Review Paper:

Remote Sensing based Early Warning Systems for Detection and Assessment of Landslides: A Case Study of Himachal Pradesh, India

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Abstract

Case studies within the framework of "Remote Sensing-Based Early Warning Systems for Slope Failures" present real-world instances of applying remote sensing technologies in monitoring slopes and detecting changes in elevation. The study focuses on Himachal Pradesh, India, known for its rugged terrain and varying climatic conditions. Himachal Pradesh, situated in North-West India, spans from 30°22'40" to 33°12'20" north latitudes and 75°45'55" to 79°04'20" east longitudes. With altitudes ranging from 271 meters to 6,751 meters, this mountain region exhibits diverse topography and climate. Geospatial data reveals its complexities, combining elevation, slope, hillside and roughness information to offer insights into the terrain's dynamics. The geological map highlights the State's Precambrian formations shaped by the collision of the Indian and Asian landmasses, resulting in the distinctive Himalayan landscape.

The region has also experienced concentrated orographic precipitation, glacial activity and rapid erosion. Analyzing historical earthquakes and active faults reveals the seismic activity's correlation with landslides, highlighting their potential to trigger slope failures. The landslide inventory map records 6,289 landslides, outlining their distribution and movement patterns. Further insight is gained from the Landslide sustainability map, classifying regions into susceptibility levels. Integrated geospatial analyses provide a comprehensive understanding of Himachal Pradesh's terrain, offering practical applications in risk assessment, infrastructure planning and environmental conservation.

Keywords: Remote Sensing, Himachal Pradesh, Faults, Landslide Inventory, Land Use and Land Cover, Landslide Sustainability.

Introduction

Slope failures including landslides and rockfalls are natural hazards that pose significant risks to human lives, infrastructure and the environment. These events can be triggered by various factors such as heavy rainfall, seismic activity, or human-induced changes in the landscape. Detecting and predicting slope failures in their early stages are critical for implementing timely mitigation measures and reducing the potential impacts on vulnerable areas[12]. Traditional monitoring methods for slope failures often involve physical inspections, ground-based sensors and manual data collection. While these approaches have provided valuable insights, they have certain limitations such as limited coverage, time-consuming data acquisition and challenges in real-time monitoring[4].

Moreover, the dynamic nature of slope failures requires continuous and up-to-date information to enable effective disaster management. In recent years, remote sensing technologies have emerged as powerful tools for slope failure monitoring and early warning systems[43]. Remote sensing involves the acquisition of information about an object or area without direct physical contact. It allows for the collection of data from a distance, using various sensors mounted on satellites, unmanned aerial vehicles (UAVs), or ground-based devices. By leveraging remote sensing data and advanced analysis techniques, researchers and practitioners have made significant progress in improving the accuracy and efficiency of early warning systems for slope failures.

Remote sensing-based early warning systems offer several advantages over traditional methods. They enable large-scale coverage first and provide a synoptic view of the terrain, allowing for the identification of potential hazard areas over a wide area. Secondly, remote sensing data can be collected at frequent intervals, allowing for near-real-time monitoring and timely detection of changes in slope conditions[44]. This is especially crucial in areas prone to rapid slope movements. Thirdly, remote sensing data can be integrated with geospatial information systems (GIS) to assess vulnerability and to identify high-risk zones and to support decision-making for disaster preparedness and response[42].

This study explores the development and application of remote sensing-based landslide susceptibility map of Himachal Pradesh. It aims to provide a comprehensive overview of the different remote sensing technologies utilized in slope monitoring, their data processing and analysis and their integration into early warning systems. The review will present case study and real-world applications that demonstrate the effectiveness of remote sensing in landslide detection, landslide susceptibility and real-time monitoring of slope movements of Himachal Pradesh, India. The geographical location of the Himachal Pradesh is shown in the figure 1.

Overall, the integration of remote sensing technologies into early warning systems for slope failures holds great promise for improving disaster preparedness and response, minimizing risks and enhancing the resilience of communities and infrastructure in hazard-prone regions. By leveraging the power of remote sensing, researchers and stakeholders can work together to develop more effective strategies for mitigating the impacts of slope failures and safeguarding vulnerable areas[40].

Importance of Early Warning Systems for Slope Failures: Early warning systems for slope failures are crucial in safeguarding communities, infrastructure and the environment. They provide timely information to prevent damages and take preventive measures. Key reasons for the importance of these systems include saving lives, protecting infrastructure, conserving the environment, reducing economic impact, enhancing disaster preparedness and response, promoting risk communication and public awareness, enabling continuous monitoring and building resilience[12]. These systems play a vital role in minimizing the impact of slope failures and ensuring the safety of communities living in hazard-prone areas[18].

Role of Remote Sensing in Slope Failure Detection and Prediction: Remote sensing plays a crucial role in the detection and prediction of slope failures, providing valuable data and insights for researchers, authorities and communities. By utilizing a range of remote sensing technologies, including satellite imagery, LiDAR and ground-based sensors, experts can efficiently monitor and assess slope conditions, enabling early warning systems and informed decision-making[5]. One of the primary advantages of remote sensing in slope failure detection is its large-scale coverage. Satellite imagery and UAV-based surveys offer synoptic views of vast areas, allowing experts to identify potential unstable slopes over extensive regions[15]. This comprehensive coverage aids in the early detection of hazardous areas and facilitates effective disaster preparedness.

Remote sensing also enables frequent data acquisition, providing real-time updates on slope conditions. This continuous monitoring is essential for identifying subtle changes in slope stability which may indicate potential failures[3]. It allows authorities to take preventive measures and issue timely warnings to at-risk communities, reducing the potential impact of slope failures on lives and infrastructure. Multi-sensor data integration is another critical aspect of remote sensing's role in slope failure detection[17].

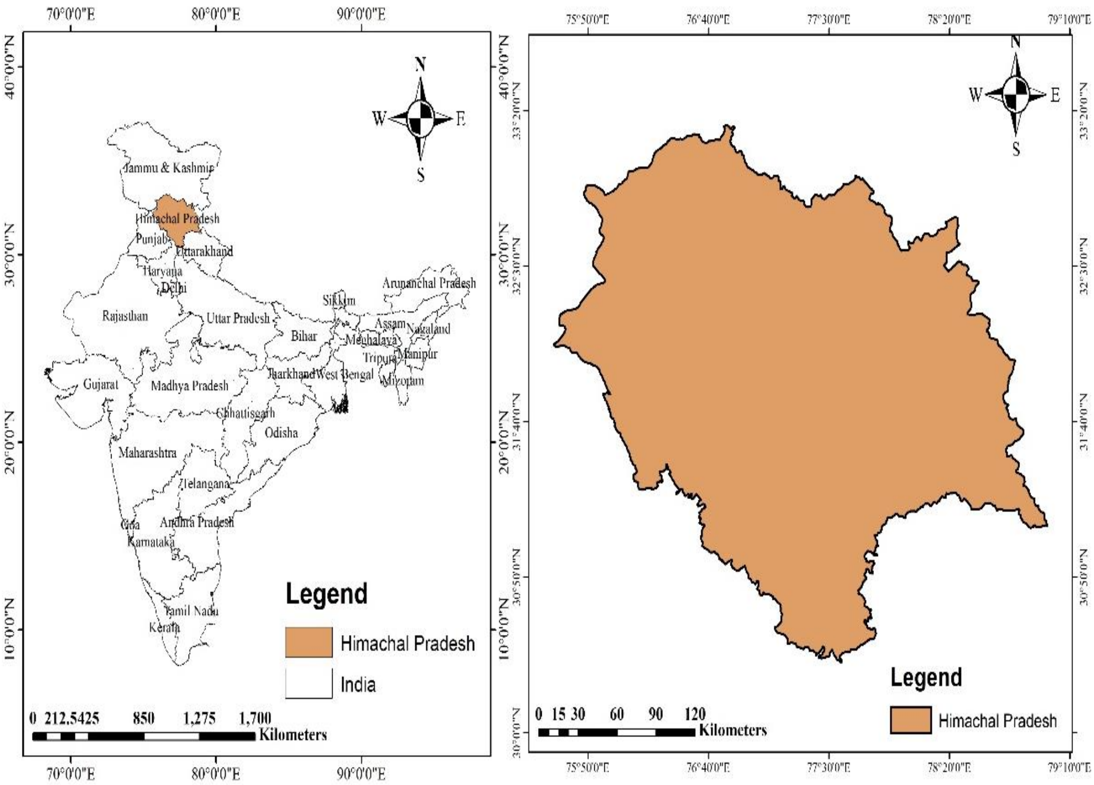

Figure 1: Location map of the Himachal Pradesh from India.

By combining data from various sensors such as optical and radar imagery, LiDAR scans and ground-based sensors, experts gain a more comprehensive understanding of slope characteristics[20]. This integrated approach enhances the accuracy and completeness of slope stability assessments and improves predictive models. Remote sensing aids in the detection of anomalies that might indicate potential slope instability. Ground movement, surface deformation and changes in vegetation patterns are the indicators that can be identified through remote sensing data. Detecting these anomalies early allows for the implementation of proactive measures to mitigate slope failure risks.

Moreover, remote sensing data contributes to hazard zoning and vulnerability assessments. By analyzing slope characteristics, geological features and historical landslide events, experts can delineate high-risk areas and prioritize mitigation efforts. This information is invaluable for disaster preparedness and land use planning in hazard-prone regions. The integration of remote sensing data into predictive models, such as machine learning algorithms, improves slope failure prediction accuracy. These data-driven models analyze historical data and real-time inputs to forecast potential slope failures, providing valuable insights for decision-making and response planning. Overall, the role of remote sensing in slope failure detection and prediction is instrumental in enhancing disaster risk reduction efforts.

The technology's ability to provide large-scale coverage, frequent data updates, anomaly detection and data-driven predictive modeling empowers authorities and communities to proactively manage slope stability and minimize the impact of slope failures on lives, infrastructure and the environment. The various remote sensing techniques such as LiDAR (Light Detection and Ranging), Satellite Imagery, Synthetic Aperture Radar (SAR), Photogrammetry, Unmanned Aerial Vehicles (UAVs), InSAR (Interferometric Synthetic Aperture Radar), GPS (Global Positioning System) have been used[32,39].

Review of Literature

Li et al[28] analyzed a novel method for mapping temporal landslides, blending image fusion and object-oriented supervised classification. This approach ensures high detection precision with minimal manual intervention. Traditionally, image fusion merges high-resolution panchromatic and color images, but this study adopts a unique approach. By fusing a lower-res panchromatic image and a higher-res aerial photo, change deformations post-earthquake and rainfall are highlighted more efficiently[23]. Landslide detection relies on object-oriented supervised classification which requires predefined classes and training samples.

To prevent misclassification, no bare ground class is initially defined; instead, expert GIS knowledge is employed for refinement. The method achieves 90.1% and 94.2% recognition accuracy for earthquake-induced and new landslides respectively[28]. The integration of ArcGIS and remote sensing boosts recognition accuracy by segmenting joint landslides. This swift approach holds potential for creating temporal landslide inventory maps, aiding disaster response.

Pradhan et al[37] have mentioned the integration of AI-based algorithms for analyzing satellite images to detect landslides as a rapidly advancing field with immense potential for mitigating landslide hazards. This review explores various AI techniques employed in landslide detection and examines factors influencing their reliability. This approach holds promise in preventing casualties, property damage and ecological harm through timely and precise landslide hazard information. Challenges remain including the need for high-quality data, yet AI models can refine themselves over time, enhancing accuracy. The progress in this research realm stands to safeguard lives in landslide-prone areas by enabling improved monitoring and risk management[37].

Li et al[27] employed two phases. Phase one employs the Faster-RCNN algorithm to detect and label loess landslide features, utilizing transfer learning on a pre-trained model. In phase two, a 2D segmentation U-Net with inception blocks is utilized for precise pixel-level prediction of landslide regions. The resulting segmentation boundaries are compared with expert-provided ground truth labels. The proposed framework offers an efficient and visual solution for loess landslide identification.

Case studies demonstrate its effectiveness in tackling complex image-based landslide detection and segmentation tasks. Unlike conventional methods, this approach enables fully automated, high-quality identification and segmentation, supported by enhanced segmentation performance from the integrated inception blocks. Compared to recent publications, this framework is better suited for loess landslide tasks, potentially offering insights to mitigate future landslide hazards.

Moine et al[31] introduced a formal grid with qualitative indicators for landslides, which converts these into quantitative criteria for object-oriented image classification. Expert knowledge underpins the semi-automatic method. Spatial and spectral resolutions are crucial for detection. Potential enhancements include incorporating topological relationships and additional data like DTMs or lidar for roughness assessment. The method is tested for distinguishing 'ablation' and 'accumulation' zones. Future goals involve applying it to large landslides (>100000m²) using DTM lidar, exemplified by the 'La Valette' earthflow in the Barcelonnette basin.

Dikshit and Satyam[10] employed the FlaIR hydrological model to forecast rainfall-triggered landslides, focusing on Chibo in West Bengal, India. Analyzing a July 2015 event, a mobility function value of 0.27 indicates landslide likelihood beyond this threshold. Lithology-informed parameters like transfer and mobility functions reveal rainfall-landslide connections. Model accuracy hinges on calibrated parameters using rainfall and landslide time series. Integration with a probabilistic model and new tiltmeters aids to refinement and broader applications[33].

Addressing the dearth of accurate remote sensing landslide datasets, Ji et al[22] crafted a comprehensive dataset encompassing high-resolution satellite images, precise delineated landslide borders and detailed DEM. Rigorous validation through historical inventory comparison, boundary refinement and field surveys ensured dataset precision. Our innovative 3D attention mechanism, generating unified spatial-channel attention maps, outperformed existing methods. The ResNet-50 with this attention module yielded optimal results, validated by robust detection scores and real-world application in Zhijin county, showcasing the dataset's potential for advanced deep learning-based landslide detection using optical satellite imagery.

Abraham et al[3] described a landslide prediction system for Idukki district, India, using the Sigma model. It incorporates long-term and short-term rainfall effects, utilizing statistical rainfall data and cumulative distribution functions to establish thresholds. The system issues alert levels based on rainfall severity, optimizing for each area's unique conditions. Calibration and validation were conducted, showcasing effectiveness in predicting landslides while highlighting false alarm issues. The model's simplicity, multiple warning levels and incorporation of temporal data make it a valuable early warning tool. Improved data resolution could enhance its performance, contributing to effective landslide risk reduction.

Abraham et al[1] explored Shetran model's utility in simulating Kalimpong's moisture content and assessing 2D Bayesian landslide probabilities using rainfall severity and antecedent moisture. Historical data, satellite info and Bayesian analysis determine landslides' likelihood. Shetran predicts region's moisture effectively without field data. Rainfall thresholds were defined by frequentist method.

Incorporating antecedent moisture revealed its role in triggering landslides, even for less severe rainfalls. The study enhances empirical thresholds with a 2D probabilistic approach, showcasing its superiority. Shetran emerges as an alternative for moisture estimation and landslide prediction, crucial for the landslide-prone area.

Abraham et al[2] investigated the impact of rainfall-induced landslides in Kalimpong's Chibo area. Six Mems sensors monitor unstable slopes for three monsoon seasons, providing real-time data on tilt rates and moisture content. Tilt sensors prove effective in predicting slow movements and failure time, related to antecedent rainfall rather than peak intensity. Long-term and short-term rainfall both affect slope stability, emphasizing the need for refined thresholds. The study highlights the importance of local site conditions alongside rainfall for an efficient early warning system.

Dikshit et al[11] addressed the limitations of existing methods linking rainfall thresholds to landslides. They proposed a Bayesian approach considering all rainfall aspects, enhancing landslide understanding and forecasting. Analyzing 7 years of data, the study employs one-dimensional and two-dimensional approaches.

Mohan et al[30] critically examined the employment of remote sensing combined with machine learning and deep learning in landslide detection. They emphasized recent techniques for mapping susceptibility, identified promising approaches needing refinement and suggested research directions. Enhanced data augmentation and neural network architecture exploration are warranted. Addressing challenges in shapeless and spectrally indistinct regions necessitates feature fusion. The study's focus is on applying Mask RCNN for hilly region landslide detection and evaluating transfer learning's efficacy.

Fu et al[16] introduced Swade, an automatic landslide dating technique using Landsat time series. This method eliminates cloud interference, fills data gaps and reduces seasonal effects through wavelet denoising and stepwise linear fitting. Swade accurately detects landslide occurrences with up to 80% accuracy in the two most-probable date ranges, outperforming other methods like harmonic modeling and LandTrendr. Further enhancement could come from combining multi-source optical and SAR imagery, as well as analyzing vegetation disturbances in comparison to wildfires.

Fiorucci et al[14] utilized digital aerial ortho-photographs and high-resolution satellite images to compile a multi-temporal landslide inventory from September 2004 to June 2005. Visual interpretation effectively detected recent landslides, even those lacking distinctive morphological cues. This innovative approach advances the systematic creation of multi-temporal inventories, particularly in diverse landscapes driven by slope processes. Established criteria for landslide mapping from stereoscopic aerial images were successfully applied to monoscopic satellite images, showcasing the utility of trained geomorphologists. The research also linked rainfall events, not necessarily extreme, to slope failures, crucial for hazard assessment. The contrast between regional erosion and landslide mobilization rates highlighted agricultural influences on heightened landslide occurrence.

Casagli et al[6] highlighted the significance of remote sensing in landslide detection, monitoring and prediction. Advanced technologies offer extensive data on slope instabilities across scales. Improved algorithms and sensors enable monitoring of previously challenging fast landslides and contouring instabilities. Data underutilization persists, indicating the need for enhanced sharing within the scientific community.

Expanding monitoring to developing regions and low-income countries is essential. Integrating techniques like the European Ground Motion Service and NISAR mission's dual-frequency SAR satellite promise deeper insights. Instrumentation cost-effectiveness balance is crucial for effective long-term monitoring.

Data Acquisition and Processing

Data acquisition and processing are critical components of remote sensing-based early warning systems for slope failures[35,36]. They involve the collection of relevant data using various remote sensing technologies and the subsequent analysis and interpretation of the acquired data. Proper data acquisition and processing are essential to ensure the accuracy, reliability and effectiveness of the early warning system. Here are the key aspects of data acquisition and processing in slope monitoring[5].

Data Acquisition Methods

Satellite Imagery: Acquiring satellite images over the study area at regular intervals provides valuable information on changes in slope conditions over time[9,13].

LiDAR Data: Conducting LiDAR survey generates high-resolution elevation data that helps in detecting subtle changes in slope topography.

Synthetic Aperture Radar (SAR): SAR sensors onboard satellites or aircraft can provide all-weather and day-and-night monitoring capabilities, capturing surface movements.

Photogrammetry: Using aerial photographs or UAV-captured images allows for the creation of 3D terrain models and the detection of slope changes.

InSAR: Interferometric SAR data provides precise measurements of ground deformation, detecting millimeter-scale movements.

Data Pre-processing: Before analyzing the acquired data, pre-processing steps are performed to clean, correct and enhance the raw data. Pre-processing may involve tasks such as radiometric calibration, geometric correction, atmospheric correction (in the case of satellite imagery) and noise removal.

Data Integration and Fusion: In some cases, multiple sources of data are integrated or fused to improve the overall understanding of slope behavior. For instance, combining LiDAR data with satellite imagery or integrating SAR data with GPS measurements can provide more comprehensive insights into slope movements.

Data Registration and Alignment: If data from different sensors or time periods are used, it is essential to register or align the data correctly to ensure consistency and accuracy in the analysis.

Data Interpolation and Smoothing: Data interpolation techniques are applied to fill gaps or missing data points, especially in cases where some areas are not covered by the remote sensing technology used. Smoothing techniques may be used to reduce noise and improve the visualization of trends.

Change Detection Analysis: Change detection algorithms are applied to compare data from different time periods and identify areas where significant slope movements or changes have occurred. This helps in pinpointing potential slope failure hotspots.

Feature Extraction: Feature extraction methods are used to identify specific slope characteristics or patterns that may indicate instability. These features can include surface displacement rates, slope angles, curvature and other relevant parameters.

Data Visualization: Effective data visualization techniques are employed to present the processed data in a comprehensible manner. Visualization helps in identifying trends, anomalies and potential slope failure risks.

Data Validation and Quality Assessment: The processed data is validated to ensure its accuracy and reliability. Quality assessment involves evaluating the data's consistency and comparing it with ground truth measurements or other reliable sources.

Data Storage and Management: A robust data storage and management system is essential to handle the large volume of remote sensing data collected over time. Proper archiving and organization facilitate easy retrieval and long-term analysis. Data acquisition and processing are iterative processes in slope monitoring with continuous updates and improvements as new data becomes available. These processes form the foundation for accurate slope failure prediction and early warning system implementation, ultimately contributing to enhanced safety and risk reduction in vulnerable areas.

Study area

Himachal Pradesh, located in North-West India, spans between 30°22'40" to 33°12'20" north latitudes and 75°45'55" to 79°04'20" east longitudes. This predominantly mountainous State shares an international border with China and is nestled within the Himalayas. The altitude across the region varies from 271 meters to a towering 6,751 meters above mean sea level. Himachal Pradesh is enveloped by Jammu and Kashmir to the north, Tibet to the northeast, Uttaranchal to the east/southeast, Haryana to the south and Punjab to the southwest/west. Distinguished by its intricate mountain ranges, the State is characterized by deep gorges, valleys and diverse climatic conditions. Its climate spectrum ranges from semi-tropical in the lower hills to semi-arctic in the cold desert zones of Spiti and Kinnaur.

The altitudinal gradient further accentuates this climatic diversity, extending from 350 meters in the plains of Kangra and Una to almost 7,000 meters in the Central Himalayan range of Lahaul and Spiti. Occupying a compact geographical layout, Himachal Pradesh is almost entirely mountainous, encompassing altitudes that vary from 300 meters in the plains of Kangra and Una to nearly 7,000 meters in the Central Himalayan range of Lahaul and Spiti. Its total geographical expanse covers approximately 55,673 square kilometers, accounting for about 1.69% of India's total land area. The satellite map of the study area is shown in figure 2.

Elevation and Geological map of the study area: The elevation map of the study area, Himachal Pradesh, showcases the spatial distribution of elevation, ranging from 271 meters to 6751 meters. Employing a choropleth representation, the map employs a color gradient to vividly depict the altitudinal variations across the region. The legend employs a spectrum of colors to convey the elevation ranges, aiding quick comprehension. Labels and annotations provide context, while isopleth lines reveal contour intervals, aiding in perceiving the terrain's steepness. The interactive digital format allows users to explore the elevation data across different geographic subregions and offers a temporal element for observing elevation changes over time, enhancing the map's utility in environmental planning, risk assessment and scientific analysis. The elevation map of Himachal Pradesh is shown in figure 3.

Geology map of the Himachal Pradesh

The geological composition of Himachal Pradesh primarily consists of Precambrian formations that underwent assembly and deformation as a consequence of the India-Asia collision and the subsequent Himalayan orogeny[38]. Himachal Pradesh, a State situated in the Western Himalaya region (as depicted in fig. 1), is characterized by a rugged topography, encompassing altitudes spanning from 271 meters to 6751 meters. The geological substrates prevalent in this area predominantly stem from the Indian craton and exhibit ages varying from the Paleoproterozoic era to contemporary times.

It is widely accepted within the scientific community that approximately 50-60 million years ago, the Indian craton underwent collision with the Asian landmass. This collision led to extensive thrusting and folding of rock sequences within the region, resulting in significant geological transformations. The geographic features of the area have also been markedly influenced by concentrated orographic precipitation, glacial activity and rapid erosion processes. These forces have collectively contributed to shaping the distinctive landscape observed in Himachal Pradesh today and the detailed geological map of the Himachal Pradesh is shown in figure 4.

Surface details of the Himachal Pradesh: In conjunction with the obtained data on Himachal Pradesh, the region's comprehensive geospatial characteristics are further illuminated. The slope map, delineating the topographical steepness, exhibits a maximum value of 86.55, depicting areas of pronounced gradient and gentle slopes[21].

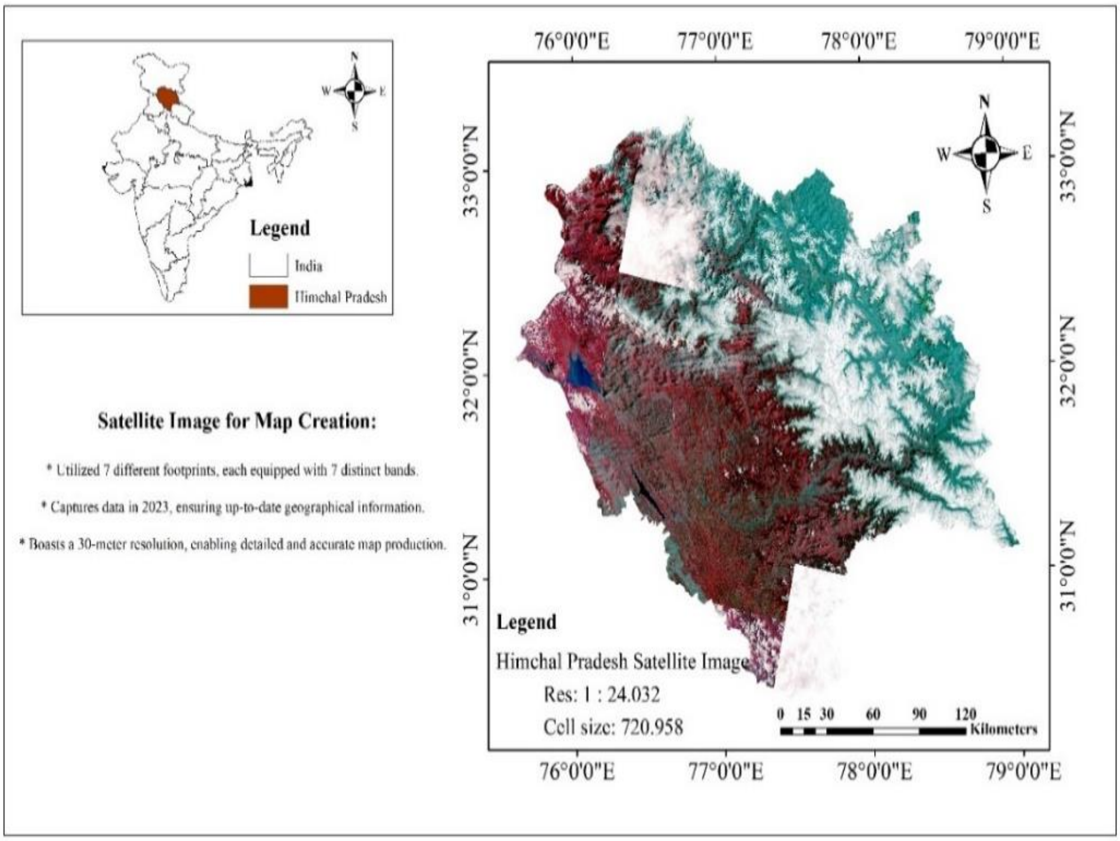

Figure 2: Satellite map of Himachal Pradesh with 30-meter resolution.

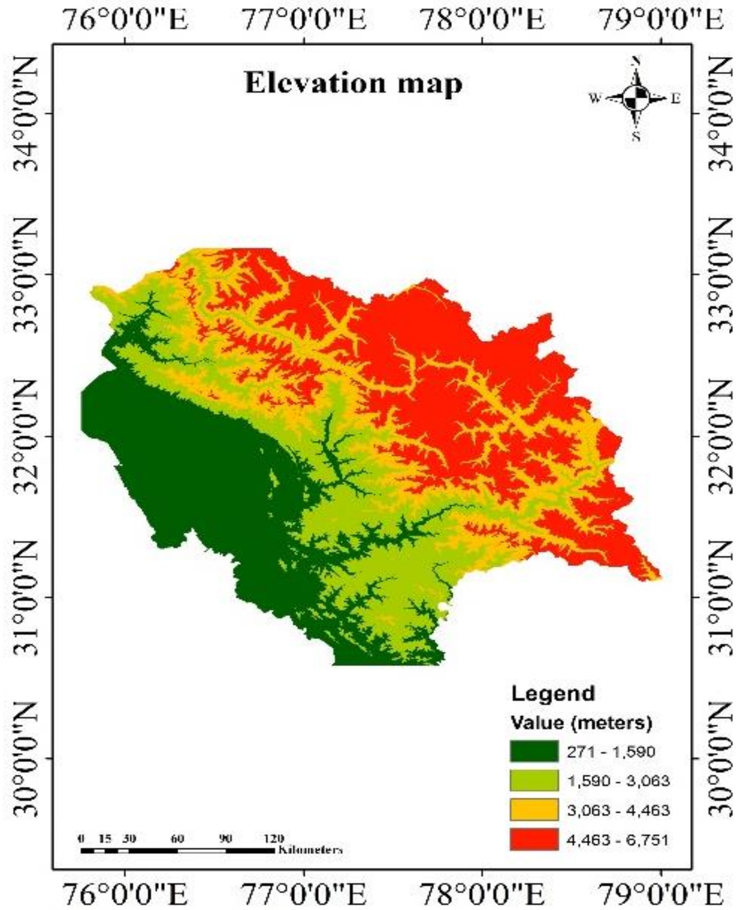

Figure 3: Elevation map of Himachal Pradesh, India.

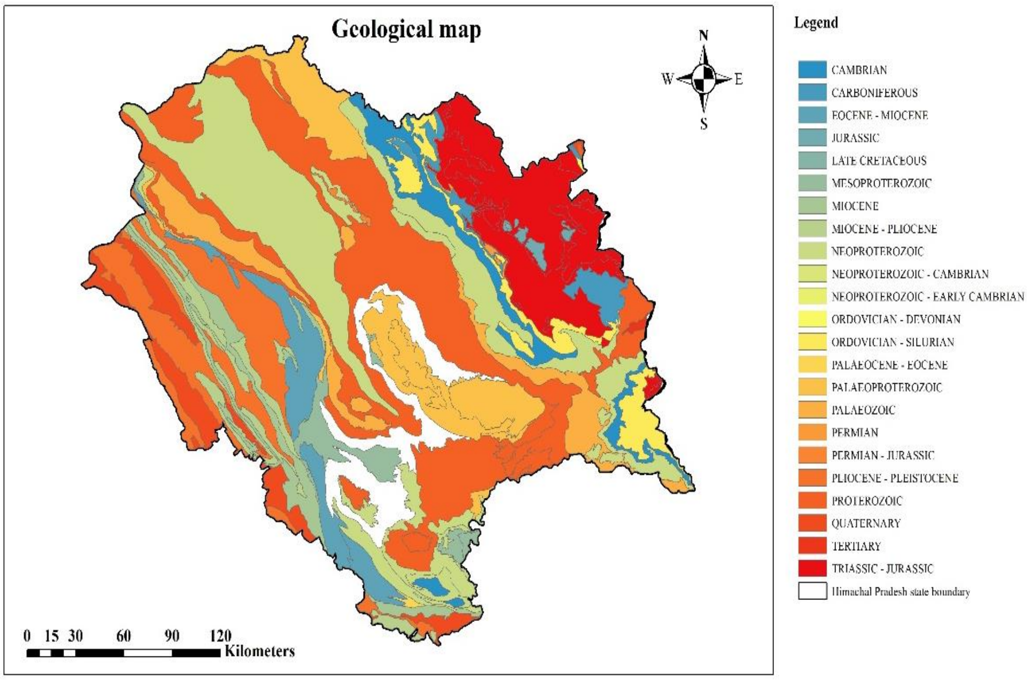

Figure 4: Geological map of the Himachal Pradesh

Simultaneously, the roughness map, highlighting terrain ruggedness, showcases a peak value of 1,610, illustrating the variability in surface irregularities across the landscape. The aspect map, crucial for understanding the direction a slope faces, demonstrates a maximum value of 359.93, encapsulating a full spectrum of orientations[34]. This information aids in comprehending sunlight exposure, drainage patterns and potential erosion hotspots.

Additionally, the hillside map, featuring a maximum value of 255, contributes to a holistic comprehension of landforms and elevations, thus enhancing terrain analysis. These intricate maps, collectively represented in figure 5, amalgamate multiple layers of geospatial data. Their integration offers valuable insights into Himachal Pradesh's topographical nuances, aiding informed decision-making across diverse sectors. These maps find relevance in fields such as urban planning, natural resource management, disaster risk assessment and environmental conservation where the interplay between elevation, slope, aspect and roughness profoundly influences landscape dynamics[29].

Historical Earthquakes and Active Faults in Himachal Pradesh: An Overview

Earthquakes are natural geological phenomena caused by the sudden release of energy in the Earth's crust, resulting in seismic waves that propagate through the ground[24]. These events can vary in magnitude, causing ground shaking, damage to structures and in some cases, triggering secondary hazards like landslides. A total of 366 earthquake events were recorded after declustering, spanning from 1945 to 2019. The magnitude range of these events is 3.2 to 6.5 M_w, with varying depths from 1 to 225 km. The data was compiled from multiple earthquake data sources. Earthquakes can trigger landslides due to the intense ground shaking and changes in the stress distribution within slopes. This can weaken the stability of hills and mountains, leading to the downslope movement of rock and soil.

Understanding the spatial distribution of earthquakes, faults and other geological features is crucial for assessing the potential landslide risks in a region. The study region includes Himachal Pradesh and encompasses a total of 1278 identified faults, categorized as "Fault Inferred" and "Fault Interpreted." The interaction of these faults plays a significant role in the seismic activity of the area, potentially contributing to earthquake occurrence and landslide susceptibility.

The spatial distribution of earthquake events, faults, active faults, road networks and rivers in Himachal Pradesh is illustrated in figure 6. This visual representation provides insights into the geological context and potential relationships between seismic activity, fault systems and landscape features within the region.

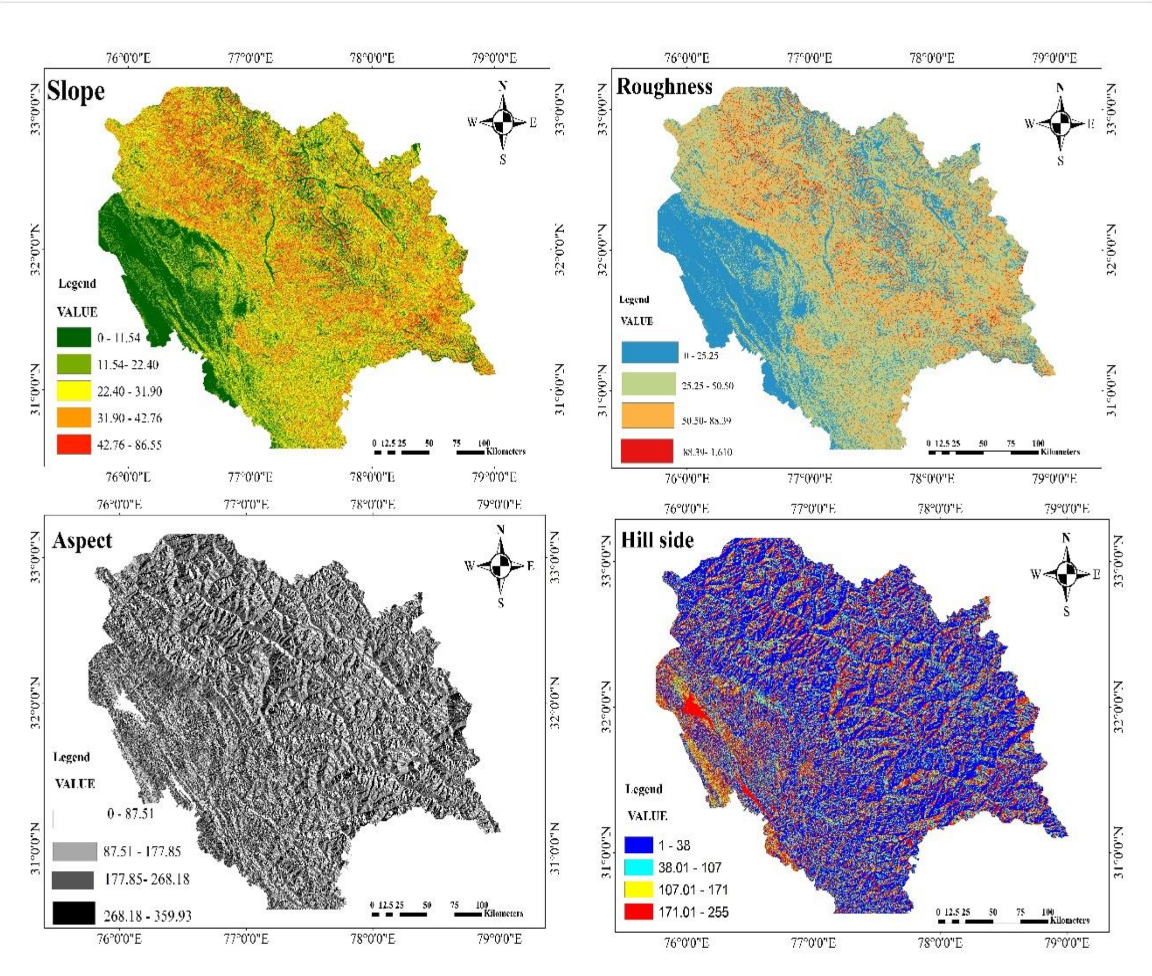

Figure 5: The slope, roughness, aspect and hillside map of Himachal Pradesh, India

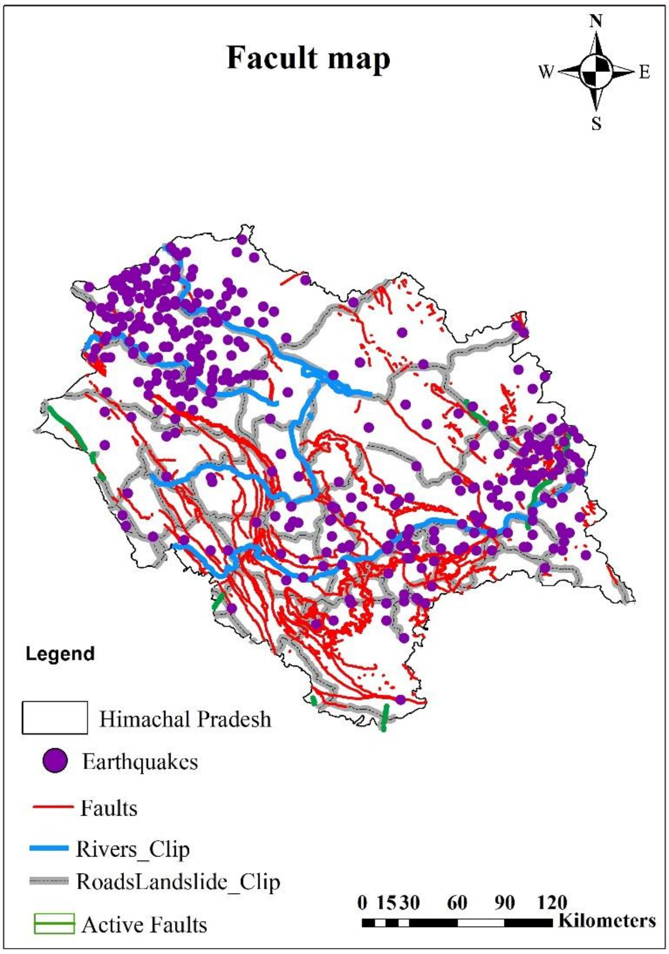

Figure 6: Spatial distribution of earthquake events and the orientation of faults

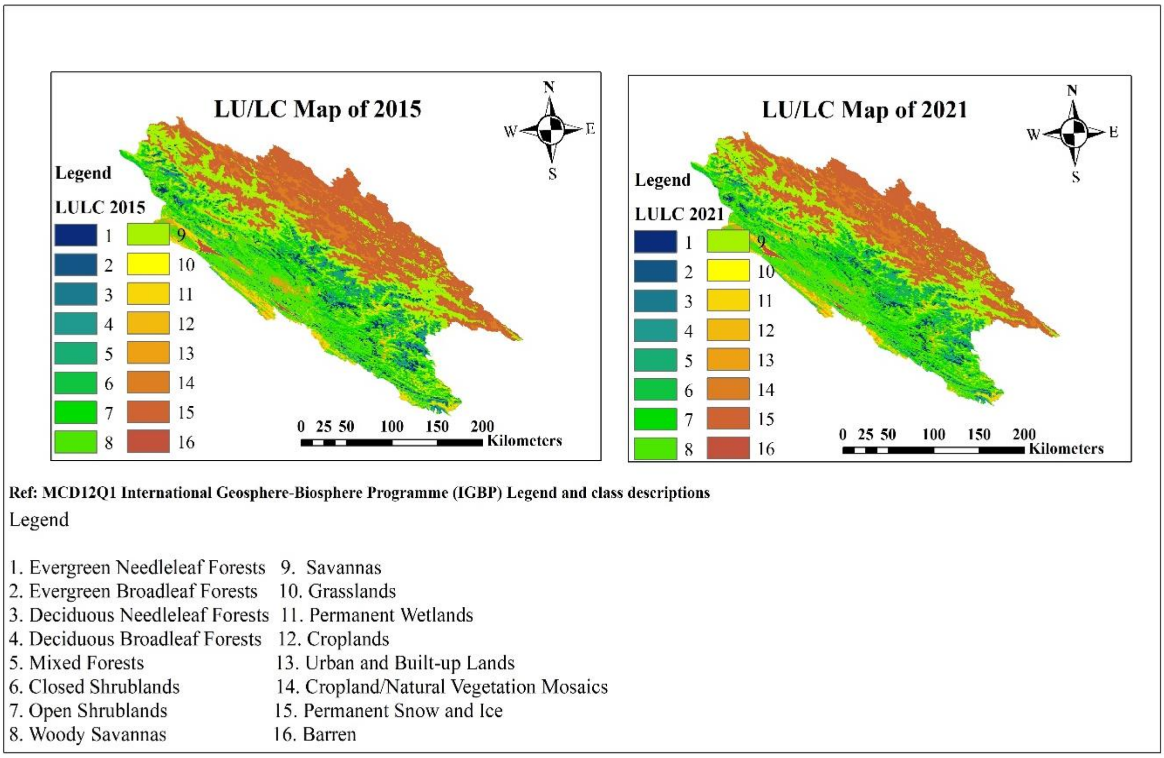

Figure 7: Land Use and Land Cover Map of Himachal Pradesh (2015 and 2021)

Land use/Land cover map: The development and analysis of land use and land cover maps are of paramount importance in various fields. These maps, generated for the years 2015 and 2021, provide valuable insights into the distribution and transformation of landscapes. The identification of different land use and land cover categories such as Evergreen Needleleaf Forests, Grasslands, Urban and Built-up Lands, Croplands and more, offers a comprehensive understanding of how the land is utilized.

In the context of landslide prediction, these maps are instrumental. They serve as crucial data sources for assessing the susceptibility of different areas to landslides. The information contained in these maps can aid in identifying regions prone to landslides based on factors such as slope, land cover type and human activities. For instance, areas with high degrees of urbanization or agricultural activities might be more susceptible to landslides due to changes in terrain and soil stability[25].

The land use and land cover maps specifically developed for Himachal Pradesh, showcased in figure 7, provide a visual representation of the region's diverse landscape. This visual information, combined with geological and seismic data, can contribute to a holistic understanding of landslide risks. By integrating these maps with other relevant data, researchers and planners can make informed decisions to mitigate potential landslide hazards, protect infrastructure and ensure the safety of communities.

Landslide Inventory of Himachal Pradesh

Creating a comprehensive Landslide Inventory map holds immense significance in understanding and mitigating landslide hazards[19]. This map captures the spatial distribution and characteristics of landslides within a given region, offering critical insights into their triggers, behavior and potential impact on the landscape. Within Himachal Pradesh, a total of 6289 landslides have been documented. These events exhibit a range of causes including factors such as extensive slope cutting, fractured rock, lack of toe support, anthropogenic activities and the presence of highly jointed carbonaceous shale on steep slopes, among others. These factors contribute to the vulnerability of slopes and the propensity for landslides to occur.

The movement patterns of these landslides vary, encompassing rapid, extremely rapid and slow movements. Their distribution types include Confined, Retrogressive, Enlarging and Widening. These distinctions provide insights into the dynamics and potential impacts of different landslide events[41]. The Landslide Inventory map for Himachal Pradesh, depicted in figure 8, serves as a visual tool for understanding the spatial distribution of landslides across the region.

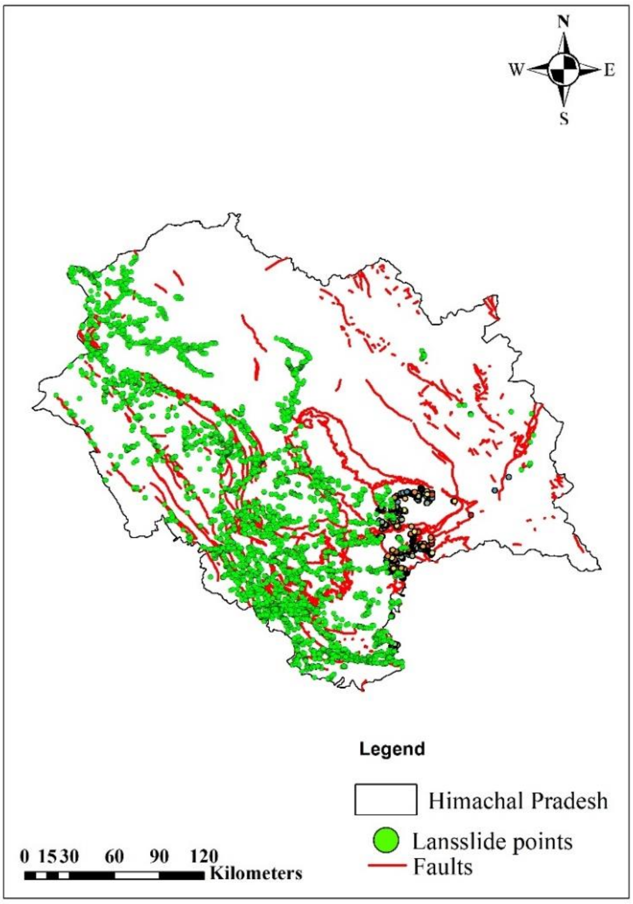

Figure 8: Landslide Inventory map of Himachal Pradesh

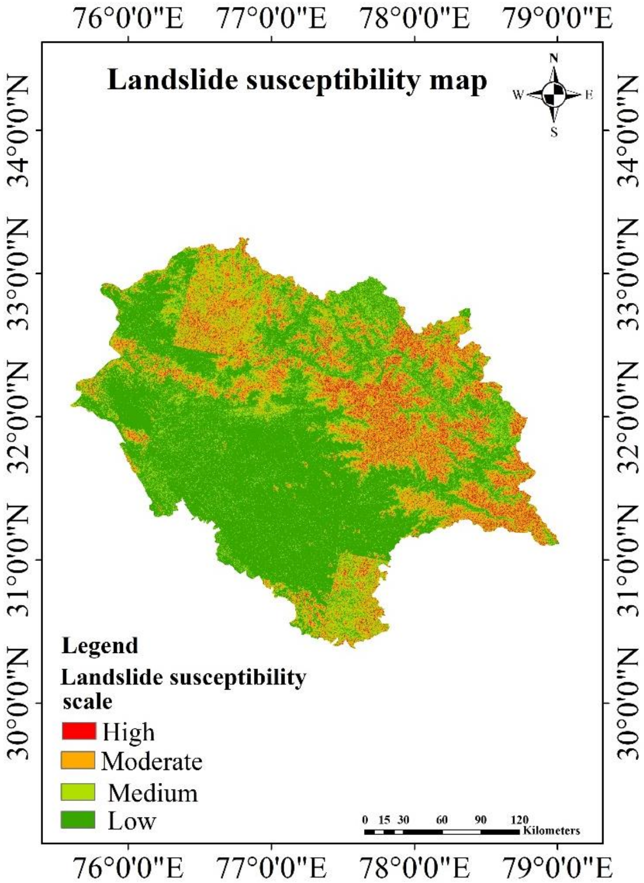

Fig. 9: Landslide Sustainability Map of Himachal Pradesh: Classifications of High, Moderate, Medium and Low Susceptibility

By analyzing this map alongside geological, topographical and climatic data, experts can make informed decisions regarding land use planning, infrastructure development and disaster risk reduction strategies[8]. This proactive approach helps in minimizing the potential damage and loss caused by landslides, safeguarding both natural resources and human lives.

Landslide sustainability map of Himachal Pradesh: The Landslide sustainability map serves as a crucial tool for assessing the long-term stability and viability of landscapes in relation to potential landslide hazards. Within the context of Himachal Pradesh, this map is categorized into four distinct classes: high, moderate, medium and low. These classes represent varying levels of landslide susceptibility and the associated risks they pose to the environment and communities[7].

The classification process considers a range of factors including geological conditions, topographical features, land cover and historical landslide events. This comprehensive analysis enables the identification of areas that are more resilient to landslides as well as those that are more prone to such events.

By presenting this information in a visual format, the Landslide sustainability map aids decision-makers, urban planners and disaster management teams in making informed choices about land use, infrastructure development and risk reduction strategies. The integration of such maps into planning processes enhances the overall sustainability of a region, promoting responsible development that considers both short-term goals and long-term resilience[45].

Figure 9 showcases the Landslide sustainability map of Himachal Pradesh, offering a clear representation of the varying levels of sustainability across the landscape. This map is an invaluable resource for steering development initiatives towards areas of lower landslide susceptibility, contributing to the preservation of natural resources, the protection of communities and the overall well-being of the region.

Conclusion

This study offers a comprehensive analysis of leveraging remote sensing technologies to monitor slopes, detect potential hazards and contribute to effective early warning systems. The study delves into the unique geospatial characteristics of Himachal Pradesh, a mountainous region characterized by diverse altitudes and geological formations. It highlights the significance of elevation and geological mapping in understanding terrain dynamics and the integration of slope, roughness and hillside maps for comprehensive terrain analysis. The study also sheds light on historical earthquakes and active faults, emphasizing their relevance in the context of seismic activities and potential landslide triggers.

Furthermore, the investigation covers the development of vital maps including land use and land cover, landslide inventory and landslide sustainability. These maps play a pivotal role in assessing vulnerability, predicting hazards and guiding sustainable development practices. The study's rich insights collectively underscore the significance of remote sensing in enhancing landslide prediction, risk assessment and landscape management strategies for Himachal Pradesh and similar regions worldwide.

References

1. Abraham M.T., Satyam N., Pradhan B. and Alamri A.M., Forecasting of landslides using rainfall severity and soil wetness: A probabilistic approach for Darjeeling Himalayas, *Water*, **12(3)**, 804 **(2020)**

2. Abraham M.T., Satyam N., Pradhan B. and Alamri A.M., IoT-based geotechnical monitoring of unstable slopes for landslide early warning in the Darjeeling Himalayas, *Sensors*, **20(9)**, 2611 **(2020)**

3. Abraham M.T., Satyam N., Shreyas N., Pradhan B., Segoni S., Abdul Maulud K.N. and Alamri A.M., Forecasting landslides using SIGMA model: a case study from Idukki, India, *Geomatics, Natural Hazards and Risk*, **12(1)**, 540-559 **(2021)**

4. Bhukya M.N. and Kota V.R., A quick and effective MPPT scheme for solar power generation during dynamic weather and partial shaded conditions, *Engineering Science and Technology, an International Journal*, **22(3)**, 869-884 **(2019)**

5. Carrara A., Cardinali M., Guzzetti F. and Reichenbach P., GIS technology in mapping landslide hazard, In Geographical information systems in assessing natural hazards. Dordrecht, Springer Netherlands, 135-175 **(1995)**

6. Casagli N., Intrieri E., Tofani V., Gigli G. and Raspini F., Landslide detection, monitoring and prediction with remote-sensing techniques, *Nature Reviews Earth & Environment*, **4(1)**, 51-64 **(2023)**

7. Chandu Kavitha, Akasapu Dharma Raju and Samudrala Venkata Jagannadha Kumar, Human Discomfort Index as a measure of biometeorological parameters influencing population: A study over selected cities of Andhra Pradesh, *Disaster Advances*, **15(1)**, 24-29 **(2022)**

8. Das S., Sarkar S. and Kanungo D.P., A critical review on landslide susceptibility zonation: recent trends, techniques and practices in Indian Himalaya, *Natural Hazards*, **115(1)**, 23-72 **(2023)**

9. Desai V.D., Fazelpour F., Handwerger A.L. and Daniels K.E., Forecasting landslides using community detection on geophysical satellite data, *Physical Review E*, **108(1)**, 014901 **(2023)**

10. Dikshit Abhirup and Satyam Neelima, Application of FLaIR model for early warning system in Chibo Pashyor, Kalimpong, India for rainfall-induced landslides, *Natural Hazards and Earth System Sciences Discussions*, **2017**, 1-18 **(2017)**

11. Dikshit A., Sarkar R. and Satyam N., Probabilistic approach toward Darjeeling Himalayas landslides-A case study, *Cogent Engineering*, **5(1)**, 1537539 **(2018)**

12. Donati D., Stead D., Onsel E., Mysiorek J. and Chang O., Remote Sensing and Geovisualization of Rock Slopes and Landslides, *Remote Sensing*, **15(15)**, 3702 **(2023)**

13. Esposito M., Palma L., Belli A., Sabbatini L. and Pierleoni P., Recent advances in internet of things solutions for early warning systems: A review, *Sensors*, **22(6)**, 21-24 **(2022)**

14. Fiorucci F., Cardinali M., Carlà R., Rossi M., Mondini A.C., Santurri L., Ardizzone F. and Guzzetti F., Seasonal landslide mapping and estimation of landslide mobilization rates using aerial and satellite images, *Geomorphology*, **1(2)**, 59-70 **(2011)**

15. França Pereira F., Sussel Gonçalves Mendes T., Jorge Coelho Simões S., Roberto Magalhães de Andrade M., Luiz Lopes Reiss M., Fortes Cavalcante Renk J. and Correia da Silva Santos T., Comparison of LiDAR-and UAV-derived data for landslide susceptibility mapping using Random Forest algorithm, *Landslides*, **20(3)**, 579-600 **(2023)**

16. Fu Sheng et al, The SWADE model for landslide dating in time series of optical satellite imagery, *Landslides*, **20(5)**, 913-932, **(2023)**

17. Gade M.S.L. and Rooban S., Run time fault tolerant mechanism for transient and hardware faults in alu for highly reliable embedded processor, In 2020 International Conference on Smart Technologies in Computing, Electrical and Electronics (ICSTCEE), 44-49 **(2020)**

18. Guo Z., Torra O., Hürlimann M., Abancó C. and Medina V., FSLAM: A QGIS plugin for fast regional susceptibility assessment of rainfall-induced landslides, *Environmental Modelling & Software*, **150**, 105354 **(2022)**

19. Gupta V. and Singh K., Landslide susceptibility mapping along Chandigarh-Shimla road corridor NH-5, Himachal Pradesh, India, AIP Conference Proceedings, AIP Publishing **(2023)**

20. Jaboyedoff M., Oppikofer T., Abellán A., Derron M.H., Loye A., Metzger R. and Pedrazzini A., Use of LIDAR in landslide investigations: a review, *Natural Hazards*, **61**, 5-28 **(2012)**

21. Jahandar O., Abdi E. and Jaafari A., Assessment of slope failure susceptibility along road networks in a forested region, northern Iran, *Physics and Chemistry of the Earth*, Parts A/B/C, **128**, 103272 **(2022)**

22. Ji Shunping, Dawen Yu, Chaoyong Shen, Weile Li and Qiang Xu, Landslide detection from an open satellite imagery and digital elevation model dataset using attention boosted convolutional neural networks, *Landslides*, **17**, 1337-1352 **(2020)**

23. Kalyani G., Janakiramaiah B., Prasad L.N., Karuna A. and Babu A.M., Efficient crowd counting model using feature pyramid network and ResNeXt, *Soft Computing*, **25(15)**,10497-10507 **(2021)**

24. Kothiala A., Nayek P.S., Gade M. and Kala U.V., November. Seismic Landslide Hazard Assessment of Mandi Town, Himachal Pradesh, Symposium in Earthquake Engineering, Singapore, Springer Nature Singapore, 257-267 **(2022)**

25. Kumar S., Singh V. and Saroha J., Interpretation of land use/land cover dynamics with the application of geospatial techniques in sarbari khad watershed of Himachal Pradesh, India, *Geo Journal*, **88(3)**, 2623-2633 **(2023)**

26. Kumari C.U., Murthy A.S.D., Prasanna B.L., Reddy M.P.P. and Panigrahy A.K., An automated detection of heart arrhythmias using machine learning technique: SVM, Materials Today: Proceedings, **45(1)**, 1393-1398 **(2021)**

27. Li Huajin, Yusen He, Qiang Xu, Jiahao Deng, Weile Li and Yong Wei, Detection and segmentation of loess landslides via satellite images: A two-phase framework, *Landslides*, **19(3)**, 673-686 **(2022)**

28. Li Yange, Guangqi Chen, Bo Wang, Lu Zheng, Yingbin Zhang and Chuan Tang, A new approach of combining aerial photography with satellite imagery for landslide detection, *Natural Hazards*, **66**, 649-669 **(2013)**

29. Maxwell A.E. and Shobe C.M., Land-surface parameters for spatial predictive mapping and modeling, *Earth-Science Reviews*, **226**, 103944 **(2022)**

30. Mohan A., Singh A.K., Kumar B. and Dwivedi R., Review on remote sensing methods for landslide detection using machine and deep learning, *Transactions on Emerging Telecommunications Technologies*, **32(7)**, 3998 **(2021)**

31. Moine Monique, Anne Puissant and Jean-Philippe Malet, Detection of landslides from aerial and satellite images with a semi-automatic method. Application to the Barcelonnette basin (Alpes-de-Hautes-Provence, France), Landslide processes-from geomorphologic mapping to dynamic modelling, 63-68 **(2009)**

32. Moretto S., Bozzano F. and Mazzanti P., Remote sensing approaches and related techniques to map and study openings, *Remote Sensing*, **13(18)**, 3735 **(2021)**

33. Nagarjuna T., Lakshmi S. and Nehru K., USRP 2901-based SISO-GFDM transceiver design experiment in virtual and remote laboratory, *The International Journal of Electrical Engineering and Education*, **59(4)**, 350-365 **(2022)**

34. NASA Shuttle Radar Topography Mission (SRTM), Shuttle Radar Topography Mission (SRTM) Global, Distributed by Open Topography, https://doi.org/10.5069/G9445JDF, Accessed: 2023-08-14 **(2013)**

35. Padmaja B., Myneni M.B. and Krishna Rao Patro E., A comparison on visual prediction models for MAMO (multi activity-multi object) recognition using deep learning, *Journal of Big Data*, **7(1)**, 1-15 **(2020)**

36. Pon V.D., Wilson K.J., Hariprasad K., Ganesh V., Ali H.E., Algarni H. and Yahia I.S., Enhancement of optoelectronic properties of ZnO thin films by Al doping for photodetector applications, *Superlattices and Microstructures*, **151(1)**, 106790 **(2021)**

37. Pradhan Biswajeet, Mustafa Neamah Jebur, Helmi Zulhaidi Mohd Shafri and Mahyat Shafapour Tehrany, Data fusion technique using wavelet transform and Taguchi methods for automatic landslide detection from airborne laser scanning data and quickbird satellite imagery, *IEEE Transactions on Geoscience and Remote Sensing*, **54(3)**, 1610-1622 **(2015)**

38. Raji A., Nesakumar J.I.E.T., Mani S., Perumal S., Rajangam V., Thirunavukkarasu S. and Lee Y.R., Biowaste-originated heteroatom-doped porous carbonaceous material for electrochemical energy storage application, *Journal of Industrial and Engineering Chemistry*, **98(1)**, 308-317 **(2021)**

39. Ray R.L., Lazzari M. and Olutimehin T., Remote sensing approaches and related techniques to map and study landslides, *Landslides-Investig. Monit*, **2**, 1-25 **(2020)**

40. Saha S., Bera B., Shit P.K., Sengupta D., Bhattacharjee S., Sengupta N., Majumdar P. and Adhikary P.P., Modelling and predicting of landslide in Western Arunachal Himalaya, India, *Geosystems and Geoenvironment*, **2(2)**, 100158 **(2023)**

41. Spandana K. and Rao V.S., Internet of things (Iot) based smart water quality monitoring system, *International Journal of Engineering & Technology*, **7(3.6)**, 259-262 **(2018)**

42. Teodoro A.C. and Duarte L., The role of satellite remote sensing in natural disaster management, Nanotechnology-Based Smart Remote Sensing Networks for Disaster Prevention, Elsevier, 189-216 **(2022)**

43. Yan Y., Xiong G., Zhou J., Wang R., Huang W., Yang M., Wang R. and Geng D., A whole process risk management system for the monitoring and early warning of slope hazards affecting gas and oil pipelines, *Frontiers in Earth Science*, **9**, 812527 **(2022)**

44. Yao J., Yao X. and Liu X., Landslide detection and mapping based on SBAS-InSAR and PS-InSAR: A case study in Gongjue County, Tibet, China, *Remote Sensing*, **14(19)**, 4728 **(2022)**

45. Yue L., Jayapal M., Cheng X., Zhang T., Chen J., Ma X., Dai X., Lu H., Guan R. and Zhang W., Highly dispersed ultra-small nano Sn-SnSb nanoparticles anchored on N-doped graphene sheets as high performance anode for sodium ion batteries, *Applied Surface Science*, **512(1)**, 145686 **(2020)**.

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