorithms often do not perform well and currently face several limitations, such as the low interpretability of the influence of factors, the possibility of overfitting in unbalanced datasets, and high computational requirements. (Hong et al. 2019; Pradhan et al. 2023; Tang et al. 2023). These challenges underscore the critical need for expert validation to improve the reliability and practical applicability of these models. Conversely~~, while explainable~~, methods based solely on expert opinions may introduce bias~~es~~ and variation~~s~~. (Erener et al. 2016; Yalcin 2008).

The objective of this research is to explore the effectiveness of using the frequency ratio model and prediction rate to analyz~~s~~e the landslide hazard of the Kamati River, a tributary of the Cauvery River that flow~~sing~~ through southern India. The main objective of this research is to identify their strengths and weaknesses and explore their potential to influence successful risk reduction measures. In this study~~work~~, a comprehensive point mapping of landslide susceptibility in this area using the relative frequency (RF) and prediction rate (PR) is reported.

The site is a hilly area that has already experienced several landslides, mainly in the south-western part, and no research has been conducted in this area of the basin or the region situated in~~by~~ western the part of the basin~~hat has ever been done~~. Therefore, determining the condition of slopes and identifying

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landslide-prone areas is~~were~~ a crucial task~~s~~. Th~~is~~ise study presents a ~~very~~ comprehensive approach for~~by~~ mapping landslide-prone areas using relative frequency and prediction rate, which generates a landslide-prone area index (LSI) and a susceptibility map. The evaluation of the ~~model's~~ effectiveness of the model and the identification of high-risk areas on the south-western slopes of the Kabani River B~~b~~asin provide valuable insights into precautionary measures to mitigate the impact of landslides due to the nature of rainfall and erosion. By improving landslide anticipation and management, this research contributes to the reliability and safety of the region, not only in the studied region, but also beyond its geographical boundaries.

## 2. MATERIALS AND METHODS

In this study, a landslide occurrence table was created by collecting as much data as possible on recent and past landslides, and evaluating the relationship between each conditioning factor and landslide probability. Using the provided methodology chart (Figure 1), ~~the~~ landslide probability was assessed, and the main factors that ~~have~~ caused landslides in the past were identified. The frequency ratio model was used to predict the probability of their occurrence in the future, owing ~~due~~ to the influence of the same factors.

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### 2.1 Methodology

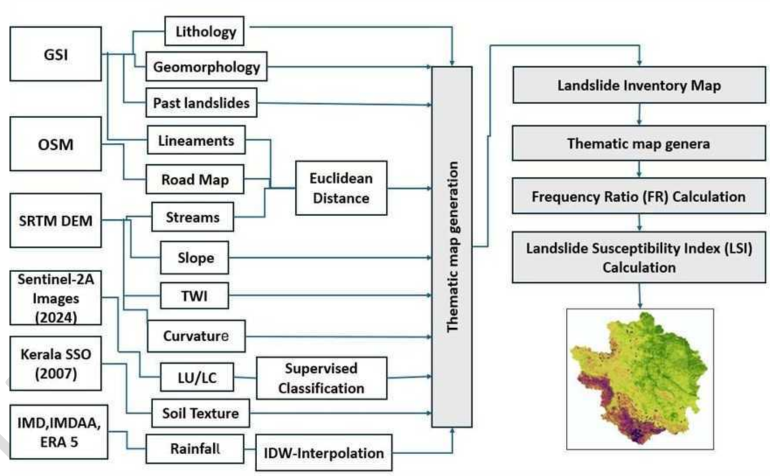


Fig 1: Methodology of Frequency ratio

### 2.2 Frequency ratio (FR) method

The FR method is used to rely on the concept of a favo~~u~~rable function and to calculate the statistics between previous landslides and the occurrence of landslides, and the statistics between the conditioning factors of the landslide (Chung and Fabbri 1999; Vijith and Madhu 2008). Values greater than FR 1 indicate a strong relationship between the factor and the occurrence of landslides, whereas~~while~~ a value below 1 reflects a weak relationship (Lee and Sambath 2006; Vijith and Madhu 2008; Sharma and Mahajan 2018).

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A contingency table was prepared to calculate the corresponding FR for each landslide conditioning factor, and the ratio of landslide occurrence to non-occurrence was calculated using Eqs. (1), as follows:

$$W_{ij} = FL_{ij} / FN_{ij} \quad (1)$$

where $W_{ij}$ is the FR of the ith class attribute of the jth causal factor, $FL_{ij}$ is the FR of the landslides that occurred in the ith class of the factor j, and $FN_{ij}$ is the FR of the non-occurred landslides in the class 'i' of the factor 'j.' The landslide susceptibility index (LSI) was computed by the summation of the FRs of all the landslide conditioning factors, followed by Eq. 2. $\mathrm{LSI} = \sum \quad Wij$ (2)

3. STUDY AREA

The Kabani R~~r~~iver is an eastward-~~ ~~flowing river (KRB area=1685 km²), an integral part of the southern Indian Cauvery R~~r~~iver system, also known as Dakshina Ganga. The selected drains were~~in~~ between the latitudes of 11°29'37.75″~~ ″~~N and~~to~~ 11°59'5.93″~~ ″~~N and ~~the~~ longitudes of 74°46'44.54″~~ ″~~E and~~to~~ 76°18'1.26″~~″~~E (figure 2). The KRB characteriz~~s~~ed the dendritic pattern, and the channel wa~~i~~s in the 7th order. The Kabani River originates from the northern Wayanad high range of elevations (2140 m above MSL) from the Western Ghats~~,~~ by the confluence of two rivers, the Panamaram and Mananthavady Rivers. Wayanad is a tableland in the state of Kerala, with ~~the~~ elevations ranging from 700 to 2100 m~~meters~~ above the Mean Sea Level~~, in the state of Kerala~~. The regional geology is dominated by Precambrian rocks,~~;~~ and the predominant rock types include gneisses, schists, and granites (Nagaraju and Papanna, 2009).

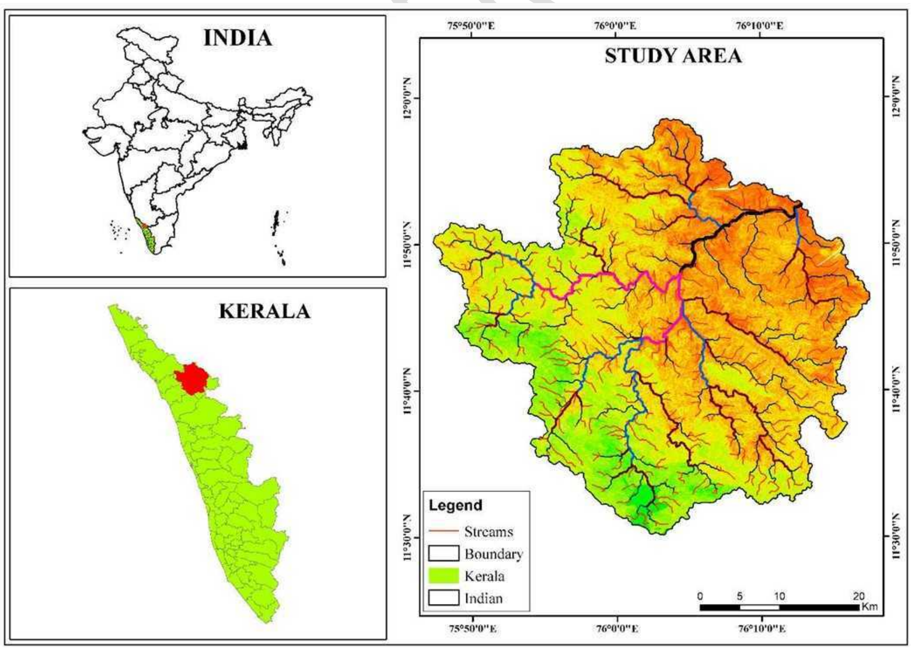


Fig 2. Location Map of the Study Area

The Wayanad P~~p~~lateau is very complex, ~~it~~ leading~~s~~ to the formation of different landscapes through tectonic~~the~~ activities ~~of tectonics~~ such as faults, folds, and joints, and ~~also continues~~ denudation activities mo~~u~~lding their structure. The following climate of the KRB in the~~o~~ predominant tropical monsoon condition is~~,~~ characterized by distinct wet and dry seasons~~,~~ with marked high temperature variation.

The period from~~of~~ June to September resulted~~brings~~ in~~to~~ a high amount of precipitation, while~~and~~ the post-monsoon period from October to November experienced~~s~~ a reduction in the quantity of rainfall. The mean annual rainfall is~~extended~~ between ~~the range of~~ 1200 mm and 2500 mm. Rainfall is more in the south-west, as it moves to the north~~-~~east, ~~it~~ moving~~es~~ from a heavy to low rainfall distribution. The highest temperature is found along the gently undulating terrain of the plateau, and the mean annual temperature is between 22.5°C and 35.8°C (Achu et al., 2021). This~~at~~ remarkably controls the region's hydrological pattern, and ~~it~~ is also directly influenced by ~~the~~ diverse soil types, from clay to loam in texture. It ~~together~~ promotes ~~the~~ different land~~-~~ use practices, such as agroforestry, paddy, plantation crops, and tree plantations.

The study area is rich in diverse systems and lush topography aligned with~~from~~ evergreen and deciduous forests in the Western Ghats, and this region (Anoop and Ganesh., 2023) supports a wide range of flora and fauna, including several types of endemic and endangered species.

## 4. RESULTS AND DISCUSSIONS

### 4.1 Data preparation and Landslide causative data and Factor selection

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#### 4.1.1 Lithology

Lithology is a major factor that directly controls landslide events, and variations in its composition also cause changes in the permeability of rocks and soil, which controls slope stability (Kavzoglu et al. 2014). The study area, which is associated with the Precambrian Metamorphic Shield of Southern India, reveals~~discloses~~ the dominance of high-grade metamorphic rocks.

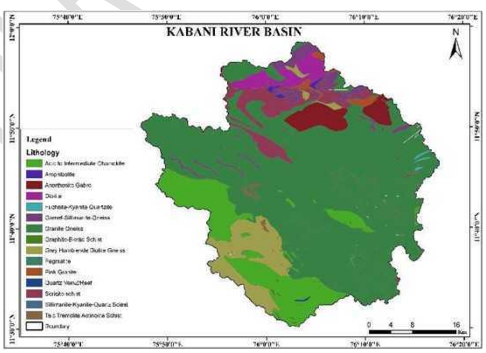


Fig: 3 Lithology

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#### 4.1.2 Geomorphology

Geomorphology displays the surface features and characteristics of an area and indicates its susceptibility to hilly slopes and denudational processes. Different landforms have different susceptibilities~~y~~ to mass movements~~ and~~;~~,~~ therefore, geomorphology is considered to be an essential factor in the initiation of shallow landslides (Krishnan et al. 2015). Among the various landforms, the rolling plain covers roughly 50% of the study area, followed by ~~the ~~highly dissected hills and valleys, and valley fills (areal coverage = 24% and 20%) (Fig. 4a).

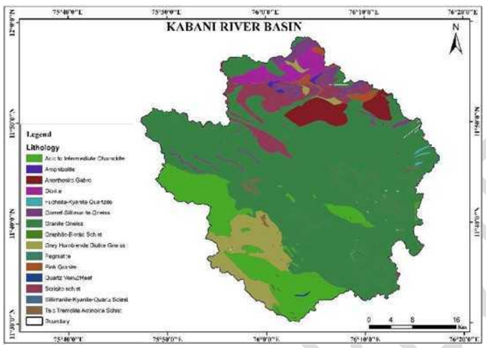


Figure 4a, source: Geological Survey of India

### 4.1.3 Slope Angle

Slope angle is widely used in landslide probability modelling~~,~~ and is considered to be the most critical (Anpazhagan and Sajinkumar 2011; Achu et al. 2020; Febi et al. 2020). Because~~Since~~ the magnitude of the sliding mass is directly related to the slope angle (Meaton et al. 2015; Chen et al. 2018), the slope angle is considered ~~to be ~~one of the most important landslide factors. The slope angle of the study was in~~are~~ the steepness range~~s~~ from 0° to 65.56°. The slope angle was reclassified into six different classes: ≤~~, such as~~ ~~<=~~ 5°, 6–10°, 11–20°, 21–30°, 31–40°, and ~~>~~≥ ~~=~~41°.

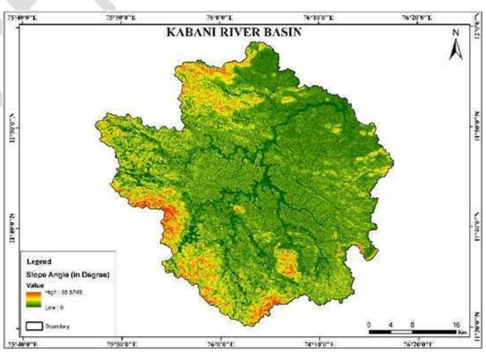


Figure 4b, source: SRTM DEM

### 4.1.4 Soil Texture

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The porosity and permeability of soil play a crucial role in ~~the case of~~ shallow landslide acceleration. In this region, the majority of ~~the~~ previously occurringed landslides ~~through~~ werethe influenced byof intense rainfall triggered by the excess pore-water pressure generated in the soil (Kuriakose et al. 2009). Four soil textural classes characterizse the soils of the study area:~~, viz.,~~ clay (69.43% area), loam (18.36%), gravelly clay (11.28%), and gravelly loam (0.93%) (Fig. 4c).

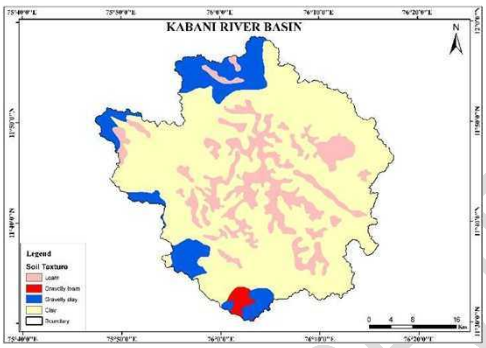


Figure 4c, Soil Texture, source: Kerala State Survey Organisation

#### 4.1.5 Slope Curvature

The curvature of the slope signifies the morphology, convergence, and divergence of the surficial water flow and identifies ~~the~~ slope stability (Ding et al. 2017). The nNormal curvature is a combination of the plan ~~curvature~~ and profile curvatures, which was established in thise study. Convex slopes are often considered more stable than~~compared to~~ concave slopes because the former quickly drains ~~the~~ water into the lower slope area, whereas~~while~~ the latter is more likely to be unstable because water concentrates on the lower slope, leading to slope instability. (Stocking 1972).

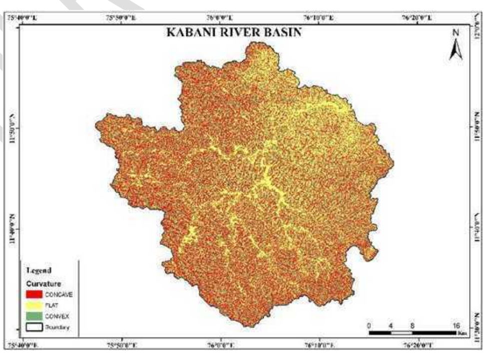


Figure. 4d, Curvature, source: SRTM DEM

#### 4.1.6 Topographic Wetness Index (TWI)

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One of the important topographic variables is TWI, which indicates~~implies~~ the saturation and runoff concentration of the soil (Beven and Kirkby 1979). The TWI wa~~i~~s calculated based on the local slope and upslope contributing area affecting the soil moisture content in a calculation unit, where α represents the upslope area and β represents the slope angle (Devkota et al. 2013). The TWI of the study area were~~was~~ ~~re~~classified into three classes. We classified the values as~~of~~ low, medium, and high for ~~the~~ analysis purposes, that is~~i.e.~~, < 5, 6–10, and >10, respectively.

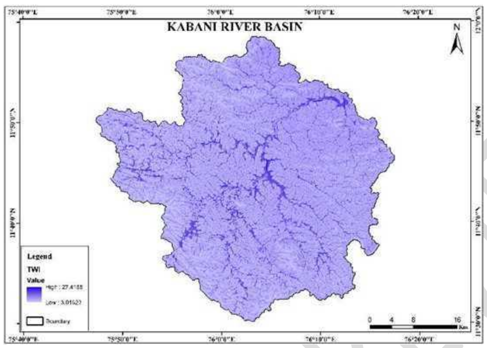


Figure. 4e: Topographic Wetness Index, source: SRTM DEM

#### 4.1.7 Land use/Land cover

Specifically, in rugged landscapes, unplanned land use/~~-~~land cover modification often leads to topographic changes that affect~~ing~~ slope stability (Kayastha et al. 2013). The land use/land cover map was generated using ~~the~~ Sentinel 2A satellite images. Among the different land use/land cover types, c~~C~~offee agro~~-~~forestry (40.82%) was dominant~~dominates~~, followed by Deciduous Forest (20.88%), a~~A~~griculture (12.00%), Evergreen Forest (11.84%), t~~T~~ea (4.96%), b~~B~~arren land (4.29%), HA Grasslands (1.27%), p~~P~~addy fields (1.09%), w~~W~~ater bod~~y~~ies (1.03%), t~~T~~ree plantations (1.00%), b~~B~~uilt-up areas (0.55%), and f~~F~~orest plantations (0.26%).

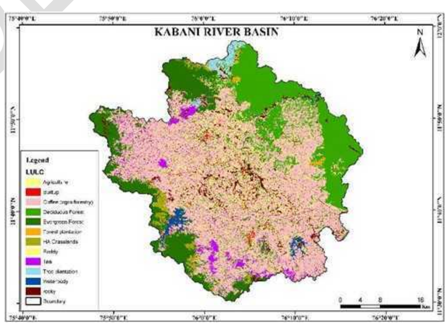


Figure.4f: LULC, source: Sentinel 2A Image

#### 4.1.8 Rainfall

This nature of rainfall events is the most critical landslide triggering factor in ~~the~~ southern WG, and~~along with~~ the majority of past landslide occurrences in the region were correlated with extreme rainfall events (Thampi et al. 1995). A~~The~~ rainfall choropleth map was generated using the IDW technique, and~~through~~ the rainfall data of twenty-four rain gauge stations for 2019 were collected from the IMD. The annual rainfall over the area was reclassified into three zones:~~, namely,~~ < 2500 mm, 2501–3500 mm, and > 3501 mm~~ for the analysis~~.

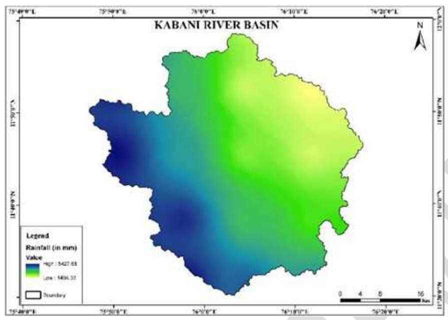


Fig 4g : Rainfall, source: IMD IMDAA Era 5

### 4.1.9 Distance to Lineaments

The distance from the l~~L~~ineaments map wa~~i~~s obtained~~prepared~~ from the Geological Survey of India (GSI). The relationship between the lineament distance and landslides was determined~~is found out~~ using <200, 200–400, 400– 600, 600–800, and >800 m, and the distance between the lineaments wa~~i~~s calculated using the Euclidean distance due to the risk of slope~~the~~ imbalance~~ of slope~~.

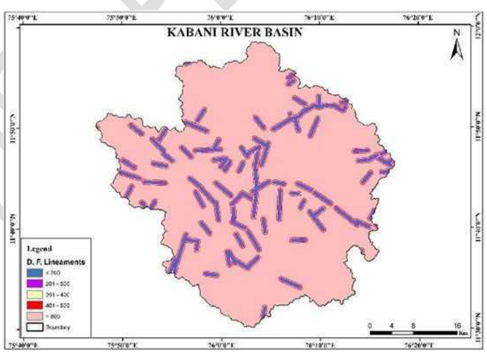


Figure. 4h : Lineaments, source: Geological Survey of India

### 4.1.10 Distance to Roads

Road construction is a human-made process~~cut and creation~~ that causes slope instability (Bui et al., 2011). Road construction with ~~a~~ steeper slopes is associated with a higher risk of accidents. Owing~~Due~~ to the potential for slope instability, the distance between roads was calculated using Euclidean distance. The study area wais classified into five~~5~~ groups based on the~~,~~ distance~~such~~ from the road:~~as;~~ <100, 101-200, 201-300, 301-500 and >500~~ based on the distance from the road~~.

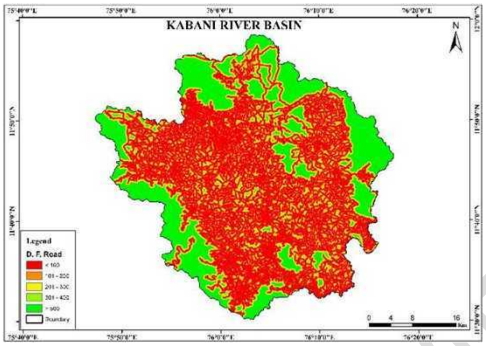


Fig. 4i: Road, source: Open Series Map

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### 1.1.1 Distance to Streams

Rivers in a watershed are the result of long-term interactions between creations that trigger slope instability, geographical features in the impact of water, ~~and~~ topography, and slope (Bui et al., 2011). The distance from the streams is one of the proximity parameters, and the distance between the streams is calculated using the Euclidean distance because~~due~~ of~~to~~ the risk of slope~~the~~ instability~~ of the slopes~~. They we~~a~~re classified as~~into~~ <100, 101-200, 201-300, 301-500, and >500 (Fig. 4j) for the analysis.

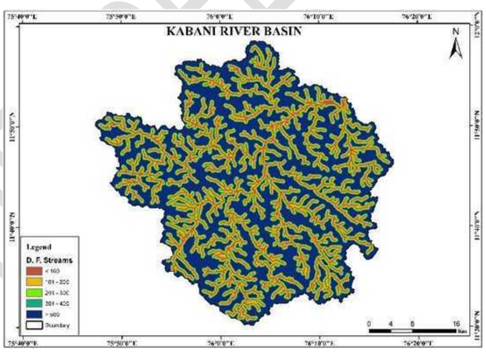


Fig. 4j: Rivers, source: SRTM DEM

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## 1.2 Analysis of the factors influencing landslides

The frequency ratio and prediction rate for all classes were obtained from all the prepared conditioning factors of the training dataset. The ratio of landslides and domains, frequency ratio, relative frequency, and prediction rate for each class and factor are l~~d~~ist~~play~~ed in Table 5a. ~~The~~ F~~f~~requency ratios are~~is~~ frequently used in landslide susceptibility studies~~research~~. However, in this case, standardiz~~s~~ation between 0 and 1 was applied to allow for a better comparison and understanding of the impact on the LSI calculation. As such, the prediction rate provides~~offers~~ a weighting of the variables that affect the landslide susceptibility index.

Table. 1: The ratio of landslides and domains, frequency ratio, relative frequency, and prediction rate for each class and factor

| | *Count* | *Fnij* | *Previous* | *FLij* | *Wij* | *FR* |
|---|---|---|---|---|---|---|
| **CURVATURE** | | | | | | |
| Concave | 638464 | 0.34106 | 107 | 0.601 | 1.762 | 176.2 |
| Flat | 638256 | 0.34095 | 35 | 0.196 | 0.576 | 57.67 |
| Convex | 595256 | 0.31798 | 36 | 0.202 | 0.636 | 63.6 |
| **LU/LC** | | | | | | |
| Agriculture | 225015 | 0.12018 | 38 | 0.213 | 1.776 | 177.6 |
| Tea | 92970 | 0.04965 | 15 | 0.084 | 1.697 | 169.7 |
| Paddy | 20410 | 0.0109 | 1 | 0.005 | 0.515 | 51.53 |
| Rocky | 80326 | 0.0429 | 6 | 0.033 | 0.785 | 78.57 |
| Built-up | 10350 | 0.00553 | 2 | 0.011 | 2.032 | 203.2 |
| Deciduous Forest | 390954 | 0.2088 | 26 | 0.146 | 0.699 | 69.95 |
| Coffee (agroforestry) | 764104 | 0.4081 | 79 | 0.443 | 1.087 | 108.7 |
| Evergreen Forest | 221525 | 0.11831 | 10 | 0.056 | 0.474 | 47.48 |
| Water body | 19367 | 0.01034 | 0 | 0 | 0 | 0 |
| Forest Plantation | 4829 | 0.00258 | 0 | 0 | 0 | 0 |
| H.A Grasslands | 23747 | 0.01268 | 1 | 0.005 | 0.442 | 44.29 |
| Tree plantation | 18764 | 0.01002 | 0 | 0 | 0 | 0 |
| **SOILTEXTURE** | | | | | | |
| Clay | 1299961 | 0.69429 | 142 | 0.797 | 1.149 | 114.9 |
| Loam | 343856 | 0.18365 | 6 | 0.033 | 0.183 | 18.35 |
| Gravelly Clay | 211215 | 0.11281 | 12 | 0.067 | 0.597 | 59.76 |
| Gravelly Loam | 17328 | 0.00926 | 18 | 0.101 | 10.92 | 1092 |
| **GEOMORPHOLOGY** | | | | | | |
| Pediment | 10966 | 0.00586 | 1 | 0.005 | 0.959 | 95.92 |
| Valley Fill | 378476 | 0.20214 | 23 | 0.129 | 0.639 | 63.92 |
| Water Body - River | 27079 | 0.01446 | 3 | 0.016 | 1.165 | 116.5 |
| Rolling Plain | 935137 | 0.49944 | 72 | 0.404 | 0.809 | 80.98 |
| Active Quarry | 320 | 0.00017 | 0 | 0 | 0 | 0 |
| Residual Mound | 39361 | 0.02102 | 3 | 0.016 | 0.801 | 80.17 |
| Pedi plain | 9791 | 0.00523 | 0 | 0 | 0 | 0 |
| Channel Bar | 2625 | 0.0014 | 0 | 0 | 0 | 0 |
| Residual Hill | 2808 | 0.0015 | 0 | 0 | 0 | 0 |
| Plateau Remnant | 10505 | 0.00561 | 0 | 0 | 0 | 0 |
| Ridge | 4584 | 0.00245 | 0 | 0 | 0 | 0 |
| Hills and Valleys | 450709 | 0.24072 | 76 | 0.426 | 1.773 | 177.3 |
| **LITHOLOGY** | | | | | | |

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**Commented [SA14]:** Rewrite as "LULC"

| | | | | | | |
|---|---|---|---|---|---|---|
| Garnet-Sillimanite- Gneiss | 50951 | 0.02725 | 0 | 0 | 0 | 0 |
| Sericite Schist | 97442 | 0.05211 | 4 | 0.022 | 0.431 | 43.12 |
| Amphibolite | 5520 | 0.00295 | 0 | 0 | 0 | 0 |
| Pink Granite | 14909 | 0.00797 | 0 | 0 | 0 | 0 |
| Diorite | 52066 | 0.02784 | 5 | 0.028 | 1.008 | 100.8 |
| Granite Gneiss | 1172789 | 0.62712 | 61 | 0.342 | 0.546 | 54.64 |
| Grey Hornblenblende | 136386 | 0.07293 | 30 | 0.168 | 2.31 | 231 |
| Biotite Gneiss | | | | 539 | 995 | 995 |
| Talc Tremolite Actinolite | 13629 | 0.00729 | 1 | 0.005 | 0.77 | 77.08 |
| Schst | | | | 618 | 874 | 744 |
| Pegmatite | 127 | 6.79E-05 | 0 | 0 | 0 | 0 |
| Quartz Vein/Reef | 2295 | 0.00123 | 1 | 0.005 | 4.577 | 457.7 |
| Acid to Intermediate | 252525 | 0.13503 | 74 | 0.415 | 3.078 | 307.8 |
| Charnockite | | | | 73 | 754 | 754 |
| Silimanite-Kyanite- | 345 | 0.00018 | 0 | 0 | 0 | 0 |
| Quartz Schist | | | | | | |
| Anorthosite Gabbro | 66526 | 0.03557 | 1 | 0.005 | 0.157 | 15.79 |
| Graphite-Biotite Schist | 1646 | 0.00088 | 1 | 0.005 | 6.382 | 638.2 |
| Fuchsite-Kyanite | 2956 | 0.00158 | 0 | 0 | 0 | 0 |
| Quartzite | | | | | | |
| **SLOPE ANGLE** | | | | | | |
| 0-5 | 583398 | 0.31165 | 9 | 0.05 | 0.162 | 16.22 |
| 5.1-10 | 644301 | 0.34418 | 41 | 0.23 | 0.669 | 66.92 |
| 10.1-20 | 498176 | 0.26612 | 96 | 0.539 | 2.026 | 202.6 |
| 20.1-30 | 117967 | 0.06302 | 30 | 0.168 | 2.674 | 267.4 |
| 30.1-40 | 25976 | 0.01388 | 2 | 0.011 | 0.809 | 80.97 |
| > 40.1 | 2158 | 0.00115 | 0 | 0 | 0 | 0 |
| **RAINFALL** | | | | | | |
| < 2,500 | 540558 | 0.2887 | 0 | 0 | 0 | 0 |
| 2,501 - 3,500 | 527551 | 0.28176 | 21 | 0.117 | 0.418 | 41.87 |
| > 3,500 | 804252 | 0.42954 | 157 | 0.882 | 2.053 | 205.3 |
| **TWI** | | | | | | |
| Low | 1158069 | 0.61864 | 146 | 0.82 | 1.325 | 132.5 |
| Medium | 584369 | 0.31217 | 31 | 0.174 | 0.557 | 55.78 |
| High | 129515 | 0.06919 | 1 | 0.005 | 0.081 | 8.119 |
| **DISTANCE FROM STREAMS** | | | | | | |
| Very Near | 300503 | 0.16049 | 34 | 0.191 | 1.19 | 119 |
| Near | 253602 | 0.13545 | 25 | 0.14 | 1.036 | 103.6 |
| Average | 260174 | 0.13896 | 21 | 0.117 | 0.849 | 84.9 |
| Far | 410488 | 0.21924 | 41 | 0.23 | 1.05 | 105 |
| Very Far | 647594 | 0.34587 | 57 | 0.32 | 0.925 | 92.58 |
| **DISTANCE FROM ROAD** | | | | | | |
| Very Near | 897595 | 0.47939 | 139 | 0.78 | 1.628 | 162.8 |

**Commented [SA15]:** Previously, it is mentioned "Distance to Streams". Kindly make it uniform throughout.

| | | | | | | |
|---|---|---|---|---|---|---|
| Near | 333893 | 0.17833 | 19 | 0.106 | 0.598 | 59.85 |
| Average | 145550 | 0.07774 | 14 | 0.078 | 1.011 | 101.1 |
| Far | 123485 | 0.06595 | 4 | 0.022 | 0.34 | 34.07 |
| Very Far | 371838 | 0.19859 | 2 | 0.011 | 0.056 | 5.657 |
| **DISTANCE FROM LINEAMENT** | | | | | | |
| Very Near | 112219 | 0.05993 | 6 | 0.033 | 0.562 | 56.24 |
| Near | 123530 | 0.06598 | 12 | 0.067 | 1.021 | 102.1 |
| Average | 132972 | 0.07102 | 5 | 0.028 | 0.395 | 39.55 |
| Far | 129427 | 0.06913 | 3 | 0.016 | 0.243 | 24.38 |
| Very Far | 1374213 | 0.73395 | 152 | 0.853 | 1.163 | 116.3 |
| **LSI (sum of wij) = 73.61519** | | | | | | |

Regarding the elevation factor, the area between 700 and 2028.67 metres exhibits a high RF value, which suggests that this region is susceptible to landslides and that such events have occurred more frequently in the past, particularly during periods of heavy rainfall. The RF value wa~~i~~s greater for slopes ranging from 0° to 65.56°. Most global case studies have shown that high relief and steep slopes are primary causes of landslides (Y. Hong et al., 2007). Research indicates a distribution of landslides on flat surfaces~~,~~ caused by the base of the landslide or ~~the~~ underlying bedrock (Cestras et al., 2022). Similarly, landslides tend to occur more often on concave slopes than on steep ones~~slopes~~. Concave slopes often concentrate water at their lower edges; however, they are generally more stable because the water flow is more evenly distributed (Gimire & Timalsina, 2020). The TWI represents the relationship between the amount of water accumulated in a specific area and the slope of the stream (Bevan & Kirkby, 1979; Benzogag et al., 2020).

TWI also showed that landslides we~~a~~re likely in our scenario, with TWI ranging from 3.01 to 27.41, indicating large landslides. Because~~Due~~ of~~to~~ the ease of construction, ~~and~~ slope cutting, and evacuation, especially in the study area, most roads are built on river~~-~~banks. This may be due to the high risk in the upper reaches.

Rainfall ~~naturally~~ causes landslides. The annual average rainfall also increases with an~~the~~ increase in the study area, and the relative frequency suggests that rainfall above 3312 mm is more likely to cause landslides. Because~~Since~~ our region is known for its frequent rainfall events, in some areas, ~~the possibility of~~ landslides may occur~~ring~~ more frequently ~~is possible~~ if rainfall exceeds this figure (Sestrař et al., 2019). Finally, from a structural perspective, there is a correlation between the relative frequency values and ~~the~~ road crossing faults; landslides are also likely to occur in areas located within 200 m of the road, stream, and lineament.

### 1.3 Landslide susceptibility map and validation

The landslide susceptibility map of the Kabani River Basin displays a clear spatial pattern, where the western and southwestern regions show high and intense landslide susceptibility, as indicated by the red to orange areas. These areas ~~certainly~~ fit the distribution of previous landslide events, as shown as black dots on the map. In contrast, the northeastern and eastern parts of the river basin, which are green, remained relatively stable. This spatial distribution highlights the dominant influence of the topographic, climatic, and geological parameters.

One of the primary contributors to this pattern is the high rainfall in the western part, where the Kabani River Basin is located o~~i~~n the lee side of the Western Ghats. The region receives intense monsoon rainfall, which increases the soil saturation and reduces the slope stability. In addition, the presence of loamy soils, which retain water and become unstable when wet, renders~~makes~~ this region particularly vulnerable to landslides. Loamy soils are fertile but structurally weak under saturated conditions, especially on sloping terrains. The s~~S~~loping structure is an important factor~~,~~ because~~as~~ sloping areas are more susceptible to gravitational movement.

The more the terrain is disturbed, the more sensitive are the sloped areas~~ are~~. Steep slopes accelerate surface runoff, erosion, and ~~the~~ downward movement of soil and debris. This is evident in the south and southwest, where extreme susceptibility overlaps with the steep terrain. In addition, the curvature of the terrain also plays a role: concave slopes collect water and increase saturation, whereas~~while~~ steep slopes may be more susceptible to mass movement.

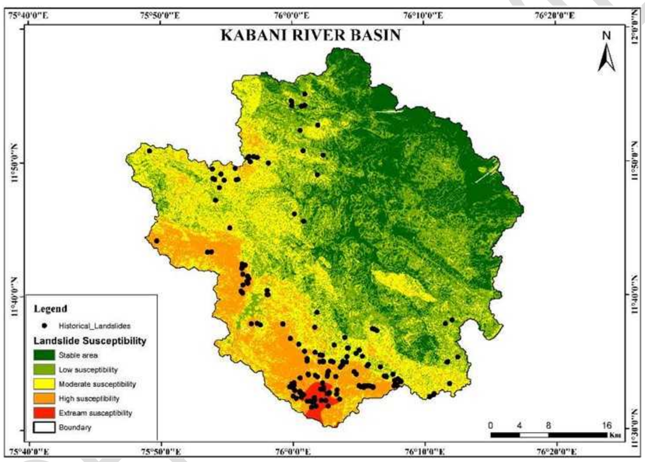


Fig. 5 : Landslide Susceptibility Map

The Topographic Wetness Index (TWI)~~, which~~ measures the moisture accumulation and is partially related~~connected~~ to the instability of the surface. High potentials in the valleys and depressions are often associated with areas of moderate to high potential. In addition, distance to streams affects drainage and erosion processes, with areas near streams experiencing more intense subsoil erosion, and proximity to roads introducing~~es~~ man-made instability from slope cutting and construction. The g~~G~~eological and structural constraints also contributed significantly~~make an important contribution~~. The type and composition of the lithology ~~—~~and~~the~~ bedrock ~~—~~influence~~s~~ the strength of the slope and the nature of ~~the~~ weathering; weaker and weathered rocks, such as phyllites or schists, are more likely to fail. Similarly, in terms of land use, different types of cultivation can accelerate landslides in some places, while simultaneously~~at the same time~~ decreasing the impact of landslides o~~i~~n others. Distance to lineament and~~,~~ structural features, such as faults and fractures, can indicate areas of weakness where landslides are more likely to be initiated. Geomorphology, which includes landform classifications, such as escarpments, pediments, and valleys, can help explain why some areas naturally initiate mass movement. For example, rugged hills and escarpments exhibit high landslide densities because~~due~~ of~~to~~ the instability of the area.

The integration of diverse factors, such as climatology, topography, hydrology, and geology, demonstrates a holistic approach to~~used in the~~ vulnerability assessment, which helps to more accurately identify areas at risk in the Kabani River Basin. The correlation between the slope, soil type, and historical landslide locations confirms the effectiveness of this geospatial model in identifying hazardous areas, aiding disaster mitigation, and land use planning in the Kabani River Basin.

## 5. SUMMARY AND CONCLUSION

~~The~~ L~~l~~andslide susceptibility assessment in the Kabani River Basin highlights the~~a~~ complex interplay of natural and anthropogenic factors that influence~~ing~~ slope stability. The western and southwestern regions, characteriz~~s~~ed by steep slopes, high rainfall, loamy and clay soils, and weak geomorphology, showed higher or more severe susceptibility than the northeastern regions. Key contributing parameters such as curvature;~~,~~ topographic wetness index (TWI);~~,~~ proximity to roads, streams, and lineaments;~~,~~ and lithological and geomorphological distributions and variations make ~~the~~ hazard mapping more accurate. The close alignment of past landslide events with areas identified as having high ~~-~~probability ~~particularly~~ confirms the reliability of the model. This analysis also underscores the importance of integrated geospatial approaches to~~in~~ landslide hazard zoning. Effective mitigation strategies in ~~the~~ river basins, land use planning, and infrastructure development should be prioritiz~~s~~ed for these high-risk areas to reduce potential landslides in the future.

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