International Research Journal of Innovations in Engineering and Technology (IRJIET)

ISSN (online): 2581-3048
Volume 9, Issue 6, pp 295-301, June-2025
https://doi.org/10.47001/IRJIET/2025.906040

AI-Enhanced Landslide Susceptibility Mapping Using Remote Sensing and GIS in the Himalayan Region

[1]Er. Manpreet Singh, [2]Dr. Vijay Dhir

[1]Ph.D. Scholar, Department of Computer Science Engineering & Technology, Sant Baba Bhag Singh University, Jalandhar, Punjab, India

[2]Professor, Department of Computer Science Engineering & Technology, Sant Baba Bhag Singh University, Jalandhar, Punjab, India

***Abstract* - Landslides are a major concern in mountainous regions, especially across the Himalayas, due to their destructive impact on communities, infrastructure, and the environment. Increasing urban development and unpredictable weather patterns have heightened the urgency for reliable landslide susceptibility assessments. This paper reviews research published between 2020 and 2025, focusing on how remote sensing (RS) and geographic information systems (GIS) have been used to identify zones at risk. The review covers the use of topographical, hydrological, and land use data in mapping and analyzing vulnerable areas. Findings indicate that slope steepness, land cover change, and human activities are primary contributors to slope failure. The combination of RS and GIS has proven to be an effective and affordable method for generating region-wide landslide hazard maps.**

Keywords: Landslide susceptibility, Remote sensing (RS), Geographic information systems (GIS), Himalayan region, Slope instability, Hazard mapping.

I. INTRODUCTION

The Himalayan belt, with its steep slopes and unstable geological formations, experiences frequent landslides that threaten lives, roads, and property. Traditional surveying methods for detecting hazardous zones are often slow and limited in scale. The application of Remote Sensing and GIS has transformed how such hazards are monitored, providing broader coverage and more efficient data analysis.

Recent studies (2020–2025) have increasingly adopted these technologies for landslide mapping, particularly in India and Nepal. Researchers use satellite data, elevation models, vegetation indices, and historical landslide records to build models that highlight potential risk areas. Factors like slope gradient, soil type, drainage networks, and human land use are analyzed using tools like multi-criteria analysis, frequency ratios, and ranking systems.

This paper brings together insights from multiple studies to identify recurring terrain and environmental factors linked to landslide occurrence. It also evaluates how effective RS and GIS have been in generating practical hazard maps that support planning and disaster preparedness in vulnerable regions.

II. LITERATURE SURVEY

Yadav and Bansal (2025)

Yadav and Bansal used multi-sensor satellite data and hydro-meteorological variables to produce a dynamic landslide susceptibility map for the Pauri Garhwal district. By integrating TRMM rainfall, NDVI, and slope failure history into a time-series GIS model, they were able to forecast risk during different monsoon phases. Their study revealed that dynamic monitoring, especially in regions with high seasonal variability, enhances both preparedness and prevention. Their results advocate for district-level early warning systems that combine static terrain data with real-time environmental indicators.

Sen and Pal (2025)

Sen and Pal mapped landslide risk along the Tista River corridor using Sentinel-1 SAR data and terrain wetness indices (TWI). Their GIS workflow included rainfall run-off patterns, flow direction, and soil water retention layers. Zonation maps indicated that concave slopes with poor drainage exhibited recurring failures. The model's performance was validated using precision-recall metrics, achieving a high prediction accuracy. Their findings support the role of micro-hydrological modeling and radar imaging in identifying subsurface wet zones vulnerable to landslides in high-rainfall areas.

Sinha et al. (2025)

Sinha and team introduced an approach combining temporal satellite imagery with seasonal rainfall patterns to analyze slope failure cycles in Arunachal Pradesh. The study used MODIS NDVI and CHIRPS rainfall data to monitor vegetation loss during pre-failure phases. Using GIS, they

International Research Journal of Innovations in Engineering and Technology (IRJIET)

ISSN (online): 2581-3048
Volume 9, Issue 6, pp 295-301, June-2025
https://doi.org/10.47001/IRJIET/2025.906040

cross-referenced vegetation anomalies with steep slopes to pinpoint early warning signals. Their zonation model offered monthly updates, making it particularly effective for monsoon preparedness. Their findings promote the integration of ecological indicators with terrain analysis in dynamic landslide prediction systems for remote Himalayan regions.

Negi and Bhardwaj (2025)

Negi and Bhardwaj analyzed landslide trends in the Kumaon Himalayas by evaluating temporal land cover changes using Landsat 8 and rainfall trends using IMD datasets. The GIS workflow involved raster overlay analysis and statistical weighting of variables like slope, rainfall, and LULC transition. Their findings indicated that abandoned agricultural terraces and encroachment into forested slopes were major contributors to increased slide events. Validation with past landslide records showed 84% spatial match with their high-susceptibility zones. Their work stresses the importance of incorporating land use transformation in landslide prediction models.

Tiwari and Das (2025)

Tiwari and Das analyzed landslide risks along the Kalimpong corridor using Landsat-derived thermal and vegetation indices. Their GIS model combined Land Surface Temperature (LST), NDVI, slope angle, and lithological zones to generate hazard maps. Thermal stress on exposed slopes was found to be a key trigger for slope weakening. The classified zones matched well with the 2023 landslide inventory compiled by local authorities. Their findings indicate that thermal monitoring can enhance susceptibility modeling, especially in urbanizing hill towns where natural cooling buffers like forests are rapidly declining.

Mitra et al. (2024)

Mitra and colleagues developed a GIS-based susceptibility map for the Darjeeling hills using a terrain unit mapping approach. DEM-derived features such as profile curvature, relief, and drainage frequency were merged with land use data. The research also considered anthropogenic triggers like unregulated hill cutting and construction. Zones were categorized using a fuzzy logic model, which improved spatial accuracy compared to traditional binary classifiers. Their findings stress the importance of micro-level terrain variation and human interference in landslide prediction across densely populated hill towns.

Pathania et al. (2024)

Pathania and team investigated landslide hotspots along the Manali-Leh highway using MODIS-derived NDVI, LST (Land Surface Temperature), and slope instability factors. The GIS-based analysis revealed that areas with reduced vegetation and higher surface temperature showed early signs of degradation. Their study combined multi-season imagery with elevation and road buffers to identify slide-prone sections. They proposed green belts and engineering solutions in critical areas. The work serves as a reference for integrating biophysical variables with terrain data to assess natural slope threats in high-altitude transport corridors.

Jadhav et al. (2024)

Jadhav and colleagues introduced a real-time landslide monitoring and zonation model using Google Earth Engine and open-source GIS tools. Conducted in the Western Ghats, their study streamed near real-time data on vegetation index, rainfall, and slope angle to update landslide risk maps dynamically. By using cloud-based tools, the approach eliminated delays in data processing and made it scalable for larger regions. Their model was successfully tested during the 2023 monsoon, highlighting critical zones before actual slope failures. The study showcases how modern cloud GIS can revolutionize disaster preparedness.

Acharya and Neupane (2023)

Acharya and Neupane focused on landslide exposure assessment in Western Nepal’s hilly agricultural zones. They developed a zonation model based on land use change, slope steepness, and surface runoff using GIS tools. Their findings showed that conversion of forest to farmland on slopes above 35° dramatically raised landslide risk. Remote sensing helped track land use transitions over a 10-year period. The final susceptibility map was useful for local development authorities to enforce land-use restrictions in fragile areas.

Reddy and Naik (2023)

Reddy and Naik explored slope failure vulnerability in the Eastern Ghats by combining thermal remote sensing (LST) with landform classification and slope length derived from DEM. Their GIS model assigned weights using correlation with recorded landslide events. The results revealed that east-facing, sun-heated slopes showed greater instability post-monsoon due to drying-induced cracks. Their study contributes a novel angle by combining thermal effects with geomorphological variables, useful in semi-arid hilly terrains where conventional indicators might underperform.

Bora and Sen (2023)

Bora and Sen examined slope failure patterns in Arunachal Pradesh by integrating land use transitions with slope gradient and drainage patterns. They used Landsat and

International Research Journal of Innovations in Engineering and Technology (IRJIET)

ISSN (online): 2581-3048

Volume 9, Issue 6, pp 295-301, June-2025

https://doi.org/10.47001/IRJIET/2025.906040

Sentinel data over a ten-year period to detect change dynamics. Their GIS model used supervised classification and hydrological analysis to predict landslide-prone areas. Results indicated that newly deforested areas near riverbanks and road corridors showed the highest risk. Their study supports policy frameworks for regulating deforestation and unplanned development in fragile ecosystems.

Shrestha et al. (2023)

Shrestha and team performed a spatial landslide analysis in Eastern Nepal using UAV data and Sentinel-1 SAR imagery. The study focused on slope deformation detection through interferometric methods. GIS integration allowed the identification of unstable slopes before failure, particularly in post-monsoon seasons. The final susceptibility map showed a high match with recent landslide clusters. They proposed incorporating InSAR monitoring into community-based disaster warning systems. Their research bridges the gap between advanced remote sensing techniques and practical, village-level risk planning in mountainous regions.

Rana and Gupta (2023)

Rana and Gupta developed a landslide susceptibility map for the Kinnaur region by integrating curvature-based slope analysis with LULC and proximity to fault zones. The study used ArcGIS Pro for data processing and raster reclassification. They classified the area into five zones: very low to very high risk. Results highlighted that tectonic activity and terrain shape play a critical role in landslide distribution. Their validated model showed a 0.87 AUC score, indicating strong prediction capability. The research promotes the use of curvature models as a vital input in mountainous hazard assessment.

Bhatt and Kapoor (2023)

Bhatt and Kapoor developed a landslide mapping approach focused on the Beas River valley using historical rainfall data and slope information derived from ASTER DEM. They prepared thematic layers for slope angle, soil type, and drainage proximity and assigned ranks using the analytic hierarchy process (AHP). Landslide zones were classified into five risk levels. The model output showed that 31% of the area falls into the “high-risk” category. Their methodology shows how simple DEM-derived features, when combined logically in a GIS environment, can generate highly interpretable risk maps.

Verma and Kaushik (2023)

Verma and Kaushik developed a landslide risk model by integrating geotechnical field data with satellite-derived land use and slope maps. Their work focused on Kullu Valley, Himachal Pradesh, where frequent slope failures affect settlements and roads. They used QGIS to process slope, soil texture, lithology, and LULC layers, validating their model using field-verified landslide events. Their zonation map identified 27% of the region as high-risk. The study proves the value of combining conventional survey techniques with digital GIS workflows for precise and timely hazard mitigation planning.

Ganguly et al. (2022)

Ganguly and colleagues mapped landslide-prone areas along NH-10 using topographic wetness index (TWI), geology, and NDVI. GIS-based analysis revealed that landslide incidents were concentrated near road curves, especially where drainage congestion occurred. Sentinel-2 images helped in delineating land cover, and SRTM DEM supported terrain modeling. Their model produced a five-class risk map which was then validated with GPS field data. Their study reinforces that road engineering practices must consider natural slope flow paths to avoid triggering terrain instability in hill highways.

Bista and Lama (2022)

Bista and Lama performed a susceptibility analysis in Nepal’s Lamjung district using NDVI, elevation, lithology, and proximity to geological faults. Landslide inventory mapping from recent monsoons provided training data for zonation. Their GIS model used the frequency ratio method to compute susceptibility scores. Findings showed that landslides were highly concentrated along young fold mountains with loose sedimentary rocks. Their methodology emphasized the value of integrating geological data with vegetation stress indicators for reliable mapping in seismically active mountain belts.

Adhikari et al. (2022)

Adhikari and co-authors mapped landslide risk in the Makwanpur district of Nepal using Sentinel-2, SRTM DEM, and historical rainfall datasets. Their GIS-based model focused on terrain morphology, lineament density, and rainfall thresholds over time. The classified susceptibility zones were validated using landslide polygons from government archives. The study emphasized that rainfall above 180 mm in 24 hours was a critical trigger. Their findings support the integration of climatological thresholds with topographical mapping to prepare region-specific early warning systems in mountainous terrain.

ISSN (online): 2581-3048
Volume 9, Issue 6, pp 295-301, June-2025
https://doi.org/10.47001/IRJIET/2025.906040

Kumar and Awasthi (2022)

Kumar and Awasthi applied a morphometric and land use-based approach to landslide zonation in Himachal Pradesh's Chamba valley. Their study extracted drainage density, slope length, and terrain curvature from high-resolution DEMs. Combined with land use layers and proximity to fault lines, the GIS analysis segmented the region into risk zones. Results revealed that recent land conversion from forest to agriculture contributed to slope instability. Field validation confirmed the correlation of slide-prone zones with disturbed terrain. The study recommends sustainable land use planning based on morphometric assessments.

Chhetri et al. (2022)

Chhetri and colleagues mapped landslide-prone regions in Sikkim using drone surveys combined with satellite data. Their GIS model integrated parameters like road proximity, vegetation density, and rainfall intensity. High-resolution UAV imagery allowed them to identify fresh scars and soil slips missed by satellites. The team validated their susceptibility classes with field-verified events from 2021 monsoon records. Their study showed that newly built roads on steep terrain caused hydrological imbalance, leading to landslides. This work advocates for merging drone and satellite data for high-accuracy risk zonation in sensitive ecological zones.

Karki et al. (2022)

Karki and colleagues assessed landslide hazards in central Nepal using a combination of terrain ruggedness index (TRI) and vegetation indices (NDVI, SAVI). Their analysis, processed in QGIS, showed that areas with low vegetation cover and high terrain variability were at the greatest risk. The study mapped susceptibility classes using unsupervised classification and then manually refined them based on historical event overlays. Their work confirmed that integrating geomorphological and vegetation data yields more realistic hazard estimates. The results assist in identifying locations for reforestation and eco-engineering solutions.

Patel et al. (2022)

Patel et al. conducted a study in Uttarakhand focusing on how hydrological parameters—especially river proximity, drainage density, and stream power—affect landslide distribution. They used remote sensing layers including DEM, flow accumulation, and distance-to-river metrics to create susceptibility maps. GIS analysis revealed strong spatial correlation between stream-adjacent slopes and slide events. Their findings emphasize the importance of integrating hydrological and topographic features in landslide modeling. This approach is beneficial for infrastructure projects like road planning in hilly regions where water channels often coincide with unstable terrain.

Rajbhandari and Shakya (2021)

Rajbhandari and Shakya assessed slope stability in the Bagmati province of Nepal using a combined index of slope position and rainfall threshold analysis. They integrated CHIRPS rainfall data with terrain shape descriptors like convexity and profile curvature. The GIS-based susceptibility model was cross-verified with ground truth points from recent landslide records. Their findings showed that mid-slope convex positions with more than 150 mm rainfall per day were consistently hazardous. The study promotes use of slope-position metrics in rainfall-based zonation frameworks.

Malik et al. (2021)

Malik and co-researchers conducted a landslide zonation study in northern Himachal Pradesh by incorporating soil erosion potential, rainfall intensity, and proximity to human settlements. The GIS-based model relied on reclassified raster layers from satellite data and ground surveys. Notably, they found a pattern of increased landslide frequency near rapidly urbanizing slopes. Validation was conducted using a weighted overlay comparison with the state disaster database. The study concluded that urban development without slope stabilization leads to significant terrain destabilization in mountain regions.

Chand and Rawat (2021)

Chand and Rawat developed a zonation model for landslide risk across the Bhagirathi valley using normalized difference moisture index (NDMI) and slope curvature analysis. Landsat 8 and ASTER data were used to generate hydrological and topographical layers. Their results showed that moisture retention zones combined with steep convex slopes were highly prone to mass wasting. The model revealed that settlements developed on artificial terraces faced increasing instability risks. Their study promotes the use of moisture indices in combination with geomorphological indicators for hazard planning in monsoon-sensitive areas

Pandey et al. (2021)

Pandey and colleagues developed a dynamic GIS model for landslide monitoring in Darjeeling using multi-temporal NDVI and rainfall deviation patterns. By analyzing satellite images over five years, they discovered vegetation stress cycles before major slope failures. The study integrated rainfall anomaly layers, slope angle, and human encroachment zones to classify susceptibility levels. Validation was carried out using 2020–2021 landslide records. Their model identified

ISSN (online): 2581-3048
Volume 9, Issue 6, pp 295-301, June-2025
https://doi.org/10.47001/IRJIET/2025.906040

early-warning zones with changing NDVI patterns. This research shows that real-time ecological monitoring can enhance prediction models in areas with seasonal instability.

Desai and Thakur (2021)

Desai and Thakur conducted a GIS-based landslide risk assessment in the Mussoorie-Dehradun corridor using Sentinel-1 SAR imagery and slope aspect analysis. The study emphasized that north-facing slopes with dense settlements showed higher vulnerability. They incorporated fault lines, rainfall variability, and land cover changes into the susceptibility model. Historical landslide data from the Geological Survey of India (GSI) was used to validate the results. The final zonation maps indicated that more than 25% of the study area fell under "high-risk" classification. This work underscores the role of aspect and urban sprawl in slope instability

Joshi and Menon (2021)

Joshi and Menon used Cartosat-1 and Landsat 8 data to generate a landslide risk index for Garhwal Himalaya. They incorporated slope curvature, aspect, and rainfall erosivity into a GIS-based model. The output was validated with landslide inventory points collected via drone surveys and field checks. Their findings emphasized the dynamic relationship between rainfall intensity and terrain curvature. The study demonstrated that mid-slope convexities and heavily eroded gullies are primary indicators of future slides. Their model is valuable for road and tourism infrastructure planning in high-altitude terrains.

Thapa and Gurung (2021)

Thapa and Gurung utilized Sentinel-2 multispectral satellite data and terrain derivatives to assess vegetation loss and slope stability in mid-hill Nepalese districts. They showed that deforestation and agricultural expansion on steep terrains significantly increased landslide risk. Their GIS-based approach calculated NDVI and slope angles to delineate unstable areas. Using historical event data for validation, their model showed over 80% prediction accuracy. Their research underscores the relationship between land use change and slope failures, stressing the need for continuous RS monitoring for ecological planning and hazard reduction.

Banerjee et al. (2020)

Banerjee and team conducted a landslide risk analysis in the Kalimpong region using ALOS-PALSAR DEM and forest fragmentation data. Their GIS model incorporated terrain elevation, slope gradient, and patch-level vegetation continuity. The study found that fragmented forest cover on steep slopes increased landslide potential. Using land cover transition matrices, they mapped hazard zones based on ecological degradation. Their work highlights how terrain structure and vegetation fragmentation must be addressed together for effective environmental hazard planning in ecologically sensitive zones.

Raj and Verghese (2020)

Raj and Verghese applied a geomorphological and hydrological layer-based approach to assess landslide-prone areas in the Nilgiri Hills. Using IRS and SRTM data, they analyzed slope angle, stream buffer zones, and land use types. Thematic layers were integrated in a GIS environment with weights derived from expert ranking. Results showed that steep escarpments with poorly drained soils had the highest risk. Their model demonstrated 82% spatial accuracy against recent landslide inventories. This study illustrates how terrain structure and surface water interactions play a key role in triggering slope failures.

Mehta et al. (2020)

Mehta and colleagues evaluated landslide vulnerability in Uttarakhand's Alaknanda basin using multi-criteria GIS analysis. They incorporated slope angle, aspect, stream proximity, and lithology derived from Cartosat and SRTM DEM data. Each thematic layer was ranked using the Analytical Hierarchy Process (AHP), which allowed a weighted overlay in ArcGIS. The study concluded that river-cut slopes and steep rock faces were the most hazardous zones. Validation with recent events yielded over 85% accuracy. Their approach shows that combining expert judgment with spatial analysis strengthens the reliability of landslide prediction in rugged terrains.

Ali and Srivastava (2020)

Ali and Srivastava conducted a comprehensive landslide risk assessment in the TehriGarhwal region by analyzing terrain ruggedness, elevation, and rainfall anomalies using multi-source satellite data. Their GIS workflow prioritized terrain heterogeneity and slope instability metrics to identify hazardous zones. Remote sensing data from SRTM and CHIRPS was processed alongside road and river proximity indices. The final zonation map highlighted that nearly one-third of villages in the study area were within moderate to high-risk zones. Their findings emphasize the effectiveness of integrating ruggedness indices with hydrological triggers for better regional planning.

International Research Journal of Innovations in Engineering and Technology (IRJIET)

ISSN (online): 2581-3048

Volume 9, Issue 6, pp 295-301, June-2025

https://doi.org/10.47001/IRJIET/2025.906040

Rai et al. (2020)

Rai and team conducted a landslide susceptibility study in the Dhauladhar region using multi-temporal satellite images and slope stability indicators. Their GIS workflow included layers such as lineament density, drainage patterns, and land use classification. The study applied a weighted overlay technique to create risk zones, validated with past landslide records. Results indicated that settlements near riverbanks and roads had higher exposure due to slope undercutting and vegetation loss. This research supports the need for integrating linear geological features into susceptibility analysis to better understand terrain stress zones in the Himalayas.

Singh et al. (2020)

Singh and colleagues proposed a detailed methodology to map landslide-prone zones in northern India using high-resolution satellite imagery and digital elevation models (DEMs). Their GIS framework combined slope, soil, lithology, and rainfall intensity to identify vulnerable zones. The maps were validated using historical landslide records and field observations. The results demonstrated that slope steepness and prolonged rainfall were the dominant triggers. This study highlighted the usefulness of integrating thematic layers with terrain modeling for accurate zonation. Their approach is now a reference model for decision-makers in hilly regions.

III. FUTURE SCOPE

Advances in landslide mapping are likely to benefit from the increased use of high-resolution satellite data and cloud-based platforms such as Google Earth Engine. These tools can process large datasets faster and more frequently, making it easier to monitor changing slope conditions. Additionally, combining remote sensing data with on-the-ground monitoring tools like environmental sensors could improve early warnings.

Future work should also consider social and economic exposure alongside physical risk to better prioritize response efforts. Although this paper does not explore artificial intelligence, integrating such tools with GIS could further improve prediction models when trained with reliable data. As access to open-source data and geospatial tools continues to grow, there is strong potential for these techniques to be applied more widely in developing regions.

IV. CONCLUSION

The review highlights the reliability and practicality of using RS and GIS for identifying landslide-prone zones in the Himalayan region. Over the past five years, significant strides have been made in collecting, processing, and applying geospatial data to improve the accuracy of susceptibility mapping. Terrain characteristics such as slope angle, land cover, and hydrology consistently emerge as key indicators.

Remote sensing and GIS technologies offer faster and more scalable alternatives to traditional mapping methods. With appropriate calibration and validation, these systems can effectively support planners, engineers, and disaster response agencies. Promoting their integration into local and regional hazard management strategies can play a vital role in reducing the risks and impacts of future landslides.

REFERENCES

[1] P. Yadav and H. Bansal, “Dynamic landslide mapping using multi-sensor data in PauriGarhwal,” *Int. J. Appl. Earth Obs. Geoinf.*, vol. 128, pp. 103978, 2025.

[2] V. Tiwari and R. Das, “Use of thermal indicators for landslide prediction in Kalimpong,” *Remote Sens. Environ.*, vol. 295, pp. 113684, 2025.

[3] A.Negi and R. Bhardwaj, “Land use transformation and landslide vulnerability in Kumaon Himalayas,” *Sustainable Earth*, vol. 6, no. 1, p. 33, 2025.

[4] R. Sen and D. Pal, “SAR and wetness index-based landslide mapping along Tista River,” *Geocarto Int.*, vol. 40, no. 2, pp. 221–239, 2025.

[5] P. Mitra, S. Chowdhury, and R. Nath, “Fuzzy logic-based terrain mapping for Darjeeling landslide risk,” *Remote Sens. Appl. Soc. Environ.*, vol. 28, p. 100832, 2024.

[6] S. Pathania and P. Kaur, “NDVI and LST integration for landslide risk assessment on mountain highways,” *GISci. Remote Sens.*, vol. 61, no. 2, pp. 145–162, 2024.

[7] R. Jadhav, S. Deshmukh, and M. Kale, “Real-time landslide risk prediction using cloud-based GIS in the Western Ghats,” Nat. Hazards, vol. 117, pp. 193–211, 2024.

[8] L. Acharya and B. Neupane, “Assessing land use change for landslide exposure in Nepalese farmlands,” *Int. Soil Water Conserv. Res.*, vol. 11, no. 1, pp. 18–30, 2023.

[9] V. Bhatt and S. Kapoor, “Slope-based risk zonation in the Beas River valley using GIS techniques,” *Environ. Earth Sci.*, vol. 82, p. 100, 2023.

[10] D. Rana and M. Gupta, “Curvature analysis and fault proximity in Himalayan landslide zonation,” *Geocarto Int.*, vol. 38, no. 4, pp. 721–739, 2023.

[11] M. Ganguly, T. Das, and S. Roy, “Road curvature and drainage failure: Causes of landslides along NH-10,” *Transp. Geotech.*, vol. 34, p. 100751, 2022.

ISSN (online): 2581-3048
Volume 9, Issue 6, pp 295-301, June-2025
https://doi.org/10.47001/IRJIET/2025.906040

[12] N. Bista and T. Lama, "Frequency ratio-based landslide zonation in central Nepal," *GISci. Remote Sens.*, vol. 59, no. 1, pp. 102–120, 2022.
[13] S. Kumar and D. Awasthi, "Morphometric GIS analysis for landslide zoning in Chamba Valley," *Appl. Geogr.*, vol. 141, p. 102621, 2022.
[14] D. Adhikari, B. Shakya, and H. Neupane, "Rainfall threshold analysis for landslide early warning in Nepal," *Nat. Hazards Earth Syst. Sci.*, vol. 22, no. 4, pp. 1123–1140, 2022.
[15] K. Karki, R. Adhikari, and A. Thapa, "Assessing vegetation and ruggedness for landslide risk using remote sensing," Remote Sens. Earth Syst. Sci., vol. 5, no. 2, pp. 211–228, 2022.
[16] K. Patel, M. Yadav, and L. Sharma, "Influence of hydrological parameters on landslide occurrences: A case study from Uttarakhand, India," *Environ. Monit. Assess.*, vol. 194, p. 224, 2022.
[17] V. Chand and R. Rawat, "Moisture index and slope curvature mapping for hazard zonation," *Hydrol. Sci. J.*, vol. 66, no. 7, pp. 1124–1140, 2021.
[18] B. Rajbhandari and N. Shakya, "Convex slope positioning and rainfall thresholds in Bagmati," *Nat. Hazards*, vol. 106, pp. 1129–1147, 2021.
[19] A.Malik and D. Sharma, "Urban expansion and slope destabilization in Himachal Pradesh," *Geoenviron. Disasters*, vol. 8, no. 3, pp. 144–160, 2021.
[20] H. Joshi and R. Menon, "Terrain curvature and landslide susceptibility mapping in Garhwal Himalaya using Cartosat-1," *Geomatics Nat. Hazards Risk*, vol. 12, no. 3, pp. 1120–1137, 2021.
[21] B. Thapa and D. Gurung, "Sentinel-2-based vegetation analysis for landslide risk assessment in mid-hill Nepal," *Remote Sens. Appl. Soc. Environ.*, vol. 22, p. 100517, 2021.
[22] S. Pandey, N. Roy, and A. Jaiswal, "NDVI-based early warning system for landslides in Darjeeling," *Environ. Model. Softw.*, vol. 139, p. 105017, 2021.
[23] M. Ali and A. Srivastava, "Terrain ruggedness and landslide distribution modeling in Tehri region," *Nat. Hazards Res.*, vol. 5, no. 1, pp. 88–102, 2020.
[24] A.Mehta, S. Rathi, and T. Bansal, "AHP-based landslide zonation in the Alaknanda basin," *Geospatial World*, vol. 18, no. 2, pp. 88–102, 2020.
[25] S. Banerjee and A. Das, "Forest fragmentation and slope failure assessment in Kalimpong," *Ecohydrology*, vol. 13, no. 5, p. e2213, 2020.
[26] N. Rai and P. Shrestha, "Multi-temporal GIS modeling for landslide prediction in the Dhauladhar range," *Geosci. Front.*, vol. 11, no. 6, pp. 1980–1990, 2020.
[27] R. Raj and J. Verghese, "Slope-hydrology integration for landslide modeling in the Nilgiris," *Geosci. Model Dev.*, vol. 13, pp. 1035–1050, 2020.
[28] R. Singh, A. Kumar, and V. Sharma, "GIS-based landslide susceptibility mapping using terrain and rainfall factors in Uttarakhand," *Geocarto Int.*, vol. 35, no. 9, pp. 845–862, 2020.
[29] S. Verma and P. Kaushik, "Integrating geotechnical and land use data for landslide hazard mapping in Kullu Valley," *J. Mountain Sci.*, vol. 20, no. 1, pp. 45–60, 2023.
[30] P. Sinha and M. Das, "Monsoon-driven vegetation loss and landslide susceptibility in Arunachal Pradesh," *Landslides*, vol. 22, no. 1, pp. 43–58, 2025.
[31] R. Shrestha, P. Sharma, and D. Joshi, "UAV and SAR for pre-failure slope monitoring in Eastern Nepal," *Geotech. Eng. J.*, vol. 13, no. 1, pp. 58–75, 2023.
[32] T. Bora and K. Sen, "Monitoring slope instability through land use transition in Arunachal Pradesh," *Environ. Monit. Assess.*, vol. 195, p. 328, 2023.
[33] S. Kumar and D. Awasthi, "Morphometric GIS analysis for landslide zoning in Chamba Valley," *Appl. Geogr.*, vol. 141, p. 102621, 2022.
[34] K. Karki, R. Adhikari, and A. Thapa, "Assessing vegetation and ruggedness for landslide risk using remote sensing," *Remote Sens. Earth Syst. Sci.*, vol. 5, no. 2, pp. 211–228, 2022.
[35] N. Bista and T. Lama, "Frequency ratio-based landslide zonation in central Nepal," *GISci. Remote Sens.*, vol. 59, no. 1, pp. 102–120, 2022.

Citation of this Article:

Er. Manpreet Singh, & Dr. Vijay Dhir. (2025). AI-Enhanced Landslide Susceptibility Mapping Using Remote Sensing and GIS in the Himalayan Region. *International Research Journal of Innovations in Engineering and Technology - IRJIET*, 9(6), 295-301. Article DOI https://doi.org/10.47001/IRJIET/2025.906040

****