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Dynamic Landslide Susceptibility Modeling and Risk Forecasting in the Nilgiris Using Geospatial Approaches

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ABSTRACT

Landslides remain a significant environmental hazard in India's hill regions, particularly in the Nilgiris district of Tamil Nadu, due to its steep terrain, fractured geology, and heavy seasonal rainfall. This study applies the Frequency Ratio (FR) model within a GIS and remote sensing framework to map landslide susceptibility and identify key contributing factors to slope instability. Ten thematic layers were used, including land use/land cover (LULC), NDVI, slope gradient, soil type and depth, geomorphology, aspect, rainfall, lineament density, and lineament proximity—derived from geological databases, DEMs, and satellite imagery. A landslide inventory was analyzed statistically to evaluate each factor's role in landslide occurrence. Results indicate that slope gradient (9.15%) and LULC (8.37%) are the most influential factors, followed by geomorphology (7.78%), soil type (7.48%), and lineament density

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(4.50%). A key innovation of this study is the integration of lineament buffer zones to assess the influence of structural discontinuities, often overlooked in regional models. The model's predictive performance was validated using the Area Under the Curve (AUC) method, yielding a value of 0.879, indicating high accuracy. The resulting susceptibility map categorizes the landscape into low, moderate, and high-risk zones, providing a critical tool for regional planning, infrastructure development, and disaster management. This research supports climate-resilient development and sustainable land-use planning in vulnerable hill regions, emphasizing that both natural terrain characteristics and human-induced land alterations significantly contribute to landslide risk.

Keywords: Slope Failure Risk; Frequency Ratio Analysis; GIS-based Mapping; Nilgiris Terrain; Landslide-prone Zones

1. Introduction

In mountainous regions, landslides remain a persistent natural hazard, causing substantial threats to human life and property. With rapid urban expansion and increasing human activity in ecologically sensitive areas, the frequency and impact of such events have intensified. The recent surge in landslide-related disasters calls for robust mechanisms to identify and manage high-risk zones effectively. Scientific studies emphasize the importance of spatial prediction tools to support regional planning and early warning systems, especially in high-rainfall regions like the Nilgiris [1–3].

Scholarly research consistently cindicates that landslide-prone zones tend to exhibit recurring instability, especially under similar geological and environmental conditions as previous events. This insight forms the backbone of predictive landslide modeling. India's mountainous regions, such as the Western Ghats, Himalayas, and certain isolated hill ranges, face persistent landslide challenges—particularly during the monsoon season. The Nilgiris, marked by complex terrain and high rainfall, are notably affected. For instance, studies employing statistical and regression-based approaches have highlighted the significant role of steep gradients in triggering slope failures during intense precipitation periods [4]. These heavy rains, particularly prevalent from June through September, often disrupt transport networks, cutting off communities and hindering emergency response efforts. Indigenous populations residing in unstable zones are especially at risk, reinforcing the need for localized risk assessments. This study utilizes the Frequency Ratio model, emphasizing topographic and structural variables over direct rainfall inputs to create a targeted susceptibility map for the district. Such maps, when integrated with remote sensing and GIS platforms, serve as strategic tools for planners and disaster mitigation agencies.

Various natural and anthropogenic factors including landform structure, geology, hydrological pathways, and climatic dynamics contribute to landslide formation. Effectively predicting these events requires spatial analysis tools that can accommodate the complex interactions among these elements [5]. Broadly, two approaches are used for susceptibility mapping: quantitative models, which depend on statistical or computational simulations, and qualitative models, which draw from expert assessments and field observations [6]. This study primarily utilizes secondary geospatial datasets to perform landslide susceptibility analysis. Land cover classification and vegetation metrics were derived from Landsat 8 imagery obtained through the USGS archives, while elevation and slope data were sourced from SRTM (Shuttle Radar Topography Mission) datasets.

Additional information on soil composition and geological profiles was accessed from the Geological Survey of India. Historical records of landslides were consulted for model calibration and validation. All thematic layers were generated using ArcGIS, and terrain characteristics were derived using a Digital Elevation Model to assess stability and vulnerability across the landscape.

Vegetation patterns across the study area were evaluated using the Normalized Difference Vegetation Index (NDVI), calculated from red and near-infrared reflectance values available in Landsat 8 imagery. Simultaneously, structural discontinuities in the terrain—referred to as lineaments—were detected by preprocessing the same satellite data. A directional filtering-based algorithm, operated through PCI-Geomatica software, was employed to identify linear features indicative of geological fractures. These extracted lineaments were subsequently processed in ArcGIS to generate density and proximity maps, which helped assess their influence on slope instability. For land cover classification, a supervised classification approach using key spectral bands (green, red, and near-infrared) was implemented. Training data based on known land use types ensured accurate classification, allowing for a detailed analysis of surface dynamics within the study region.

A range of methodologies has been explored in the literature for assessing landslide susceptibility, each offering distinct strengths. These include inventory-based techniques, expert-driven frameworks, and statistical models [7]. Both deterministic and probabilistic approaches are also used, with growing attention now being given to machine learning algorithms, which provide promising accuracy in predictive modeling. Despite the advancement of such techniques, traditional methods such as the Information Value Method, Weight of Evidence, and Frequency Ratio (FR) remain widely adopted due to their computational simplicity and demonstrated effectiveness [8]. In this study, the FR method was selected for its statistical transparency and proven reliability. By integrating landslide occurrence data with thematic maps of influencing factors, the FR approach quantifies the relative probability of landslides for different environmental conditions. Frequency ratios were computed for each classified factor to evaluate their influence on slope failure risk.

2. Study Area

The Nilgiris constitute one of India's oldest mountain ranges and are located at the confluence of Tamil Nadu, Kerala, and Karnataka. This area holds significant geographical and ecological importance because it is part of the Western Ghats. Owing to its unique and diversified ecosystems, the Nilgiris was the first place in India to be designated as a biosphere reserve, and is recognized globally as one of the fourteen biodiversity hotspots. The Nilgiris have a lot of different heights, with some areas being as low as 900 m and others being as high as 2600 m above sea level.

The Nilgiris is not only important for the environment, but it is also a famous hill station and a major tourist destination, both of which contribute substantially to the local economy and livelihoods. It is the only district in Tamil Nadu that is completely on the Nilgiri Plateau, at the junction of the Western and Eastern Ghats. There are also eight hydroelectric power plants in the area that help provide Tamil Nadu with electricity,further enhancing its regional importance. The Nilgiris district spans an area of approximately 2551 square kilometres, encompassing key administrative areas such as Ooty, Coonoor, Gudalur, Kotagiri, Kundah, and Pandalur. For this study, the focus is on the southern and southeastern parts of the district, where landslides happen more often. The research area is between latitudes 11°11′28″ N and 11°32′10″ N and longitudes 76°36′7″ E and 77°00′18″ E. It covers roughly 936 square kilometres of land. The Southwest monsoon (June to August) and the Northeast monsoon (October to December) are the two primary rainfall seasons in the Nilgiris region. The climate remains generally mild, with average maximum temperatures around 20.7 °C and minimum temperatures near 9.6 °C. The humidity levels stay rather consistent throughout the year, typically ranging between 75.8% and 76.9%. **Figure 1** shows the geographic extent and spatial configuration of the study area.

3. Data and Methodology

A lot of environmental factors, including geological formations, landform characteristics, water flow patterns, and weather conditions, can cause landslides. Accurately predicting landslide events requires the the complex and often interrelated nature of triggering factors. Researchers have come up with both qualitative and quantitative ways to assess landslide susceptibility over time. Quantitative methods typically involve statistical analysis, physical modelling, or computational simulations, whereas qualitative methods rely more on expert judgement, terrain interpretation, and geomorphological insights. This investigation relied primarily on secondary geospatial data to construct and analyze landslide susceptibility. Multispectral satellite imagery from the Landsat 8 OLI sensor, accessed via USGS repositories, facilitated land cover classification and vegetation analysis. Additionally, terrain elevation and slope data were obtained from the SRTM dataset. Soil profiles and geological attributes were sourced from the Geological Survey of India, offering insights into physical ground conditions. Historical landslide incident data and susceptibility records were compiled from district-level archives, aiding in both model training and validation.

All spatial data were processed using ArcGIS to generate thematic layers essential for the FR-based susceptibility assessment. A Digital Elevation Model (DEM) was created and processed using ArcGIS for terrain analysis, including the mapping of slopes and elevations. This proved to be a useful tool for for identifying stable and unstable terrain zones. Satellite-based datasets were used to collect a number of important environmental indicators, such as the Normalised Difference Vegetation Index (NDVI), surface moisture levels, lineament patterns, and their density. Land use and land cover (LULC) classification in the study area was conducted using imagery from the Landsat 8 satellite. In a supervised classification method done with ArcGIS 10.8, spectral bands 3 (green), 4 (red), and 5 (near-infrared) were used. This approach utilized training data based on known land cover types, enabling accurate identification and categorisation of distinct surface features. NDVI values were also derived from the same satellite imagery, providing information about the health and density of plants in different parts of the study area.

$$NDVI = \frac{Band5 - Band4}{Band5 + Band4}$$

In remote sensing, vegetation conditions in this study were evaluated using NDVI, derived from spectral data collected by Landsat 8. Specifically, reflectance values from the red (Band 4) and near-infrared (Band 5) bands were processed to estimate vegetation health across the terrain. In parallel, geological lineaments were identified by preprocessing the satellite imagery to highlight structural discontinuities. The LINE detection algorithm, executed through PCI-Geomatica software, extracted linear features based on directional contrast. These features were then imported into ArcGIS for further spatial analysis, including density mapping and proximity buffering to evaluate their potential influence on landslide susceptibility.

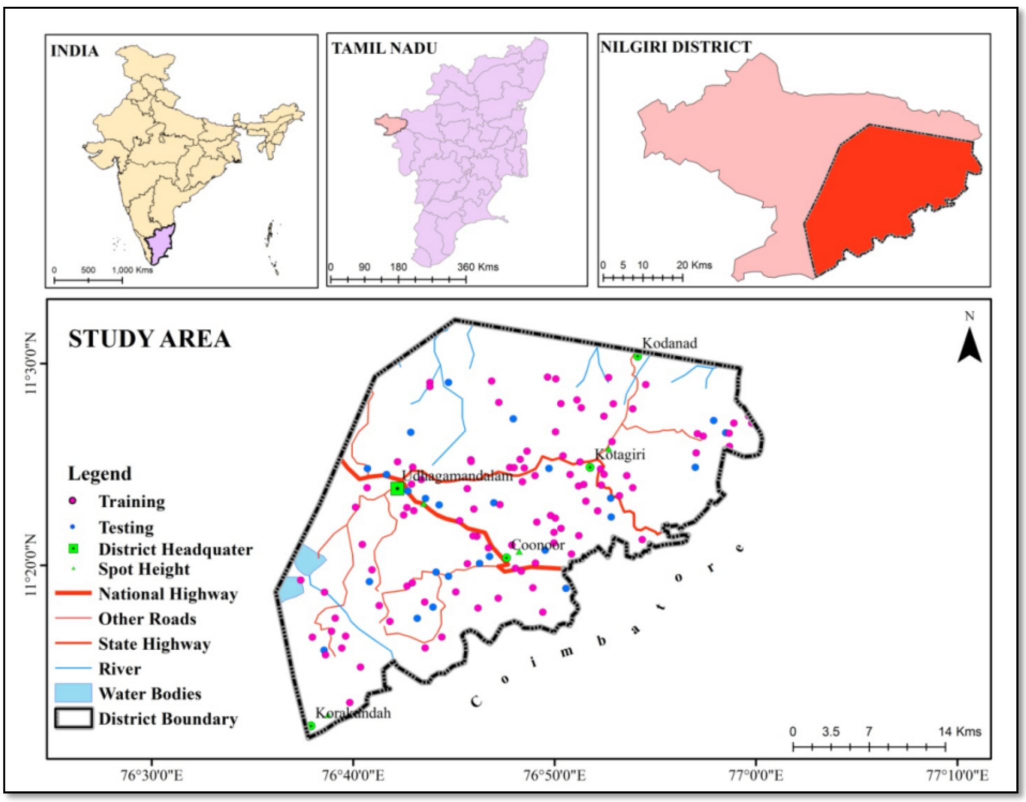

Figure 1. Location of the Study area.

The literature has examined a number of different methods for assessing landslide susceptibility, each with its advantages and limitations. There are a lot of different types of these methods, such as inventory-based studies [9], expert-driven evaluation models [10], and statistical approaches [11]. Along with these, deterministic and probabilistic models, as well as non-parametric and distribution-free methods, have been used in many different regions [12]. Machine learning and deep learning approaches have become more popular for modelling landslip susceptibility in recent years due to their strong predictive performance. Several traditional methods are still widely used, along with these more advanced ones. These include the Information Value Method (IVM) [13], the Weight of Evidence (WOE) model [14], and the Frequency Ratio (FR) technique [15], to name a few [16]. The Frequency Ratio approach continues to be widely adopted due to its computational simplicity and effectiveness as a bivariate statistical tool. Using GIS platforms to analyze geographical data, the Frequency Ratio (FR) approach is a useful tool to assess how different environmental conditions affect the likelihood of landslides [17]. To make accurate forecasts regarding the risk of landslides, it is essential to have a good grasp of the physical topography and the exact conditions that cause slope failures. The FR method is becoming more popular in recent studies due to its ease of use and effectiveness. It has also been found to be reliable in determining landslip susceptibility [18,19]. The landslip inventory and the aspect map of the research area were combined to use the Frequency Ratio (FR) method. We used specific statistical formulae to calculate the frequency ratios for each class of contributing factors. These ratios show how much these factors affect the number of landslides.

$$\alpha = \frac{PC_i}{\sum_{i=1}^{n} PC_i}$$

Where, PC_i = no. of pixel in respective class of a individual parameter,

n = no. of classes

α = Ratio of the parameters

$$\beta = \frac{LS_i}{\sum_{i=1}^{n} LS_i}$$

Where, LS_i = no. of landslide episodes

n = no. of classes

β = ratio of the landslides

$$\textit{Frequency Ratio, FR} = \frac{\beta}{\alpha} \text{ X } 100$$

4. Result and Discussion

Choosing the best variables for modelling landslip susceptibility is a challenging part of spatial analysis. There is no one universal way to identify these conditioning elements, especially when using GIS. But for a reliable assessment, the chosen metrics must be measurable, spatially meaningful, and closely tied to the landscape's physical and environmental features [20]. In this study, 10 of these characteristics were examined, including soil type and depth, slope, aspect, density of vegetation (NDVI), geomorphology, rainfall, and land use and land cover patterns. Each of these factors plays a different role in maintaining the terrain stable. Soil type is one of the most critical characteristics that might cause landslides. Slopes built of soils that aren't very stable or well-compacted are more likely to fail, especially during intense rainfall. Earlier research, like the one by Wieczorek et al. (1996), found that areas with clay-heavy soils and loose deposits are more likely to have unstable slopes since they don't drain well and their structures aren't very strong.

4.1. Soil Structure in Nilgiris

There are three primary types of soil in the research area (see **Figure 2**): sandy clay loam, rocky terrain (rock land), and clay loam. The distribution of these soil types is not uniform across the area. Sandy clay loam is the most common type of soil. It covers a large area from the west to the east and is also found in small pockets in the north. The southern and southeastern parts of the district have more rocky ground, whereas the eastern section has a smaller area of clay loam. The geographical distribution of soil types in the Nilgiris region's defined research area is shown in the figure, which is essential for estimating the susceptibility of landslides. Three main soil types are depicted on the map: rock land (in light brown), clay loam (in brown), and sandy clay loam (in light green), which is the dominant kind. These soil types have a major impact on water infiltration capacity and slope stability, which in turn affects the likelihood of landslides. In a supervised classification framework, the map further superimposes training (red dots) and testing (blue dots) data points that are utilized for model building and validation. In order to calibrate and assess the dynamic landslide susceptibility model, these georeferenced samples were crucial (**Figure 2**).

Sandy clay loam is the most common type of soil in terms of area covered, occupying about 798 square kilometres, or about 85.3% of the study area. Next comes rocky terrain, which makes up about 133.8 square kilometres, or 14.3%. Clay loam, on the other hand, is only found in a small area, covering only around 3.4 square kilometres, or 0.3% of the region. These variations in how the soil is spread out have a significant impact on how stable the slope is and how the ground reacts to water. This is what causes the landslides that happen in the Nilgiris.

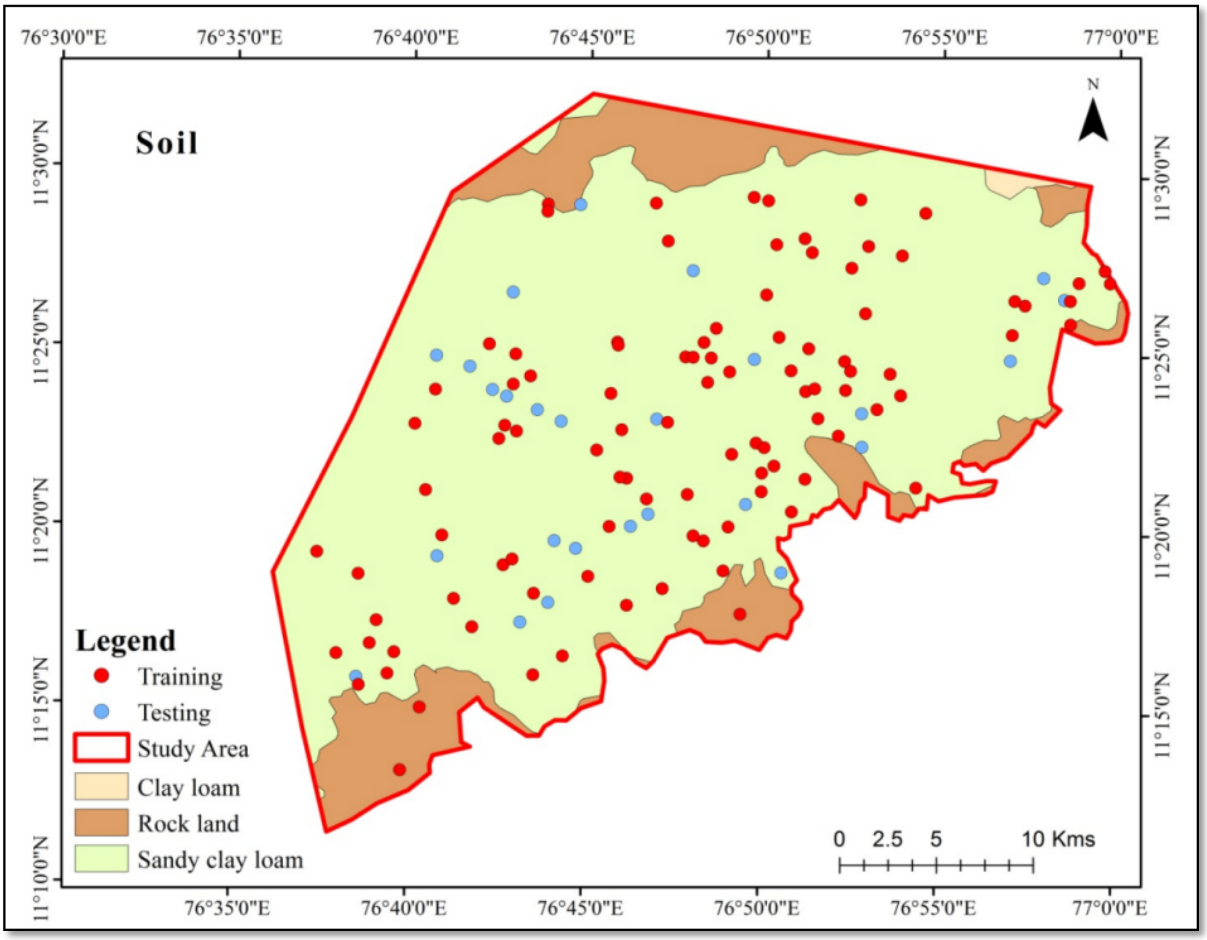

Figure 2. Soil Map.

4.2. Soil Depth

When figuring out how stable a slope is and how likely it is to experience a landslip, the depth of the soil is very important. Deeper soils are usually better at holding water, supporting deeper root systems, and enhancing slope strength. When soil gets deeper, it can soak up more rain, which helps reduce surface runoff and lowers the risk of erosion. On the other hand, shallow soils don't have these stabilising features and are more likely to fail, especially during heavy rain, which makes landslides more likely in these places. The geographical distribution of soil depth classes in the landslide-prone Nilgiris region is depicted on this map, which is essential for risk forecasting and dynamic landslide susceptibility modeling. Three main soil depth categories very deep soils (>150 cm), deep soils (100–150 cm), and rock land are present in the research region, which is indicated in red. The subsurface hydrology, root anchoring, and slope stability—all of which have a major impact on the onset and spread of landslides are determined in large part by these variations in soil depth (**Figure 3**). The majority of the research area is made up of very deep soils, which are shown in green. These soils have a comparatively larger ability to retain water, which can result in higher pore water pressure during periods of intense rainfall. Because of their differing infiltration and drainage properties, the deep soils (shown in purple) and rock land (brown regions) represent zones that may have distinct landslide triggering processes.

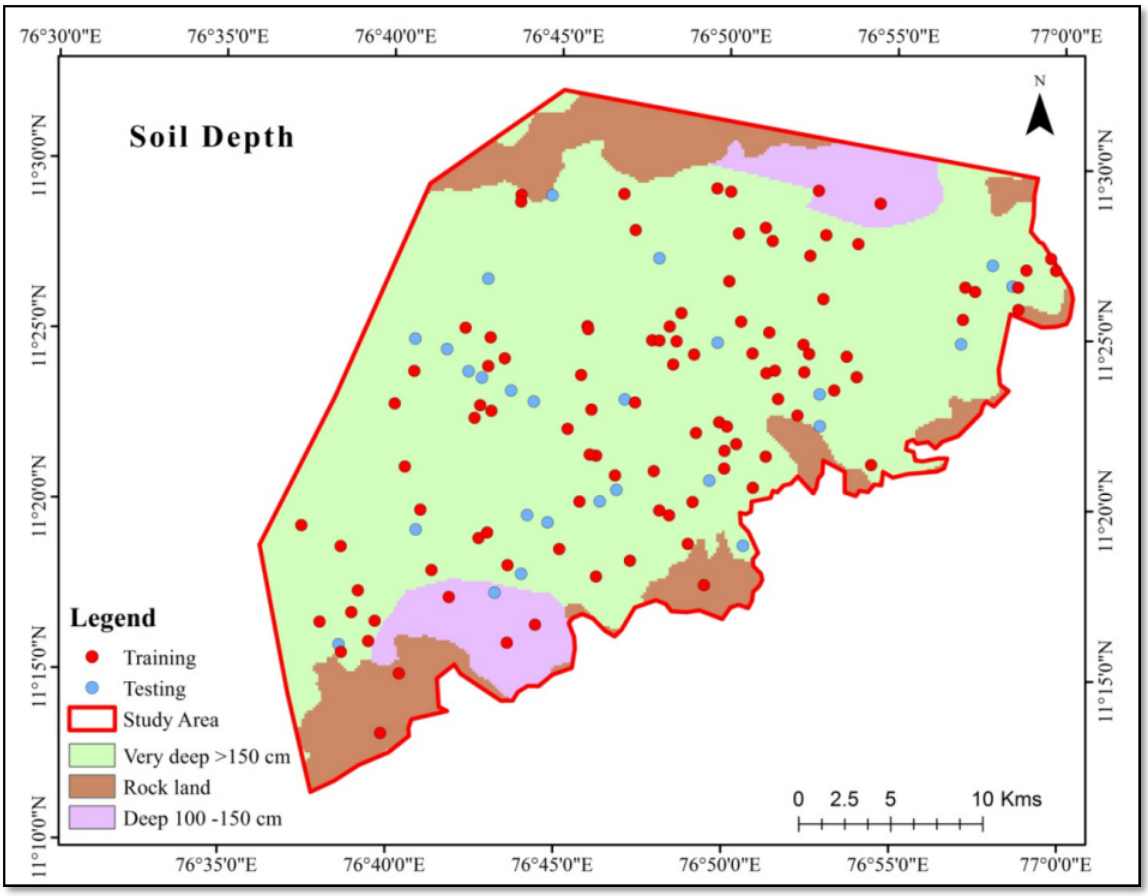

Figure 3. Soil Depth Map.

The northern and eastern margins of the research area are where most of the areas with little or no soil depth are located. These areas are mostly rocky outcrops. There are also a few small areas of similar terrain in the southeast. Most of the soils that are between 100 and 150 centimetres deep are concentrated in the extreme north and south of the district. These variations in depth have a significant effect on both the stability of the slope and the passage of water through the soil. These are two important factors in accurately modelling landslide susceptibility.

4.3. Slope

One of the most important factors that affects how stable a piece of land is the slope gradient. The ground is more likely to shift when the angle of inclination rises because the gravitational attraction on surface materials gets stronger. Because there is a direct link between slope gradient and mass movement, steeper slopes are more likely to experience landslides. Slope gradient is often seen as the most important cause of slope failures in landslip research [21]. The slope classification map (**Figure 4**) shows that the research area has slopes that range from flat land to inclines that are as steep as 50 degrees. We categorised the slopes into five groups: 0–5°, 5–15°, 15–30°, 30–50°, and over 50° to better understand the terrain. Most of the northern part of the Nilgiris has mild slopes that are usually between 0 and 5 degrees. As you move west and into the central region, these gentle slopes slowly turn into steeper ones that are between 5 and 15 degrees.

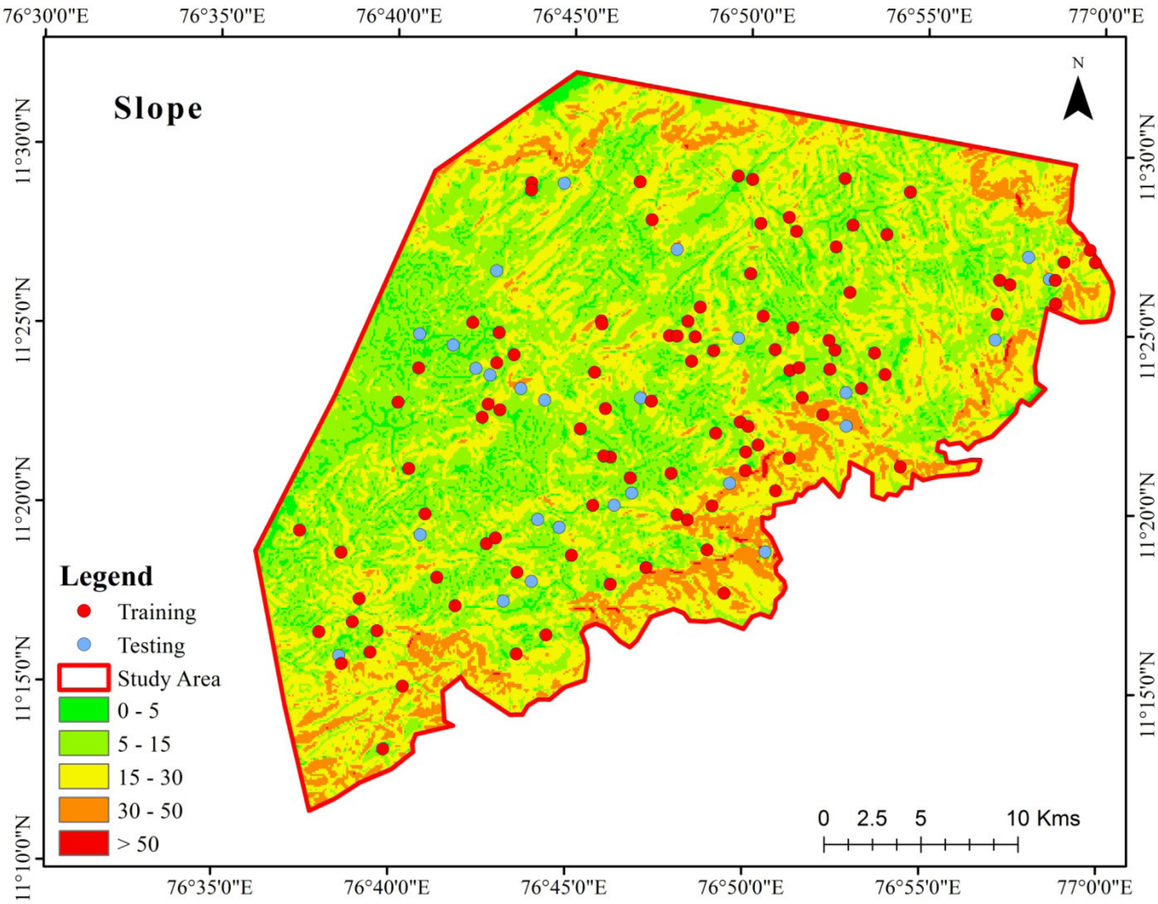

Figure 4. Slope Map.

As you go east and south in the area, the slopes usually stay between 15 and 30 degrees. This type can also be found in the southwestern part and in a few places in the central district. Steeper slopes, between 30° and 50°, cover less of the landscape but are very noticeable in the northeastern region and at the edges of the southeastern zone. Steep slopes that are more than 50° are not very common. They usually only occur in small areas in the southeast and on rocky outcrops in the southwest. Different slope angles clearly affect the danger of landslides because steeper slopes are usually less stable and more likely to fail. These steeper slopes frequently indicate areas of the landscape that are more likely to be damaged.

4.4. Slope Aspect Distribution

The aspect of a slope, or the direction it faces, can have a significant effect on how likely it is to slide down because it changes the conditions that help keep the slope stable. The direction of the slope is very important for controlling the amount of vegetation cover and moisture retention, both of which help keep the soil together and strong. When these stabilising parts get weaker, the risks of the slope failing increase substantially. Aspect also affects microclimatic conditions, which change the physical properties of slope materials over time. Some of these conditions are the amount of rainfall, how much sunlight the slope gets, and which way the wind blows (which affects whether the slope stays wet or dries out), and how much surface weathering there is. The amount of sunshine a slope gets depends on its orientation. This influences how fast water evaporates, how fast plants develop, and how fast soil breaks down, all of which increase the risk of landslides. Slope aspect is usually considered to be an essential factor in determining how likely a landslip is to happen because it affects several crucial environmental parameters. The direction of a slope impacts how much geochemical weathering happens and how stable it is overall. Slopes that don't get as much vegetation because they don't get enough sunshine or are exposed to harsh weather, or that dry up and degrade more quickly, are more likely to fail. Therefore, aspect is a useful tool for predicting landslides and assessing hazards.

Figure 5 illustrates the spatial distribution of slope aspects across the Nilgiris region, highlighting the terrain's complexity and its influence on landslide susceptibility. The study area is predominantly mountainous, with only 1.52 km² (0.17%) classified as flat terrain, mostly located in the central part of the region. The slope orientation shows significant spatial variability. North-facing slopes account for approximately 110.4 km² (11.80%), closely followed by northeast-facing slopes at 109.2 km² (11.67%), and east-facing slopes, which also cover about 110.4 km² (11.80%). These dominant aspects are primarily observed in the central, eastern, and western zones of the study area. In contrast, the northwest and southeast parts of the region are characterized by east- and southeast-facing slopes, respectively.

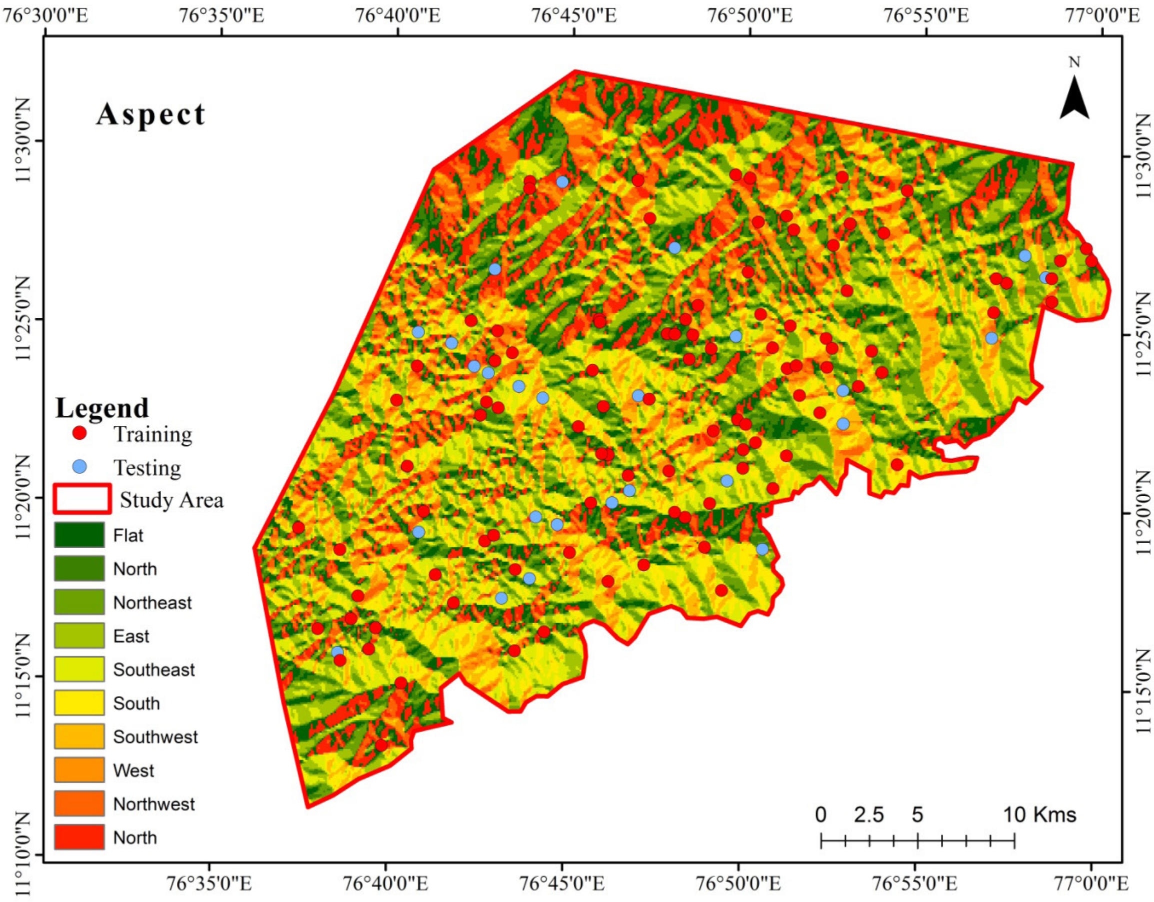

Figure 5. Aspect Map.

Slope aspect plays a crucial role in influencing microclimatic conditions such as solar radiation exposure, soil moisture retention, and vegetation growth all of which directly affect the likelihood of slope failure. Therefore, understanding the spatial variation in aspect is essential for accurately modeling landslide susceptibility and enhancing dynamic risk forecasting in this terrain-sensitive region. The most common slope direction is southeast, which covers 137.5 square kilometres, or 14.17% of the area. Next are the south-facing hills, which occupy 124.4 square kilometres (13.30%), and the southwest-facing terrain, which covers 99.2 square kilometres (10.61%). West-facing slopes take up 94.6 square kilometres, which is 10.11% of the total area. The slopes that face northwest are a little larger, covering 125.4 square kilometres or 13.43%. There is also a separate 14.04 square kilometre area, or about 1.55%, that is listed as north-facing terrain. This could be because of overlapping data entries or errors made in prior classifications. This range of slope orientations shows how diverse the topography is in the area and points to the many microclimatic and geophysical conditions that affect how stable or unstable particular parts of the landscape can be.

4.5. Normalised Difference Vegetation Index (NDVI)

The Normalised Difference Vegetation Index (NDVI) is an important factor in forecasting how likely a landslip is to happen. Vegetation is very important for keeping slopes stable because plant roots help hold the soil together and slow down erosion on the surface. Slopes with a lot of vegetation on them are usually more stable and less likely to break down. On the other hand, slopes with little or no vegetation on them are more likely to erode and slide down. In general, greater NDVI values mean that the vegetation is healthier and denser, which usually means that it is better at resisting slope collapse.

Using the Normalized Difference plant Index (NDVI), a crucial biophysical indicator incorporated into landslide susceptibility models, **Figure 6** shows the geographical distribution of plant density in the research region. Slope stability is affected differently by the low, moderate, and high vegetation cover classifications that the NDVI map assigns to the area. Large swaths of the northern and northwest Nilgiris are covered in dense vegetation, mostly forest landscapes, as shown by high NDVI values (green). Because deep-rooted vegetation improves soil cohesion and decreases surface flow, these areas are often less vulnerable to landslides.

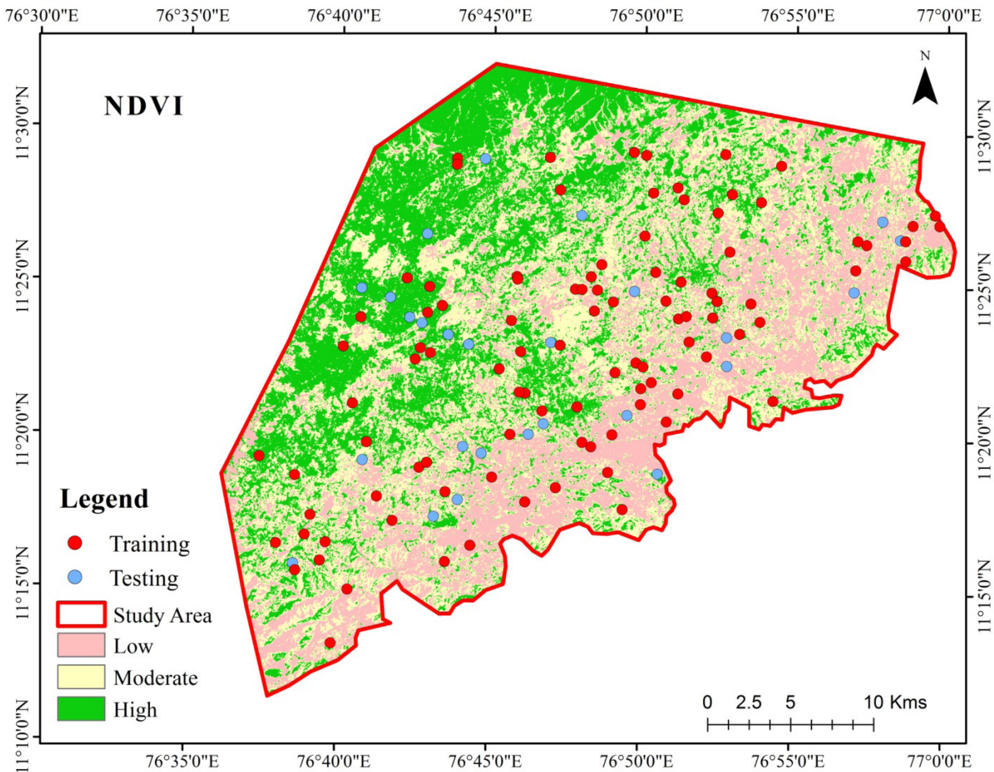

Figure 6. NDVI Map.

The spatial analysis suggests that about 42.3% of the studied area, or 395.9 square kilometres, has low vegetation cover. There are 238.6 square kilometres of land with moderate vegetation cover, which is 25.5% of the entire area. There are also 301.3 square kilometres of land with thick vegetation, which is 32.2% of the total area. These differences in vegetation density have a big effect on how well slopes hold up against erosion and are a major component in figuring out how likely a landslip is to happen in a given area.

4.6. Geomorphology

Geomorphological traits are crucial for finding and studying places that are likely to have landslides. Hansen [22] states that landform morphology and the underlying lithology has a big effect on surface evolution over time. The type of rock below them determines the basic properties of geological materials, such as strength, permeability, and porosity. Geomorphology is an important part of landslip risk assessment since these factors directly affect how likely it is that a slope will give way under stress.

The configuration of natural landforms, such as ridgelines, valleys, and degraded hilltops, has a direct effect on water accumulation, the mobilization of soil and debris, and the development of ground stress concentrations. For this reason, geomorphology is typically a key part of geospatial models that try to assess landslide susceptibility. It helps show the natural weaknesses of the environment and the specific conditions that could cause slope failures.

The contour of the terrain, especially when you look at the slope gradients, plays a vital role in determining both the behavior and intensity of landslide activity. This study breaks down the geomorphological environment into four primary groups: dome-shaped denudational hills, structurally controlled ridges, weathered hilltops, and upper piedmont slopes associated with valleys. The risk of landslides is different for each type of landform because of its own physical structure and the geology underneath it. Weathered hilltops are predominantly located in the western and northwestern parts of the research region, as shown in **Figure 7**. They span around 74.4 square kilometres, or about 7.9% of the total landscape. Dome-shaped denudational hills are more limited in extent, covering about 4.3 square kilometres in the northeastern corner. Valley features appear only in a few isolated zones in the eastern half of the region, covering around 0.70 square kilometres, or 0.07% of the entire study area.

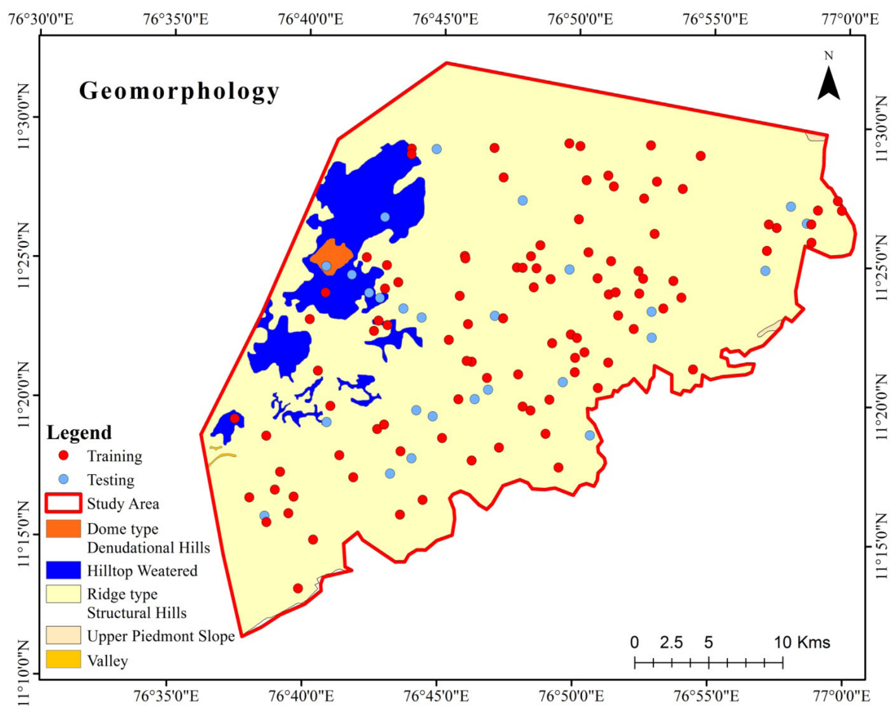

Figure 7. Geomorphology Map.

The most common geomorphological feature in the studied area is ridge-type structural hills, which cover around 854 square kilometres, or about 91.3% of the total territory. These ridges are not only the dominant part of the terrain, but they are also associated with more landslides.

Landform features like ridges and patterns of land use and land cover have a significant impact on the occurrence of landslides. Slope stability is directly impacted by human activities that alter soil structure, vegetation density, and surface runoff, such as urbanization, agriculture, and deforestation. In particular, deep-rooted vegetation is essential for binding soil and preventing erosion. Thus, determining landslide risk requires an awareness of and mapping of land use and vegetation, especially in areas that are vulnerable to environmental changes or anthropogenic activity.

4.7. Land Use Land Cover Change

Land cover plays a critical role in keeping slopes stable because it influences surface water flow and soil moisture retention. There are six main types of land use and land cover considered in this study. **Figure 8** shows that most of the water bodies are in the southwestern half of the study area. Most of the agricultural areas are found in the western part, with small patches of them distributed in the middle and northern parts.

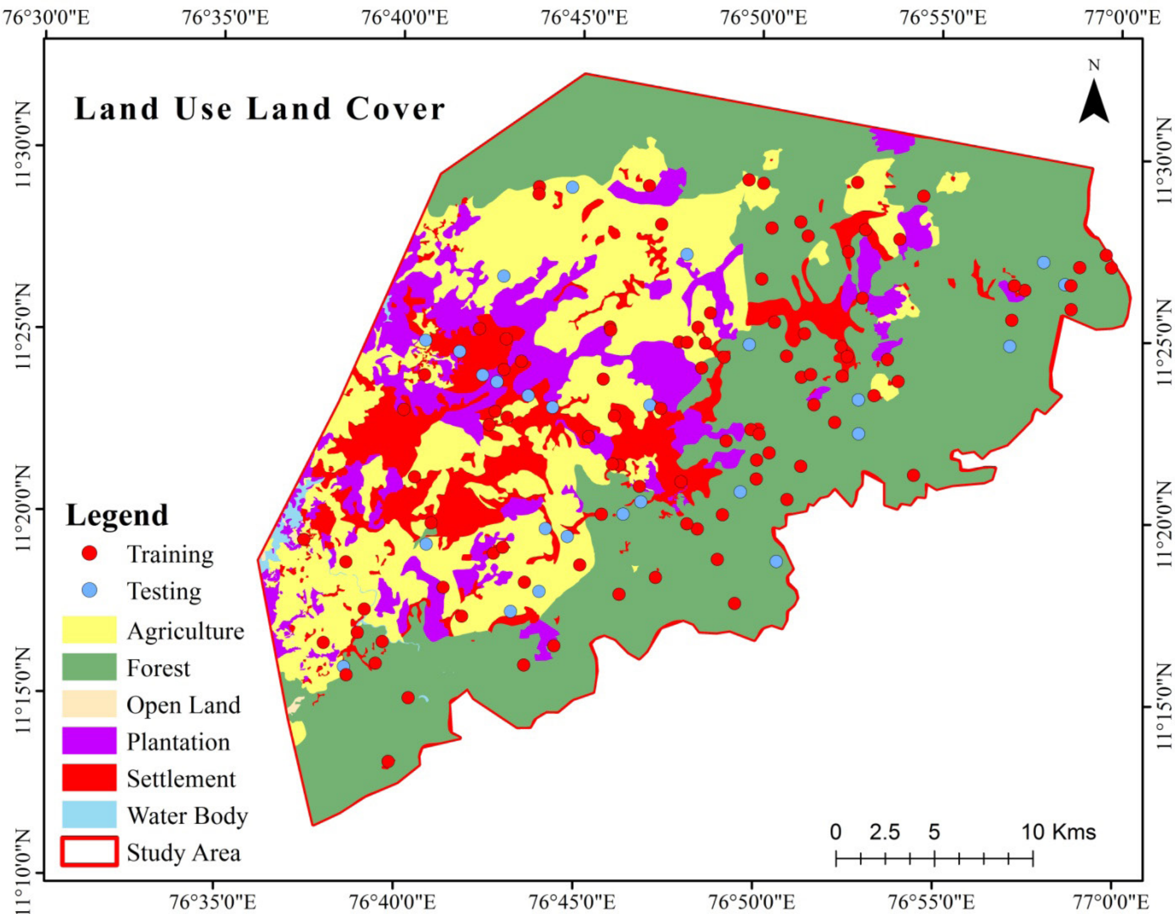

Figure 8. Land Use Land Cover Map.

The Nilgiris region's LULC distribution map, which is shown in the figure, supports the main goal of the research project "Dynamic Landslide Susceptibility Modeling and Risk Forecasting in the Nilgiris Using Geospatial Approaches." A variety of land cover types may be seen in the spatial representation, each of which affects the terrain's hydrological and geomorphic behavior and, consequently, the vulnerability to landslides. Forest cover, which makes up 482.2 km² (51.5%) of the entire study area, is the most common land cover (**Figure 8**). In the north, northeast, south, and southeast sections, these wooded areas are extensively distributed. Because of their extensive root systems, which bind soil and reduce surface flow, forests are essential for stabilizing slopes and lowering the risk of landslides in these areas.

The study area's central and western regions are home to the majority of the 236.6 km² (25.2%) of agricultural land, which makes up the second-largest category. Although agriculture sustains local livelihoods, its expansion frequently results in the removal of native vegetation and disturbance to soil structure, increasing the risk of erosion and slope collapse in these areas. In regions with steep topography or those close to lineaments, this risk is further elevated. The majority of the 107.0 km² (11.4%) of plantation lands are located in the northern, central, and western regions. Plantations typically lack the structural complexity of natural forests, although providing some vegetative cover. Monoculture plantings, especially during periods of heavy rainfall, may worsen soil degradation and decrease slope cohesiveness, raising the risk of landslides.

There are sporadic clusters in the east, but the majority of the 104.8 km² (11.2%) of built-up or settlement areas are concentrated in the central, western, and northeastern regions. Because of land grading, construction, and infrastructure development, which alter the natural drainage and slope profiles, these developed regions are extremely vulnerable. Shallow landslides and runoff are also exacerbated by the growth of impervious surfaces. Despite its small size (1.2 km² or 0.13%), open land is scattered across the northern, central, and southern borders. These exposed or thinly vegetated areas are more vulnerable to shallow landslide occurrences and surface erosion. Lastly, water bodies make up 4.0 km² (0.42%), and they are usually found in depressions or lower elevations.

The geographic robustness of the susceptibility modelling process is improved by the overlay of training and testing points (shown in red and blue, respectively) utilized for model validation across different LULC classes. Robust predictive modeling is supported by the distribution of these points, which guarantees that all land cover groups are fairly represented. The map's geographical arrangement and quantitative descriptions of the various land cover categories directly contribute to the study's landslide susceptibility modeling objective. Forest-dominated regions are less vulnerable, but agricultural, plantation, openland, and built-up areas particularly those that overlap with geological features like lineaments need to be assessed for risk at higher levels.

4.8. Lineament Phenomena

Lineaments are straight lines on the Earth's surface that usually indicate geological phenomena including faults, joints, ridges, and fractures beneath the surface. These features highlight zones of crustal weakness, especially in tectonically active places. Their analysis is crucial in landslide studies because they influence subsurface water flow, alter rock and soil strength, and thereby increase slope failure susceptibility. In the Nilgiri region, lineaments natural linear features like faults and fractures are closely linked to valleys and drainage patterns, especially in highly weathered and eroded terrain. Their presence significantly influences slope stability and the likelihood of landslides. Based on lineament density, the region is divided into three classes: low density (66.01%), moderate density (19.94%), and high density (14.05%), with higher densities concentrated in the western, central, northern, and eastern parts of the district. To assess the influence of proximity to lineaments, buffer zones were created at 500-meter intervals. The 0–500 m zone covers 28.3%, primarily in the western and central-western areas, and is highly susceptible to landslides. The 500–2000 m buffer covers 18.57%, mainly in the eastern and northern parts, while areas beyond 2000 m make up 53.1%, mostly in the eastern and southern regions, and are considered relatively more stable (**Figure 9**).

These distance-based buffer zones give us important information about how geological characteristics affect landslide susceptibility across different parts of the landscape. They are a crucial component in making landslide prediction models more accurate. These findings show that areas located near or within zones of high lineament density are more vulnerable to landslides due to increased rock fracturing and enhanced water infiltration. This spatial analysis is crucial for improving landslide prediction and land-use planning.

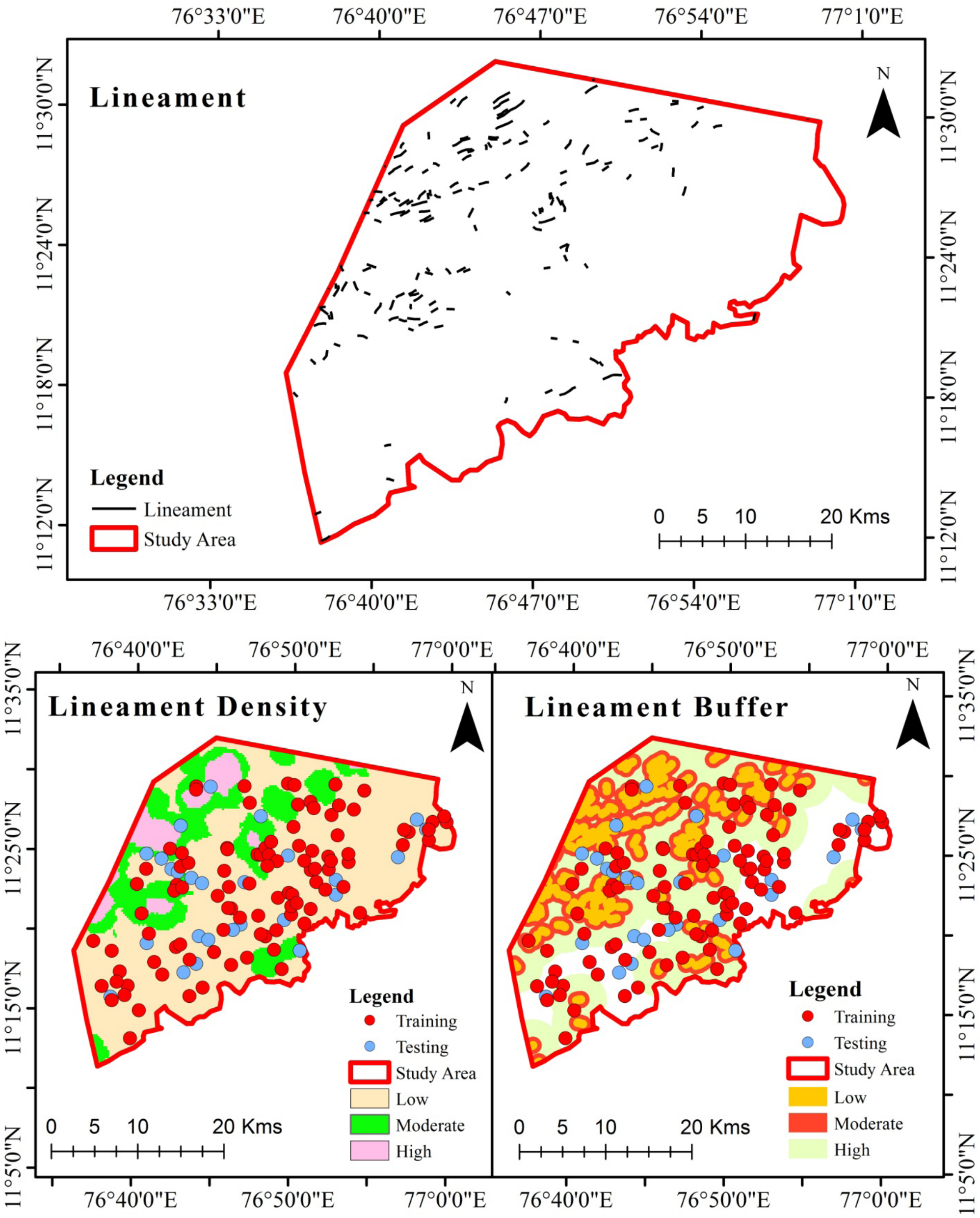

Figure 9. Lineament, Lineament Density and Lineament Buffer map of Nilgiri district.

4.9. Frequency Ratio Method

The study used the Frequency Ratio (FR) model to look at the spatial correlations between landslip events and the associated conditioning factors. This bivariate statistical method uses the locations of recorded landslip incidents and the patterns of possible triggering conditions to figure out how likely it is that a landslip will happen. The method shows how different factors affect the chance of slope failure by comparing areas with and without landslides in similar conditions. is used to analyze how different environmental features correspond with past landslide occurrences. For each contributing factor, the ratio is determined by comparing the The Frequency Ratio (FR) technique was employed to examine the spatial relationship between historical landslide records and various conditioning factors. This approach involves comparing the distribution of landslide occurrences within individual factor classes to their overall spatial extent in the study area. By calculating the ratio between the observed and expected distributions, the model helps identify which terrain conditions are more prone to slope failure. A ratio greater than 1 implies a stronger association with landslide incidence, while a ratio below 1 suggests a weaker correlation. The model indicated that slopes ranging between 15° and 30° were more prone to landslides, showing higher FR values and demonstrating significant susceptibility. Surprisingly, even steeper slopes those between 30° and 50° exhibited lower FR scores, suggesting localized stability, possibly due to compact rock formations or dense vegetation cover. Lower-angle slopes showed reduced frequency ratios, reflecting decreased gravitational stress. Similarly, southeast- and south-facing slopes recorded the highest susceptibility, likely due to variations in solar radiation exposure and surface moisture retention. The complete frequency ratio values for all parameters are compiled in **Table 1** to provide a comparative understanding of influencing variables.

Table 1. Result of the frequency ratio model for each factor.

Parameters	Class	Frequency Ratio
Land use land cover	Water Body	0
	Agriculture	1.87
	Plantation	0.42
	Forest	0.13
	Open land	0
	Settlement	5.77
Soil Depth	Very deep > 150	1.29
	Deep 100 – 150	0
	Rock land	0.3
NDVI	Low	0.75
	Moderate	1.05
	High	1.46
Soil	Sandy clay loam	1.44
	Rock land	0.48
	Clay loam	0.12
Slope	0 – 5	0.57
	5–15	1.15
	15 – 30	1.22
	30 – 50	0.31
	> 50	0
Geomorphology	Ridge type Structural hills	1.39
	Upper Piedomont slope	0.67
	Hilltop Weathered	1.29
	Dome type Denudational hills	0.75
	Valley	0
Lineament Density	Low	1.14
	Moderate	0.81
	High	0.28
Lineament Buffer	0 – 500	0.92
	500 – 2000	1.17
	> 2000	1.26
Aspect	Flat	0
	North	0.91
	Northeast	0.88
	East	0.95
	Southeast	1.45
	South	1.76
	Southwest	1.06
	West	0.92
	Northwest	0.28
	North	0.49

Figure 10 shows how several environmental and geological conditions affect the likelihood of landslides in the study area. Among all variables, the slope gradient emerged as the most influential, contributing 9.15% to the landslide susceptibility index. This suggests that areas with steeper inclines are naturally more prone to ground failure due to the increased gravitational force acting on surface materials, a relationship clearly illustrated in the susceptibility map.

Land Use and Land Cover (LULC) is the second most important element, after slope gradient, contributing 8.37% to the model. This shows how crucial it is for human activities like farming, cutting down trees, and building cities, as well as natural vegetation patterns, to affect slope stability. These changes in how land is used often mess up natural drainage and make the soil less stable, which makes landslides more likely in such regions. After slope gradient and land use, geomorphology is the third most important element, accounting for 7.78% of the landslip susceptibility model. This shows how important the landforms and terrain structures below the surface are in determining how slopes react to environmental stimuli. Soil type is also important, contributing 7.48% to susceptibility due to its influence on soil moisture retention and resistance to shear stresses.

Lineament density, which shows the concentration of geological structures such as faults and fractures, constitutes 4.50% of the whole model. Soil depth, critical for water absorption and root stability, contributes 4.42%. The Normalised Difference Vegetation Index (NDVI) measures vegetation cover, which has a lower effect, making up only 2.6% of the susceptibility. The lineament buffer zones show that being close to geological faults has the least effect, adding only 1.81%. This means that being close to these kinds of structures doesn't have a big effect on starting a landslip in this area. **Figure 10**'s graph makes it easy to see how important each component is in relation to the others. This information can help you decide which risk reduction initiatives to focus on first and how to better prepare for landslides in the whole region.

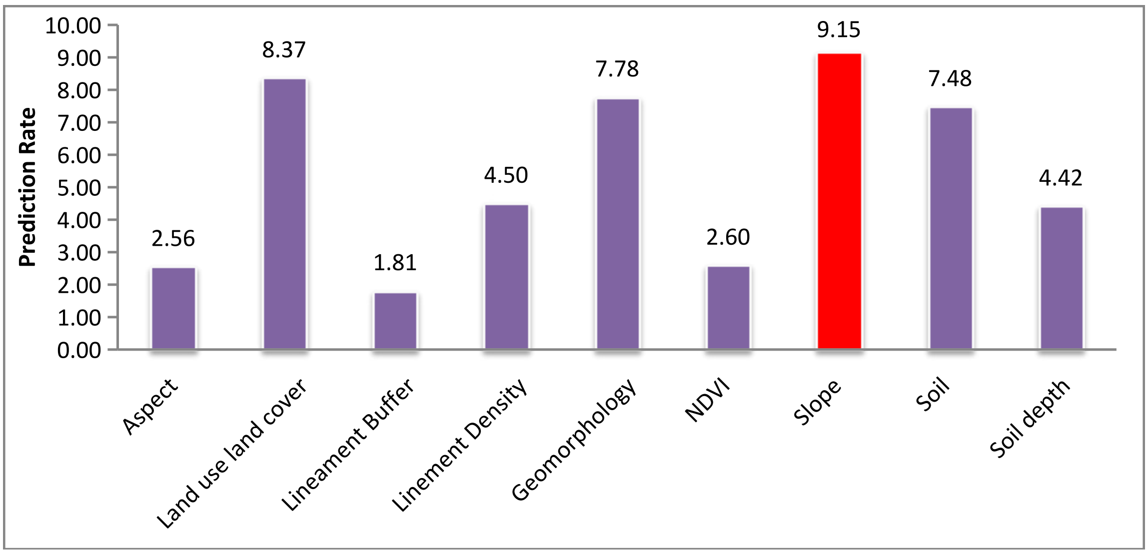

Figure 10. Percentage Shares of Parameters.

4.10. Landslide Susceptibility Map

This study's landslide susceptibility map highlights the areas within the research region that are more prone to future landslide occurrences. The major goal of making these kinds of maps is to clearly show areas with different levels of danger. This information can then be used to plan effective hazard management and mitigation measures. Numerous factors—including climatic conditions, lithology, geological structure, hydrological dynamics, and long-term landscape evolution—contribute to landslide susceptibility. However, it is frequently hard to combine all of these in one predictive model. Rather than attempting to include every available variable, this study focused on a small number of observable characteristics, such as slope, soil type, lithology, and land use/land cover, each represented as a separate spatial layer. The Frequency Ratio (FR) model and historical landslide records, were employed to figure out and map landslide risk across the whole area. The susceptibility map in **Figure 11** shows the terrain divided into three groups: low, moderate, and high risk. While low-susceptibility areas are widely distributed across the region, they are especially prevalent in the western and northeastern regions. Moderate-risk zones include a lot of the centre area and go a little bit towards the northern parts. Notably, a lot of reported landslides fall into this moderate-risk areas—likely due to the influence of variable rainfall intensity and the strength of the monsoon season change.

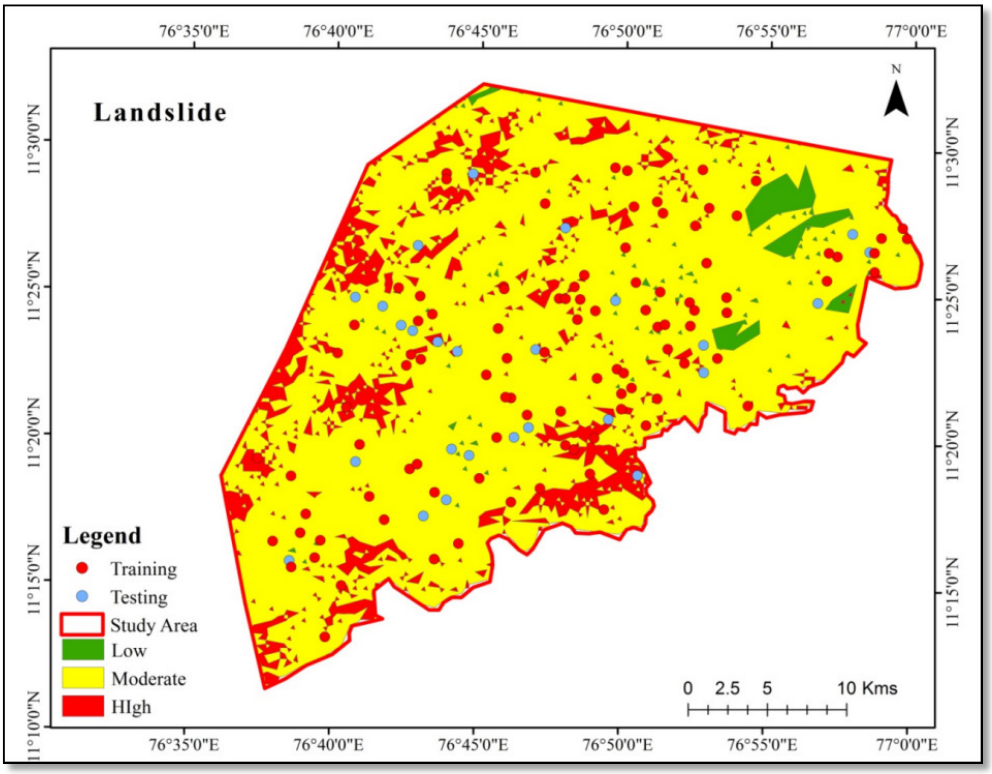

Figure 11. Landslide Susceptible Map using Frequency Ratio.

Some areas of the district have also become unstable because of human activities, especially those related to tourism development and infrastructure expansion. High-susceptibility zones are larger and cover the eastern, southern, and parts of the western areas. These high-risk regions need targeted attention and proactive mitigation strategies to reduce the potential for damage to both lives and property.

4.11. Model Validation

We checked the accuracy of the landslip susceptibility assessment by comparing known landslip locations with the hazard zones predicted by the Frequency Ratio (FR) model. We made success rate and prediction rate curves to see how well the model worked, and we determined the Area Under the Curve (AUC) values for both the training and validation datasets. The Area Under the Curve (AUC) is a widely accepted metric for assessing a model's ability to discriminate between landslide-prone and stable areas. It is a good way to reflect the reliability and consistency of the model's predictive capacity [23]. The model performed well, getting an AUC score of 0.879 on the training dataset, indicating high predictive accuracy, as seen in **Figure 12**. The validation dataset had a lower AUC of 0.63, suggesting a moderate agreement between the projected susceptibility and actual landslip incidences.

These results show that the Frequency Ratio model used in this study offers a reasonably reliable prediction of landslide susceptibility. According to frequently accepted classification standards, the model is in the "good" category. This shows that it works well for continuous risk appraisal and disaster management efforts in the area.

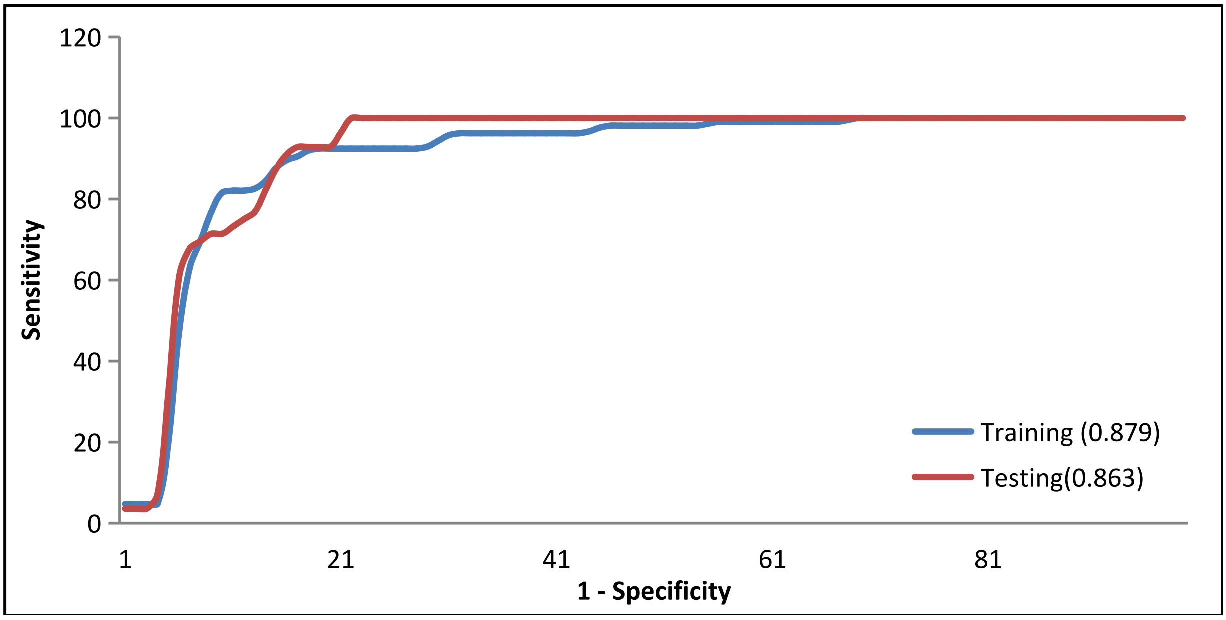

Figure 12. Accuracy Assessment for Frequent Ratio.

5. Conclusion

The study's results clearly reveal that a mix of land use patterns, geological factors, and topographical features have a significant impact on landslides in the Nilgiri area. This study uses the Frequency Ratio (FR) model in conjunction with geospatial tools to provide a thorough evaluation of the Nilgiris' landslide vulnerability. According to the research, the most important elements influencing the incidence of landslides are soil type (7.48%), geomorphology (7.78%), land use/land cover (8.37%), and slope gradient (9.15%). The study highlights how human-induced changes, such as urbanization, agricultural growth, and deforestation, drastically affect slope stability and heighten susceptibility in already fragile situations.

High-risk areas are precisely identified on the landslide susceptibility map produced by this model, especially in the district's central, eastern, and western regions. The model's robustness is evidenced by the validation findings (AUC = 0.879). Areas close to geological discontinuities, particularly those within 500 meters, are more vulnerable to slope collapse because of structural flaws and water infiltration routes, according to lineament density and proximity studies. These results have important implications for infrastructure development, disaster mitigation, and land-use planning. Policymakers, planners, and emergency services may utilize the susceptibility map to prioritize actions, control building in high-risk areas, and create early warning systems.

Incorporating dynamic meteorological data, like soil moisture and rainfall, and using machine learning approaches should enhance model accuracy and improve temporal forecasts for future studies. Evaluating social exposure to geohazards might also benefit from the integration of community vulnerability indices. Overall, this study promotes sustainable development planning in mountainous, environmentally sensitive areas like the Nilgiris and offers a repeatable framework for landslide risk predictions.

Taken together, these results show that the Frequency Ratio technique works well for assessing landslip susceptibility and provides planners, engineers, and policymakers with useful information on how to make land-use decisions and manage risk to lower landslip risks.

Author Contributions

All authors contributed equally to the writing and preparing of the manuscript. Each author was involved in the preparation of the original draft, as well as the revision and final approval of the submitted version. All authors have read and agreed to the published version of the manuscript.

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Informed Consent Statement

Not applicable.

Availability of DataThe datasets generated and analyzed during this study are available from the corresponding author upon reasonable request.

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Conflicts of Interest

All the authors also declare that there is no conflict of interest in relation to the research, authorship, and publication of this study.

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