iJRASET
International Journal For Research in
Applied Science and Engineering Technology

INTERNATIONAL JOURNAL FOR RESEARCH
IN APPLIED SCIENCE & ENGINEERING TECHNOLOGY

Volume: 14 Issue: VII Month of publication: July 2026

DOI: https://doi.org/10.22214/ijraset.2026.84294

www.ijraset.com

Call: 08813907089 | E-mail ID: ijraset@gmail.com

International Journal for Research in Applied Science & Engineering Technology (IJRASET)
ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.538
Volume 14 Issue VII July 2026- Available at www.ijraset.com

Graph Representations for Slope Instability and Landslide Kinematics: From Fracture Networks to Physics-Informed Graph Learning

Mohit Sheode
Research Scholar, Department of Civil Engineering, MANIT, Bhopal, Madhya Pradesh, India

Abstract: Slope instability develops through connected processes: discontinuities intersect, blocks transfer load, water follows preferential pathways, and deformation propagates between parts of a slope. Many conventional methods represent these components separately, which can obscure the relationships that control failure and movement. This narrative review examines how graph representations can provide a common language for slope stability and landslide kinematics. Four application layers are examined: fracture and discontinuity graphs, sensor and monitoring graphs, spatiotemporal deformation graphs, and physics-informed graph neural networks. The article first introduces nodes, edges, adjacency matrices, graph Laplacians, message passing, and graph convolution in accessible language. It then compares how graph structure has been used to describe rock-mass topology, combine distributed observations, forecast displacement, and couple data-driven learning with geotechnical and hydrological constraints. The synthesis shows that graph methods are most useful when edges express a defensible structural, mechanical, hydrological, or observational relationship. Evidence maturity is uneven: fracture topology and monitoring-network design are comparatively established, graph-based displacement forecasting is growing but remains case-dependent, and physics-informed graph learning is still emerging. A multiscale framework is proposed to connect fracture-scale mechanisms, slope-scale monitoring, and regional decision support. Priority needs include benchmark datasets, uncertainty-aware graph construction, physically meaningful edge design, spatial and temporal holdout testing, cross-site validation, and transparent comparison with non-graph baselines.

Keywords: graph representation; slope instability; landslide kinematics; fracture network; graph neural network; physics-informed learning.

I. INTRODUCTION

Landslides are difficult to understand because a slope does not behave as a collection of independent points. A joint may intersect another joint, a moving block may load a neighboring block, rainfall may raise pore-water pressure along connected pathways, and displacement may spread from an upper deformation zone toward a road, river, or settlement. These interactions occur across scales, from centimeter-scale cracks to kilometer-scale slope systems. Graph theory is useful precisely because it was developed to describe systems made of interacting parts. In its simplest form, a graph contains nodes and edges. A node represents an entity, such as a fracture intersection, rock block, monitoring station, InSAR pixel, slope unit, or infrastructure element. An edge represents a relationship between two entities, such as physical contact, fracture intersection, spatial proximity, correlation, hydrological connection, stress transfer, or temporal influence. This description is simple, but the scientific challenge is substantial: the nodes and edges must represent the real slope process rather than being chosen only for computational convenience.

Graph concepts have already been used broadly in geomorphology and the geosciences to describe connected landforms, flows, spatial systems, and changing networks [10], [18]. Fracture-network research has shown that graph topology can describe intersections, branches, connectivity, and pathways that are difficult to summarize using orientation statistics alone [21]. At the same time, slope-monitoring research has developed networks of GNSS receivers, wireless sensors, microseismic instruments, optical-fiber systems, and radar observations [7], [20], [27]. These traditions, however, have commonly progressed in parallel.

The recent growth of GNNs creates an opportunity to connect these traditions. A GNN learns from both the attributes of individual nodes and the pattern of relationships between them. This makes it attractive for landslide problems in which deformation is spatially coupled, observations are irregularly distributed, and the same forcing does not affect every part of a slope equally. Early studies have used graph-convolution and graph-deep-learning architectures to predict landslide displacement from monitoring networks [11], [28]. More recent work has introduced dynamic and multi-relation graphs, in which the network can change over time or contain different edge types [14], [26].

©IJRASET: All Rights are Reserved

Despite this progress, a focused synthesis connecting structural graphs, monitoring graphs, landslide kinematics, and physics-informed graph learning remains limited. Existing reviews generally concentrate on graph theory in the geosciences [10], [18], fracture topology [21], monitoring infrastructure [20], [27], landslide artificial intelligence [1], [15], knowledge graphs [16], or physically based stability modeling [22]. The missing contribution is therefore not another broad artificial-intelligence survey, but a narrative synthesis of graph representations as a unifying layer across slope structure, observation, motion, and mechanics.

This article addresses that gap through a beginner-oriented but technically rigorous narrative. It explains the mathematical foundations needed to read graph-based landslide studies, classifies applications in slope stability and landslide kinematics, compares classical graph analysis with graph neural networks and physics-informed models, evaluates uncertainty and validation practices, and proposes a unified multiscale framework. The central argument is that graph theory is most valuable when it provides a physically meaningful representation layer connecting geological structure, monitoring observations, deformation dynamics, and engineering decisions.

II. GRAPH THEORY FOUNDATIONS

A graph is represented by (1), where V denotes the set of nodes and E denotes the set of edges. In a rock slope, V may contain mapped discontinuities or blocks; in a monitoring application, it may contain GNSS receivers or persistent scatterers. An edge is introduced when two nodes satisfy a defined relationship, which may be binary, such as fracture intersection, or weighted, such as displacement correlation [3], [17].

$$G = (V, E) \tag{1}$$

The adjacency matrix A stores these connections. For an unweighted graph, A_{ij} equals 1 when nodes i and j are connected and 0 otherwise. In the weighted form given in (2), A_{ij} may represent distance-based similarity, correlation, contact area, estimated hydraulic conductance, or another justified relationship [3], [17]. A numerical edge weight should not be interpreted as physical influence unless its meaning is explicitly established.

$$A_{ij} = w_{ij} \text{ if } (i, j) \in E; \text{ otherwise } A_{ij} = 0 \tag{2}$$

The degree of node i is obtained from (3) as the number or total weight of its connections [17]. A highly connected fracture intersection may provide several possible pathways through a rock mass, while a highly connected monitoring station may be informative for several neighboring zones. Degree is easy to calculate, but it does not automatically measure mechanical importance. Other useful measures include betweenness centrality, which identifies nodes lying on many shortest paths, and connected components, which divide a network into internally connected groups.

$$k_i = \Sigma_j A_{ij} \tag{3}$$

The graph Laplacian combines the degree matrix D and adjacency matrix A, as defined in (4) [3]. It is central to spectral graph analysis and graph convolution because it describes how a value differs from values at neighboring nodes. In landslide monitoring, this can represent spatial smoothness; in fracture analysis, it can reveal connected subnetworks. However, excessive smoothness may hide sharp boundaries such as active scarps or shear zones.

$$L = D - A \tag{4}$$

A. Graph Theory, Network Analysis, and GNNs

Classical graph theory provides the mathematical objects and properties used to study connectivity. Network analysis applies those properties to a real system, for example by calculating fracture-node degree, identifying articulation points, or examining sensor-network robustness. Neither activity necessarily involves machine learning. A GNN is different because it learns numerical representations by repeatedly combining information from a node and its neighbors.

In a message-passing GNN, each node receives messages from neighboring nodes, aggregates them, and updates its hidden state according to the generic formulation in (5) [6]. The same computational structure can represent information exchange among monitoring locations, but a learned message is not itself a measured stress or water flux. Its physical interpretation depends on the edge definition, input variables, constraints, and validation.

$$h_v^{(l+1)} = \phi \left[h_v^{(l)} ,\ \mathrm{AGG}_{u \in N(v)}\ \psi(h_v^{(l)}, h_u^{(l)}, e_{uv}) \right] \tag{5}$$

A graph convolutional network (GCN) uses the normalized adjacency operator in (6) to combine neighboring features [12]. The self-loop in $\tilde{A} = A + I$ allow a node to retain its own information, while normalization prevents nodes with many neighbors from dominating solely because they have more connections.

$$H^{(l+1)} = \sigma(\tilde{D}^{-1/2}\, \tilde{A}\, \tilde{D}^{-1/2}\, H^{(l)}\, W^{(l)}) \tag{6}$$

International Journal for Research in Applied Science & Engineering Technology (IJRASET)
ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.538
Volume 14 Issue VII July 2026- Available at www.ijraset.com

Graph attention networks replace fixed neighbor weighting with learned attention coefficients. This can be useful where one station, fracture, or deformation zone is more informative than another. Attention should still be interpreted cautiously: a high learned weight does not prove a causal mechanical link [24].

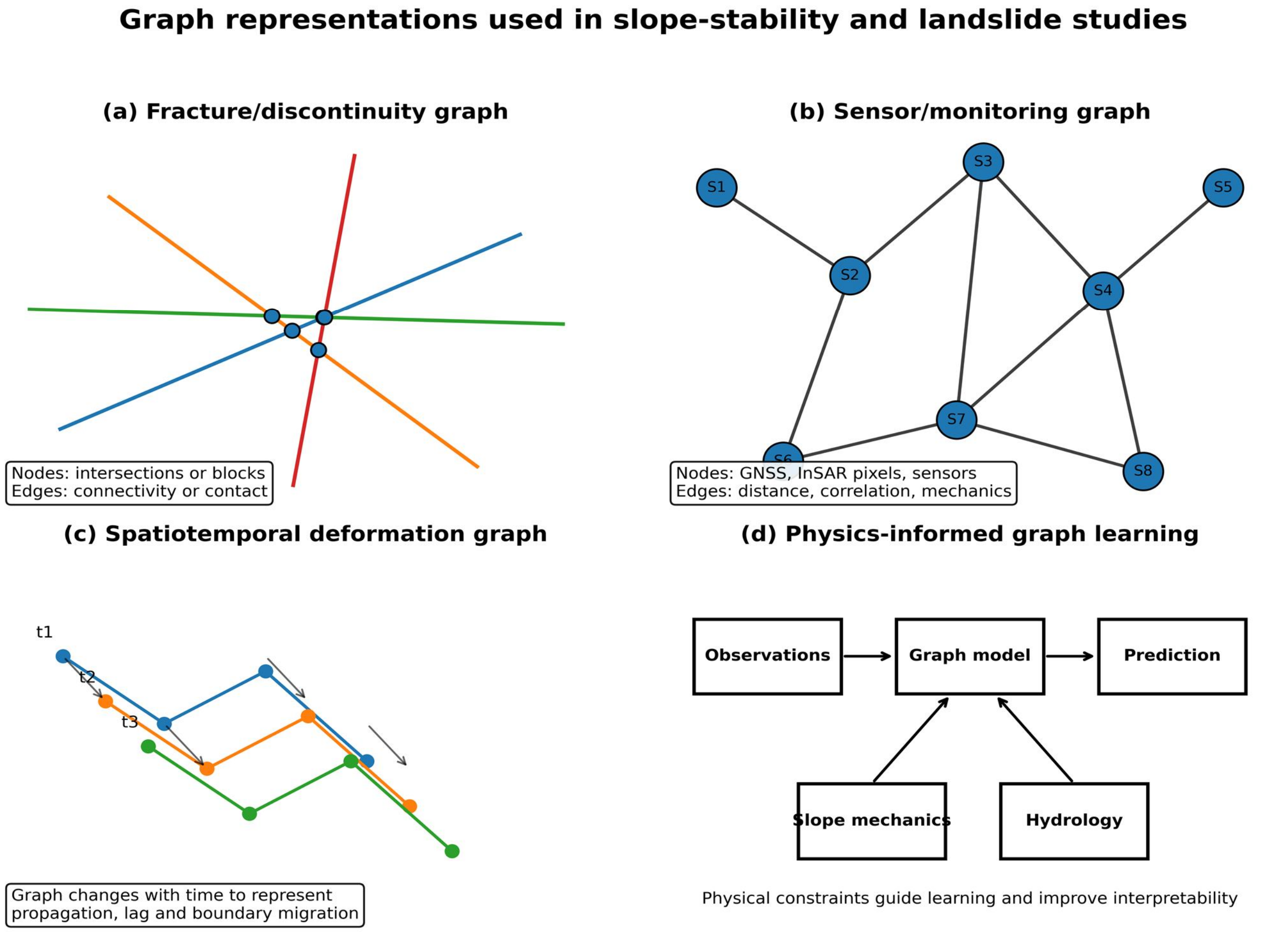


Fig. 1. Four graph representations used in slope-stability and landslide studies: fracture/discontinuity, sensor/monitoring, spatiotemporal deformation, and physics-informed graph learning.

TABLE I
BEGINNER-ORIENTED DISTINCTION AMONG RELATED APPROACHES

Approach	Main question	Typical output	Learning involved?
Graph theory	How is the system connected?	Components, paths, degree, centrality, spectra	No
Network analysis	Which real entities or pathways are structurally important?	Topology-based interpretation and robustness	Usually no
Conventional ML	Can attributes predict an output?	Class, displacement, factor of safety	Yes, but graph structure is not explicit
GNN	Can node attributes and connectivity jointly predict an output?	Node, edge, or whole-graph predictions	Yes
Physics-informed GNN	Can graph learning satisfy physical constraints?	Predictions plus constraint residuals	Yes, with physical constraints

III. FRACTURE AND DISCONTINUITY GRAPHS FOR SLOPE STABILITY

Rock-slope stability is strongly controlled by discontinuities. Their orientation determines whether sliding or toppling is kinematically possible; their persistence and spacing influence block size; and their intersections create pathways and detachable blocks. Traditional stereographic and kinematic analyzes remain essential, but they commonly summarize discontinuities as sets. A graph adds explicit information about which features intersect or connect.

Fracture-network topology is often described using nodes located at fracture intersections and edges representing fracture segments between intersections. Alternative representations treat each fracture as a node and each intersection as an edge. The first representation is suited to pathway analysis, while the second is useful for studying fracture-to-fracture connectivity. Sanderson et al. [21] emphasized that graph measures can separate geometric description from topological connectivity and can help compare networks collected at different scales.

For slope stability, the most useful graph is not always the most geometrically detailed graph. A stability graph may represent blocks as nodes and contacts as edges. Edge attributes can include contact area, joint orientation, friction angle, cohesion, aperture, persistence, or hydraulic transmissivity. Directed edges may represent a preferred downslope or seepage direction. Such choices allow the graph to connect with kinematic release, load transfer, and potential failure paths.

Discrete fracture networks derived from laser scanning, photogrammetry, digital mapping, or field surveys provide a natural input for graph construction [8]. Studies combining remote sensing with numerical modeling demonstrate that three-dimensional structural data can improve slope characterization [9], [25]. The graph perspective adds a further question: how sensitive is the inferred connectivity to missed, truncated, or falsely mapped discontinuities? Mapping bias can change connected components and critical paths even when average orientation statistics appear stable.

An important research direction is graph-native failure analysis. Instead of using a graph only to describe the fracture system, a model could estimate the probability that a connected set of blocks becomes removable under changing water pressure or seismic loading. The output might be a failure-mode label, a critical subgraph, or a probability of progressive release. Such models must be checked against block-theory reasoning, field evidence, and numerical simulation. Otherwise, graph connectivity may be mistaken for mechanical instability.

For soil slopes and simplified shallow translational landslides, graph models can be linked to the infinite-slope factor-of-safety expression in (7) [22]. This representative formulation assumes a potentially sliding layer approximately parallel to the ground surface, effective-stress conditions, and spatially defined material and pore-pressure terms. Here, c' is effective cohesion, φ' is effective friction angle, γ is unit weight, z is soil thickness, β is slope angle, and u is pore-water pressure. Consequently, (7) is applicable to shallow translational failure under these assumptions and should not be generalized to deep-seated, rotational, block, or toppling failures.

$$FS = [\, c' + (\gamma\, z \cos^2\beta - u) \tan\varphi' \,] \,/\, [\, \gamma\, z \sin\beta \cos\beta \,] \qquad (7)$$

A graph can connect neighboring soil columns or slope units, allowing pore pressure, material uncertainty, or failure probability to propagate through hydrological or terrain-based edges. The value added by the graph is therefore interaction; the factor-of-safety equation remains the mechanical reference.

IV. SENSOR AND MONITORING GRAPHS

Monitoring systems are already networks in an engineering sense, but they are not always analyzed as graphs. Wireless-sensor-network studies focus on communication, energy use, data transmission, and warning architecture [7], [20], [27]. A graph-learning study asks a different question: which sensors should exchange information in the model, and what does that connection mean for slope behavior?

Nodes may represent GNSS stations, inclinometers, extensometers, piezometers, microseismic sensors, ground-based radar cells, InSAR measurement points, or optical-fiber segments. Edges can be based on Euclidean distance, elevation difference, shared drainage, geological domain, displacement correlation, time lag, line of sight, or an estimated mechanical connection. A single graph can also contain several edge types. For example, one edge relation may represent spatial adjacency and another may represent rainfall-response similarity. Distance is a convenient edge rule, but it is not always physically adequate. Two nearby stations separated by a fault or ridge may behave independently, while distant stations located on the same deep-seated slide may move coherently. Correlation-based edges can adapt to observed behavior, but they may change with season, data gaps, or common external forcing. A robust graph should therefore combine data evidence with geomorphological and geotechnical knowledge.

GNSS displacement forecasting has become a prominent graph-learning application. Jiang et al. [11] combined graph convolution with a gated recurrent unit to model spatial and temporal dependence. Yang et al. [28] also used graph deep learning for landslide displacement prediction. Dynamic graph approaches extend this idea by allowing connectivity to evolve as deformation patterns change [14]. These studies show the promise of graph learning, but the evidence remains dominated by individual case studies and should not yet be interpreted as universal superiority.

Sensor graphs also support practical network design. Node-removal experiments can reveal whether predictions depend excessively on one station. Edge-ablation tests can compare geological, distance, and correlation graphs. A model intended for warning should be tested under missing data, communication failure, delayed measurements, and sensor drift. These tests connect graph analysis with the operational reliability concerns identified in slope-monitoring reviews.

V. SPATIOTEMPORAL GRAPHS FOR LANDSLIDE KINEMATICS

Landslide kinematics describes how movement varies in space and time. A time series from one point can show acceleration, seasonal movement, or response to rainfall, but it cannot by itself show how movement propagates across the slope. Schulz et al. [23] demonstrated the value of combining ground-based InSAR, structural mapping, and long-term monitoring to interpret controls across hourly to decadal timescales. A spatiotemporal graph formalizes this integration.

A time-varying landslide system can be represented by the dynamic graph in (8), where X_t contains node observations such as displacement, velocity, coherence, rainfall, pore pressure, or temperature. The node set may remain fixed while edge weights change, or both nodes and edges may change when valid observations appear, disappear, or migrate. This flexibility is especially relevant for InSAR, where coherence and visible deformation zones can vary through time.

$$G_t = (V_t, E_t, X_t) \tag{8}$$

Temporal information can be represented in two main ways. In a snapshot approach, a separate spatial graph is created for each acquisition and a recurrent or temporal-convolution model links the snapshots. In a space–time graph, each location at each time is a node, with spatial edges connecting locations within one time step and temporal edges connecting the same or related locations between steps. The first approach is easier to implement; the second represents propagation more explicitly but can become computationally large.

Multi-relation models are valuable because kinematic dependence is not one-dimensional. Wang et al. [26] described a multi-relation spatiotemporal graph architecture for landslide-displacement prediction. A landslide graph may similarly include spatial-neighbor, elevation, hydrological, lithological, and correlation relations. The scientific question is not how many relations can be added, but which relations improve prediction consistently and remain interpretable across sites.

Graph-based kinematic models should be compared with strong non-graph baselines, including persistence, linear and seasonal models, Kalman filtering, recurrent networks, and transformers. Cai et al. [2], for example, integrated Kalman filtering with multiplatform time-series InSAR for high-temporal-resolution dynamic monitoring. A GNN should be preferred only when the network representation provides demonstrable improvement, robustness, or interpretability beyond these alternatives.

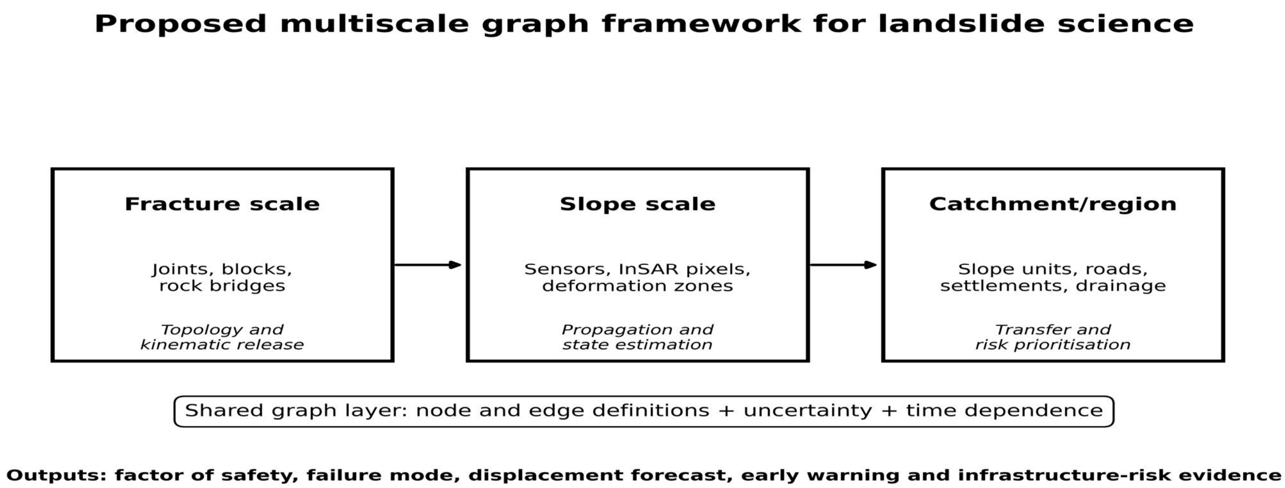


Fig. 2. Proposed multiscale graph framework linking fracture-, slope-, and regional-scale representations through shared node, edge, uncertainty, and temporal information.

VI. PHYSICS-INFORMED GRAPH LEARNING

Purely data-driven graph models learn patterns from observations, but a good statistical fit does not guarantee mechanically possible behavior. Physics-informed learning addresses this concern by adding physical equations, boundary conditions, conservation laws, or engineering constraints to the learning objective. The broader physics-informed neural-network literature demonstrates how differential-equation residuals can be included in training [19]. In slope applications, the relevant constraints may involve force equilibrium, Mohr–Coulomb strength, Darcy flow, mass conservation, or known displacement boundaries.

A physics-informed GNN is attractive because the graph already represents interacting parts of the slope. Nodes can store state variables such as displacement, pore pressure, stress, saturation, or material properties. Edges can represent contacts, flux pathways, or neighborhood interactions. The model can learn unresolved relationships while a loss term penalizes violation of selected physical principles.

To combine empirical fit with physical consistency, a generalized physics-informed graph-learning objective is expressed in (9). The data term measures disagreement with observations; the mechanical term may penalize force imbalance, constitutive inconsistency, or disagreement with a stability indicator; the hydrological term may represent water-balance, seepage, or pore-pressure residuals; and the regularization term controls model complexity, graph roughness, or unstable edge weights. The weighting coefficients λm, λh, and λr determine the balance among these components and therefore require justification and sensitivity analysis. This review-derived expression extends the physics-informed neural-network principle described in [19].

$$\mathscr{L} = \mathscr{L}\text{data} + \lambda m\, \mathscr{L}\text{mechanics} + \lambda h\, \mathscr{L}\text{hydrology} + \lambda r\, \mathscr{L}\text{regularization} \tag{9}$$

Physics-guided slope-learning studies have begun to connect neural models with three-dimensional slope stability and rainfall-induced processes [4], [29]. These studies provide important foundations, although most are not yet fully graph-based. Conversely, GNN displacement studies often model spatial dependence but include limited explicit mechanics. The main opportunity is therefore at the intersection: graph models whose topology and training constraints both arise from geotechnical reasoning.

Physical constraints do not automatically solve interpretability. An incorrect or oversimplified equation can bias a model, and a low physics residual does not prove that the graph edges are correct. Hybrid models should report the physical assumptions, dimensional consistency, normalization, boundary conditions, loss weights, and sensitivity to imperfect parameter values. They should also be compared with the underlying physics-only model to show what the graph component contributes.

VII. UNCERTAINTY, VALIDATION, AND RELIABILITY

Graph models contain uncertainty at several levels. Observation uncertainty includes measurement noise, decorrelation, sensor drift, and missing data. Parameter uncertainty includes strength, permeability, and material variability. Topology uncertainty concerns whether nodes or edges are missing, false, or incorrectly weighted. Model uncertainty arises because several graph architectures can fit the same data, while transfer uncertainty appears when a model trained at one landslide is applied to another. Reliability studies in structurally controlled and large rock slopes further show that uncertainty treatment must reflect the relevant failure mechanism [5], [13].

Topology uncertainty is particularly important and often overlooked. In a fracture graph, an unmapped discontinuity can create or remove a critical pathway. In an InSAR graph, thresholding coherence may change the connected deformation domain. In a correlation graph, a short time window may create unstable edges. A trustworthy study should repeat its analysis under alternative edge rules, thresholds, and spatial scales.

Validation should match the intended use. A displacement-forecast model requires testing on future periods that were not used for training. A cross-site model requires an external landslide. A fracture graph requires comparison with field mapping, three-dimensional models, or observed block release. A physics-informed model requires both predictive metrics and physical-residual checks. Randomly splitting neighboring points into training and test sets is usually insufficient because information can leak across space and time.

Useful prediction metrics include mean absolute error (MAE), root mean square error (RMSE), mean absolute percentage error where displacement is safely non-zero, and interval coverage for probabilistic models. Classification tasks require precision, recall, F1 score, receiver-operating-characteristic or precision–recall curves, and calibration. Network robustness can be evaluated by removing nodes, perturbing edges, adding noise, or simulating communication failure. Stability models should additionally report factor-of-safety error, failure probability, or agreement with observed failure mode.

International Journal for Research in Applied Science & Engineering Technology (IJRASET)
ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.538
Volume 14 Issue VII July 2026- Available at www.ijraset.com

Explainability should focus on geotechnically meaningful questions. Which edges influence a prediction? Does the model identify a known active zone? Are important nodes stable across seasons and model initializations? Does removing a hydrologically meaningful edge reduce performance more than removing a random edge? Such tests are more informative than presenting attention weights alone.

TABLE II
RECOMMENDED VALIDATION EVIDENCE FOR DIFFERENT GRAPH APPLICATIONS

Application	Minimum validation	Stronger evidence	Common weakness
Fracture graph	Comparison with mapped intersections/components	Independent mapping, 3D models, observed block release	Topology treated as error-free
Sensor graph	Held-out times and missing-node tests	Independent season or external network	Random split causes leakage
Kinematic forecast	Future-period MAE/RMSE and baseline comparison	Event-based and cross-site validation	Only one landslide studied
Physics-informed GNN	Accuracy plus physical residuals	Comparison with physics-only and data-only models	Loss weights not tested
Regional graph	Spatially blocked validation	Transfer to another region and calibration	Nearby slope units in both train and test sets

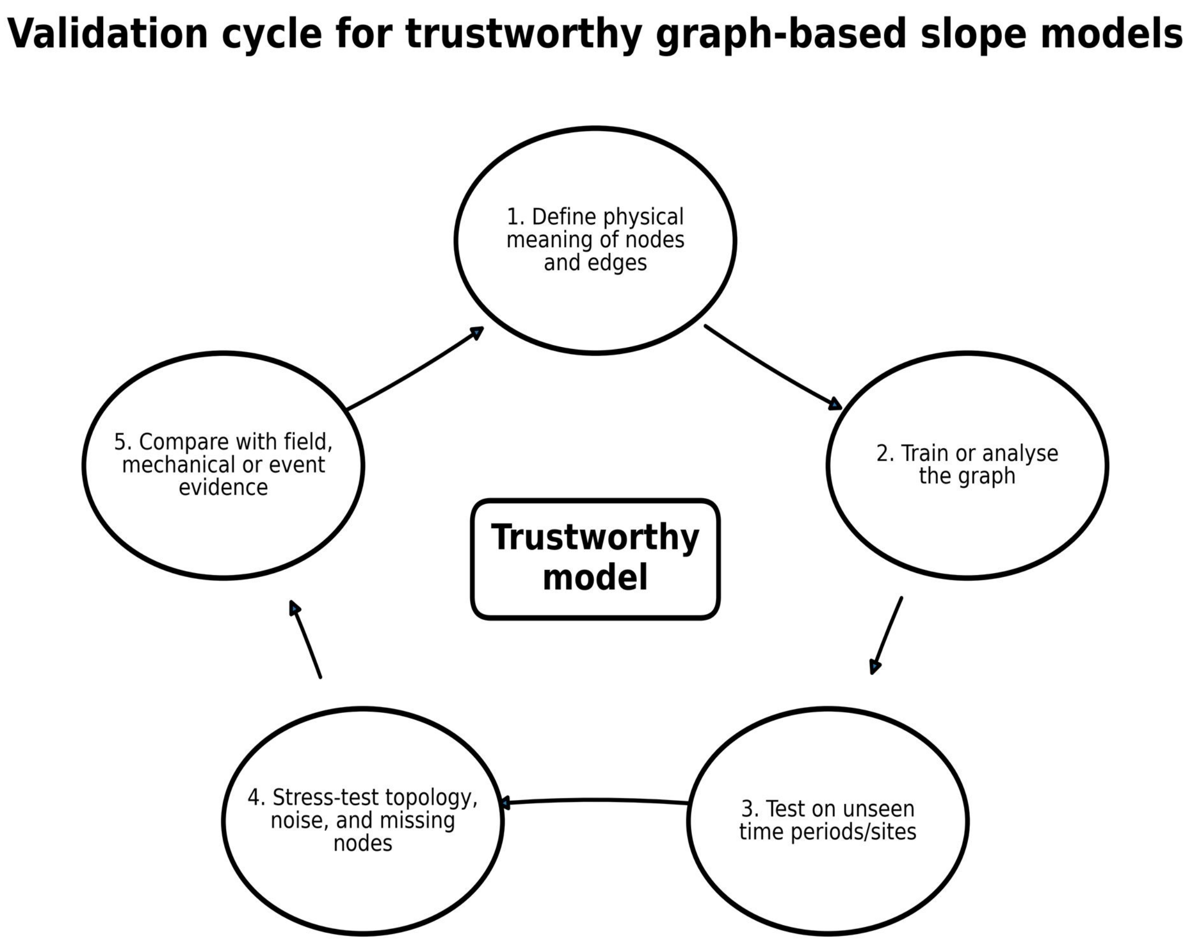


Fig. 3. Iterative validation cycle for trustworthy graph-based slope models.

VIII. COMPARATIVE SYNTHESIS: WHAT GRAPH METHODS ADD

Graph methods are not automatically superior to conventional approaches. Their main advantage is the explicit representation of relationships. They are most useful when connectivity is scientifically important, observations are irregular, or interactions change through time. They add less value when the target depends mainly on local attributes and the edge structure is arbitrary.

For fracture-controlled rock slopes, graph theory adds topological information beyond orientation and density. For monitoring networks, graph analysis adds redundancy, centrality, and robustness assessment. For kinematics, spatiotemporal graphs add propagation and time-lag representation. For physics-informed learning, graphs provide a discrete structure on which mechanical or hydrological interactions can be enforced. These benefits are distinct and should not be reduced to a single claim of improved accuracy.

The literature reveals a clear maturity gradient. Classical fracture topology and sensor-network engineering are established foundations, although their direct use in stability inference is still developing. GNN-based displacement forecasting is expanding but remains dominated by site-specific case studies. Physics-informed graph learning for slopes is the least mature layer and should be presented as an emerging research direction. Claims of superior performance should therefore be restricted to the conditions, datasets, and validation designs actually tested.

TABLE III
CRITICAL COMPARISON OF MAJOR GRAPH-BASED APPROACHES

Theme	Graph contribution	Current maturity	Priority limitation
Fracture/discontinuity	Connectivity, pathways, critical subgraphs	Established topology; emerging prediction	Mapping and topology uncertainty
Monitoring network	Sensor relations, redundancy, robustness	Established engineering network; emerging learning	Physical meaning of edges
Spatiotemporal kinematics	Propagation, lag, changing domains	Emerging	Limited external validation
Physics-informed GNN	Coupled data and mechanics	Early-stage	Constraint selection and parameter uncertainty
Multiscale integration	Links block, slope, and regional evidence	Conceptual/experimental	Scale transfer and computational complexity

IX. A UNIFIED MULTISCALE FRAMEWORK

The proposed framework contains three graph scales connected by shared physical and observational information. At the fracture scale, nodes and edges represent discontinuities, blocks, contacts, and potential pathways. Outputs include connected components, removable blocks, critical paths, and uncertain failure mechanisms. At the slope scale, nodes represent sensors, radar cells, InSAR measurement points, or deformation zones. Outputs include current state, spatial coupling, acceleration, and warning evidence. At the regional scale, nodes represent slope units, infrastructure segments, settlements, drainage elements, or known landslides. Outputs include transfer assessment, prioritization, and risk communication. Information should move between scales in both directions. Structural graphs can guide sensor placement and edge definition. Monitoring observations can update the probability that a structural pathway is active. Regional rainfall or seismic forcing can modify slope-scale graph states. Regional models should not simply average local graphs; they should preserve uncertainty about which local mechanisms are known and which are inferred. A practical implementation can begin without a complex end-to-end GNN. Researchers may first create graph objects and calculate interpretable network metrics, then compare them with established stability or kinematic measures. A second stage can introduce supervised graph learning. A third stage can add physical constraints and multiscale transfer. This staged path is more transparent and reproducible than beginning with a large black-box architecture.

A. Research Directions

Future work should create open benchmark graphs containing raw observations, explicit node and edge definitions, uncertainty labels, and independent validation data. Graph construction should combine distance with geology, hydrology, mechanics, and learned dependence, while topology sensitivity should be quantified under missing fractures, missing sensors, alternative thresholds, and changing spatial scales.

Validation should use temporally and spatially blocked tests, external landslides, and event-based evaluation. Physics-informed GNNs should be compared with physics-only and data-only baselines, and explainability tests should be designed around geological and engineering hypotheses rather than generic feature-importance graphics.

Multiscale graphs should preserve local mechanism information while supporting regional infrastructure-risk decisions. Researchers should also report computational cost, data requirements, failure cases, and operational limitations alongside predictive accuracy.

X. PRACTICAL APPRAISAL CHECKLIST

A beginner can appraise a graph-based slope study using six questions. What exactly is represented by a node? What physical or observational statement is made by an edge? Is the graph directed, weighted, dynamic, or multirelational? Would the topology change under another threshold, scale, or data gap? Is the model compared with a strong non-graph baseline? Is validation separated across space, time, or sites in a way that matches the intended application? These questions often reveal more about scientific reliability than the name of the neural-network architecture.

For a first study, a simple graph is often preferable. For example, monitoring points can be connected using a small number of alternative rules: distance, same geomorphological zone, and displacement correlation. Basic network metrics and a simple GCN can then be compared with a non-graph regression model. Edge-ablation and missing-node tests can reveal whether the graph adds genuine information. Physical interpretation should be discussed before attempting dynamic or attention-based architectures.

TABLE IV
MINIMUM REPORTING CHECKLIST FOR A GRAPH-BASED SLOPE OR LANDSLIDE STUDY

Reporting item	Minimum information
Nodes	Entity, spatial support, features, missing-data treatment
Edges	Rule, direction, weight, threshold, physical interpretation
Time	Static or dynamic graph; acquisition alignment; lag treatment
Model	Architecture, hyperparameters, loss, software, random seeds
Physics	Equation, assumptions, units, boundary conditions, loss weight
Validation	Spatial/temporal split, baselines, external data, metrics
Uncertainty	Observation, parameter, topology, and model uncertainty
Reproducibility	Data availability, code, graph files, preprocessing

XI. LIMITATIONS OF THE NARRATIVE SYNTHESIS

The relevant literature is distributed across geomorphology, structural geology, geotechnical engineering, remote sensing, sensor systems, and machine learning. Terminology is inconsistent, and some publications use network language without defining a formal graph. This fragmentation complicates retrieval and comparison and may cause relevant studies to be missed unless searches include discipline-specific terms and citation chaining.

The rapid growth of graph neural networks and physics-informed learning means that the evidence base continues to change quickly. The synthesis is therefore bounded by the literature available at the time of preparation, and recent publications may alter the maturity assessment presented here.

Because this article is a narrative synthesis, it does not claim exhaustive database coverage or provide bibliometric screening counts. It emphasizes representative peer-reviewed studies and conceptual integration across structural geology, monitoring, remote sensing, geotechnical engineering, and graph learning.

Direct comparisons among studies are limited because datasets, scales, graph definitions, target variables, and validation protocols differ substantially.

XII. CONCLUSION

Graph representations offer a coherent way to describe the connected nature of slope instability and landslide movement. At the structural scale, graphs represent fractures, blocks, contacts, and possible release pathways. At the monitoring scale, they connect distributed sensors and remote-sensing observations. At the kinematic scale, dynamic graphs represent propagation, time lags, and changing deformation domains. At the modeling scale, graph learning can be combined with mechanical and hydrological constraints. The central lesson is that a graph is scientifically useful only when its nodes and edges have defensible meaning. The strongest near-term advances will come from uncertainty-aware topology, physically meaningful edge design, transparent comparison with conventional methods, and external validation across time and sites. A multiscale framework linking fracture mechanisms, slope-scale observations, and regional decision support is promising, but it should be developed incrementally and tested against field evidence rather than presented as a fully mature operational solution.

REFERENCES

[1] S. Akosah, I. Gratchev, D.-H. Kim, and S.-Y. Ohn, “Application of artificial intelligence and remote sensing for landslide detection and prediction: Systematic review,” Remote Sensing, vol. 16, no. 16, Art. no. 2947, 2024, doi: 10.3390/rs16162947.

[2] J. Cai, G. Liu, H. Jia, R. Zhang, et al., “A new algorithm for landslide dynamic monitoring with high temporal resolution by Kalman filter integration of multiplatform time-series InSAR processing,” International Journal of Applied Earth Observation and Geoinformation, vol. 110, Art. no. 102812, 2022, doi: 10.1016/j.jag.2022.102812.

[3] F. R. K. Chung, Spectral Graph Theory. Providence, RI, USA: American Mathematical Society, 1997.

[4] A. Dahal and L. Lombardo, “Towards physics-informed neural networks for landslide prediction,” Engineering Geology, Art. no. 107852, 2025, doi: 10.1016/j.enggeo.2024.107852.

[5] M. K. Elmouttie and G. V. Poropat, “Quasi-stochastic analysis of uncertainty for modelling structurally controlled failures,” Rock Mechanics and Rock Engineering, vol. 47, pp. 2115–2131, 2014, doi: 10.1007/s00603-013-0410-y.

[6] J. Gilmer, S. S. Schoenholz, P. F. Riley, O. Vinyals, and G. E. Dahl, “Neural message passing for quantum chemistry,” in Proceedings of the 34th International Conference on Machine Learning, vol. 70, 2017, pp. 1263–1272.

[7] P. Giri, K. Ng, and W. Phillips, “Wireless sensor network system for landslide monitoring and warning,” IEEE Transactions on Instrumentation and Measurement, vol. 68, no. 4, pp. 1210–1220, 2019, doi: 10.1109/TIM.2018.2861999.

[8] L. Guo, X. Li, Y. Zhou, and Y. Zhang, “Generation and verification of three-dimensional network of fractured rock masses stochastic discontinuities based on digitalization,” Environmental Earth Sciences, vol. 73, pp. 7075–7088, 2015, doi: 10.1007/s12665-015-4175-3.

[9] M. Havaej, J. Coggan, D. Stead, and D. Elmo, “A combined remote sensing–numerical modelling approach to the stability analysis of Delabole Slate Quarry, Cornwall, UK,” Rock Mechanics and Rock Engineering, vol. 49, pp. 1227–1245, 2016, doi: 10.1007/s00603-015-0805-z.

[10] T. Heckmann, W. Schwanghart, and J. D. Phillips, “Graph theory—Recent developments of its application in geomorphology,” Geomorphology, vol. 243, pp. 130–146, 2015, doi: 10.1016/j.geomorph.2014.12.024.

[11] Y. Jiang, H. Luo, Q. Xu, L. Hao, et al., “A graph convolutional incorporating GRU network for landslide displacement forecasting based on spatiotemporal analysis of GNSS observations,” Remote Sensing, vol. 14, no. 4, Art. no. 1016, 2022, doi: 10.3390/rs14041016.

[12] T. N. Kipf and M. Welling, “Semi-supervised classification with graph convolutional networks,” in International Conference on Learning Representations, 2017.

[13] A. Kumar, B. Pandit, and G. Tiwari, “Reliability-based stability analysis of large rock slopes with different failure mechanisms using response surface methodology,” Environmental Earth Sciences, vol. 81, 2022, doi: 10.1007/s12665-022-10624-1.

[14] J. Li, J. Qin, K. Kang, X. Ding, et al., “Enhanced spatiotemporal landslide displacement prediction using dynamic graph-optimized GNSS monitoring,” Sensors, vol. 25, no. 15, Art. no. 4754, 2025, doi: 10.3390/s25154754.

[15] P. Lima, S. Steger, T. Glade, and F. G. Murillo-García, “Literature review and bibliometric analysis on data-driven assessment of landslide susceptibility,” Journal of Mountain Science, vol. 19, pp. 1670–1698, 2022, doi: 10.1007/s11629-021-7254-9.

[16] X. Ma, “Knowledge graph construction and application in geosciences: A review,” Computers & Geosciences, vol. 161, Art. no. 105082, 2022, doi: 10.1016/j.cageo.2022.105082.

[17] M. E. J. Newman, Networks: An Introduction. Oxford, UK: Oxford University Press, 2010.

[18] J. D. Phillips, W. Schwanghart, and T. Heckmann, “Graph theory in the geosciences,” Earth-Science Reviews, vol. 143, pp. 147–160, 2015, doi: 10.1016/j.earscirev.2015.02.002.

[19] M. Raissi, P. Perdikaris, and G. E. Karniadakis, “Physics-informed neural networks: A deep learning framework for solving forward and inverse problems involving nonlinear partial differential equations,” Journal of Computational Physics, vol. 378, pp. 686–707, 2019, doi: 10.1016/j.jcp.2018.10.045.

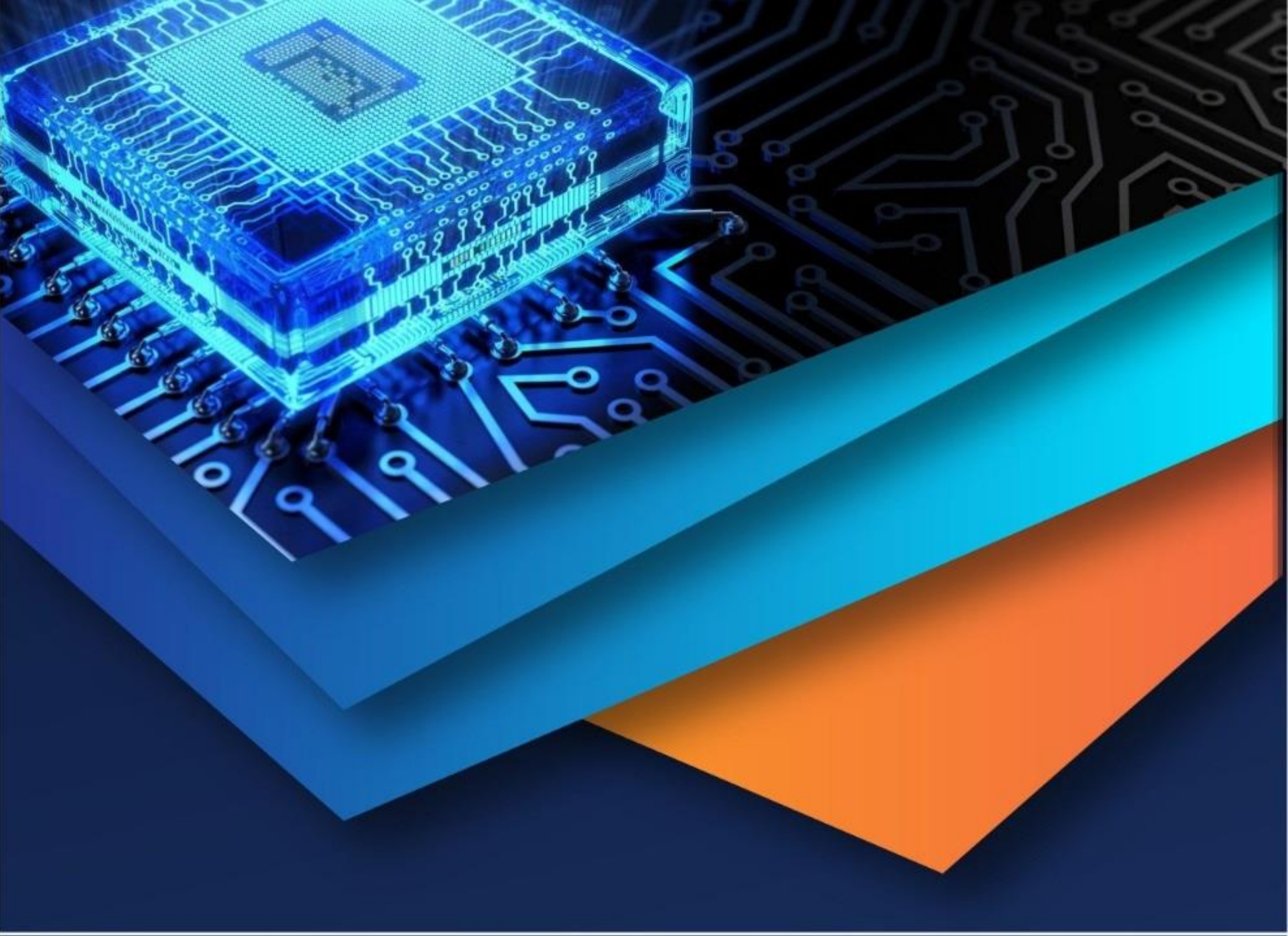
[20] M. Ragnoli, M. Scarsella, A. Leoni, V. Stornelli, et al., “Wireless sensor network-based rockfall and landslide monitoring systems: A review,” Sensors, vol. 23, no. 16, Art. no. 7278, 2023, doi: 10.3390/s23167278.

[21] D. J. Sanderson, D. C. P. Peacock, C. W. Nixon, and A. Rotevatn, “Graph theory and the analysis of fracture networks,” Journal of Structural Geology, vol. 125, pp. 155–165, 2019, doi: 10.1016/j.jsg.2018.04.011.

[22] G. Sannino, M. Bordoni, M. Bittelli, R. Valentino, et al., “Deterministic physically based distributed models for rainfall-induced shallow landslides,” Geosciences, vol. 14, no. 10, Art. no. 255, 2024, doi: 10.3390/geosciences14100255.

[23] W. H. Schulz, J. A. Coe, P. P. Ricci, J. Panosky, et al., “Landslide kinematics and their potential controls from hourly to decadal timescales: Insights from integrating ground-based InSAR measurements with structural maps and long-term monitoring data,” Geomorphology, vol. 285, pp. 121–136, 2017, doi: 10.1016/j.geomorph.2017.02.011.

[24] P. Veličković, G. Cucurull, A. Casanova, A. Romero, P. Liò, and Y. Bengio, “Graph attention networks,” in International Conference on Learning Representations, 2018.
[25] C. Vanneschi, A. Rindinella, and R. Salvini, “Hazard assessment of rocky slopes: An integrated photogrammetry–GIS approach including fracture density and probability of failure data,” Remote Sensing, vol. 14, no. 6, Art. no. 1438, 2022, doi: 10.3390/rs14061438.
[26] Z. Wang, X. Fang, W. Zhang, C. Chen, et al., “Multi-relation spatiotemporal graph residual network model with multi-level feature attention: A novel approach for landslide displacement prediction,” Journal of Rock Mechanics and Geotechnical Engineering, 2025, doi: 10.1016/j.jrmge.2024.09.038.
[27] D. K. Yadav, S. Jayanthu, S. K. Das, P. Mishra, et al., “Critical review on slope monitoring systems with a vision of unifying wireless sensor networks and the Internet of Things,” IET Wireless Sensor Systems, vol. 9, pp. 167–180, 2019, doi: 10.1049/iet-wss.2018.5197.
[28] C. Yang, Y. Yin, J. Zhang, J. Liu, et al., “A graph deep learning method for landslide displacement prediction based on global navigation satellite system positioning,” Geoscience Frontiers, vol. 15, Art. no. 101690, 2024, doi: 10.1016/j.gsf.2023.101690.
[29] Z. Zhang, B. Wang, Z. Li, and D. Dias, “Physics-guided neural network-based framework for 3D modeling of slope stability,” Computers and Geotechnics, Art. no. 106801, 2024, doi: 10.1016/j.compgeo.2024.106801.



10.22214/IJRASET

INDEX COPERNICUS

45.98

ISRA JIF

IMPACT FACTOR: 7.129

TOGETHER WE REACH THE GOAL

IMPACT FACTOR: 7.429

ISI

INTERNATIONAL JOURNAL FOR RESEARCH

IN APPLIED SCIENCE & ENGINEERING TECHNOLOGY

Call : 08813907089 (24*7 Support on Whatsapp)