

RESEARCH ARTICLE

Integrating SBAS-InSAR Deformation Monitoring and AHP-GIS for Landslide Susceptibility Assessment Along the Ghazi-i-Millat Corridor, Azad Jammu and Kashmir, Pakistan

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ABSTRACT

This study applies the Small Baseline Subset InSAR (SBAS-InSAR) technique, together with an Analytic Hierarchy Process (AHP)-GIS weighted-overlay framework, to assess surface deformation and landslide susceptibility along the Ghazi-i-Millat Road (GMR), Azad Jammu and Kashmir, Pakistan. Time-series analysis of 91 Sentinel-1 acquisitions (January 2021-December 2023) indicates a mean Line-of-Sight (LOS) velocity ranging from -14.50 to +15.00 mm/year, with a maximum cumulative LOS displacement of approximately +130 mm and -96 mm over the three-year observation period; a localized maximum LOS velocity of 17.07 mm/year was also recorded. Because LOS displacement records motion toward or away from the sensor rather than true vertical or slope-parallel movement, these values are interpreted as indicators of possible ground instability rather than direct proof of active landsliding. Landslide susceptibility mapping incorporates eight causative parameters, slope gradient, slope aspect, geology, drainage network, fault proximity, road proximity, NDVI, and NDWI, combined through AHP-derived weights in a GIS weighted-overlay model. Dense vegetation cover is associated with qualitatively reduced SBAS-InSAR coherence and data reliability, consistent with well-documented vegetation-induced radar decorrelation. The weighted-overlay analysis assigns the greatest relative importance to slope gradient, followed by drainage network and road proximity, and the resulting susceptibility map places the majority of the mapped landslide inventory within the considerable-to-very-high susceptibility classes. The findings support the value of combining SBAS-InSAR deformation monitoring with

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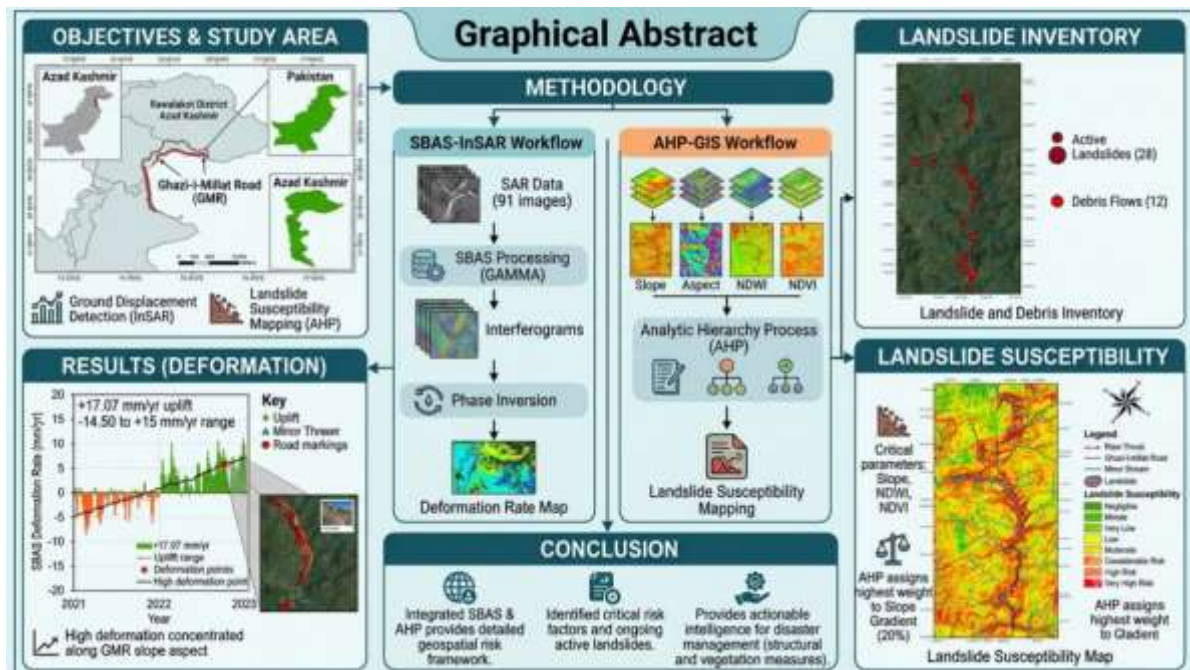
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AHP-GIS susceptibility mapping as a regional decision-support tool for infrastructure planning, slope stabilization, and drainage management along this economically important corridor, while underscoring the need for independent field validation, ascending/descending geometric decomposition, and quantitative uncertainty assessment in future work.

Keywords: Small Baseline Synthetic Aperture Radar (SBAS), Analytic Hierarchy Process (AHP), Ghazi-Millat Road (GMR), Landslides



1. Introduction

Landslides are among the most pervasive natural hazards globally, particularly in mountainous and hilly regions [1]. These phenomena often result in significant socio-economic disruptions, environmental degradation, and loss of life [2]. Given the complex interplay of geological, hydrological, and anthropogenic factors that contribute to landslide occurrences, identifying landslide-prone zones has become a critical research focus [3]. In recent years, advanced geospatial technologies have proven to be powerful tools for assessing and predicting landslide susceptibility, aiding in developing mitigation strategies to minimize damage [4]. The Ghazi-i-Millat Road, an economic corridor stretching from Rawalakot to Azad Pattan in Azad Kashmir, is a vital transportation artery for local communities and regional commerce [5]. This corridor traverses rugged and geologically unstable terrain, making it highly susceptible to landslides, particularly during the monsoon season and periods of seismic activity [6]. Frequent landslide events disrupt transportation and trade and threaten nearby populations' safety and the integrity of critical infrastructure [7]. Understanding the spatial distribution of landslide susceptibility along this corridor is paramount for long-term sustainable development and disaster risk reduction [8].

Recent advances in Synthetic Aperture Radar (SAR) remote sensing technologies, particularly the Small Baseline Subset Interferometric Synthetic Aperture Radar [9] (SBAS-InSAR) technique, have revolutionized the field of geohazard monitoring [10]. SBAS-InSAR allows for the precise detection of ground deformation

over time, enabling researchers to map landslide-prone areas with high accuracy, even in regions with dense vegetation and cloud cover limitations that often hinder optical remote sensing methods ^[11]. By leveraging the SBAS-InSAR approach, this study aims to provide a comprehensive geospatial analysis of ground deformation along the Ghazi-i-Millat Economic Corridor, identifying zones with elevated landslide susceptibility.

In addition to SBAS-InSAR, the Analytic Hierarchy Process (AHP) is employed in this study to enhance landslide susceptibility assessment. AHP is a multi-criteria decision-making (MCDM) method that systematically evaluates various factors contributing to landslides, such as slope gradient, soil type, land use, and rainfall patterns ^[12]. By integrating AHP with SBAS-InSAR, this study applies a combined deformation-monitoring and multi-criteria susceptibility mapping approach to a previously unassessed transport corridor, quantifying ground deformation and the relative importance of landslide-triggering factors for this specific setting.

The objective of this research is twofold. First, it seeks to delineate landslide-susceptible zones along the Ghazi-i-Millat Road using SBAS-InSAR and AHP methodologies. Second, it aims to offer a decision-support framework for local governments and infrastructure planners to prioritize mitigation efforts, enhance road safety, and promote sustainable development in this economically strategic corridor. Given the reliance of regional economies on the uninterrupted functioning of transportation networks, such an assessment is crucial for reducing landslide-induced disruptions and ensuring resilience in the face of climate change and other environmental pressures.

This study fills a critical gap in the existing body of landslide research by employing an integrated SBAS-InSAR and AHP approach. While numerous studies have focused on landslide susceptibility mapping in various regions, few have combined high-precision remote sensing techniques with MCDM methods in the context of economically vital corridors such as the Ghazi-i-Millat Road. This research, therefore, offers a regional application of an established methodological combination, together with practical insights for landslide susceptibility management, with implications for broader applications in other geologically unstable regions.

2. Study Area

The study area is within the Rawalakot district of Azad Jammu and Kashmir (AJK), a region renowned for its rugged terrain and scenic landscapes in northern Pakistan. Specifically, the research focuses on the Ghoin Valley, a geographically significant area that straddles the Ghazi-i-Millat Road (GMR) a critical economic corridor linking Rawalakot to Azad Pattan.

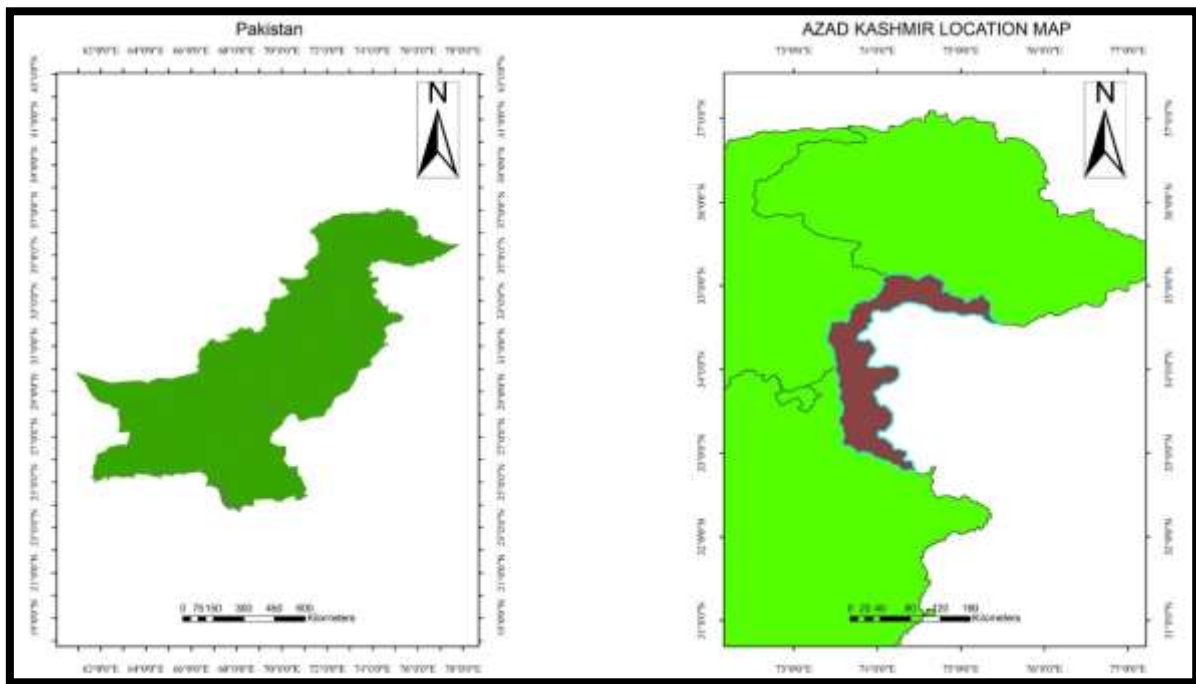


Figure 1. The image displays the location of the study area along GMR.

This corridor traverses a challenging environment with steep slopes and sharp elevation changes, making it highly susceptible to landslides and ground instabilities ^[13]. The topography of the study area is predominantly mountainous and hilly, marked by sharp ridgelines, road cuts, escarpments, and active debris flows ^[14]. These features contribute to the region's natural beauty and present significant infrastructure development and safety challenges ^[15]. The steep slopes and road cuts along the GMR are particularly prone to landslide events, which threaten the stability of the road and the surrounding environment ^[16]. The complex interplay of geological formations and frequent heavy rainfall during the monsoon season further exacerbates the area's susceptibility to landslides, making it a critical zone for geospatial and risk analysis ^[17]. Strategically located, the GMR is a key artery for transportation, economic trade, and regional connectivity between Pakistan and Azad Kashmir. However, its geological instability necessitates continuous monitoring and management to prevent landslide-induced disruptions. This study aims to comprehensively analyze the landslide susceptibility in this vital corridor, offering insights that will contribute to safer infrastructure planning and long-term resilience. Wadia investigated the geology of the headmost study area ^[18]. In the study area, lithostratigraphic units are exposed from Miocene to Pliocene rocks succession and recently exposed alluvium in the Sub-Himalayas laterally the eastern limb of Hazara Kashmir Syntaxis (HKS) ^[19]. Chinji Formation of the late Miocene age, Kamli Formation of the late Miocene age, and Murree Formation of the early Miocene age are documented in the study area (figure 1.2).

3. Methodology

This study utilizes an integrated approach combining SBAS-InSAR and the AHP to assess landslide

susceptibility along the GMR in the Ghoin Valley, Rawalakot district, Azad Jammu and Kashmir. The methodological framework is designed to accurately identify, quantify, and map landslide-prone zones in a mountainous region known for its complex topography and geological instability. The following steps outline the methodological approach adopted in this research and is shown in **Figure 2**.

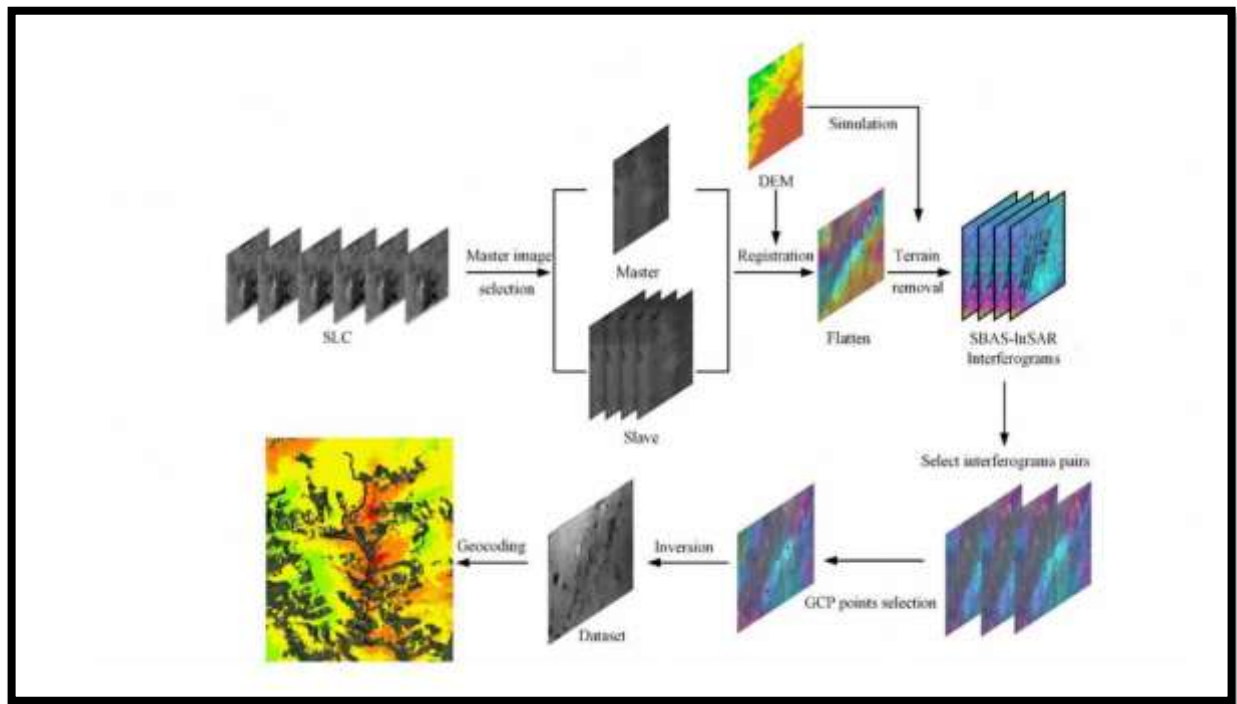


Figure 2. Gamma software data processing algorithm.

3.1. SBAS-InSAR Analysis for Ground Displacement Detection

To detect and map ground displacement along the Ghazi-i-Millat Road (GMR) in the Ghoin Valley, we apply the Small Baseline Subset - Interferometric Synthetic Aperture Radar (SBAS-InSAR) technique ^[20], utilizing Sentinel-1 SAR data and the GAMMA software suite. This approach enables precise monitoring of surface deformations over time. The processing workflow, illustrated in the accompanying diagram, involves the following stages:

Data Preparation and Preprocessing:

Single Look Complex (SLC) Data Collection: We collected 91 SLC images from Sentinel-1 SAR acquisitions, which capture radar backscatter signals to represent the surface characteristics of the Ghoin Valley over multiple periods. **SAR Imagery:** Sentinel-1 satellite SAR data covering the study area from January 2021 to December 2023 were acquired for the SBAS-InSAR analysis. This data was used to detect ground deformation and subtle changes in terrain, providing insight into potential landslide-prone zones. All 91 Sentinel-1 images were used for performing SBAS processing in the GAMMA software.

Topographic Maps and DEM:

The Shuttle Radar Topography Mission (SRTM) sourced a digital elevation model (DEM)

with a resolution of 30 meters to model slope gradients ^[21] and elevation profiles, critical factors in landslide susceptibility. Preprocessing involves Master Image Selection: From this stack of SLC images, we select one master image as the primary reference for comparisons with the remaining images (slave images).

Image Registration:

Using a Digital Elevation Model (DEM), we registered each slave image to the master image to ensure all images share a consistent spatial reference. This registration corrects minor geometric distortions that may arise from satellite movement or topographic variations.

Simulation and Terrain Flattening:

Simulation and DEM-Based Terrain Removal: We removed terrain effects using the DEM to produce flattened interferograms, effectively isolating deformation signals from natural terrain variations. This step reduces the influence of topography, making ground displacement signals more visible.

Interferogram Generation:

SBAS-InSAR Interferogram Production: We generated 546 interferograms from the preprocessed images. Each interferogram represents the phase difference between pairs of SLC images, corresponding to relative ground displacement across observation periods.

Interferogram Pair Selection:

We selected specific interferogram pairs with minimal spatial and temporal baselines to reduce decorrelation and improve sensitivity to subtle ground movements. The SBAS technique ensures that these interferograms accurately reflect long-term deformation trends.

Ground Control Point (GCP) Selection and Inversion:

Ground Control Point (GCP) Selection: We identify Ground Control Points (GCPs), stable locations on the ground with known coordinates, to anchor the displacement calculations with precise reference points.

Phase Inversion: We then invert the phase information from the selected interferograms to calculate displacement values at each GCP over time. This step translates phase differences into measurable displacements, allowing us to quantify surface movement across the study area.

Displacement Mapping and Geocoding:

We georeference the displacement data, aligning the results with geographic coordinates for accurate spatial mapping. Final Displacement Map Creation: We visualize the processed data in a displacement map, highlighting zones of significant ground deformation. Regions with persistent or accelerating displacement are classified as high-deformation zones, indicating potential landslide-prone areas.

To complement the SBAS-InSAR analysis, the AHP method was used to evaluate multiple

landslide-triggering factors in a multi-criteria decision-making framework. The steps involved in AHP are as follows:

- **Thematic Layers:** Sentinel-2 collects geospatial layers, including slope, aspect, geology, drainage pattern, NDVI, and NDWI, to form the input for the AHP analysis.
- **Selection of Criteria:** Key factors influencing landslide susceptibility were selected based on literature review and expert consultation. These include slope, aspect, geology, proximity to drainage, NDVI, and NDWI.
- **Pairwise Comparison:** A pairwise comparison matrix is constructed, assigning relative weights to each criterion based on its influence on landslide occurrence. Expert judgment and past studies were referenced to ensure the accuracy of weight assignments.
- **Weighted Overlay Analysis:** The weights from the AHP process are applied to the thematic layers, creating a landslide susceptibility index (LSI) for the study area. This index categorizes the region into nine ordinal susceptibility classes, ranging from negligible to very high, based on the combined influence of all factors.

The landslide susceptibility map generated from the AHP is compared against the field-verified landslide and debris-flow inventory of the study area ^[22]. We note that this comparison, based on the same inventory used to inform parameter selection, provides only a qualitative check of spatial correspondence and does not constitute an independent statistical validation; ROC-AUC or success-rate/prediction-rate analysis against an independent inventory would be required to establish predictive performance.

The results from both SBAS-InSAR and AHP are integrated into a comprehensive geospatial landslide susceptibility map ^[23]. The final maps provide a detailed visual representation of ground deformation trends and high-susceptibility zones along the GMR in the Ghoin Valley. The map is developed using ArcGIS and other geospatial tools, with clear demarcations of low, medium, and high susceptibility zones. The final susceptibility map is crucial for local authorities, infrastructure planners, and policymakers. By identifying the most vulnerable sections of the GMR, the study provides a decision-support framework for mitigation planning, prioritizing slope stabilization, drainage improvements, and road safety measures. The results also contribute to developing early warning systems, which can help reduce the risk of landslide-induced road closures and accidents.

3.2. Landslide Inventory

The landslide inventory is an assemblage of data that incorporates knowledge of landslides' location, activity, type, and physical characteristics ^[24]. The landslide inventory is heavily affected by the sort and class of accessible information. The landslide inventory of the study area prepared in the GIS develops a foundation for determining the landslide hazard along the GMR. However, the Google Earth data-based landslide inventory provides realistically detailed, accurate information and visual interpretation ^{[25][26][27][28][29][30]}. The

advantage of using Google Earth data is that it enables semi-automated landslide detection based on morphological parameters of mapped landslides [31][32][33][34][35]. Further, this research focused on automatized landslide mapping, the criteria of landslide inventory, and then the susceptibility map along the GMR. The Landslide inventory map was prepared using GIS (Figure 3). This landslide inventory map is critical in determining the location of all the landslides and debris flows along the GMR in the Poonch, Azad Kashmir district. Its primary focus is on the significant geomorphological elements influencing slope stability. Twenty-eight active landslides and twelve debris flows are marked on the inventory map and are confirmed during multiple field GPS-based field surveys, as shown in **Figure 3**.

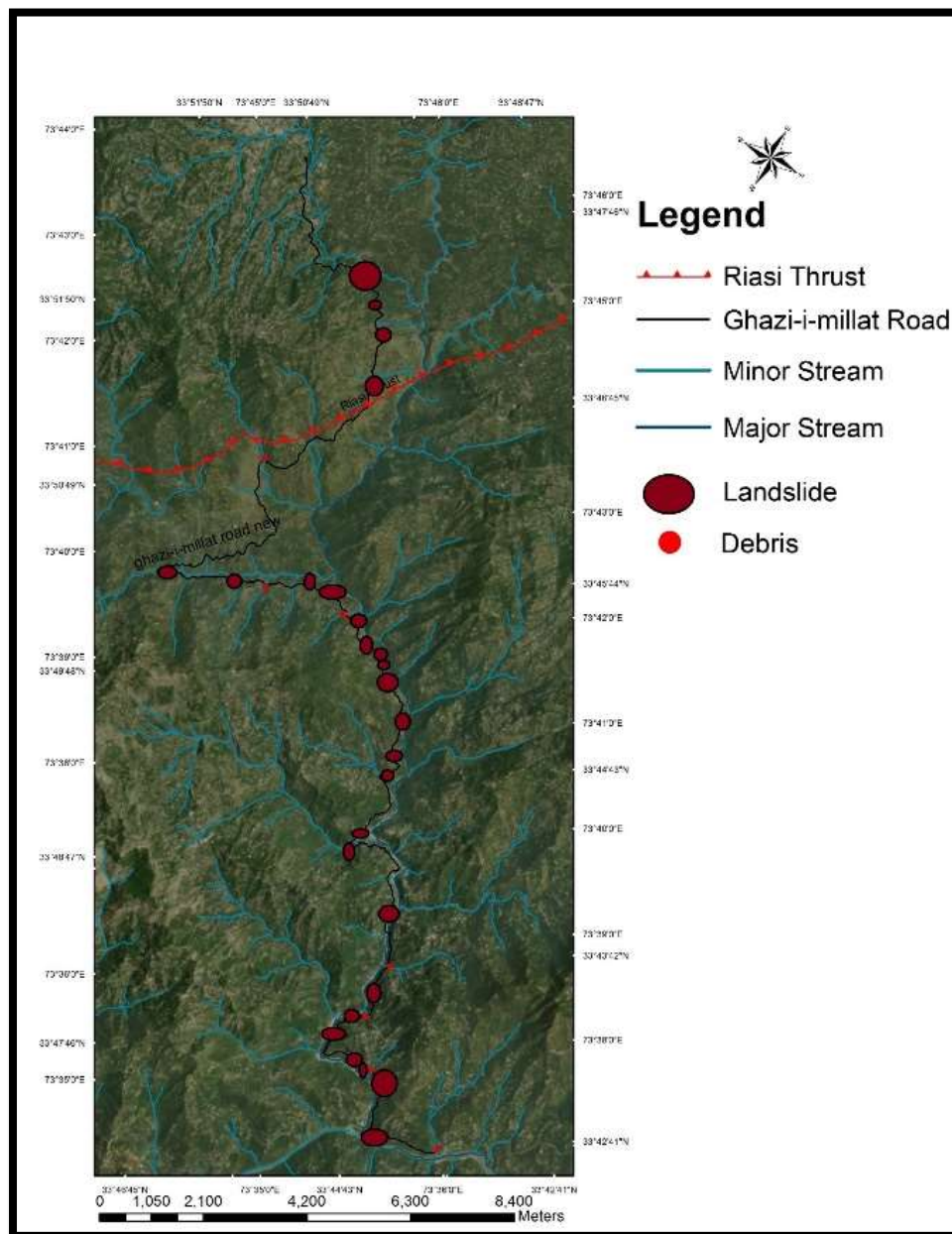


Figure 3. Map showing the debris and landslide Inventory of the study area.

4. Results

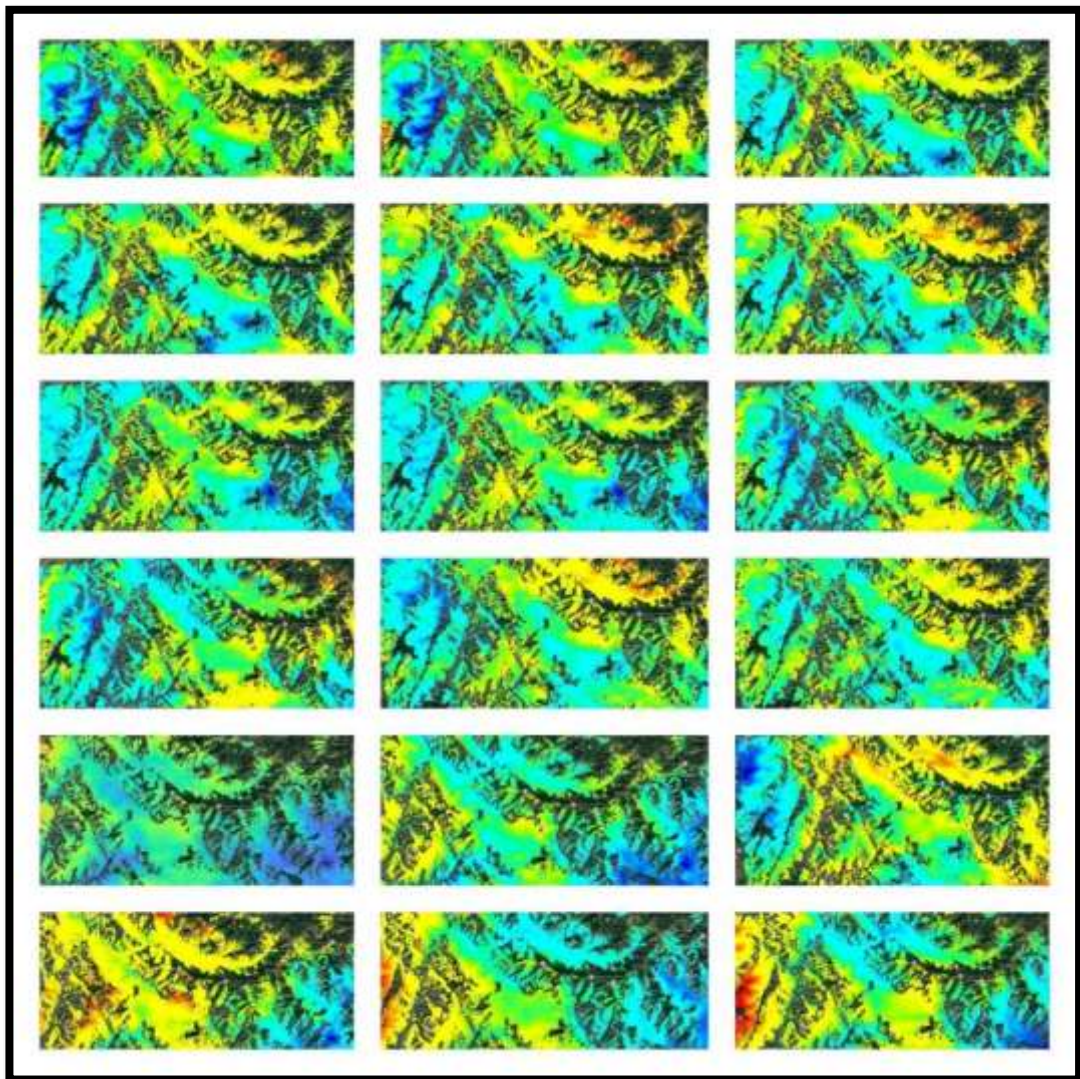


Figure 4. InSAR timeseries (2021-2023).

5. SBAS-InSAR Results

The Surface Deformation Rate along the Line of Sight (LOS) direction is calculated using SAR data and analyzed with the SBAS InSAR technique. A deformation threshold of 0.3 mm/year was applied. Positive LOS deformation values indicate surface movement toward the satellite sensor, while negative values represent deformation directed away from the sensor. The observed cumulative LOS displacement across the GMR reached a maximum of approximately +130 mm and a minimum of approximately -96 mm over the three-year observation period, particularly within the Ghoin Valley and adjacent regions flanking the GMR. Expressed as a mean annual velocity, deformation across the GMR ranges from -14.50 to +15.00 mm/year, with a localized maximum LOS velocity of 17.07 mm/year. The LOS-measured deformation deviates from actual surface displacement patterns due to topographic effects. Notably, high deformation concentrations are predominantly along the slope aspect of the GMR, exhibiting substantial ground motion

on the steep slope bodies. This distribution aligns closely with the spatial pattern of LOS deformation points. However, the deformation rate along the slope direction exhibits greater magnitude than the LOS direction, underscoring the influence of slope dynamics on surface instability. These results suggest that the observed deformations reflect significant geomorphological processes in the study area, with notable variations driven by topographical influences and slope-specific stresses.

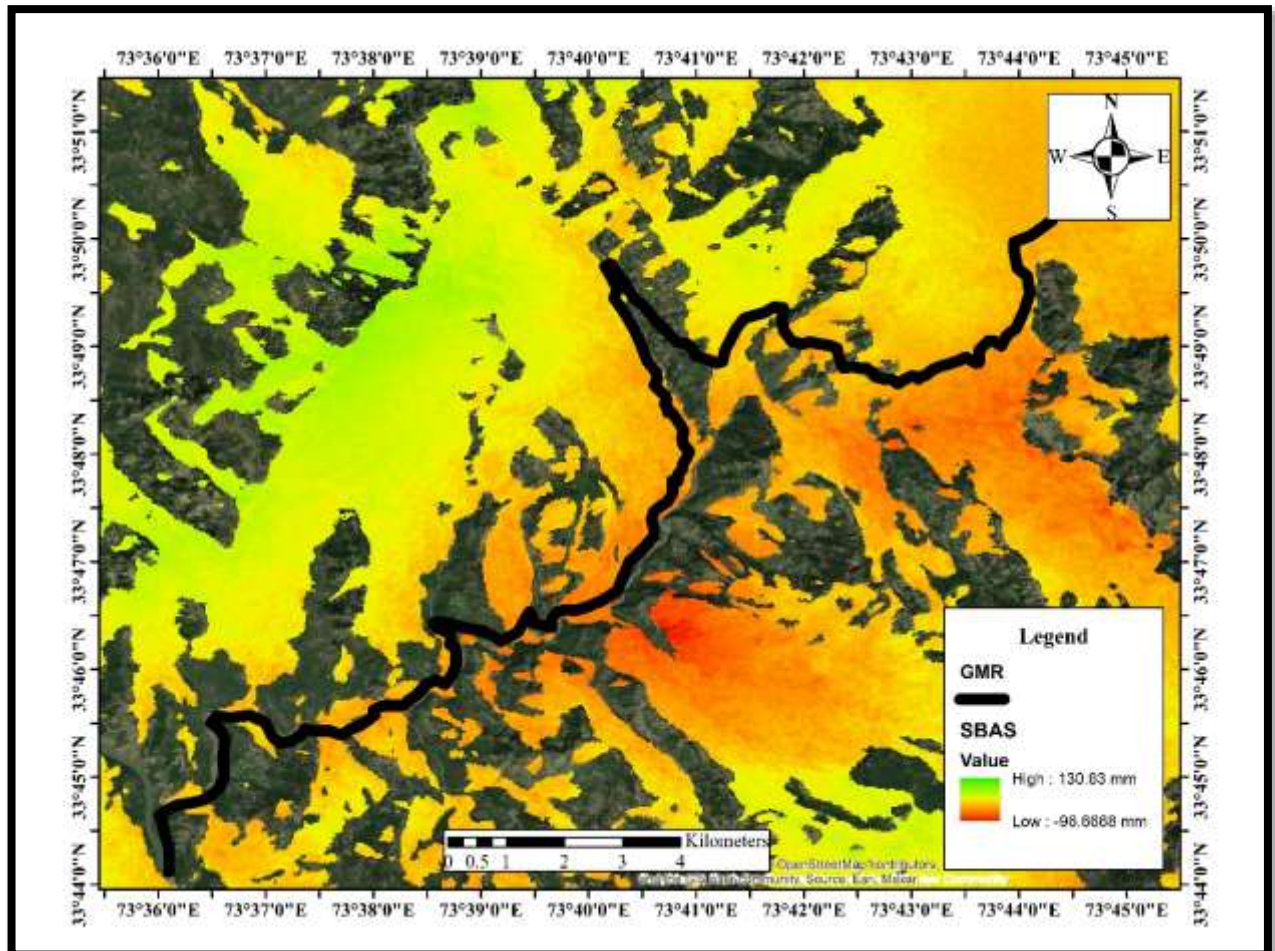


Figure 5. SBAS 3 YEARS

6. Susceptibility Mapping

The susceptibility mapping was initiated by preparing an inventory map of 28 landslides along the GMR in the study area. The landslide inventory map facilitated considering the distinctive causative elements that control various slope movements. GPS field survey determines the active, recent, and old landslides along the GMR. The topographic factors, elevation, and slope gradient along the slope aspect are derived out of the Digital Elevation Model (DEM), Normalized Differentiated Water Index (NDWI), and Normalized Differentiated Vegetation Index (NDVI) are obtained from the Sentinel hub. The analytic Hierarchy Process (AHP) technique prepares a landslide susceptibility map along the Ghazi-i-Millat road. The weighted Overlay tool is applied to overlay analysis using AHP. The Weighted Overlay tool lets us implement distinct steps in a

single tool's general overlay analysis process. Weighted Overlay tool follows these steps as:

1. Reclassifies standards involving raster into a mutual assessment scale of appropriateness, preference, hazard, or some corresponding scales.
2. Multiplies the cell standards individually input raster by raster's weight importance.
3. Adds subsequent cell standards composed to yield output raster.

Weighted Overlay proceeds single integer rasters as input, so rasters of slope gradient, slope aspect, NDVI, NDWI, lithology, drainage network, fault, and road are reclassified into integers before they are used. Then, all selected input rasters are allotted a weight percentage based on importance. The total influence for all rasters is equal to 100 %. Then, the Weighted Overlay technique is applied. Then, as a result, a susceptibility analysis map of landslides in the study area along the GMR was obtained.

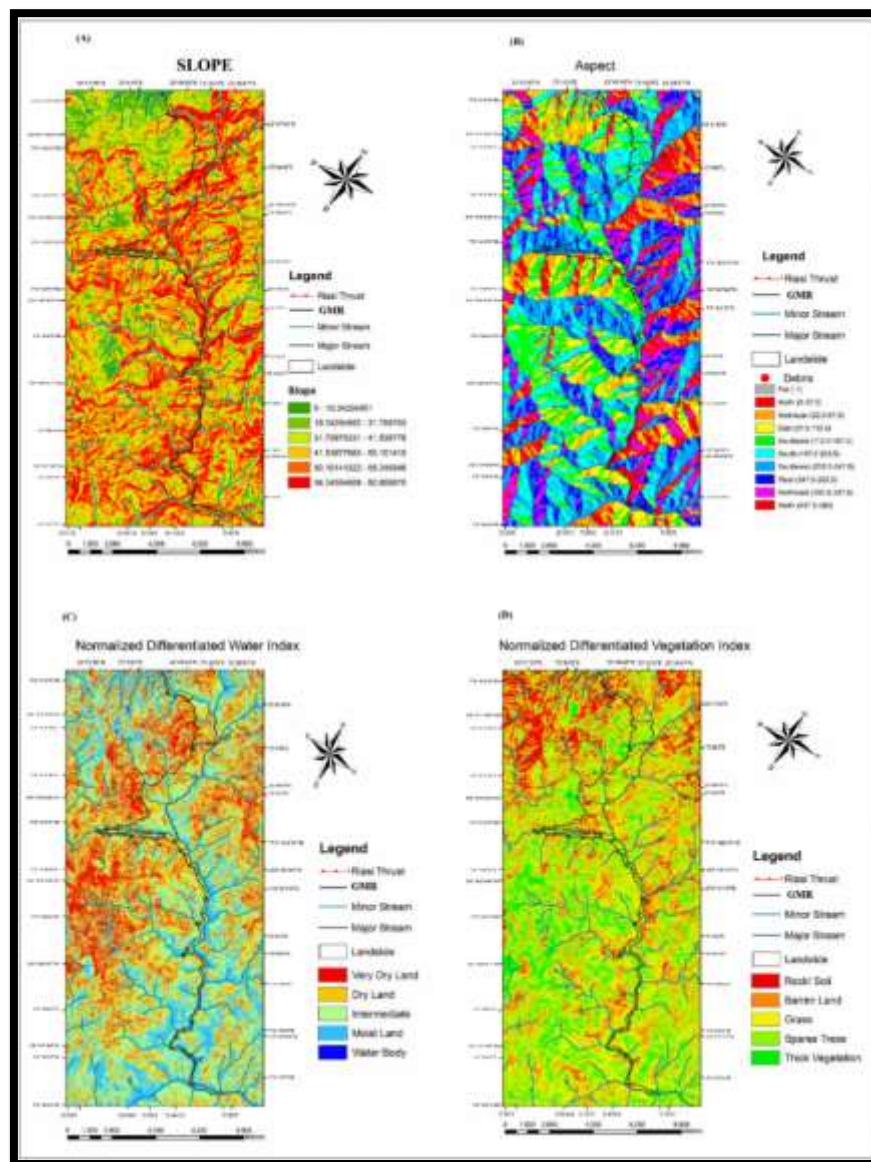


Figure 6. Slope gradient map of the study area, reclassified into nine susceptibility classes (see Table 1)

7. Slope

The most accessible element is the effect of slope steepness on landsliding. Steeper inclines usually have greater coincidental land sliding. Geomorphological features and topographic configurations significantly influence the stability of slopes in terms of both surface erosion and the gravitational movements of the earth's material. The slope gradient map of the study area is prepared in GIS using the Digital Elevation Model (DEM) of the study area. The slope gradient map of the study area is shown in Figure 6. The slope gradient map's slope angle values are derived in degrees and divided into nine classes to illustrate the landslide hazard potential due to the slope gradient along the GMR. The division of six courses of slope gradient is given in Table 1. The GMR lies in the high-risk and very high-risk zone, and some of the roads lie in a vulnerable zone.

Table 1. Division classes of slope angle of slope gradient map.

S. No.	Slope angle range (Degrees)	Color	Classes
1	0 - 10	Dark Green	Negligible
2	10 - 20	Green	Minute
3	20 - 30	Light Green	Very Low
4	30 - 40	Yellowish Green	Low
5	40 - 45	Yellow	Moderate
6	45 - 50	Yellowish Orange	Vulnerable
7	50 - 60	Orange	Considerable Risk
8	60 - 70	Red	High Risk
9	70 - 80	Dark Red	Very High Risk

8. Slope Aspect

The Slope Aspect indirectly affects the exposure to light, breeze, and rain, thus incidentally distressing other elements that aid in landslides, such as vegetation cover, soil wetness, and soil width. The aspect map prepared for the study area is branched into ten classes and illustrated in **Table 2**. Twenty-eight landslides are found in east—and southeast-facing orientation; others lie in the remaining courses. The aspect map is also a result of DEM and is prepared in GIS (Figure 7).

Table 2. Division classes of aspect map of the study area.

Sr. No.	Orientation (Degrees)
1	Flat (-1)
2	North (0 -22.5)
3	Northeast (22.5 – 67.5)
4	East (67.5 – 112.5)
5	Southeast (112.5 – 157.5)
6	South (157.5 – 202.5)
7	Southwest (202.5 – 247.5)
8	West (247.5 – 292.5)
9	Northwest (292.5 – 337.5)
10	North (337.5 – 360)

9. NDWI

Normalized Differentiated Water Index (NDWI) is used to analyze the moisture framework of the study area. The NDWI efficiently enhances the moisture information of the study area in the present research work and the preparation of the landslide susceptibility map. It is sensitive to promote land, which results in escalated water bodies. Water bodies have low reflectance. It only reflects within the visible portion of the electromagnetic spectrum. Water bodies in their liquid state generally have higher reflectance on the Blue (0.4 - 0.5 μm) spectrum than Green (0.5 - 0.6 μm) and Red (0.6 - 0.7 μm) spectra clear water with the most prominent reflection in the visible spectrum in the blue section. So, water appears blue. Turbid water has a higher visible reflectivity spectrum. There is no reflection in Near Infrared (NIR) and beyond. Gao designed NDWI to improve the water characteristics of the landscapes (Gao, 1996). This study uses the Near-Infrared (NIR) and Short-Wave Infrared (SWIR) band combination proposed by Gao (1996), sometimes distinguished from the classic McFeeters Green/NIR water index and referred to as the Normalized Difference Moisture/Water Index. NDWI is calculated using the following formula:

$$NDWI = \frac{NIR - SWIR}{NIR + SWIR}$$

NDWI is derived from Sentinel-2A multispectral (MSI) imagery and displayed in Figure 8. It is classified into five classes: arid land, dry land, intermediate, moist land, and water body. According to the NDWI map prepared for the study area, the GMR lies in the moist land-to-water body classes. Furthermore, the landslides marked on the inventory lie in the same classes.

Table 3. Division classes of NDWI map.

Color	Description
Red	Very Dry Land
Yellow	Dry Land
Green	Intermediate
Sky Blue	Moist land
Dark Blue	Water Body

10. NDVI

Normalized Difference Vegetation Index (NDVI) calibrates shrubbery by calculating the difference between near-infrared (which shrubbery greatly reflects) and red-light shrubbery absorbs). NDVI regularly varies from -1 to +1. However, there is no separate frontier for each land cover. While we get negative values, it will be water, and there is no doubt about this. On the other hand, there is an excellent possibility that there are dense green leaves if we obtain an NDVI value close to +1; if there are no green leaves, there may be domestic land, barren land, or rock, or only soil cover when the NDVI value is close to zero. NDVI uses the NIR and red channels in its formula:

$$NDVI = \frac{NIR - RED}{NIR + RED}$$

Healthy vegetation (chlorophyll) reflects near-infrared (NIR) and green light more than other wavelengths. Red and blue light are further absorbed. For this reason, our eyes see plants as green. If we could see near-infrared, it would also be vital for vegetation. NDVI is derived from Sentinel-2A multispectral (MSI) imagery. It is displayed in Figure 9. The NDVI is divided into five classes, represented by different colors, as illustrated in Table 4.

Table 4. Division classes of NDVI.

Sr. No.	Color	Classes
1	Red	Rock / Soil
2	Orange	Barren Land
3	Yellow	Grass
4	Light Green	Sparse Trees
5	Green	Thick Vegetation

11. Landslide Susceptibility Map

Landslide vulnerability is studied along GMR by applying the weighted overlay technique using a Geographic Information System (GIS). It has been developed using eight causative parameters. These parameters include slope gradient, slope aspect, NDVI, NDWI, drainage network, road, fault, and geology. All eight parameters are assigned a specific weight after reclassification in GIS. The reclassification of eight parameters is shown in Table 5. The weighted index of all eight parameters is illustrated in Table 6. The cumulative sum of all the eight weights is equal to a hundred. The slope gradient has been assigned a maximum weight of 20 out of hundred because it is recognized as the primary cause of landslides during field surveys. Then, a weighted overlay tool is run, which, as a result, provides us with a landslide susceptibility map. The derived landslide susceptibility map of the study is divided into nine classes: negligible, minute, very low, low, moderate, vulnerable, considerable risk, high risk, and very high risk (Figure 9). In the present research work, our primary focus was on landslide hazard analysis along the GMR, so it is observed in the landslide susceptibility map that all the landslides marked along the road lie in the three classes that are considerable risk, high risk, and very high risk (Figure 9).

The landslide susceptibility map indicates that the road constructed is susceptible to slope failures. The landslides along the road are road cuts triggered by rainwater penetration in the existing material, high slope gradients, same slope aspect, different vegetation index, different water index, and loose lithology. Three rock formations are recorded in the study area. Chinji formation, Kamlial formation, and Murree formation. All three formations contain dominantly sandstone and clays in different ratios. Clays are porous and contain absorption abilities and swelling properties, so as a result of precipitation, they absorb water. Due to high slope angles along the road, they tend to fail the slopes, resulting in landslides blocking the highway and causing

damage to the road and remedial measures such as parapet walls and bioengineering, etc. This results in a loss of cost for repairing roads and delay in economic activities of the affected area. The landslide susceptibility map is displayed in Figure 10.

Table 5. The reclassification index of eight parameters used as weighted overlay inputs.

Sr. No	Parameter	Reclassification
1	Slope Gradient	(1 1; 2 2; 3 3; 4 4; 5 5; 6 6; 7 7; 8 8; 9 9)
2	Slope Aspect	(0 4; 1 7)
3	Fault	(1 1; 2 2; 3 3; 4 4; 5 5; 6 6; 7 7; 8 8; 9 9)
4	Drainage Network	(1 1; 2 2; 3 3; 4 4; 5 5; 6 6; 7 7; 8 8; 9 9; 10 9)
5	NDVI	(1 1; 2 2; 3 3; 4 4; 5 5; 6 6; 7 7; 8 Restricted; 9 Restricted)
6	NDWI	(1 1; 2 2; 3 3; 4 4; 5 5; 6 6; 7 7; 8 8; 9 9)
7	Geology	(1 9; 2 8; 3 7; 4 6; 5 5; 6 4; 7 3; 8 2; 9 9)
8	Road	(1 9; 2 8; 3 7; 4 6; 5 5; 6 4; 7 3; 8 2; 9 1) – buffer-distance classes from the road centerline (Sr. No. 1 = greatest distance/lowest contribution, Sr. No. 9 = closest/highest contribution); exact class breaks to be confirmed against the GIS proximity buffers used.

Table 6. The weighted index of all the eight input parameters.

Sr. No	Parameter	Weight
1	Slope Gradient	20
2	Slope Aspect	10
3	Fault	10
4	Drainage Network	15
5	NDVI	10
6	NDWI	10
7	Geology	10
8	Road	15
		Cumulative sum = 100

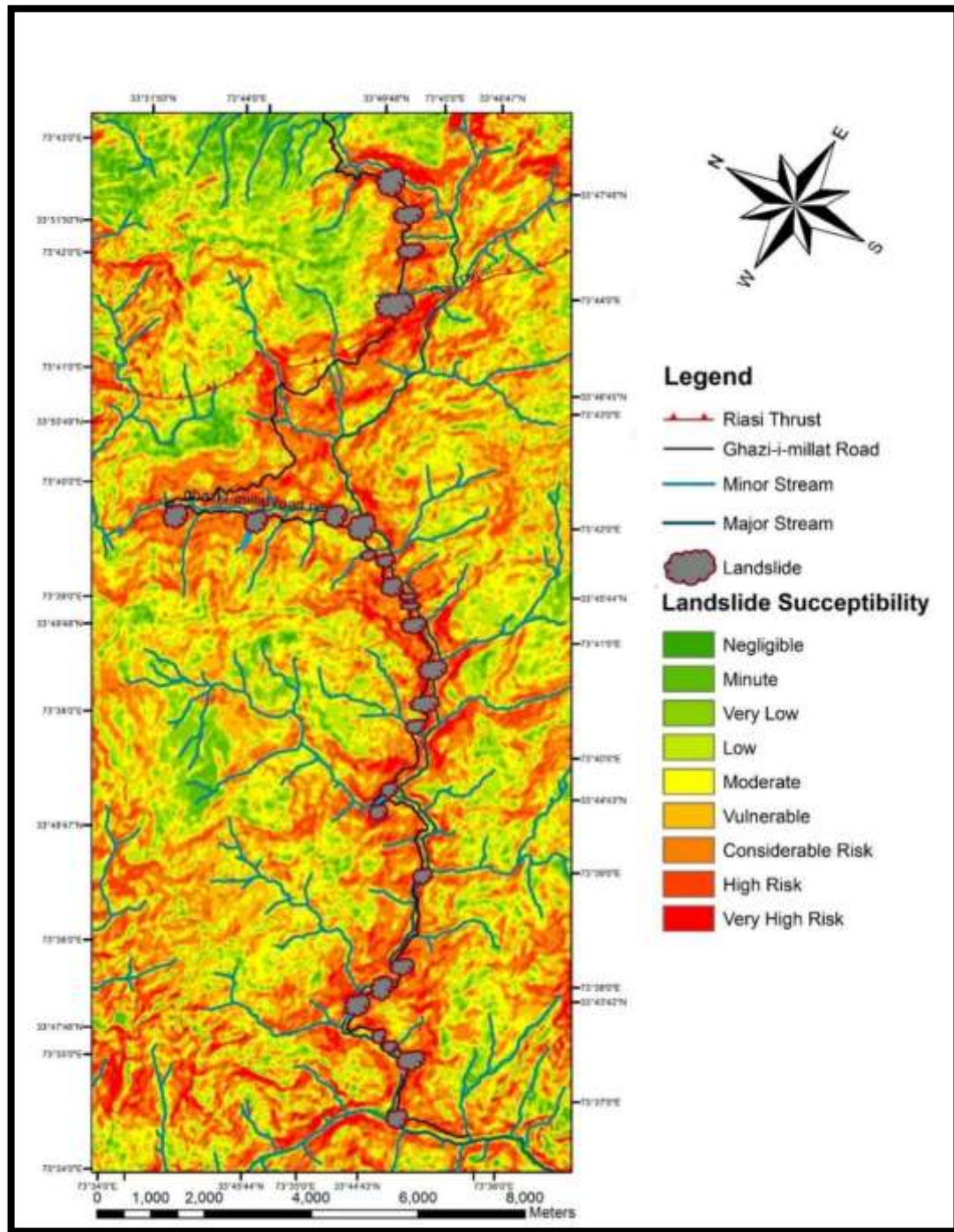


Figure 7. Landslide susceptibility map.

12. Discussion

The Surface Deformation Rate along the Line of Sight (LOS) direction is calculated using SAR data and analyzed with the SBAS InSAR technique. A deformation threshold of 0.3 mm/year was applied. Positive LOS deformation values indicate surface movement toward the satellite sensor, while negative values represent deformation directed away from the sensor. The observed mean annual deformation rate across the GMR ranged from -14.50 mm/year to +15.00 mm/year, with deformation primarily concentrated between -11

and +15 mm/year, particularly within the Ghoin Valley and adjacent regions flanking the GMR; over the full three-year observation period this corresponds to a maximum cumulative LOS displacement of approximately +130 mm and -96 mm. The LOS-measured deformation deviates from true surface displacement due to the radar viewing geometry, which is sensitive to the vertical and horizontal components of motion in different proportions depending on slope aspect and incidence angle. A localized maximum LOS velocity of 17.07 mm/year is recorded along the GMR; because this value represents motion toward the sensor rather than a directly resolved vertical or slope-parallel displacement, it is treated here as an indicator of possible ground instability warranting further monitoring rather than as independent proof of active landsliding. Notably, high deformation concentrations are predominantly along the slope aspect of the GMR, exhibiting substantial ground motion on the steep slope bodies. This distribution aligns closely with the spatial pattern of LOS deformation points. However, the deformation rate along the slope direction exhibits greater magnitude than the LOS direction, underscoring the influence of slope dynamics on surface instability. These results suggest that the observed deformations reflect significant geomorphological processes in the study area, with notable variations driven by topographical influences and slope-specific stresses.

The landslide susceptibility mapping along the Ghazi-i-Millat Road (GMR) highlights the significant impact of factors like slope gradient, slope aspect, soil moisture (NDWI), and vegetation cover (NDVI) on landslide occurrences. The study revealed that steep slopes, particularly those facing east and southeast, are more prone to landslides, with high-susceptibility areas marked by reduced vegetation and high soil moisture levels, which decrease slope stability. The weighted overlay analysis, using the Analytic Hierarchy Process (AHP) in a GIS framework, assigned the highest weight to slope gradient (20%), underscoring its critical role in landslide susceptibility, followed by drainage networks and proximity to roads (15% each), which exacerbate erosion and soil weakening due to water infiltration and road cuts. Zones near fault lines and drainage networks were identified as particularly vulnerable due to seismic activity and groundwater flow, intensifying erosion. The susceptibility map effectively stratified susceptibility levels along the GMR, designating many sections as high or very high susceptibility, indicating a need for further investigation and, where confirmed by field assessment, interventions such as retaining walls, improved drainage, and vegetation restoration. This AHP-GIS model offers a replicable regional approach to landslide susceptibility assessment, providing insights that can support disaster management and infrastructure planning in similarly susceptible regions, pending the independent validation discussed above.

13. Limitations and Future Work

This study has several limitations that constrain the strength of the conclusions that can be drawn from it, and that define priorities for follow-up work. First, the SBAS-InSAR processing parameters reported here (91 Sentinel-1 acquisitions, 546 interferograms, January 2021-December 2023) are not yet accompanied by the full processing metadata needed for independent reproduction or evaluation, including orbit direction and relative orbit/frame, master/reference acquisition date, spatial and temporal baseline thresholds, multilooking

factors, coherence threshold, phase-unwrapping method, atmospheric and orbital correction procedures, and the location of the reference point or reference area used to anchor the time series. These details, together with a quantitative uncertainty assessment for the reported deformation velocities (for example from stable-area residuals or time-series scatter), should be reported in any subsequent version of this work.

Second, the reported LOS deformation values have not been decomposed into vertical and horizontal components. Because a single ascending or descending LOS measurement conflates these components in a way that depends on incidence angle and slope aspect, the interpretation of any individual value as "uplift" or as direct evidence of landsliding should be treated with caution until ascending/descending decomposition, GNSS measurements, or field displacement data become available for cross-validation.

Third, the AHP weighting scheme presented in Table 6 is not yet accompanied by the complete pairwise comparison matrix, the number and background of the experts consulted, or the associated consistency index (CI) and consistency ratio (CR) that would demonstrate the internal consistency of the judgments used. A weight-sensitivity analysis, in which the susceptibility map is recomputed under plausible variations in the AHP weights, would further clarify how robust the mapped susceptibility classes are to the specific weighting scheme adopted.

Fourth, the susceptibility map is compared only against the landslide and debris-flow inventory that also informed parameter selection and weighting, which risks circularity. A statistically independent validation, for example using a held-out subset of the inventory, ROC-AUC or success-rate/prediction-rate curves, would provide a more defensible measure of predictive performance than the qualitative spatial correspondence reported here.

Finally, the relationship between vegetation cover and SBAS-InSAR performance is discussed qualitatively in this study. A quantitative comparison of NDVI with interferometric coherence, valid-observation density, or deformation uncertainty across vegetation classes would substantiate this relationship more rigorously and is identified as a priority for future work, along with an assessment of layover, shadow, and foreshortening effects given the steep terrain of the study area.

14. Conclusion

This study has applied the SBAS-InSAR technique to assess surface deformation along the Ghazi-i-Millat Road (GMR), providing insights into the geomorphological processes shaping this region. Our analysis revealed a mean annual deformation rate ranging from -14.50 mm/year to +15.00 mm/year, with movements mainly concentrated between -11 mm/year and +15 mm/year, corresponding to a maximum cumulative LOS displacement of approximately +130 mm and -96 mm over the three-year record. A localized maximum LOS velocity of 17.07 mm/year is of particular interest and is consistent with, though not on its own proof of, active ground instability in these sectors; it underscores the need for continuous monitoring, independent field or GNSS validation, and timely follow-up in these vulnerable sections. Integrating SBAS InSAR with advanced landslide susceptibility mapping has enabled us to construct a detailed spatial framework that identifies the key

factors influencing slope stability. Our study has highlighted critical determinants of landslide susceptibility, including slope gradient, slope aspect, soil moisture, and vegetation cover. The weighted overlay analysis, which prioritized slope gradient as a dominant factor, reinforces its pivotal role in controlling landslide susceptibility. Such nuanced insights into the interrelationships among geomorphological variables enhance our understanding of the local deformation dynamics and provide a robust basis for predictive modeling in similar geological settings. Likewise, this investigation's application of an integrated AHP-GIS framework to the GMR corridor demonstrates the practical value of combining these established methods for a regional geohazard assessment. This methodological combination is replicable and scalable, offering a tool for susceptibility evaluation that can be adapted to other regions characterized by complex terrain and active deformation. The framework's capacity to incorporate multi-criteria analysis ensures that all relevant factors are systematically considered, thereby improving the reliability and interpretability of landslide susceptibility models. The outcomes of this research have profound implications for infrastructure protection and sustainable land management in landslide-prone areas. By pinpointing zones of critical deformation and identifying the primary drivers of instability, our study furnishes decision-makers with actionable intelligence that can inform the design and implementation of targeted disaster management strategies. Structural interventions, such as the construction of retaining walls and the enhancement of drainage systems, coupled with strategic vegetation restoration, are recommended, subject to site-specific engineering assessment, to help mitigate landslide susceptibility. These proactive measures, informed by our detailed geospatial analysis, safeguard the region's infrastructural assets and ensure long-term community resilience. Besides, this study's regional application and methodological transparency contribute to the broader geohazard monitoring and susceptibility mitigation discourse. The findings not only advance the current understanding of landslide dynamics along the GMR but also lay the groundwork for future investigations to refine remote sensing techniques and enhance data fusion approaches. In doing so, this research offers a regional example of integrating deformation monitoring with multi-criteria susceptibility assessment, contributing to strategies for disaster preparedness and sustainable land management. The present work illustrates the value of combining remote sensing and geospatial analysis for characterizing geomorphological processes in a data-scarce mountain corridor. The insights derived from this study are intended to inform both further research and practical disaster-risk-reduction planning for the Ghazi-i-Millat Road, subject to the independent validation and additional processing detail identified above.

15. Recommendation

A multifaceted, scientifically grounded strategy is recommended to help manage the landslide susceptibility identified along the Ghazi-i-Millat Road (GMR). First, we recommend establishing continuous monitoring systems that integrate InSAR and ground-based sensors for real-time tracking of surface deformation. This dual-modality approach will facilitate the early detection of anomalous movements and enhance overall situational awareness, enabling prompt and effective intervention. Targeted engineering interventions should be implemented to bolster slope stability. Specifically, constructing retaining walls and deploying advanced drainage systems are essential to manage excess water and reduce destabilizing forces. In

light of the observed limitations of SBAS InSAR in densely vegetated areas—where decorrelation effects impair measurement accuracy—it is advisable to integrate supplementary monitoring techniques, ensuring a robust and reliable data framework. Additionally, comprehensive vegetation restoration programs should be prioritized in high-risk zones. Restoring native vegetation stabilizes slopes and contributes to broader ecological resilience. Concurrently, public awareness initiatives are crucial to educating local communities on landslide risks and emergency preparedness, enhancing overall community resilience. Regular updates of landslide susceptibility maps and integrated land-use planning in collaboration with local authorities will support adaptive and dynamic susceptibility management. Such proactive measures will help maintain the relevance of susceptibility assessments in the face of evolving environmental conditions. Finally, further research into the interplay of slope stability factors—together with the independent validation and processing transparency identified above—is needed to refine predictive models and strengthen the scientific basis for susceptibility mitigation strategies. These recommendations offer a comprehensive, interdisciplinary approach to reducing landslide hazards along the GMR, ultimately fostering sustainable land management and safeguarding critical infrastructure.

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Conflicts Of Interest

The authors declare no conflicts of interest.

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