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REMOTE SENSING-BASED LANDSLIDE SUSCEPTIBILITY ANALYSIS ALONG MOUNTAIN TRANSPORTATION CORRIDORS AND SETTLEMENTS

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ABSTRACT
Mountain transportation corridors and hillside settlements represent some of the most vulnerable components of regional infrastructure because they are continuously exposed to terrain instability, intense precipitation, geological discontinuities, seismic activity, vegetation degradation, and human-induced landscape modification. The increasing frequency of landslides has intensified disruptions to transportation networks, damaged residential communities, and imposed substantial economic and humanitarian consequences, highlighting the need for predictive approaches capable of identifying unstable slopes before catastrophic failure occurs. Advances in remote sensing have transformed landslide investigations by enabling continuous, multi-scale observation of terrain dynamics across large and inaccessible mountainous regions. This study presents a remote sensing-based framework for landslide susceptibility analysis along mountain transportation corridors and adjacent settlements through the integration of optical satellite imagery, Interferometric Synthetic Aperture Radar (InSAR), LiDAR-derived elevation models, multispectral vegetation indices, and geospatial terrain analytics. The framework evaluates the combined influence of slope morphology, lithology, soil moisture, land-cover transformation, rainfall intensity, drainage density, lineament distribution, and anthropogenic disturbances using machine learning-based susceptibility modelling and spatial risk classification. Time-series deformation monitoring further improves hazard detection by identifying progressive ground movement preceding slope failure. The resulting susceptibility maps provide decision-makers with actionable intelligence for corridor planning, infrastructure protection, settlement risk reduction, and emergency preparedness. The study demonstrates how remote sensing technologies can support proactive landslide risk management while enhancing the resilience, safety, and sustainability of mountain transportation systems and vulnerable communities.

Keywords:
Remote Sensing; Landslide Susceptibility; Mountain Transportation Corridors; InSAR; Geospatial Hazard Assessment; Terrain Stability.

1. INTRODUCTION: LANDSLIDE RISK ACROSS MOUNTAIN CORRIDORS AND SETTLEMENTS

1.1 Mountain Transportation Corridors as Coupled Human–Terrain Systems

Mountain transportation corridors represent coupled human–terrain systems where engineered infrastructure continuously interacts with geological, hydrological, geomorphological, and ecological processes that influence landscape stability and regional accessibility [1]. These corridors comprise roads and highways, bridges and culverts, cut-and-fill slopes, retaining structures, drainage channels, roadside communities, agricultural land, utility infrastructure, and emergency access routes that collectively sustain economic growth and social development across mountainous regions [2]. Because mountain environments are characterised by steep slopes, fractured bedrock, highly weathered soils, and variable climatic conditions, transportation infrastructure is frequently constructed within naturally unstable landscapes [3]. Excavation, embankment construction, and slope regrading modify the original hillslope geometry, altering stress distribution and reducing natural slope equilibrium [4]. Engineering works further disturb hydrological processes by redirecting surface runoff, increasing infiltration pathways, removing vegetation cover, and imposing additional loads on weathered materials. These changes increase pore-water pressure, reduce soil shear strength, and accelerate erosion during prolonged or intense rainfall events [2]. Expansion of settlements and agricultural activities along transportation corridors introduces additional anthropogenic disturbances through land clearance, uncontrolled drainage, and continuous slope loading [5]. The cumulative interaction between natural terrain conditions and human modification progressively increases landslide susceptibility and infrastructure vulnerability. Consequently, mountain transportation corridors have evolved beyond simple transportation networks into integrated socio-environmental systems where slope instability directly influences mobility, economic resilience, public safety, and sustainable regional development [6].

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1.2 Landslide Consequences for Transportation Continuity and Settlement Safety

Landslides remain among the most destructive natural hazards affecting transportation infrastructure within mountainous environments because they simultaneously threaten engineering assets and human settlements located along steep terrain [1]. Slope failures frequently block highways, damage bridges, collapse retaining structures, and obstruct drainage systems, thereby interrupting passenger movement, freight transportation, tourism, and emergency response operations. Prolonged transportation disruption also reduces regional productivity by restricting access to markets, healthcare facilities, educational institutions, and other essential public services [6]. Residential communities located adjacent to unstable slopes experience substantial risks from ground deformation, debris burial, structural collapse, and utility failure following major landslide events [7]. Agricultural land may also be destroyed through sediment deposition, soil displacement, and surface erosion, thereby reducing food production and household income in mountain communities. Different landslide mechanisms generate distinct patterns of infrastructure damage and exposure depending on geological and hydrological conditions [8]. Shallow landslides primarily affect road shoulders and drainage systems during extreme rainfall, whereas deep-seated landslides progressively undermine pavements, bridge foundations, and retaining structures over extended periods [5]. Rockfalls, debris flows, rotational slides, and translational slides further increase operational risks because of their varying movement velocities, travel distances, and destructive capacities. The spatial complexity and limited accessibility of mountain terrain therefore necessitate advanced monitoring techniques capable of identifying unstable slopes before catastrophic infrastructure failure occurs [2].

1.3 Research Gap, Aim and Contributions

Significant progress has been achieved in remote sensing and landslide susceptibility modelling over recent decades; however, several scientific and operational limitations continue to constrain their application to mountain transportation corridors [1]. Existing landslide inventories remain incomplete in many mountainous regions because inaccessible terrain, inconsistent reporting practices, and limited long-term monitoring reduce the availability of representative training datasets [3]. Numerous investigations evaluate isolated landslide sites rather than continuous transportation corridors where geological, hydrological, and anthropogenic conditions vary considerably over long distances. Consequently, relationships between transportation infrastructure, adjacent settlements, and terrain instability remain insufficiently represented within many susceptibility frameworks [7]. Variations in the selection of conditioning variables, spatial resolution, digital elevation models, and modelling algorithms also reduce consistency between published studies, while limited attention has been devoted to uncertainty analysis and comparative model evaluation [5]. Furthermore, susceptibility maps often remain disconnected from practical engineering applications because they provide insufficient guidance for infrastructure maintenance, transportation planning, settlement protection, and disaster risk reduction [8].

Accordingly, this study develops a remote sensing-based landslide susceptibility framework for evaluating unstable terrain affecting mountain transportation corridors and neighbouring settlements. The proposed framework integrates multi-source remote sensing datasets, constructs a comprehensive landslide inventory, extracts terrain-conditioning variables, compares multiple susceptibility modelling approaches, validates prediction accuracy using spatial and statistical techniques, evaluates infrastructure and settlement exposure, and supports evidence-based corridor management for resilient transportation systems and sustainable mountain development [9]. The framework is intended to strengthen hazard prediction, optimise maintenance prioritisation, and improve long-term infrastructure resilience under changing environmental and climatic conditions [4].

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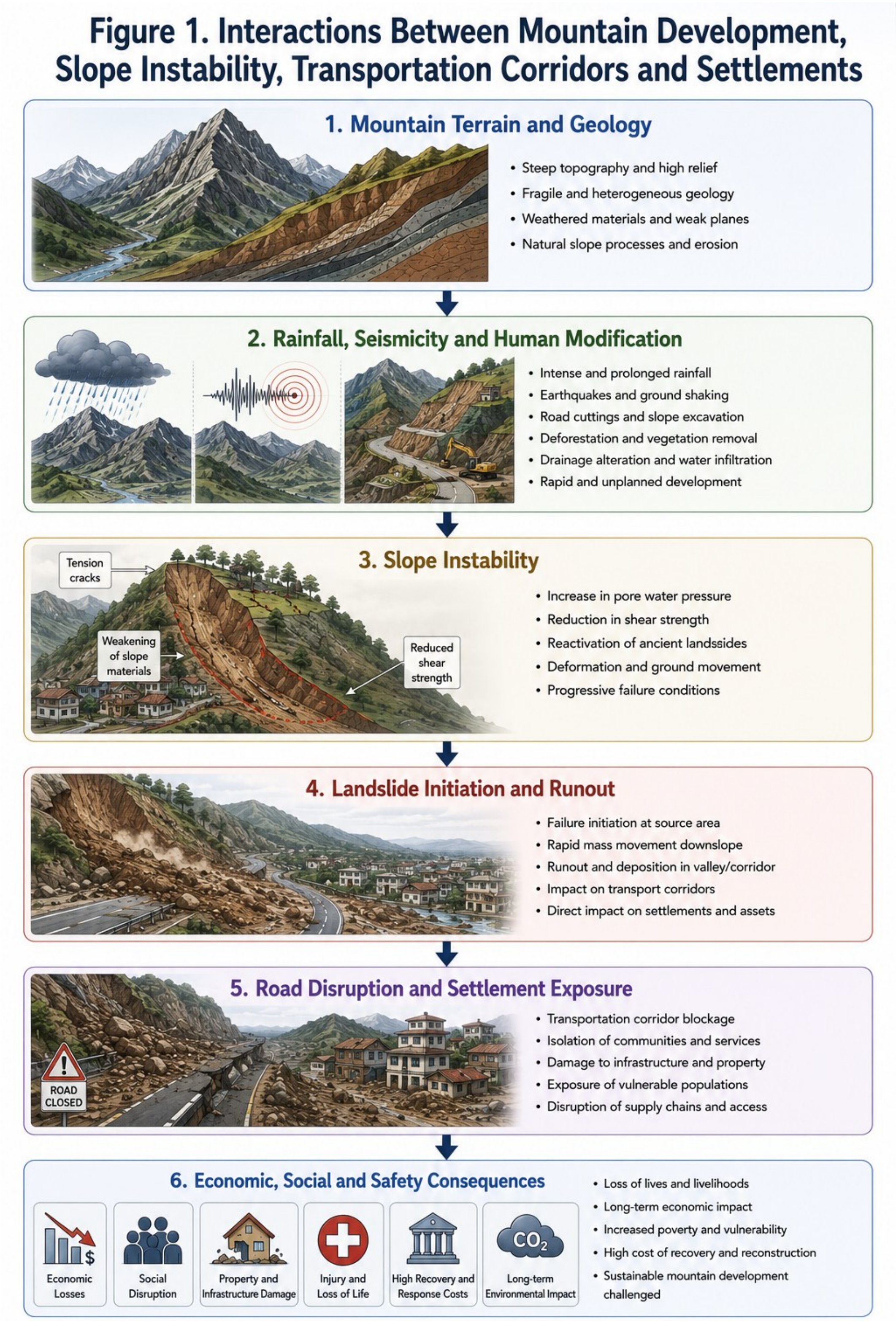

Figure 1. Interactions Between Mountain Development, Slope Instability, Transportation Corridors and Settlements

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2. LANDSLIDE PROCESSES AND CORRIDOR-SPECIFIC SUSCEPTIBILITY FACTORS

2.1 Slope-Failure Mechanisms in Mountain Environments

Slope failures occur when the resisting forces within a hillslope become insufficient to counteract the driving forces generated by gravity, resulting in downslope movement of soil, rock, or debris [6]. The stability of a slope depends on the balance between shear stress and the shear strength of slope materials, which is strongly influenced by geological, hydrological, and mechanical conditions. Shear-strength reduction commonly develops as weathering progressively weakens rock masses and soil structure, reducing cohesion and frictional resistance [9]. Intense or prolonged rainfall increases pore-water pressure within soil pores, thereby reducing effective stress and diminishing the frictional forces that resist sliding [12]. In unsaturated soils, infiltration also reduces matric suction, eliminating an important source of apparent cohesion and accelerating instability [8]. Progressive weathering further degrades mineral composition, enlarges fractures, and increases permeability, allowing greater water penetration into the slope mass [11].

Toe erosion by rivers or concentrated runoff removes lateral support from the base of slopes, whereas artificial slope undercutting during road construction produces similar reductions in resisting forces [7]. Additional structural loading from buildings, embankments, or transportation infrastructure increases normal stresses that may exceed the bearing capacity of weakened hillslopes [10]. In rock slopes, discontinuities such as joints, bedding planes, and faults frequently provide preferential failure surfaces that control block movement and rockfall initiation [13]. Earthquake-induced seismic acceleration generates transient inertial forces capable of triggering both shallow and deep-seated failures, particularly where slopes are already near limiting equilibrium [14]. Many landslides therefore evolve progressively through crack development, material weakening, and gradual deformation before catastrophic collapse occurs [6].

The mechanical behaviour of slopes is commonly described using the Mohr–Coulomb shear-strength relationship:

$$\tau_f = c' + (\sigma - u)\tan\phi'$$

where:

- τ_f= shear strength at failure
- c'= effective cohesion
- σ= total normal stress
- u= pore-water pressure
- ϕ'= effective friction angle

The equation demonstrates that increasing pore-water pressure reduces the effective normal stress $(\sigma - u)$, thereby decreasing available shear strength and making slope failure increasingly likely under both natural and human-induced loading conditions [9].

2.2 Natural Landslide-Conditioning Factors

Landslide susceptibility is governed by the interaction of multiple environmental variables that collectively determine the mechanical and hydrological behaviour of mountain slopes rather than by any single conditioning factor [6]. Slope angle directly controls the magnitude of gravitational driving stress, with steeper slopes generally experiencing greater downslope forces and reduced stability [9]. Elevation influences temperature, precipitation, vegetation distribution, and weathering intensity, thereby affecting both soil development and hydrological conditions [11]. Aspect regulates solar radiation exposure, evapotranspiration, and soil moisture, creating significant differences in vegetation density and groundwater recharge between opposing hillsides [8]. Plan and profile curvature influence the convergence or divergence of surface runoff, affecting soil-water accumulation, erosion intensity, and local pore-water pressure development [10]. Terrain relief reflects the overall energy of the landscape, where highly dissected mountain environments frequently exhibit increased erosion and slope instability [12].

Lithology controls the mechanical strength, permeability, and weathering characteristics of rock formations, while soil type determines infiltration capacity, cohesion, permeability, and susceptibility to saturation [7]. Geological structures including joints, bedding planes, folds, and faults introduce discontinuities that frequently become preferential failure surfaces during slope movement [13]. Distance to active faults also represents an important conditioning factor because fault zones commonly contain fractured and weakened materials that are highly susceptible to deformation [14]. Drainage density and proximity to streams influence runoff concentration and toe erosion, gradually reducing slope support through continuous fluvial incision [9]. Rainfall intensity governs infiltration and pore-water pressure development, whereas vegetation stabilises slopes through root reinforcement and moisture regulation [8]. Groundwater conditions further influence effective stress within slope materials, while seismic activity introduces transient dynamic loading capable of triggering failures in already weakened

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terrain [11]. Consequently, landslide occurrence reflects the combined interaction of terrain morphology, geological characteristics, hydrological processes, climatic forcing, and seismic influences rather than the isolated effect of individual variables [6].

2.3 Corridor Construction and Settlement-Induced Instability

Although natural processes establish the underlying susceptibility of mountain slopes, transportation development and expanding settlements frequently accelerate instability by modifying terrain geometry and hydrological conditions [6]. Road-cut excavation removes lateral support from hillslopes and creates over-steepened cut faces that are more susceptible to rockfalls and shallow failures [7]. Unengineered slope cutting for local access roads and residential development often ignores geological discontinuities and drainage requirements, thereby increasing instability [12]. Embankment construction introduces additional structural loading that elevates stress within already weathered foundation materials [10]. Quarrying and excavation activities generate artificial slopes while simultaneously disturbing natural rock mass integrity and groundwater flow pathways [13].

Deforestation associated with corridor development removes vegetation that provides root reinforcement and regulates soil moisture, increasing surface erosion and infiltration rates [8]. Drainage diversion during road construction frequently redirects runoff onto unstable slopes, while blocked culverts concentrate water discharge, promoting localised erosion and rapid pore-water pressure increases [11]. Building construction, particularly within rapidly expanding informal settlements, imposes additional loads on marginally stable slopes and often proceeds without adequate geotechnical assessment [9]. Agricultural terracing may reduce erosion when properly engineered but can also destabilise slopes through inappropriate excavation, poor drainage, and excessive irrigation [7]. Utility trenching disturbs soil structure and creates preferential infiltration pathways, whereas continuous traffic vibration may progressively weaken fractured rock masses and compacted embankments over extended periods [14]. Waste dumping on hillsides further increases surcharge loading while obstructing natural drainage systems, thereby increasing the likelihood of localised failures [10].

Road construction is particularly significant because it may simultaneously increase slope angle, remove toe support, redirect surface runoff, and concentrate structural loading within the same corridor segment, thereby creating multiple interacting failure mechanisms [6]. These combined anthropogenic disturbances substantially increase landslide susceptibility beyond natural background conditions and emphasise the importance of integrating engineering activities into hazard assessment frameworks [8].

Table 1. Landslide-Conditioning Factors and Their Physical Relevance to Mountain Corridors

Factor Group	Variable	Physical Influence on Instability	Remote Sensing / GIS Source	Expected Relationship
Topography	Slope angle	Controls gravitational driving stress	DEM	Positive
Topography	Elevation	Influences climate and weathering	DEM	Variable
Topography	Aspect	Controls solar radiation and moisture	DEM	Variable
Topography	Curvature	Regulates runoff concentration and erosion	DEM	Variable
Topography	Relief	Indicates terrain energy	DEM	Positive
Geology	Lithology	Determines material strength and weathering	Geological map	Variable
Geology	Geological structures	Creates discontinuity-controlled failure planes	Geological map	Positive
Hydrology	Drainage density	Concentrates runoff and erosion	GIS drainage network	Positive
Hydrology	Distance to streams	Controls toe erosion	River network	Negative
Climate	Rainfall intensity	Increases infiltration and pore-water pressure	Satellite rainfall / Meteorological data	Positive
Environment	Vegetation condition	Provides root reinforcement	NDVI	Negative
Human activity	Road cuts, settlements, quarrying	Alters slope geometry and loading	Satellite imagery / Land-use maps	Positive

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3. REMOTE SENSING DATA PREPARATION AND LANDSLIDE INVENTORY DEVELOPMENT

3.1 Multi-Source Earth Observation Data for Landslide Analysis

The increasing availability of multi-source Earth observation data has transformed landslide susceptibility assessment by enabling continuous, large-scale, and multi-temporal monitoring of mountainous environments where conventional field investigations remain difficult and expensive [13]. Rather than relying on a single sensor, modern studies integrate complementary datasets because each provides unique information describing terrain characteristics, surface processes, vegetation dynamics, or ground deformation. Multispectral satellite imagery is widely employed to identify vegetation disturbance, exposed soil, land-cover change, and newly developed infrastructure associated with unstable slopes [15]. Synthetic Aperture Radar (SAR) provides day-and-night imaging capability while penetrating cloud cover, making it particularly valuable for monitoring mountainous regions experiencing persistent cloudiness or heavy rainfall [18]. Interferometric Synthetic Aperture Radar (InSAR) extends this capability by detecting millimetre-scale ground deformation that may indicate progressive slope movement before catastrophic failure occurs [21].

Light Detection and Ranging (LiDAR) produces high-resolution three-dimensional representations of terrain capable of revealing subtle scarps, displaced materials, drainage channels, and geomorphological features even beneath partial vegetation cover [16]. Unmanned aerial vehicle (UAV) imagery supplies centimetre-scale observations suitable for detailed slope mapping, post-disaster assessment, and validation of remotely sensed interpretations [20]. Digital elevation models (DEMs) provide the topographic foundation from which numerous terrain variables essential for susceptibility modelling are derived [14]. High-resolution commercial satellite imagery enables detailed identification of road cuts, settlement expansion, and small landslides that may remain undetected in medium-resolution imagery [17]. Historical aerial photographs reconstruct previous landscape conditions and landslide occurrence, supporting long-term hazard analysis [19]. Rainfall satellite products quantify spatial and temporal precipitation variability, whereas land-cover datasets characterise vegetation, agricultural activity, and urban development that influence slope stability [22].

3.2 Terrain and Hydrological Variable Extraction

Terrain analysis transforms digital elevation models into quantitative variables that represent the physical processes governing hillslope stability and hydrological behaviour across mountain transportation corridors [13]. Slope describes terrain steepness and directly controls the magnitude of gravitational driving forces acting on slope materials [15]. Aspect regulates incoming solar radiation, evapotranspiration, vegetation distribution, and soil moisture conditions that influence infiltration and weathering [18]. Plan curvature determines whether surface runoff converges or diverges across a hillslope, whereas profile curvature controls flow acceleration, erosion potential, and sediment transport [16]. Terrain ruggedness and relative relief quantify landscape complexity by measuring variations in elevation and slope morphology, thereby identifying highly dissected terrain where instability is more likely [21]. Flow accumulation estimates the amount of upslope runoff reaching individual locations and supports the delineation of drainage pathways, while drainage density and distance to streams indicate the influence of fluvial erosion and toe undercutting on slope stability [19].

Hydrological conditions are frequently represented through the Topographic Wetness Index (TWI):

$$TWI = \ln\left(\frac{A_s}{\tan\beta}\right)$$

where:

- A_s= upslope contributing area per unit contour length
- β= local slope angle

Higher TWI values generally indicate locations where runoff converges and water accumulates, increasing soil saturation, pore-water pressure, and the likelihood of reduced shear strength within slope materials [17]. Consequently, terrain and hydrological variables collectively describe the interaction between topography, drainage processes, and moisture conditions that govern the spatial distribution of landslide susceptibility across mountainous landscapes [20].

3.3 Land-Cover and Vegetation Disturbance Assessment

Land-cover dynamics provide valuable indicators of human disturbance and environmental change that influence landslide susceptibility in mountain transportation corridors [13]. Vegetation removal associated with road construction, settlement expansion, timber harvesting, and agricultural conversion reduces root reinforcement while increasing surface runoff, soil erosion, and rainfall infiltration into weathered materials [16]. Expansion of built-up areas introduces additional structural loading, modifies natural drainage networks, and increases

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impervious surfaces that alter hydrological response [19]. Agricultural conversion frequently changes slope geometry through terracing and cultivation, whereas extensive bare-earth exposure indicates recently disturbed surfaces that remain vulnerable to erosion and shallow slope failure [15]. Forest degradation and burned areas further reduce canopy interception and root cohesion, accelerating soil moisture accumulation and decreasing slope stability [22]. Construction footprints extracted from satellite imagery also identify rapidly developing infrastructure where terrain modification may increase future landslide susceptibility [18].

Vegetation condition is commonly evaluated using the Normalised Difference Vegetation Index (NDVI):

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

Multi-temporal NDVI analysis enables the detection of vegetation decline and land-cover transitions occurring before and after infrastructure development [14]. Combined with land-cover classification, temporal NDVI changes reveal progressive slope disturbance associated with road construction, settlement expansion, forest clearance, and other anthropogenic activities that modify terrain stability and increase landslide susceptibility [20].

3.4 Landslide Inventory Mapping and Event Classification

A reliable landslide inventory provides the foundation for susceptibility modelling because it identifies the spatial distribution, characteristics, and historical occurrence of slope failures required for model training and validation [13]. Comprehensive inventories are developed by integrating multiple independent information sources to maximise spatial completeness and reduce interpretation uncertainty. Historical disaster databases provide documented records of previous landslide events, while multi-temporal satellite imagery enables visual interpretation of scarps, displaced materials, and disturbed vegetation [15]. UAV surveys produce high-resolution observations of inaccessible slopes, supporting detailed mapping of individual failure features [20]. InSAR deformation measurements identify slow-moving slopes that may not yet exhibit obvious surface evidence but demonstrate progressive instability [21]. Field investigations remain essential for confirming remotely interpreted features and validating failure mechanisms, whereas road maintenance reports frequently document slope failures affecting transportation infrastructure [18]. Community records, newspaper archives, and government disaster reports contribute additional information regarding undocumented events, infrastructure damage, trigger mechanisms, and temporal occurrence, particularly within remote mountainous regions [17].

Individual landslides are commonly divided into initiation zones where failure begins, transport zones through which displaced materials move, and depositional zones where materials finally accumulate [19]. Additional mapping distinguishes scar boundaries, runout paths, and secondary deposits that define landslide geometry and potential impact areas [22]. Inventory databases generally record geographical location, occurrence date, landslide type, affected area, triggering mechanism, confidence level, infrastructure affected, and settlement impacts, thereby providing comprehensive information for susceptibility modelling and hazard assessment [14].

Agreement between independently interpreted inventories can be evaluated using the Intersection over Union (IoU) metric:

$$IoU = \frac{| L_1 \cap L_2 |}{| L_1 \cup L_2 |}$$

where:

- L_1 and L_2 represent landslide polygons produced from different datasets or interpretation stages.

Higher IoU values indicate stronger spatial agreement and improved inventory reliability, thereby increasing confidence in subsequent susceptibility analyses and model validation [16].

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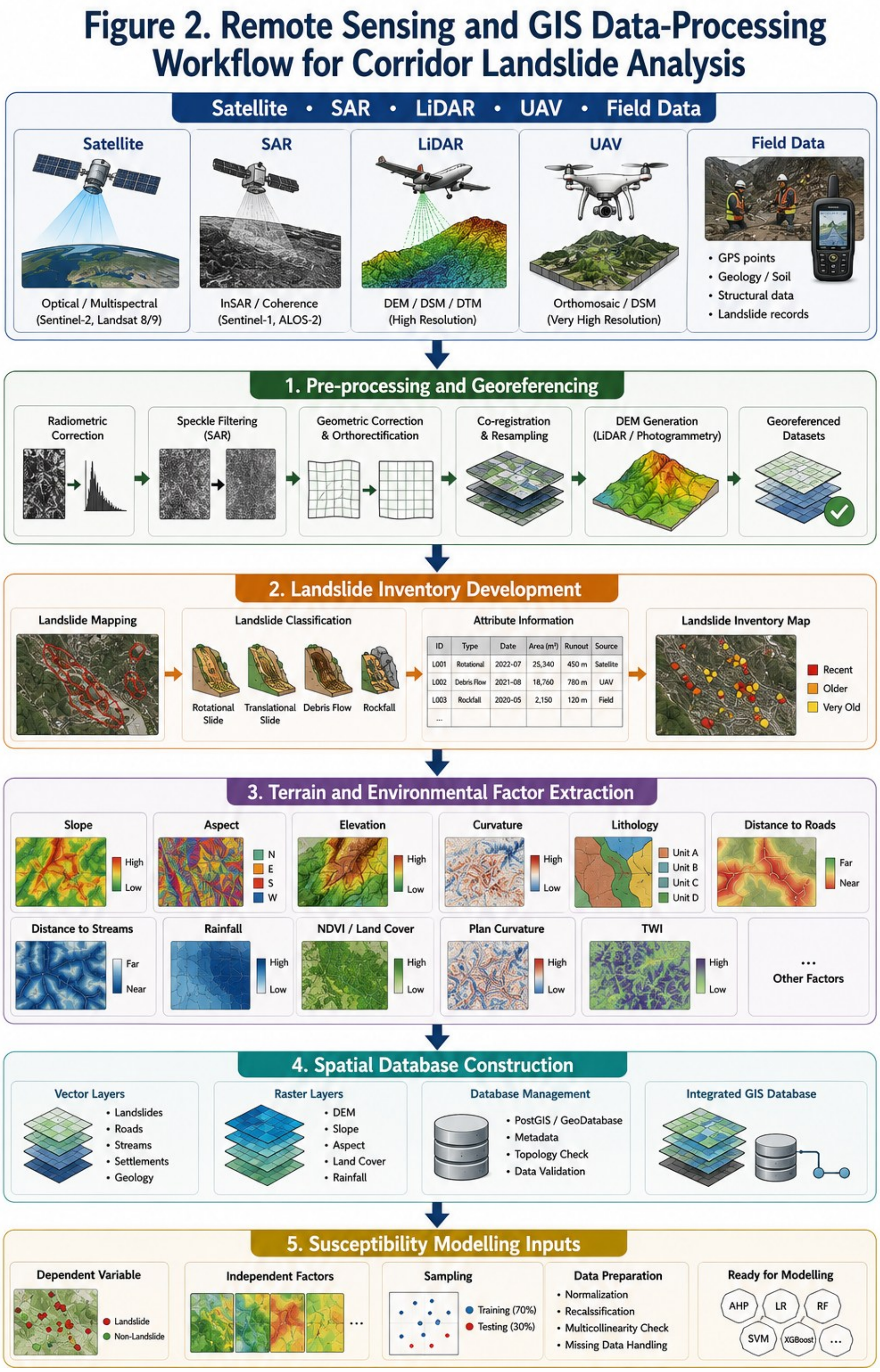

Figure 2. Remote Sensing and GIS Data-Processing Workflow for Corridor Landslide Analysis

4. LANDSLIDE SUSCEPTIBILITY MODELLING AND COMPARATIVE ANALYSIS

4.1 Sampling Design and Predictor Preparation

The reliability of a landslide susceptibility model depends largely on the quality of sampling design and predictor preparation before model development begins [20]. Model training normally requires representative samples from

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both landslide and non-landslide locations to distinguish stable from unstable terrain. Landslide samples are extracted from validated inventory polygons, whereas non-landslide samples are selected from areas with no documented evidence of slope failure while avoiding locations immediately adjacent to mapped landslides [23]. Depending on the study objective, modelling may be performed using individual pixels or terrain-based slope units. Pixel-based approaches preserve local spatial variability and are suitable for high-resolution remote sensing datasets, whereas slope-unit analysis better represents geomorphological boundaries and hillslope processes [26]. Class imbalance commonly arises because landslide pixels occupy only a small proportion of mountainous landscapes, making balanced sampling or resampling strategies necessary to reduce prediction bias [21]. Predictor variables are subsequently examined for multicollinearity using correlation analysis or variance inflation factors before model calibration [28]. Continuous variables are frequently normalised to comparable numerical ranges, while all datasets are resampled to a common spatial resolution to ensure spatial consistency [24]. Training and testing datasets should also be spatially independent because random data splitting alone may produce overly optimistic accuracy where neighbouring observations remain spatially autocorrelated [29].

4.2 Statistical Susceptibility Models

Statistical susceptibility models remain widely applied because they quantify relationships between historical landslide occurrence and environmental conditioning factors while maintaining relatively high interpretability for scientific and engineering applications [20]. Frequency Ratio evaluates the relative likelihood of landslide occurrence within different classes of individual conditioning variables by comparing landslide density with overall spatial distribution [22]. Weight of Evidence employs Bayesian probability theory to estimate the positive or negative contribution of predictor variables to landslide occurrence, whereas the Information Value method measures the predictive importance of individual terrain classes using logarithmic probability ratios [25]. Evidential Belief Functions further accommodate uncertainty by combining multiple sources of evidence into probabilistic estimates of landslide susceptibility [27].

Among statistical approaches, logistic regression remains one of the most frequently adopted techniques because it estimates the probability of landslide occurrence while simultaneously quantifying the influence of multiple predictor variables. The model is expressed as:

$$P(L = 1 \mid X) = \frac{1}{1 + \exp[-(\beta_0 + \beta_1 X_1 + \cdots + \beta_n X_n)]}$$

where:

- $L = 1$indicates landslide occurrence;
- $X_1, \dots, X_n$represent landslide-conditioning variables;
- $\beta_i$represents estimated model coefficients.

The estimated coefficients provide direct interpretation of the direction and relative magnitude of predictor effects, facilitating scientific understanding and supporting engineering decision-making [24]. Nevertheless, logistic regression generally assumes relatively simple linear relationships between predictor variables and the logarithm of event probability, limiting its ability to capture highly nonlinear terrain interactions frequently observed in mountainous environments [29].

4.3 Machine Learning-Based Susceptibility Models

Machine learning algorithms have become increasingly prominent in landslide susceptibility assessment because they can model complex nonlinear relationships and interactions among numerous terrain, geological, hydrological, environmental, and anthropogenic variables without imposing restrictive statistical assumptions [20]. Decision Trees classify terrain by recursively partitioning predictor variables into increasingly homogeneous subsets, producing transparent decision rules that remain relatively easy to interpret [26]. Random Forest improves predictive robustness by aggregating predictions from numerous independently constructed decision trees, thereby reducing variance and improving generalisation performance [22]. Support Vector Machines identify optimal decision boundaries within multidimensional feature space and perform particularly well when training datasets are limited but class separation is complex [27]. Artificial Neural Networks simulate interconnected computational neurons capable of learning intricate nonlinear relationships, although model interpretation becomes increasingly difficult as architectural complexity increases [23]. Gradient Boosting and Extreme Gradient Boosting (XGBoost) sequentially improve model performance by correcting prediction errors generated during previous iterations, often producing excellent predictive accuracy for heterogeneous environmental datasets [28]. The k-Nearest Neighbours algorithm classifies observations according to neighbouring samples within feature space, whereas Naïve Bayes estimates landslide probability by applying Bayesian probability under conditional independence assumptions [24].

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Despite their predictive capability, machine learning models require careful hyperparameter optimisation to avoid overfitting and ensure reliable model generalisation [21]. Increasing algorithm complexity also raises computational demand and frequently reduces model interpretability, particularly for ensemble and neural-network approaches [25]. Consequently, algorithm selection should be guided by data characteristics, inventory quality, computational resources, model transparency requirements, and study objectives rather than reported prediction accuracy alone, thereby ensuring that susceptibility maps remain scientifically robust, operationally interpretable, and practically applicable for mountain corridor risk management [29].

4.4 Deep Learning and Spatially Explicit Modelling

Recent advances in deep learning have significantly expanded the capability of landslide susceptibility modelling by enabling automatic extraction of spatial features directly from remotely sensed imagery and complex geospatial datasets [20]. Unlike conventional machine learning algorithms that primarily rely on manually derived conditioning variables, deep learning models learn hierarchical spatial representations from raw image data while simultaneously incorporating terrain, geological, hydrological, and environmental information [23]. Convolutional Neural Networks (CNNs) are particularly effective for image-patch classification because convolutional filters capture local spatial patterns associated with landslide scars, disturbed vegetation, exposed soil, and drainage features [27]. Semantic segmentation networks further extend this capability by assigning susceptibility classes to every image pixel, thereby producing detailed spatial representations of unstable terrain [24]. Recurrent neural networks can incorporate temporal observations from multi-date satellite imagery to analyse vegetation recovery, rainfall response, and progressive landscape changes preceding slope failure [28]. More recently, Graph Neural Networks (GNNs) have been introduced to model spatial relationships among neighbouring terrain units, while transformer-based geospatial models capture long-range spatial dependencies within extensive mountainous landscapes [21]. Although deep learning frequently achieves high predictive performance, these approaches require substantially larger training datasets, extensive computational resources, specialised hardware, and careful model optimisation. Their limited interpretability also presents challenges for engineering decision-making, making deep learning most effective when combined with physically meaningful environmental variables and comprehensive inventory datasets [29].

4.5 Ensemble Susceptibility Model

Because individual susceptibility models exhibit different strengths and limitations, ensemble modelling has become an increasingly effective strategy for improving predictive robustness and reducing uncertainty in landslide susceptibility assessment [20]. Ensemble approaches integrate predictions from multiple algorithms, thereby combining statistical interpretability with the nonlinear learning capability of advanced machine learning techniques [25]. A weighted ensemble susceptibility model may be expressed as:

$$LSI_i = w_1 P_{(R{\cdot}Fi)} + w_2 P_{(S{\cdot}VMi)} + w_3 P_{(X{\cdot}GBi)} + w_4 P_{(L{\cdot}Ri)}$$

subject to

$$\sum_{j=1}^{4} w_j = 1$$

where:

- LSI_i= landslide susceptibility index for location i;
- $P_{(R{\cdot}Fi)}$= Random Forest probability;
- $P_{(S{\cdot}VMi)}$= Support Vector Machine probability;
- $P_{(X{\cdot}GBi)}$= XGBoost probability;
- $P_{(L{\cdot}Ri)}$= Logistic regression probability.

The weighting coefficients are commonly derived from cross-validation performance, enabling models with superior predictive capability to contribute proportionally more to the final susceptibility estimate while reducing individual model bias and improving overall mapping reliability [28].

4.6 Susceptibility Classification and Spatial Interpretation

Continuous susceptibility values are generally classified into meaningful hazard categories to facilitate interpretation and support infrastructure planning, emergency preparedness, and land-use management [22]. Most studies divide model outputs into very low, low, moderate, high, and very high susceptibility classes that indicate progressively increasing probabilities of future landslide occurrence. Classification thresholds may be determined using natural breaks that maximise variance between classes, quantile classification that assigns equal numbers

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of observations to each category, equal interval methods based on numerical ranges, probability thresholds generated directly by predictive models, or landslide-density curves that relate historical landslide occurrence to susceptibility values [26]. Appropriate classification enhances the practical interpretation of susceptibility maps by clearly identifying road sections, settlements, and critical infrastructure requiring priority monitoring, engineering intervention, or long-term risk mitigation [29].

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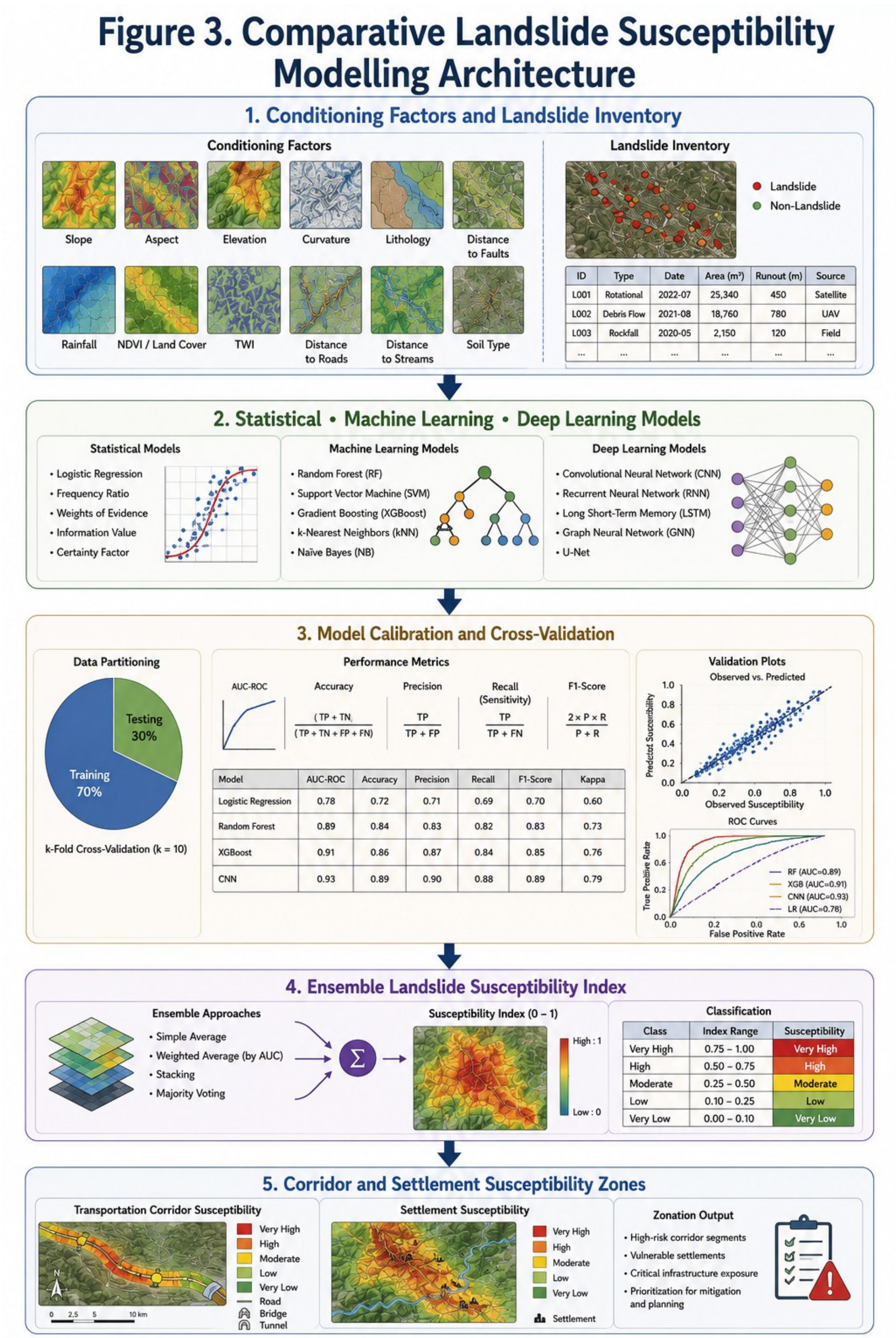

Figure 3. Comparative Landslide Susceptibility Modelling Architecture

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Table 2. Comparative Characteristics of Landslide Susceptibility Models

Model	Data Requirement	Nonlinear Capability	Interpretability	Overfitting Sensitivity	Recommended Use
Frequency Ratio	Low	Low	Very High	Very Low	Preliminary susceptibility assessment
Weight of Evidence	Low	Low	High	Low	Probabilistic factor evaluation
Logistic Regression	Moderate	Moderate	Very High	Low	Interpretable susceptibility modelling
Decision Tree	Moderate	Moderate	High	Moderate	Rule-based classification
Random Forest	Moderate	High	Moderate	Low	General-purpose susceptibility mapping
Support Vector Machine	Moderate	High	Moderate	Moderate	Complex nonlinear classification
Artificial Neural Network	High	Very High	Low	High	Large and complex datasets
XGBoost	High	Very High	Moderate	Moderate	High-accuracy predictive modelling
Deep Learning (CNN/GNN/Transformer)	Very High	Very High	Low	High	Large-scale image-based susceptibility mapping

Producing a landslide susceptibility map alone is insufficient for effective hazard management. The reliability of predictive models must be evaluated using independent validation procedures, and the resulting susceptibility patterns should be examined in relation to actual transportation corridors, bridges, settlements, and population exposure to determine their practical value for engineering decision-making and disaster risk reduction [27].

5. VALIDATION, UNCERTAINTY AND CORRIDOR–SETTLEMENT EXPOSURE ASSESSMENT

5.1 Model Performance and Spatial Validation

Robust evaluation is essential to determine whether a landslide susceptibility model accurately predicts unstable terrain while maintaining sufficient generalisation capability across different mountain environments [27]. Model performance is commonly quantified using a confusion matrix that compares predicted and observed landslide occurrences. The overall classification accuracy is expressed as:

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$$

where TP, TN, FP, and FNrepresent true positives, true negatives, false positives, and false negatives, respectively. However, overall accuracy alone may provide misleading results for imbalanced landslide datasets where stable locations substantially outnumber failure locations [31]. Consequently, additional evaluation measures include:

$$Precision = \frac{TP}{TP + FP}$$

$$Recall = \frac{TP}{TP + FN}$$

$$F_1 = 2\left(\frac{Precision \times Recall}{Precision + Recall}\right)$$

Precision measures the reliability of predicted landslide locations, whereas recall quantifies the proportion of actual landslides correctly identified by the model [29]. The F_1-score balances these complementary measures,

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providing a more informative assessment where class imbalance exists. Receiver Operating Characteristic (ROC) curves and the corresponding Area Under the Curve (ROC–AUC) evaluate discrimination ability across different probability thresholds, while precision–recall curves are particularly valuable when landslide observations represent only a small proportion of the study area [33]. Success-rate and prediction-rate curves assess model performance using training and independent validation inventories, respectively [28]. Agreement beyond chance may be quantified using the Kappa statistic, whereas spatial cross-validation minimises the influence of spatial autocorrelation by separating neighbouring observations during model assessment [35]. Event-based temporal validation further evaluates model robustness by testing predictions against landslides that occurred after model development, thereby providing a more realistic estimate of future predictive capability [30].

5.2 Sensitivity Analysis and Model Explainability

Sensitivity analysis improves understanding of how individual predictor variables influence landslide susceptibility while increasing confidence in model interpretation and practical application [27]. Variable importance measures quantify the relative contribution of each conditioning factor to predictive performance, whereas permutation importance evaluates the reduction in model accuracy following random disturbance of individual variables [32]. Partial dependence plots illustrate the average influence of individual predictors across their range of values, thereby revealing nonlinear responses that may not be immediately apparent from model coefficients [29]. More recently, Shapley Additive Explanations (SHAP) have become widely adopted because they provide both global and local interpretations by quantifying the contribution of every predictor to individual model predictions [35]. Local explanation techniques further identify why particular locations are classified as highly susceptible, supporting site-specific engineering assessment and decision-making [31]. Additional sensitivity testing may involve sequential removal of individual predictors or comparison of alternative spatial resolutions to evaluate model robustness under different data configurations [28]. These interpretability approaches reveal whether slope steepness, rainfall intensity, proximity to roads, lithological conditions, drainage characteristics, or settlement expansion primarily drives susceptibility within particular corridor segments, thereby strengthening confidence in engineering recommendations and hazard mitigation strategies [34].

5.3 Sources and Propagation of Uncertainty

Uncertainty is unavoidable in landslide susceptibility modelling because both environmental processes and geospatial datasets contain inherent limitations that influence prediction reliability [27]. Incomplete landslide inventories may omit undocumented failures, while image-classification errors introduce uncertainty into land-cover and vegetation datasets used as predictor variables [30]. Digital elevation model resolution affects the derivation of terrain variables, particularly within steep mountain landscapes where subtle geomorphological features strongly influence slope stability [33]. Geolocation inaccuracies between datasets may produce spatial misalignment, whereas temporal mismatch between satellite imagery, rainfall records, and documented landslide events may reduce the representativeness of predictor variables [29]. Additional uncertainty arises from subjective classification of geological and geomorphological factors, differences between modelling algorithms, sampling strategies, uncertain landslide occurrence dates, and continuous terrain modification resulting from infrastructure development or natural erosion [35].

A simplified uncertainty index may be expressed as:

$$U_i = \alpha U_{D,i} + \beta U_{I,i} + \gamma U_{M,i} + \delta U_{V,i}$$

where:

- U_D= data uncertainty;
- U_I= inventory uncertainty;
- U_M= model uncertainty;
- U_V= validation uncertainty;

subject to:

$$\alpha + \beta + \gamma + \delta = 1$$

The weighting coefficients represent the relative contribution of each uncertainty source to the overall uncertainty associated with location i, thereby supporting transparent evaluation of prediction confidence and risk-informed decision-making [32].

5.4 Transportation Corridor Exposure Analysis

Susceptibility maps become operationally valuable when integrated with transportation infrastructure to identify assets exposed to potential slope failures rather than simply classifying unstable terrain [27]. Geographic overlay

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analysis enables susceptibility classes to be combined with road centre lines, individual road segments, bridges, culverts, tunnels, retaining structures, maintenance depots, and designated emergency routes within a unified geospatial framework [31]. This integration identifies infrastructure located within high-risk zones and supports maintenance prioritisation, engineering intervention, and emergency response planning [29]. Exposure is commonly quantified by calculating the proportion of transportation infrastructure intersecting each susceptibility class using the corridor exposure index:

$$CE_k = \frac{L_k}{L_T} \times 100$$

where:

- CE_k= corridor exposure within susceptibility class k;
- L_k= road length located within susceptibility class k;
- L_T= total transportation corridor length.

Higher values indicate that a greater proportion of the transportation network is exposed to potential landslide hazards, thereby requiring increased inspection frequency and preventive maintenance [34]. Spatial exposure analysis also identifies critical bridges, tunnels, retaining walls, and drainage structures located within highly susceptible terrain where structural failure could interrupt regional accessibility and emergency response operations [30]. Consequently, integrating susceptibility with transportation assets transforms predictive modelling into a practical engineering tool for infrastructure resilience and sustainable corridor management [35].

5.5 Settlement and Population Exposure Assessment

Assessment of community vulnerability requires landslide susceptibility outputs to be integrated with demographic and built-environment information describing human exposure within mountainous regions [27]. Geographic overlay analysis combines susceptibility maps with building footprints, settlement boundaries, population distribution grids, schools, healthcare facilities, markets, utility infrastructure, and designated evacuation routes to identify communities facing the greatest potential risk from future landslide events [32]. This approach extends hazard assessment beyond physical terrain instability by incorporating the spatial distribution of people, essential services, and critical infrastructure supporting everyday community functioning [30]. Population exposure is particularly important where rapid settlement expansion has increased development within unstable hillslopes without corresponding improvements in engineering protection or land-use planning [35].

A combined exposure score may be expressed as:

$$E_i = w_r R_i + w_b B_i + w_p P_i + w_c C_i$$

where:

- R_i= road exposure;
- B_i= building exposure;
- P_i= population exposure;
- C_i= critical-facility exposure.

The weighting coefficients reflect the relative importance assigned to transportation infrastructure, residential development, population concentration, and essential public facilities during risk evaluation [28]. The resulting exposure assessment supports prioritisation of vulnerable communities, guides emergency preparedness planning, informs evacuation strategy development, and assists decision-makers in allocating mitigation resources to locations where landslide impacts would have the greatest social and economic consequences [34].

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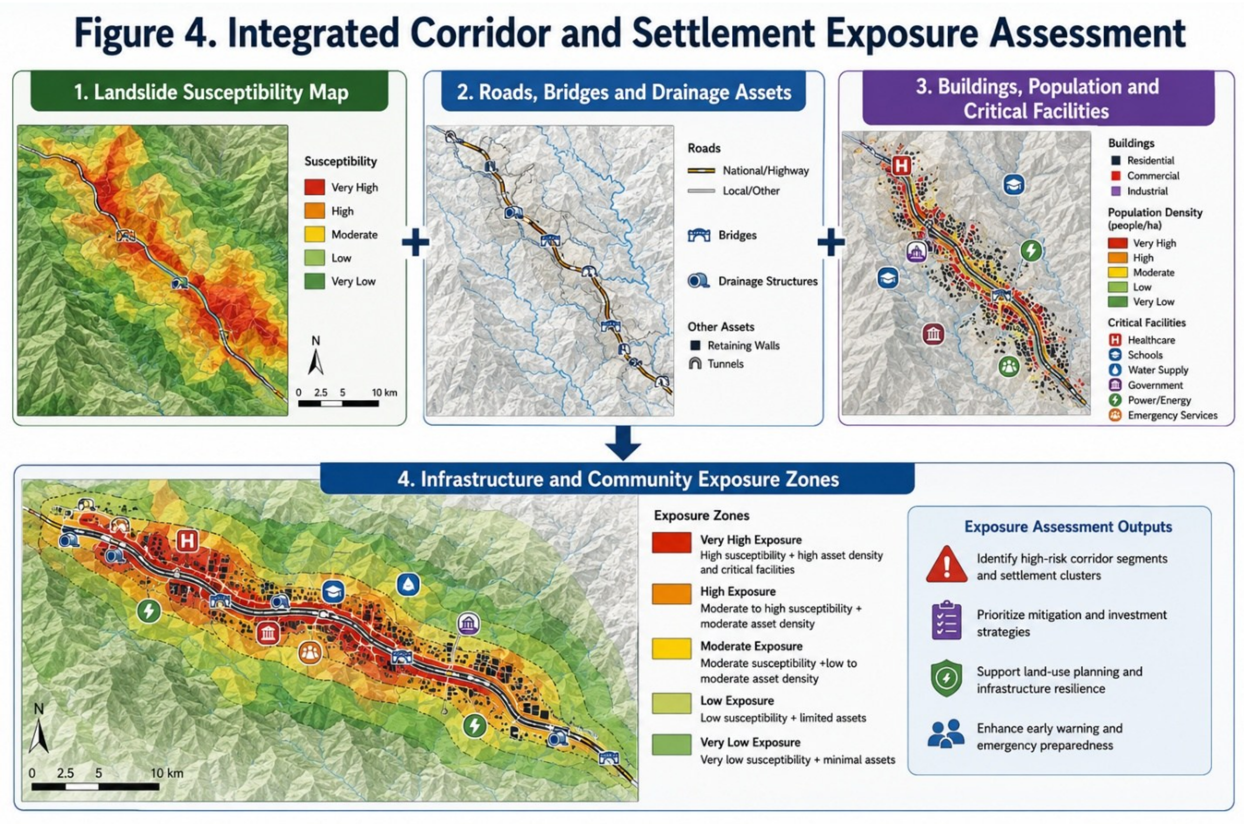

Figure 4. Integrated Corridor and Settlement Exposure Assessment

Table 3. Landslide Susceptibility, Corridor Exposure and Recommended Management Actions

Susceptibility Class	Road Exposure	Settlement Exposure	Monitoring Requirement	Recommended Intervention
Very Low	Minimal	Minimal	Routine inspection	Standard maintenance
Low	Limited	Low	Periodic monitoring	Drainage maintenance and vegetation management
Moderate	Moderate	Moderate	Scheduled geotechnical assessment	Slope stabilisation and erosion control
High	Extensive	High	Continuous monitoring	Retaining structures, drainage improvement, slope reinforcement
Very High	Critical	Critical	Real-time monitoring and early warning	Immediate engineering intervention, relocation planning where necessary, emergency preparedness

6. RISK-INFORMED CORRIDOR MANAGEMENT AND EARLY WARNING

6.1 Engineering Intervention and Maintenance Prioritisation

Effective landslide risk reduction requires engineering interventions to be prioritised according to hazard severity, infrastructure importance, and potential societal consequences rather than responding only after slope failure has occurred [33]. Slope drainage improvement remains one of the most effective mitigation measures because reducing groundwater infiltration and pore-water pressure directly enhances slope stability [36]. Retaining walls, rock bolts, and soil nailing provide structural reinforcement for unstable cut slopes and weathered rock masses, while slope regrading reduces excessive inclination and redistributes gravitational stresses [39]. Bioengineering techniques, including deep-rooted vegetation and erosion-control planting, improve long-term slope stability by reinforcing near-surface soils and regulating moisture conditions [34]. Debris barriers, enlarged culverts, erosion-

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control structures, and selective road realignment further reduce the consequences of landslide events affecting transportation corridors [37]. Maintenance activities may be prioritised using the Maintenance Priority Index:

$$MPI_i = \sum_{j=1}^{m} w_j x_{ij}$$

where x_{ij}represents evaluation criteria such as landslide susceptibility, observed ground movement, traffic importance, settlement exposure, potential failure consequences, and intervention cost, while $w_j$denotes their relative weighting [40].

6.2 Remote Sensing-Supported Early Warning

Modern landslide early warning systems increasingly integrate remote sensing observations with ground-based monitoring to provide timely identification of hazardous slope conditions before catastrophic failure occurs [33]. Near-real-time rainfall products, satellite-derived soil moisture estimates, InSAR deformation measurements, ground sensors, weather forecasts, and historical landslide records collectively provide complementary information describing evolving slope behaviour [35]. Mobile communication systems enable rapid dissemination of warnings to transport authorities, emergency responders, and exposed communities when predefined hazard conditions are exceeded [38]. Rainfall-trigger thresholds may be represented by the intensity-duration relationship:

$$I = aD^{-b}$$

where:

- I= rainfall intensity;
- D= rainfall duration;
- $a$and b= empirically calibrated parameters.

The relationship reflects the inverse association between rainfall intensity and duration required to trigger slope failure, with shorter storms generally requiring higher rainfall intensities [34]. However, threshold values should always be calibrated using local climatic conditions, historical landslide records, antecedent rainfall, soil moisture, geological characteristics, and observed slope deformation to minimise false alarms and improve operational reliability [40].

6.3 Planning Controls for Roadside Settlements

Sustainable landslide risk management requires land-use planning policies that minimise future development within highly susceptible mountain environments while protecting existing communities [33]. Development restrictions should prevent construction within identified high-susceptibility zones, whereas controlled building setbacks reduce structural loading adjacent to unstable slopes [37]. Regulations governing slope loading, excavation activities, and drainage modification are equally important because inappropriate engineering practices frequently accelerate slope instability [39]. Drainage protection measures should preserve natural runoff pathways and minimise uncontrolled infiltration resulting from urban expansion or infrastructure development [35]. Where engineering mitigation cannot provide acceptable long-term safety, relocation planning may become necessary for the most vulnerable settlements [40]. Community awareness programmes, clearly identified evacuation corridors, and hazard-informed building approval procedures further strengthen disaster preparedness while encouraging sustainable development practices consistent with long-term corridor resilience [36].

6.4 Institutional Implementation and Governance

Successful implementation of landslide susceptibility frameworks depends upon coordinated governance involving transport agencies, geological surveys, disaster-management authorities, municipal planning departments, and community organisations [33]. Clearly defined data-sharing protocols enable consistent exchange of remote sensing products, monitoring observations, engineering assessments, and hazard information between responsible institutions [38]. Monitoring responsibilities should be formally assigned to ensure continuous updating of susceptibility maps and timely identification of emerging slope hazards [35]. Efficient alert communication systems are essential for informing infrastructure managers, emergency responders, and at-risk communities before hazardous conditions escalate [39]. Regular model updating using newly acquired inventory data and remote sensing observations ensures that susceptibility assessments remain representative of changing environmental and developmental conditions, while clearly defined liability and accountability arrangements strengthen institutional transparency and effective decision-making [40].

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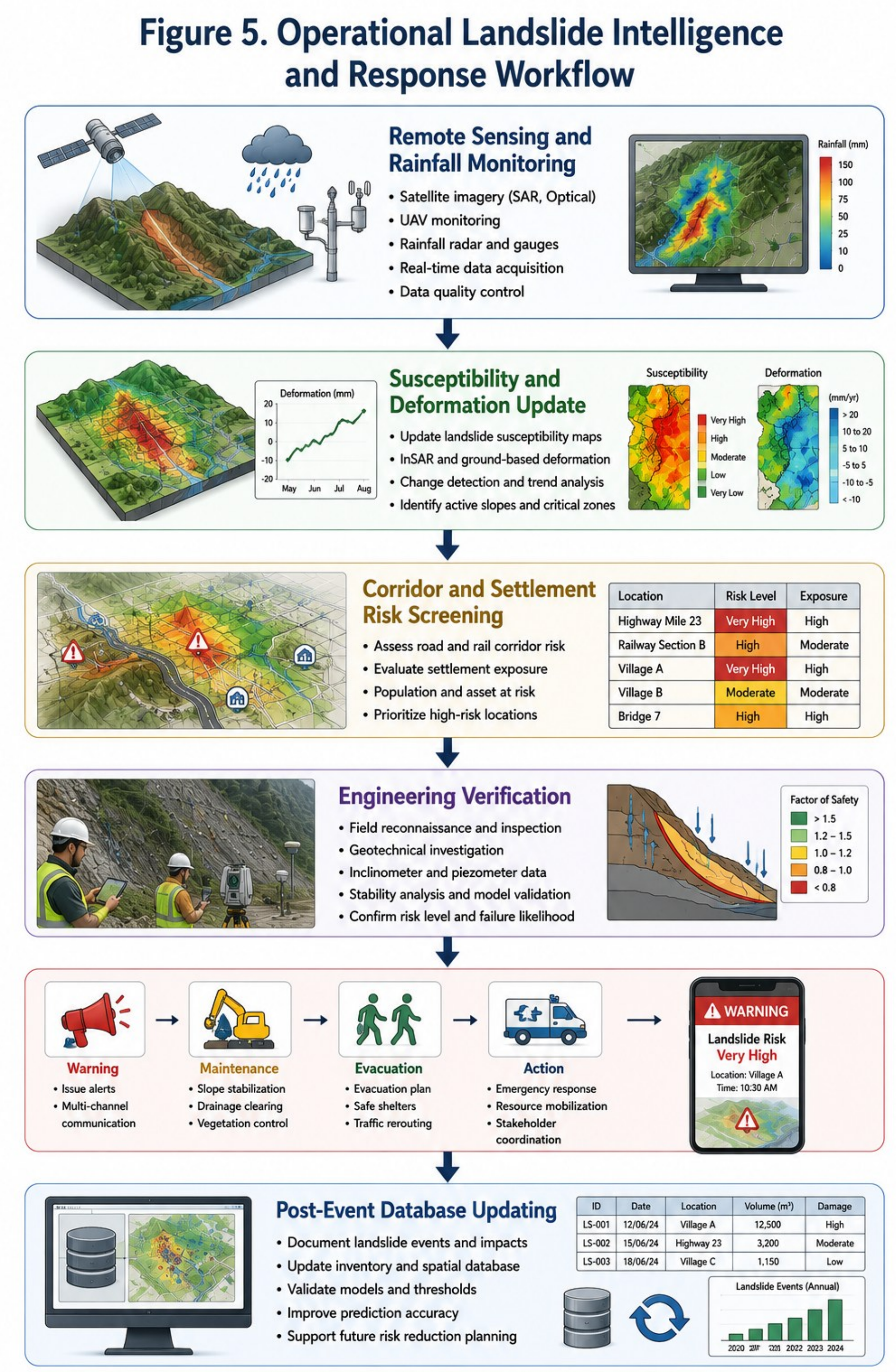

Figure 5. Operational Landslide Intelligence and Response Workflow

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7. DISCUSSION AND CONCLUSION

7.1 Methodological and Practical Implications

The proposed framework advances landslide susceptibility assessment by integrating multi-source remote sensing, physical terrain analysis, machine learning, uncertainty evaluation, corridor exposure analysis, settlement vulnerability assessment, and decision-support mechanisms within a unified geospatial workflow. Unlike conventional susceptibility studies that primarily focus on terrain classification, the framework establishes explicit connections between slope instability, transportation infrastructure, and human exposure, thereby improving its operational value for engineering planning and disaster risk reduction. The combination of complementary Earth observation datasets with physically meaningful terrain variables enhances the representation of complex mountain environments, while machine learning and ensemble modelling improve predictive capability. Incorporating uncertainty evaluation strengthens confidence in susceptibility interpretation by □rioritizat the influence of data quality, inventory completeness, and modelling assumptions. Integration of corridor and settlement exposure further enables □rioritization of engineering interventions, maintenance activities, and emergency preparedness. Nevertheless, several limitations remain, including incomplete historical landslide inventories, rapid terrain alteration resulting from infrastructure development, cloud contamination affecting optical satellite imagery, InSAR decorrelation in densely vegetated areas, differences in spatial resolution among geospatial datasets, limited transferability of predictive models between contrasting mountain environments, and the restricted availability of comprehensive ground validation data.

7.2 Conclusion and Future Research

Remote sensing-based landslide susceptibility analysis provides an effective foundation for shifting mountain corridor management from reactive road clearance and post-disaster response toward proactive hazard identification, engineering intervention, and long-term infrastructure resilience. Integrating geospatial data, predictive modelling, and exposure assessment enables more informed planning decisions while supporting safer transportation networks and vulnerable communities. Future research should focus on physics-informed machine learning, real-time satellite constellations, dynamic susceptibility mapping, landslide runout modelling, cross-corridor model transferability, community-sourced observations, uncertainty-aware early warning systems, and digital twins capable of continuously monitoring and managing mountain transportation corridors.

REFERENCE

1) Mack B, Leinenkugel P, Huth J, Gessner U, Künzer C. Pan-European Land Cover Classification with Landsat Data–Preliminary Results. InProceedings of the 36th Annual EARSeL Symposium 2016 (pp. 137-138).
2) Liao CH, Chang HS. An Environmental Resilience based on Approaching Planners Triangle for Integrated Catchment Management. In18th International Conference on Urban Planning and Regional Development in the Information Society 2013 May.
3) Landier L, Lauret N, Gastellu-Etchegorry JP, Al Bitar A, Mitraka Z, Feigenwinter C, Parlow E, Heldens W, Kotthaus S, Grimmond S, Lindberg F. Calibration of DART radiative transfer model with satellite images for simulating albedo and thermal irradiance images and 3D radiative budget of urban environment. InProceedings of the 36th EARSEL symposium 2016 (pp. 120-121).
4) Hamshaw SD. Fluvial processes in motion: Measuring bank erosion and suspended sediment flux using advanced geomatic methods and machine learning. The University of Vermont and State Agricultural College; 2018.
5) AUDU AI. *ASSESSMENT OF FLOOD VULNERABILITY IN LOKOJA METROPOLIS, KOGI STATE* (Doctoral dissertation, DEPARTMENT OF URBAN AND REGIONAL PLANNING, AHMADU BELLO UNIVERSITY, ZARIA).
6) LiDAR DE. Preliminary Slope Mass Movement Susceptibility Mapping Using DEM. Terrigenous Mass Movements: Detection, Modelling, Early Warning and Mitigation Using Geoinformation Technology. 2012 Apr 2:109.
7) Da Ponte E, Fleckenstein M, Roch M, Rodas O, Oppelt N, Kuenzer C. Forest cover loss in Paraguay and Ecosystem Service Approaches: an Upper Parana Forest Study Case. InProceedings of the 36th Annual EARSeL Symposium 2016 Jun 22.
8) Křížek M, Krause D, Raschová T. Debris flows in the Hrubý Jeseník Mountains, Bohemian Massif, Czech Republic. Journal of Maps. 2018 Nov 13;14(2):428-34.
9) Pokhrel S. *Assessment of Above Ground Biomass and Fire Risk Zonation in Selected Forest Areas of Ludhikhola Watershed Gorkha, District, Nepal* (Doctoral dissertation, University of Salzburg).

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10) Ghimire M. Historical land covers change in the chure-tarai landscape in the last six decades: Drivers and environmental consequences. InLand cover change and its eco-environmental responses in Nepal 2017 Aug 24 (pp. 109-147). Singapore: Springer Singapore.
11) Rizeei HM. Flood Risk Assessment Using Multi-Sensor Remote Sensing, Geographic Information System, 2D Hydraulic and Machine Learning Based Models. University of Technology Sydney (Australia); 2018.
12) Lato M, Bobrowsky P, Roberts N, Bean S, Powell S, McDougall S, Brideau MA, Stead D, VanDine D. Site investigation, analysis, monitoring and treatment, Canadian technical guidelines and best practices related to landslides: a national initiative for loss reduction. Geological Survey of Canada, Open File. 2016 Sep 29;8114.
13) Zhu X. GIS for environmental applications: a practical approach. Routledge; 2016 May 26.
14) Doyle C, Sullivan J, Mahtta R, Pandey B. Assessing Biophysical and Social Vulnerability to Natural Hazards in Uttarakhand, India. Washington, DC: World Bank. 2017 Jun 30.
15) Estoque RC, Murayama Y. Quantifying landscape pattern and ecosystem service value changes in four rapidly urbanizing hill stations of Southeast Asia. Landscape Ecology. 2016 Sep;31(7):1481-507.
16) Kostadinov S, Braunović S, Dragićević S, Zlatić M, Dragović N, Rakonjac N. Effects of erosion control works: case study—Grdelica Gorge, the South Morava River (Serbia). Water. 2018 Aug 17;10(8):1094.
17) Gessner U, Knauer K, Klein I, Künzer C. Assessing socio-economic and climate-related impacts on natural resources in rural areas of West Africa. InPROCEEDINGS OF THE 36th ANNUAL EARSEL SYMPOSIUM 2016 (pp. 189-189).
18) Jaboyedoff M, Choffet M, Derron MH, Horton P, Loye A, Longchamp C, Mazotti B, Michoud C, Pedrazzini A. Preliminary slope mass movement susceptibility mapping using DEM and LiDAR DEM. InTerrigenous mass movements: Detection, modelling, early warning and mitigation using geoinformation technology 2012 Apr 3 (pp. 109-170). Berlin, Heidelberg: Springer Berlin Heidelberg.
19) Fischer L. Slope instabilities on perennially frozen and glacierised rock walls: multi-scale observations, analyses and modelling. Geographisches Institut der Universität Zürich; 2009.
20) Korzeniowska K. *Object-based image analysis for detecting landforms diagnostic of natural hazards* (Doctoral dissertation, Universität Potsdam).
21) Lin YS, Chen CF, Chen YF, Chou YC, Chiang SH, Chang KH. Illegal land use change assessment using GIS and remote sensing to support sustainable land management strategies in Taiwan. Geocarto International. 2017;34(2):133-48.
22) Wohl E, Oguchi T. Geographic information systems and. Geographic information science and mountain geomorphology. 2004 Jun 30:309.
23) Pajares G. Overview and current status of remote sensing applications based on unmanned aerial vehicles (UAVs). Photogrammetric Engineering & Remote Sensing. 2015 Apr 1;81(4):281-330.
24) Owen KK. Geospatial and Remote Sensing-based Indicators of Settlement Type—Differentiating Informal and Formal Settlements in Guatemala City. George Mason University; 2012.
25) Amoako Johnson F, Hutton CW. Dependence on agriculture and ecosystem services for livelihood in Northeast India and Bhutan: vulnerability to climate change in the Tropical River Basins of the Upper Brahmaputra. Climatic change. 2014 Nov;127(1):107-21.
26) Watson CS, Carrivick J, Quincey D. An improved method to represent DEM uncertainty in glacial lake outburst flood propagation using stochastic simulations. Remote Sensing. 2017 Jul 1;9(7).
27) Xiang TZ, Xia GS, Zhang L. Mini-UAV-based remote sensing: Techniques, applications and prospectives. arXiv preprint arXiv:1812.07770. 2018 Dec.
28) Dong P, Chen Q. LiDAR remote sensing and applications. Crc Press; 2017 Dec 12.
29) Behling R, Roessner S. Spatiotemporal landslide mapper for large areas using optical satellite time series data. InWorkshop on World Landslide Forum 2017 May 29 (pp. 143-152). Cham: Springer International Publishing.
30) Ma Y. Regional Scale Multi-hazard Susceptibility Assessment: a case study in Mtskheta-Mtianeti, Georgia.
31) De Lemos HJ. A critical analysis using remote sensing and GIS techniques for spatial distribution and macro-morphological analyses of rockfalls in the Golden Gate Highlands National Park, South Africa. University of the Witwatersrand, Johannesburg (South Africa); 2013.
32) Wang Q, Kong Y, Zhang W, Chen J, Xu P, Li H, Xue Y, Yuan X, Zhan J, Zhu Y. Regional debris flow susceptibility analysis based on principal component analysis and self-organizing map: a case study in Southwest China. Arabian Journal of Geosciences. 2016 Nov;9(18):718.
33) Netzband M, Stefanov WL, Redman C, editors. Applied remote sensing for urban planning, governance and sustainability. Springer Science & Business Media; 2007 Dec 10.

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34) Pattanaik A, Singh TK, Saxena M, Prusty BG. Landslide Susceptibility Mapping Using AHP Along Mechuka Valley, Arunachal Pradesh, India. InProceedings of International Conference on Remote Sensing for Disaster Management: Issues and Challenges in Disaster Management 2018 Jun 24 (pp. 635-651). Cham: Springer International Publishing.
35) Thakur PK, Aggarwal SP, Dhote P, Nikam BR, Garg V, Bhatt CM, Chouksey A, Jha A. Hydrometeorological hazards mapping, monitoring and modelling. InRemote sensing of northwest himalayan ecosystems 2018 Oct 19 (pp. 139-169). Singapore: Springer Singapore.
36) Wang Q, Wang Y, Niu R, Peng L. Integration of information theory, K-means cluster analysis and the logistic regression model for landslide susceptibility mapping in the Three Gorges Area, China. Remote Sensing. 2017 Sep 11;9(9):938.
37) Rawat JS, Joshi RC. Remote-sensing and GIS-based landslide-susceptibility zonation using the landslide index method in Igo River Basin, Eastern Himalaya, India. International journal of remote sensing. 2012 Jun 1;33(12):3751-67.
38) Cascini LC, Bonnard C, Corominas J, Jibson R, Montero-Olarte J. Landslide hazard and risk zoning for urban planning and development. InLandslide risk management 2005 Jun 30 (pp. 209-246). CRC Press.
39) Anbazhagan S, Sajinkumar KS. Geoinformatics in terrain analysis and landslide susceptibility mapping in parts of Western Ghats, India. InGeoinformatics in applied geomorphology 2011 Jun 6 (pp. 291-315). Boca Raton: CRC Press.
40) Chakraborty S. Spatio-temporal Landslide Hazard Analysis along a Road Corridor based on Historical Information: A Case Study from Uttarakhand India. Enschede, The Netherlands, IIRS, Dehradun, India. 2008 Jan.

