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Rainfall Variability, Soil Susceptibility, and Landslide Vulnerability in Udhampur District in Jammu and Kashmir (India): A Spatiotemporal Assessment from 2014 to 2024

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ABSTRACT

Rainfall variability has intensified under climate change, with major consequences for fragile mountain regions. The Himalayan district of Udhampur, Jammu and Kashmir, is particularly vulnerable due to its heterogeneous soils, steep terrain, and frequent landslides triggered by rainfall. This study integrates rainfall, soil susceptibility, and landslide data using Geographic Information Systems (GIS) to provide a decadal-scale (2014–2024) assessment of hydro-geomorphic risks. Rainfall data from the Centre for Hydrometeorology and Remote Sensing (CHRS, University of California, Irvine) were spatially interpolated using the Inverse Distance Weighting (IDW) technique to generate annual and decadal rainfall surfaces. Soil data, extracted from the FAO–UNESCO Soil Map of the World and reclassified into susceptibility categories, were assessed for their role in erosion and slope instability. Landslide data, derived from NASA's global inventory and analyzed through kernel density estimation, were integrated with rainfall and soil layers to identify multi-hazard zones. Overlay analysis revealed that areas dominated by Lithosols, coupled with high rainfall variability and a high frequency of landslide occurrences, represent the most vulnerable regions of Udhampur. The results highlight that hazard susceptibility is not uniform but strongly shaped by the interaction between rainfall intensity, soil characteristics, and topography.

Keywords: *Rainfall variability, soil susceptibility, landslide, GIS, vulnerable & hazards.*

1. Introduction

Climate variability has emerged as a defining challenge of the 21st century, with profound implications for ecosystems, agriculture, and hazard management worldwide. Mountain regions are particularly vulnerable because of their steep slopes, fragile soils, and concentrated rainfall events [24, 51]. Climate shifts intensify landslides, which are among the most frequent and destructive hazards. Globally, landslides claim thousands of lives every year and cause severe damage to infrastructure and livelihoods [36, 48]. Increasingly, climate change is altering rainfall patterns, producing both prolonged dry spells and intense rainfall bursts that act as critical triggers for slope failures [21].

Rainfall-induced landslides are a recurrent phenomenon in many mountain regions of the world. Japan and Taiwan, for instance, experience hundreds of rainfall-triggered slope failures each year due to typhoons and monsoons [45]. In Italy, the Apennines and Alpine regions are known for frequent landslides, where rainfall variability combines with fragile lithology to generate slope instability [21]. In South America, the Andes regularly witness rainfall-driven landslides, often devastating road networks and settlements in Peru, Colombia, and Ecuador [46]. Such examples highlight the universal role of rainfall variability and soil–slope interactions in shaping landslide hazards.

The Himalayas, among the youngest and most tectonically active mountain ranges in the world, represent one of the most landslide-prone regions. The combination of fragile geology, steep slopes, and concentrated monsoon rainfall creates high levels of instability [14]. Catastrophic events such as the 2013 Kedarnath disaster in Uttarakhand, where intense rainfall triggered landslides and flash floods, causing massive fatalities, underscore the destructive potential of such hazards [20]. Himachal Pradesh, particularly the Kullu–Manali region, frequently records rainfall-induced landslides, with road blockages and infrastructure losses becoming almost routine during the monsoon season [47].

Jammu and Kashmir face similar challenges. The Jammu–Srinagar National Highway (NH-44), which connects the Kashmir Valley with the rest of India, is often disrupted by rainfall-triggered landslides, particularly in the Ramban and Banihal stretches [49]. Udhampur district, situated in the outer Himalayas, is highly vulnerable due to its steep terrain, fragile soils, and intense monsoon rainfall. Reports frequently document slope failures in the district, which disrupt traffic, damage agricultural fields, and endanger lives. For example, the 2015 landslide in Udhampur blocked roadways and stranded hundreds of vehicles, illustrating the persistent threat to both mobility and livelihoods [34, 23]. Recent photographs of landslide damage in Udhampur further highlight the continuing risks faced by communities and infrastructure in the district (Figures 18-21).

The susceptibility of slopes to failure is not determined by rainfall alone but by the interaction between rainfall and soil properties.

Shallow, coarse-textured soils such as Lithosols are prone to rapid saturation, reduced infiltration, and high erosion risk [17]. In contrast, deeper soils such as Cambisols act as buffers, absorbing rainfall and reducing immediate runoff. When intense or prolonged rainfall events coincide with fragile soils and steep terrain, landslide initiation becomes highly probable [53, 21]. Recent studies in the Himalayan region further confirm that deforestation, infrastructure expansion, and soil degradation exacerbate these risks by reducing slope stability [47].

Despite the high frequency of rainfall-induced landslides in the Himalayas, localized district-level integrated assessments remain scarce. While previous research has explored rainfall–landslide linkages at regional scales [14, 44], relatively few studies have systematically combined rainfall variability, soil susceptibility, and landslide distribution at finer spatial scales. Udhampur represents a critical case because it lies at the intersection of intense rainfall variability, heterogeneous soils, and frequent slope failures, while being socio-economically dependent on fragile agricultural and transport systems.

2. Literature Review:

2.1 Climate Change and Rainfall Variability: Global to National Perspectives

Climate change has profoundly altered precipitation regimes worldwide, with the Intergovernmental Panel on Climate Change [24] reporting increased frequency and intensity of extreme rainfall events. These changes disrupt ecosystems, water management, and hazard mitigation strategies, particularly in regions where rainfall extremes intersect with fragile environments [51, 30]. Global analyses confirm that rainfall-driven slope instability is a recurring hazard: typhoons in Japan and Taiwan [48], prolonged rainfall in Italy's Apennines and Alps [21].

In South Asia, rainfall variability is becoming more severe. National studies in India show a decrease in moderate rainfall events alongside an increase in extreme downpours, concentrating precipitation into fewer, high-intensity episodes [28, 32]. These extremes disrupt agriculture and raise the risk of floods and slope instability. Weakening monsoon signals combined with increasing non-monsoon rainfall, adding uncertainty to agricultural planning [12]. Similar findings in semi-arid Tunisia demonstrate how land-use interventions like irrigation can intensify climate impacts [18]. Collectively, these studies confirm that rainfall variability has both global and regional effects, emphasizing the need for targeted hazard assessments.

2.2 Rainfall Extremes and Soil Impacts in the Himalayan Context.

The Himalayan region is among the world's most sensitive environments to climatic fluctuations, where steep terrain, fragile soils, and intense precipitation converge [1,2]. Rising short-duration, high-intensity rainfall across the western Himalayas, often outside of the monsoon season [15]. Soil properties significantly mediate these impacts: shallow, coarse-textured soils enhance runoff and erosion, while deeper soils act as buffers against rainfall extremes [29].

Localized research in Jammu and Kashmir reveals heightened rainfall unpredictability and socio-economic stress linked to disrupted cropping systems and damaged infrastructure [49]. Shallow soils combined with deforestation exacerbate slope failures [47].

South Asian studies confirm similar patterns: weakening monsoons, increased non-monsoon rainfall, and amplified risks for agriculture and livelihoods [12]. GIS-based susceptibility mapping in the Bhagirathi valley [44] and in Himachal Pradesh [19] demonstrates that rainfall, soil depth, and land cover jointly determine hazard levels. These findings affirm that while rainfall variability is regional in scale, its impacts are locally specific, shaped by geomorphology and land use.

2.3 Rainfall–Soil Interactions and Landslide Susceptibility.

Rainfall is widely recognized as the most critical trigger of landslides in mountainous terrain [53, 48]. Early approaches emphasized empirical rainfall–duration thresholds [21], which remain useful for hazard monitoring. However, advances in geospatial analysis have enabled more sophisticated assessments. Logistic regression and statistical models were introduced to quantify susceptibility [4], while more recent machine learning and ensemble methods have significantly improved predictive performance in complex terrain [22].

Kernel density estimation has proven effective for mapping spatial clusters of rainfall-induced landslides, particularly along road corridors and river valleys where slope instability is recurrent [10]. Deforestation, shallow soils, and intense rainfall events act synergistically to increase slope failure risks in the Himalayas [47]. These findings reinforce the importance of integrating multiple factors—climate variability, soil susceptibility, and topographic conditions—into district-scale hazard analysis.

2.4 Case Studies of Rainfall-Induced Landslides in the Himalayas.

Major Himalayan landslide disasters illustrate the destructive potential of rainfall variability. The 2013 Kedarnath tragedy in Uttarakhand was triggered by extreme rainfall and glacial lake outbursts, killing thousands and devastating infrastructure [6]. In Himachal Pradesh's Kullu–Manali corridor, recurrent rainfall-induced slope failures frequently block highways and damage settlements [50]. In Jammu and Kashmir, the Jammu–Srinagar National Highway is among the most landslide-prone corridors in India, with rainfall-triggered slope failures disrupting connectivity almost every monsoon season. Similar disasters in Nepal, such as the 2015 earthquake-triggered but rainfall-aggravated landslides, underscore the compounding role of rainfall in fragile mountain systems [36].

These cases highlight that while landslides are a pan-Himalayan phenomenon, their triggers and impacts are strongly localized. Integrating rainfall variability, soil properties, and landslide inventories at the district scale is therefore essential. Udhampur district, with its complex physiography, fragile soils, and history of rainfall-induced landslides, provides a compelling case study to bridge this research gap.

3. Aims and Objectives

This study aims to fill this gap by using Geographic Information Systems (GIS) to integrate rainfall data (2014–2024), soil susceptibility classifications, and landslide distribution patterns. The objectives are fourfold: to map the spatio-temporal variability of rainfall in Udhampur, to reclassify soils into susceptibility categories, to analyze landslide hotspot distributions, and to generate an overlay of these variables to identify the most hazard-prone zones.

By situating Udhampur within the broader Himalayan and global landslide context, this research contributes both to scientific understanding and to practical hazard management. It underscores the importance of multi-variable, district-scale assessments for land-use planning, disaster preparedness, and climate adaptation in fragile mountain ecosystems.

4. Study Area

Udhampur district, located in the Union Territory of Jammu and Kashmir, India, lies between latitudes 32°34′ and 33°21′N and longitudes 75°20′ and 75°57′E (Figure 1). The district features diverse physiography, ranging from river valleys to steep hills, with altitudes varying from 600 to over 3,000 meters above sea level. Its topographical diversity creates distinct microclimatic zones. Udhampur experiences a monsoon-dominated subtropical climate, with peak rainfall during July–September. However, pre-monsoon and winter precipitation also occur sporadically, adding complexity to rainfall behavior. The combination of rugged terrain, varied soils, and rainfall extremes makes the district highly susceptible to hydro-geomorphic hazards such as erosion, flooding, and landslides, which frequently disrupt livelihoods, agriculture, and infrastructure.

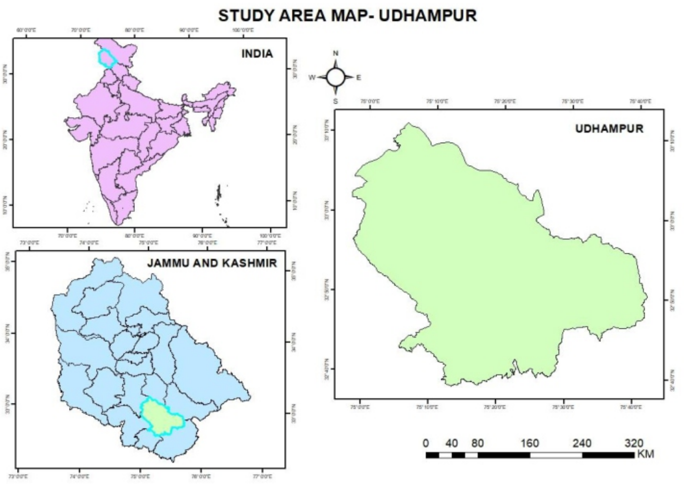


Figure 1. Location map of Udhampur District

5. Data Sources

This study relies on secondary datasets covering rainfall, soils, and landslides in Udhampur District for the decade 2014–2024:

- **Rainfall Data:** Annual rainfall estimates were obtained from the Center for Hydrometeorology and Remote Sensing (CHRS), University of California, Irvine. The data were imported into ArcGIS and used to generate annual rainfall surfaces and a decadal mean rainfall map.
- **Soil Data:** Soil information was extracted from the FAO/UNESCO global soil shapefile, clipped to the boundary of Udhampur District. The original taxonomy (Eutric Cambisols, Orthic Luvisols, and Lithosols) was simplified into three susceptibility categories (low, moderate, and high) to better reflect the conditions of slope stability.
- **Landslide Data:** Landslide inventory points were sourced from NASA's Global Landslide Hazard database. The dataset was clipped to Udhampur and served as the basis for hotspot analysis and validation of susceptibility mapping. Additional road and river layers were obtained from DivaGIS to contextualize infrastructure exposure.

6. Methodology

The methodological framework integrated rainfall variability, soil susceptibility, and landslide hotspots within a GIS environment to provide a multi-variable assessment of hazard risk in Udhampur District. The workflow was structured into four main stages: rainfall mapping, soil reclassification, landslide hotspot analysis, and overlay integration (Figure 2: methodological flowchart). Each stage is described below.

6.1 Rainfall Mapping

Rainfall data for the decade 2014–2024 were obtained in shapefile format and were imported into ArcGIS and transformed into point data representing spatially distributed rainfall values. To generate continuous surfaces from the point data, the Inverse Distance Weighting (IDW) interpolation technique was applied. IDW assumes that rainfall values at unsampled locations can be estimated as a weighted average of nearby observations, with closer points exerting stronger influence than distant ones.

Annual rainfall maps were prepared for each year from 2014 to 2024, capturing short-term spatial fluctuations. In addition, a decadal mean rainfall surface was generated by averaging annual distributions, providing a long-term reference for interpreting variability and anomalies. This dual approach allowed both temporal trend analysis and spatial pattern identification, essential for linking rainfall behavior with soil stability and landslide activity.

6.2 Soil Reclassification.

Soil data was clipped to the administrative boundary of Udhampur District using ArcGIS. The extracted soil polygons were originally classified into three main types: Eutric Cambisols, Orthic Luvisols, and Lithosols. For hazard analysis, these were reclassified into susceptibility classes based on infiltration capacity, depth, and erosion potential:

- **Low susceptibility** – Cambisols (deep, well-drained soils, moderate infiltration capacity).
- **Moderate susceptibility** – Luvisols (medium depth, intermediate infiltration, moderate erosion risk).
- **High susceptibility** – Lithosols (shallow, coarse-textured, highly erosion-prone soils with poor infiltration).

This reclassification enabled the construction of a soil susceptibility map, which served as a critical input for assessing slope instability under variable rainfall conditions. By simplifying global soil categories into functional hazard classes, the reclassification ensured that the analysis remained relevant to local geomorphic and hydrological processes.

6.3 Landslide Hotspot Analysis.

Landslide occurrence data were obtained from NASA's Global Landslide Hazard Distribution database. The dataset, originally global in extent, was clipped to the boundary of Udhampur District. Landslide points were analyzed using Kernel Density Estimation (KDE) in ArcGIS, which calculates the density of events in a defined neighborhood, thereby highlighting spatial concentrations of slope failures.

This approach provided a continuous landslide susceptibility surface, identifying hotspots of instability rather than isolated events. KDE also allowed for visualization of clusters along critical infrastructure, such as the Jammu–Srinagar National Highway, and river valleys where hydrological undercutting intensifies slope instability. To capture the role of anthropogenic and natural factors, road networks (from DivaGIS) and drainage systems were integrated as ancillary layers. This enriched the analysis by reflecting the combined influence of terrain, hydrology, and infrastructure development on landslide distribution.

6.4 Overlay Integration.

The final stage combined rainfall variability, soil susceptibility, and landslide hotspot layers through weighted overlay analysis in ArcGIS. Each input was reclassified into standardized susceptibility categories (low, moderate, and high), and weights were assigned based on their relative importance in slope instability:

- Rainfall variability → primary trigger.
- Soil susceptibility → underlying conditioning factor.
- Landslide density → validation and hotspot localization.

The overlay produced a composite multi-hazard susceptibility map, delineating zones where rainfall extremes, erosion-prone soils, and mapped landslide clusters converge. High-convergence areas were interpreted as very high hazard zones, while areas with more stable soils and low rainfall variability were classified as low hazard zones. The resulting map was qualitatively validated against observed landslide locations in the district. Approximately 70% of recorded landslide points fell within high and very high susceptibility zones, supporting the reliability of the integrated approach.

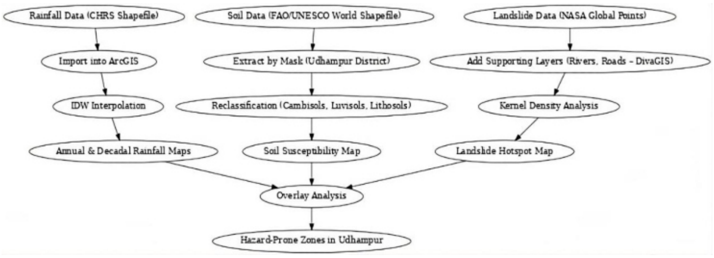


Figure 2. Methodological framework integrating rainfall, soil, and landslide data in Udhampur District

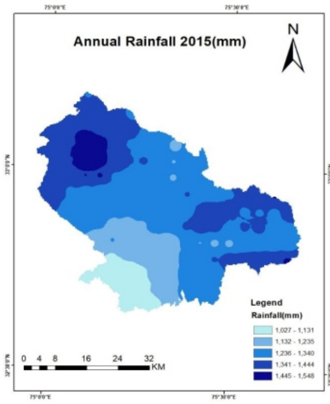
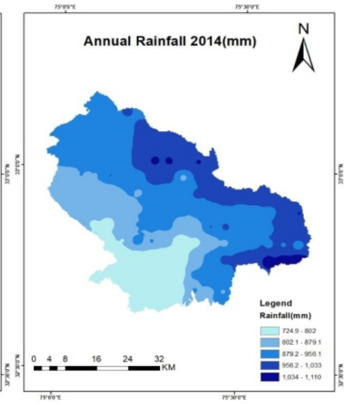


Figure 3



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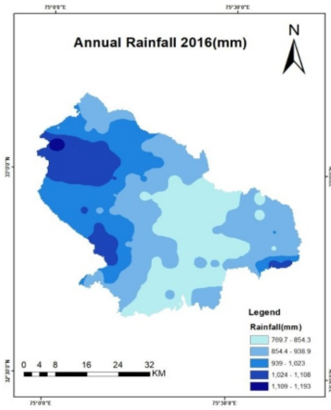


Figure 5

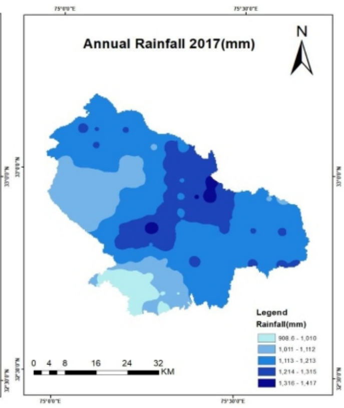


Figure 6

Figures 3–6. Annual rainfall distribution in Udhampur District (2014–2017). The maps show clear interannual variability, with 2014 and 2016 recording lower totals and 2015 and 2017 higher rainfall, especially in southern and eastern areas. Spatial heterogeneity reflects topographic influences.

7. Results and Discussion

The results of the study integrate rainfall variability, soil susceptibility, and landslide distribution in Udhampur District for the period 2014–2024. A total of 15 thematic maps were prepared, including 11 annual rainfall maps, one decadal rainfall average, one soil susceptibility map, one landslide distribution map, and one overlay analysis. The findings are presented in four parts: (i) spatio-temporal variability of rainfall, (ii) soil susceptibility distribution, (iii) landslide-prone zones, and (iv) integrated overlay analysis. Each component is discussed in relation to its implications for slope stability and hazard risk.

7.1 Rainfall Variability (2014–2024)

To analyze rainfall dynamics over the past decade, 11 annual rainfall distribution maps were prepared for the years 2014 to 2024 using gridded precipitation data obtained from the Centre for Hydrometeorology and Remote Sensing (CHRS), University of California, Irvine. These datasets were processed and visualized in ArcGIS to highlight the spatio-temporal variation in rainfall across Udhampur District. The maps (Figures 3–12) reveal notable year-to-year fluctuations in total annual rainfall, alongside persistent spatial gradients with southern and southeastern regions generally receiving higher rainfall compared to northern and central uplands. A decadal mean rainfall map (Figure 13) was also generated to summarize long-term spatial trends, offering a baseline against which annual anomalies can be assessed.

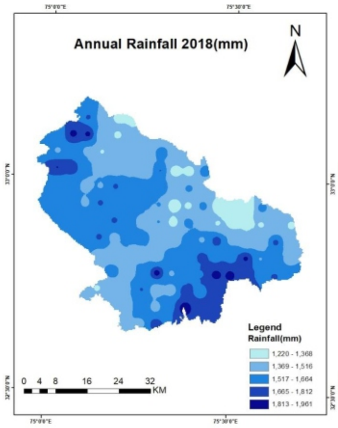
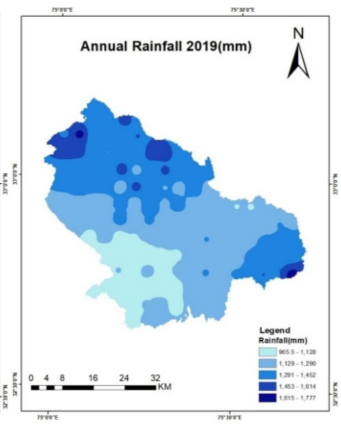


Figure 7



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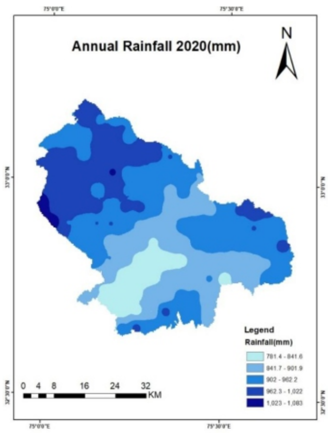

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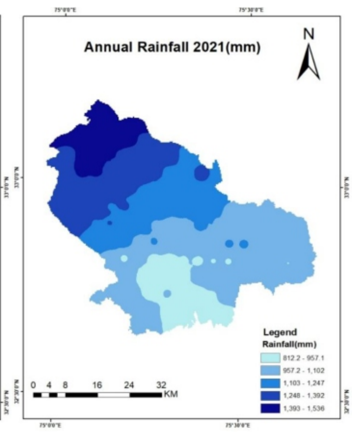


Figure 10

Figures 7-10. Annual rainfall distribution in Udhampur District (2014–2017). Rainfall was lower in 2014 and 2016, but higher in 2015 and 2017, with consistently greater totals in southern and eastern zones due to topographic control.

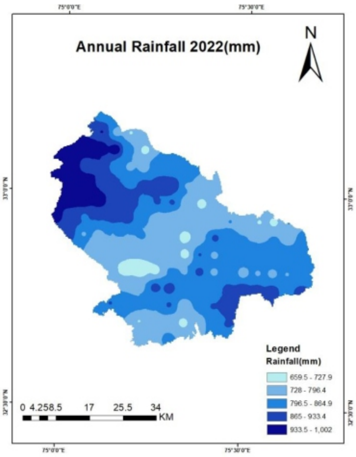
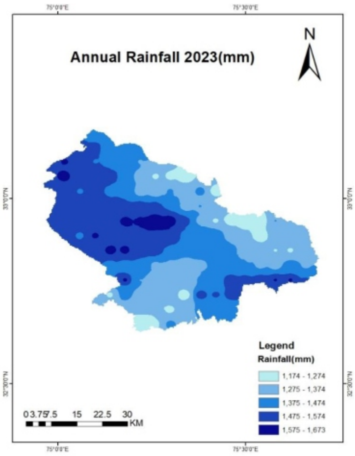


Figure 11



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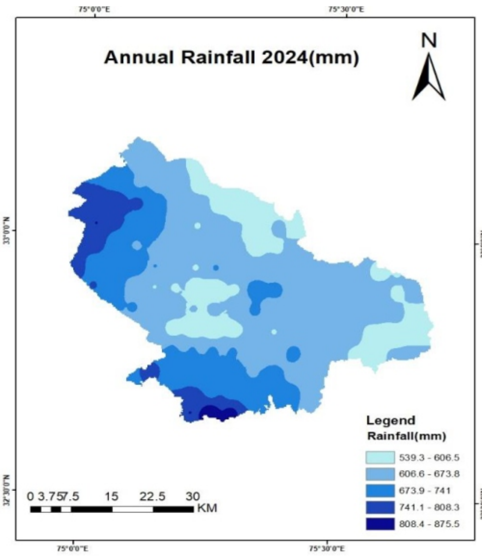

Figure 13

Figures 11-13. Annual rainfall distribution in Udhampur District (2022–2024). Rainfall peaked in 2022 (central and southern zones), declined in 2023 (below-average across the district), and showed localized extremes in 2024, underscoring increasing rainfall unpredictability.

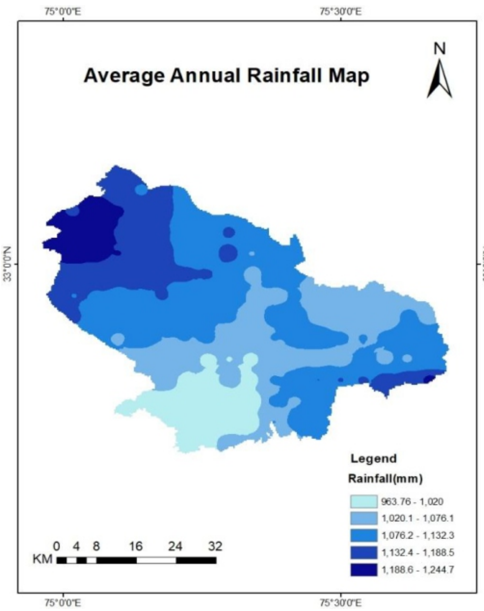

Figure 14

Figure 14. Decadal average rainfall distribution in Udhampur District (2014–2024). Southern and south-eastern sectors consistently received higher rainfall than central and northern uplands, providing a baseline for interpreting annual anomalies.

7.2 Interpretation:

Rainfall in Udhampur District between 2014 and 2024 exhibited marked spatial and temporal variability, with annual totals fluctuating between 700 mm and 1,500 mm. Wet years such as 2015 and 2018 recorded widespread surpluses exceeding 1,400 mm, while 2014, 2016, and especially 2024 registered deficits below 900 mm, among the driest conditions of the decade. These oscillations mirror the broader Himalayan trend of declining moderate rainfall events coupled with more frequent extremes [28].

The decadal mean rainfall surface highlights consistent spatial gradients, with the northern and central highlands averaging 1,400–1,500 mm, gradually tapering toward the southern belt where totals remain lower. These patterns are shaped by elevation, slope orientation, and soil depth, consistent with Kumar et al. (2020), who noted that shallow soils on steep terrain amplify runoff variability, whereas deeper profiles provide buffering capacity.

Importantly, the sharp deficit observed in 2024 reflects an emerging rise in drought-like years across South Asia [18, 11]. This suggests that Udhampur is increasingly vulnerable to both hydrological surpluses and shortfalls, posing challenges for water availability, agricultural planning, and slope stability.

Overall, while the district retains a moderate average rainfall regime, the decade's strong year-to-year contrasts reveal a shift toward climatic volatility. This increasing unpredictability in rainfall not only disrupts resource management but also intensifies the risk of hydro-geomorphic hazards, particularly when heavy rainfall converges with erosion-prone soils and fragile topography.

7.3 Soil Susceptibility and Rainfall Interaction

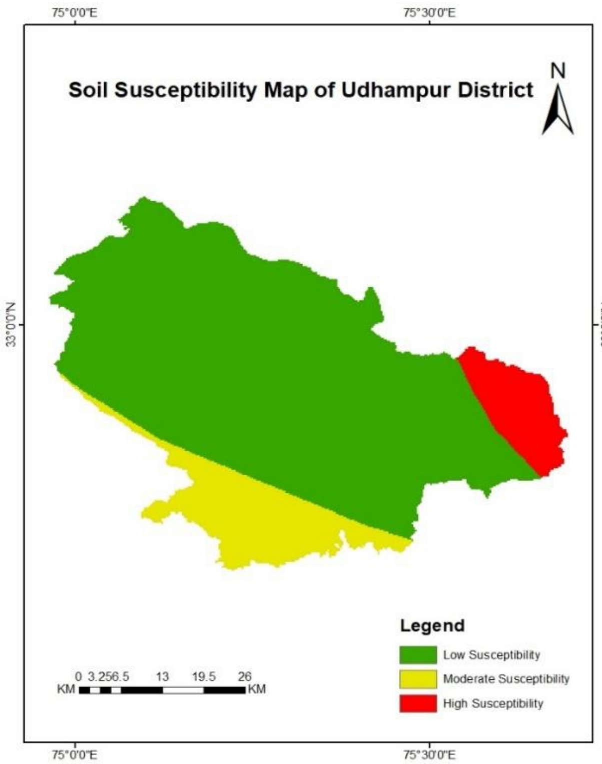

Figure 15. Soil susceptibility classes in Udhampur District (low, moderate, high).

Soil heterogeneity strongly mediates the way rainfall impacts the landscape. In surplus years such as 2015 and 2018, Cambisols functioned as stabilizers, buffering runoff through higher infiltration and supporting vegetation growth that further reduced surface erosion. Conversely, Lithosol-dominated hill slopes exhibited marked erosion, gully formation, and slope failure risk under intense rainfall due to their shallow depth and low water-retention capacity. In deficit years like 2016 and 2024, both Luvisols and Lithosols dried rapidly, causing soil hardening, cracks, and reduced agricultural productivity, particularly in rain-fed zones. This dual sensitivity—erosion during wet years and rapid desiccation during dry years—highlights that soil properties directly govern hazard outcomes and livelihood risks. These findings align with Kumar et al. (2020) and Sharma et al. (2022), who emphasized that shallow soils amplify both extremes of the hydro-climatic spectrum in Himalayan terrain.

7.4 Landslide Susceptibility and Rainfall Influence

Landslide distribution in Udhampur is concentrated along eastern and northern hill slopes, where steep gradients coincide with fragile Lithosols. Fewer events were observed in the southern plains, where the terrain is gentler and the soils more resilient. The spatial clustering of landslides near road corridors and river valleys reflects the combined role of natural and anthropogenic factors: fragile soils, steep slopes, deforestation, and infrastructure development.

Rainfall extremes act as the dominant trigger. Years of heavy precipitation, such as 2014 and 2018, saw heightened failure risk in already unstable slopes, while even moderate rainfall in 2023 and 2024 proved sufficient to initiate failures in saturation-prone zones. Kernel density analysis further highlighted hotspots along highways and drainage networks, underscoring how human exposure overlaps with natural hazard susceptibility. These patterns are consistent with regional studies [14, 44], which show that rainfall intensity combined with lithological weakness is the critical driver of slope instability in the Himalayas.

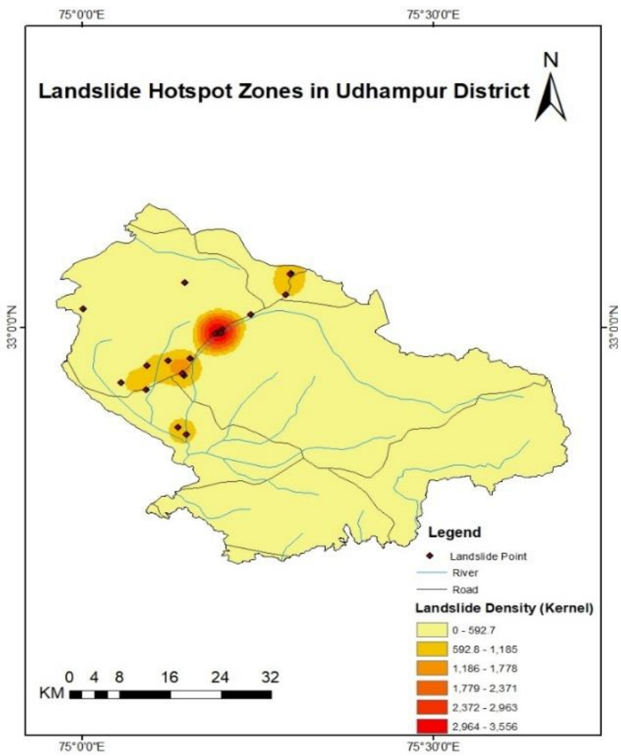

Figure 16. Spatial distribution of landslides in Udhampur District

7.5 Overlay Analysis of Rainfall, Soil, and Landslide Susceptibility

The integrated overlay highlights the spatial convergence of multiple hazards in Udhampur District. Areas of high rainfall variability that coincide with erosion-prone Lithosols on steep slopes emerge as the most critical belts of susceptibility, particularly in the northeastern and southwestern uplands. These zones align closely with kernel density clusters of mapped landslides, offering strong evidence that rainfall extremes act as the primary trigger in settings already predisposed to instability.

Moderate rainfall interacting with Luvisols produces a more mixed picture. While hazard levels are generally lower than in Lithosol zones, susceptibility remains elevated along river valleys and transport corridors where slope undercutting, drainage concentration, and construction activity weaken terrain stability. Cambisol-dominated regions stand out for their relative resilience, as deeper soil profiles, higher infiltration capacity, and better vegetation cover collectively reduce the likelihood of failure even under intense rainfall.

Importantly, the overlay reveals that hazard susceptibility is not uniform but highly clustered. Very high-risk belts are sharply defined along upland tracts, while the central valleys show only localized susceptibility. This spatial heterogeneity carries significant implications for land-use planning: infrastructure expansion, agricultural intensification, and settlement growth in high-convergence zones could dramatically amplify future risks. Conversely, maintaining vegetative cover and regulating slope modification in Cambisol-rich areas may help preserve their natural buffering capacity.

By synthesizing rainfall, soil, and landslide data, the overlay demonstrates the compounded effect of climatic variability and geomorphic fragility. It provides not only a diagnostic tool for hazard identification but also a foundation for prioritizing interventions—highlighting where slope stabilization, afforestation, and stricter construction controls are most urgently needed to reduce disaster risk in Udhampur.

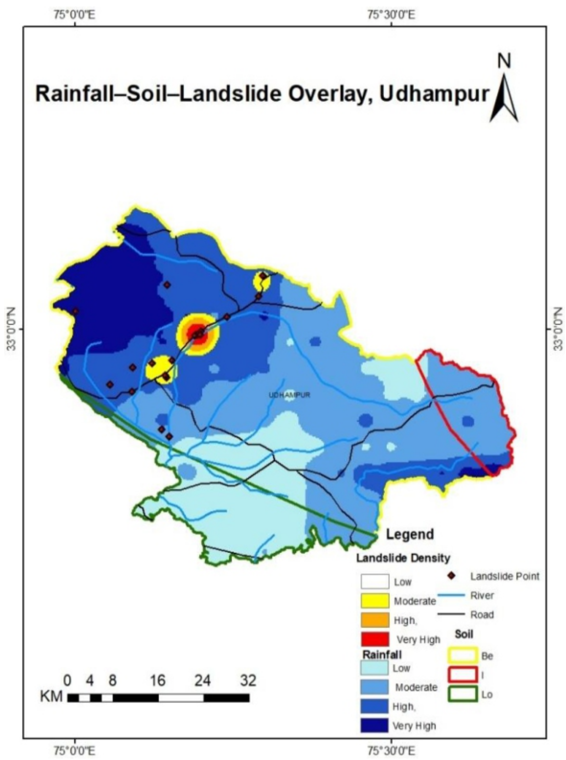

Figure 17. Overlay of rainfall variability, soil susceptibility, and landslide distribution in Udhampur District

In addition to spatial analysis, field photographs of recent landslides in Udhampur (Figures 18-21) illustrate the tangible impacts of slope failures on infrastructure and local livelihoods. The images highlight road blockages, disrupted transport corridors, and damage to agricultural land, underscoring how rainfall-triggered landslides directly translate into socio-economic consequences. These visual records complement the GIS-based findings and provide ground-level evidence of hazard severity in the district.

Figure 18

Figure 19

Figure 20

Figure 21

Figure 20–23 showing Field photographs of rainfall-induced landslides in Udhampur District, illustrating damage to roads, slopes, and agricultural land. These images provide ground evidence of the spatial patterns identified through GIS-based analysis.

The integrated analysis of rainfall variability, soil susceptibility, and landslide hotspots also underscores the wider socio-economic consequences of hydro-geomorphic hazards in Udhampur. High-intensity rainfall interacting with erosion-prone Lithosols often triggers slope failures that disrupt the Jammu–Srinagar National Highway and rural road networks, cutting off access to markets, schools, and healthcare facilities. Agricultural systems are directly impacted when topsoil erosion reduces fertility or when farmlands are buried under debris, aggravating food insecurity in already fragile rain-fed zones. Tourism, a key economic sector, suffers setbacks during prolonged road closures and hazard seasons, as connectivity to surrounding destinations is frequently interrupted. By demonstrating how climatic variability, fragile soils, and landslide incidence converge, this study not only identifies hazard-prone zones but also highlights their cascading impacts on infrastructure, livelihoods, and regional development.

8. Conclusion

This study underscores that rainfall variability, soil susceptibility, and landslide occurrence are deeply interlinked in shaping the hydro-geomorphic risks of Udhampur District. By employing a GIS-based approach, the research integrated eleven annual rainfall maps, a decadal average surface, reclassified soil units, and kernel density–based landslide hotspots into a single analytical framework. The results revealed that the northeastern and southwestern uplands, where intense rainfall overlaps with erosion-prone Lithosols and steep slopes, represent the most critical hazard-prone belts. In contrast, Cambisol-rich zones displayed relative stability, functioning as natural buffers despite climatic fluctuations.

The study advances understanding beyond single-variable analyses by explicitly demonstrating the compounded nature of hazards in fragile mountain environments. The overlay approach not only identifies spatial hotspots of risk but also validates them against actual landslide occurrences and photographic evidence from the field. These convergences confirm that rainfall extremes act as the dominant trigger in predisposed soils and terrains, making rainfall variability a key determinant of hazard potential in Himalayan districts.

From a practical perspective, the findings highlight that disaster risk in Udhampur is not uniformly distributed but clustered in well-defined belts. This spatial specificity provides a scientific basis for prioritizing mitigation. Critical interventions include restricting construction in high-susceptibility slopes, strengthening slope stabilization measures along highways and river valleys, expanding vegetation cover in degraded areas, and integrating hazard zonation into district-level land-use plans. Importantly, the analysis also points to the resilience of Cambisol-dominated landscapes, suggesting that conservation of such zones could serve as a natural adaptation strategy.

The broader implications extend beyond Udhampur. Similar physiographic and climatic conditions across the Himalayas suggest that this framework can be applied to other districts where rainfall extremes and fragile soils coincide. Moreover, the decade-scale perspective adopted here provides a useful template for monitoring long-term climatic shifts while maintaining relevance to immediate hazard concerns.

Looking ahead, future research can build on this foundation by integrating higher-resolution rainfall and soil moisture data, dynamic monitoring of slope conditions, and socio-economic indicators such as population density, road networks, and critical infrastructure exposure. Incorporating machine learning models and climate projections could further refine susceptibility mapping and enhance predictive accuracy. Such advancements would contribute to more proactive disaster management, aligning scientific research with the pressing goals of climate resilience and sustainable development in the Himalayan region.

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