

Review

Data-Assimilation-Driven Geohazard Monitoring and Early Warning Along Railways: A Review and the PAD Framework

Yan Du ^{1,2,*}, Anqi Zhang ^{1,2} , Mowen Xie ², Yujing Jiang ^{3,4} , Hongda Zhang ^{1,2} and Jingnan Liu ⁴

¹ School of Future Cities, University of Science and Technology Beijing, Beijing 100083, China; m202320201@xs.ustb.edu.cn (A.Z.); zhanghongda2022@163.com (H.Z.)

² Beijing Key Laboratory for Urban Safety and Collective Intelligence, University of Science and Technology Beijing, Beijing 100083, China; mowenxie@126.com

³ State Key Laboratory Breeding Base for Mining Disaster Prevention and Control, Shandong University of Science and Technology, Qingdao 266590, China; jiang@nagasaki-u.ac.jp

⁴ Graduate School of Engineering, Nagasaki University, Nagasaki 852-8521, Japan; ljn1203846583@163.com

* Correspondence: mutulei@163.com

Abstract

Conventional early-warning methods for geohazards along railways rely largely on single observations, empirical criteria or static analysis, and struggle to meet the demands of corridor-scale screening and dynamic tracking. To address this gap, a railway-oriented Perception–Assimilation–Decision (PAD) closed-loop early-warning framework is proposed. The evolutionary patterns of typical geohazards along railways, including landslides, rockfalls, debris flows and settlement, are reviewed together with the application scope and limitations of multi-source monitoring techniques. Additionally, differentiated assimilation strategies are clarified, with continuous deformation and hydro-mechanical state updating for plastic failure and damage-sensitive evidence and critical-state identification for brittle failure. On this basis, a mechanism–data dual-driven assimilation paradigm and a two-scale PAD organisation, comprising corridor-scale spatial screening and site-scale state updating, are introduced. Recent applications show that data assimilation has shifted from correcting a single monitoring variable toward the dynamic coupling of multi-source observations with physical models. By establishing the logical chain from multi-source perception to state updating and finally to railway engineering response, the PAD framework transforms the traditional anomaly-identification-based warning mode into closed-loop risk management. The results provide a reference for building geohazard early-warning systems and engineering-oriented response along railways.

Keywords: railways; geohazards; multi-source monitoring; data assimilation; mechanism–data dual-driven; PAD closed-loop early warning



Academic Editor: Wolfgang Kainz

Received: 20 July 2026

Revised: 3 September 2026

Accepted: 4 September 2026

Published: 11 September 2026

Copyright: © 2026 by the authors.

Published by MDPI on behalf of the International Society for

Photogrammetry and Remote Sensing.

Licensee MDPI, Basel, Switzerland.

This article is an open access article distributed under the terms and

conditions of the [Creative Commons](https://creativecommons.org/licenses/by/4.0/)

Attribution (CC BY) license.

1. Introduction

With the rapid development of China's railway network, the geological environment along railway lines has become increasingly complex and diverse. Landslides, rockfalls, debris flows and subgrade settlement occur frequently, posing a long-term threat to the safety of railway engineering, operational stability and public safety [1]. Railways often traverse mountains, hills, valleys and soft-soil areas, where geohazards are jointly controlled by topography and geomorphology, stratigraphic structure, hydrological conditions, and engineering disturbance, and thus exhibit spatial continuity, multi-hazard superposition and complex triggering mechanisms. As shown in Table 1, once key components such as

the subgrade, track structure, bridges, culverts and tunnel portals are damaged, railway service interruption and economic losses may follow, and secondary disasters may even be triggered. As the service life of the infrastructure increases, small deformations and accumulated hidden defects evolve progressively, further increasing the risk of sudden failure of facilities along the line [2].

Table 1. Typical geohazard chains and engineering risk consequences along railways [1].

Affected Component	Typical Hazards	Direct Damage	Potential Consequences
Subgrade and track structure	Landslide, subgrade settlement, mining-induced collapse, soft-soil deformation	Subgrade instability, track deformation, differential settlement, track irregularity	Speed restriction, increased maintenance pressure, and in severe cases line interruption or operational safety accidents
Cutting slopes and tunnel portals	Landslide, rockfall, falling rocks, portal collapse	Clearance intrusion by rockfall, slope instability, portal burial, lining damage	Line closure and obstructed train operation, and in severe cases collision or derailment risk
Bridge, culvert and valley-crossing sections	Debris flow, channel blockage, foundation scour, bank slope instability	Culvert blockage, pier and abutment damage, ballast burial, drainage failure	Line interruption and reduced structural safety, and in severe cases shutdown or emergency response

Traditional geohazard monitoring and risk-prevention methods mostly rely on single observations, empirical judgement or static analysis, and cannot adequately meet the requirements of large-scale, dynamic and multi-hazard risk assessment along railways [3]. In long-distance railway projects in particular, single-point monitoring cannot adequately capture hazard-chain effects and their impact on key components such as the subgrade, track, bridges, culverts and tunnel portals; existing warning systems still fall short in prediction accuracy, real-time performance and closed-loop engineering application [4]. The early warning of geohazards along railways faces the difficulty of dynamically coupling multi-source heterogeneous observations with hazard models of different failure mechanisms. Because long-distance lines have spatial continuity whereas field monitoring is typically local and sparse, existing methods cannot adequately reconcile the needs of corridor-scale screening, focused tracking and multi-hazard warning. A new warning framework that simultaneously accounts for spatial continuity, monitoring sparsity and multi-hazard differences is therefore urgently needed.

In recent years, the development of remote sensing, unmanned aerial vehicles, ground sensors, the Internet of Things and artificial intelligence has made the multi-source observation and dynamic monitoring of geohazards along railways feasible [3]. Multi-source data fusion and intelligent analysis enable the early identification of micro-deformation, landslides and settlement, laying a technical foundation for building an accurate warning system [5]. In contrast to existing reviews that focus on a single site or a single hazard type, this paper establishes a unified Perception–Assimilation–Decision (PAD) closed-loop framework that addresses the spatial continuity, engineering coupling and operational safety requirements specific to railways.

International railway reviews have examined rail-vehicle and track condition monitoring [6], optical inspection systems [7], GPR–InSAR integration for track health [8], and Earth-observation applications for railway infrastructure [9]. These studies provide detailed accounts of particular sensing technologies, asset-condition indicators or maintenance applications, whereas general landslide early-warning frameworks organise monitoring,

forecasting, warning and response at local or territorial scales [10]. The present review connects these previously separated emphases by organising observations according to hazard mechanism and railway interaction, distinguishing corridor screening from site-scale state updating, and mapping the assimilated state and its uncertainty to railway response indicators and operational actions. The substantive distinction of PAD is therefore not the naming of three sequential components, but the railway-oriented feedback chain linking multi-source perception, mechanism-conditioned assimilation and operational decision-making.

Previous studies have shown that combining multi-source observations with hazard-evolution models, and further constructing a PAD closed-loop warning system, helps to achieve dynamic identification, risk quantification and engineering decision support for geohazards along railways; the framework is shown in Figure 1. In this framework, the perception component acquires and aggregates multi-source observations along the line and provides the data basis for risk identification; the decision component, which addresses railway operation, maintenance and emergency response, formulates corresponding response strategies; and the assimilation component undertakes the state-updating function that links perception and decision. Quality-controlled monitoring data are continuously fed into the hazard-evolution model and the railway engineering-response model, and the state variables, model parameters and risk boundaries are dynamically corrected as new observations are added, so that the warning results can not only identify abnormal changes but also characterise the evolution of risk, providing a more reliable basis for risk assessment and engineering response.

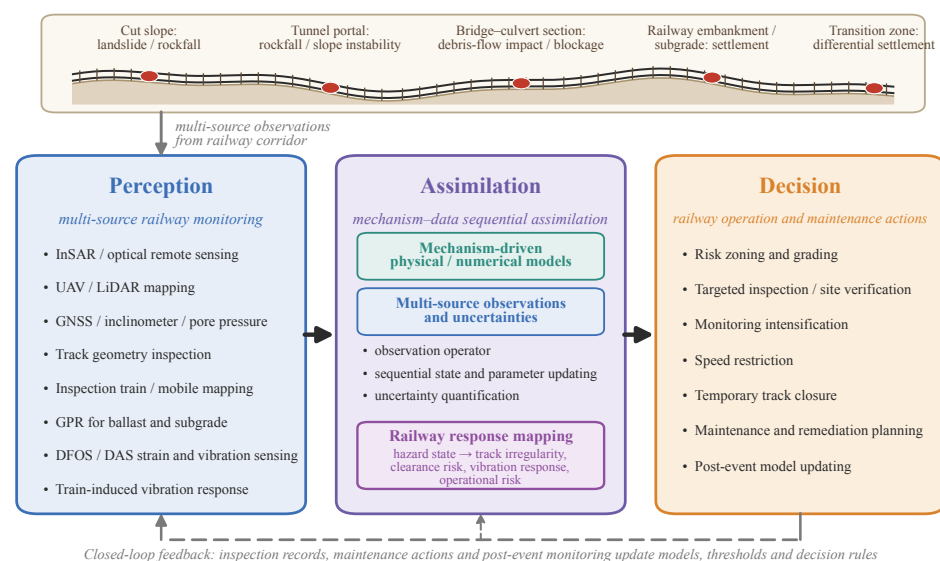


Figure 1. Perception–Assimilation–Decision (PAD) closed-loop framework for geohazards along railways: a dynamic early-warning paradigm driven by mechanism–data integration. In the workflow figures, solid arrows indicate forward information, state or decision transfer; dashed arrows indicate feedback or iterative updating; and colours distinguish process stages or functional groups rather than universal risk thresholds.

Although various risk-assessment models and monitoring methods have been proposed, a systematic monitoring, refined assessment and engineering-oriented warning framework for geohazards along railways remains incomplete [11]. For example, existing landslide monitoring along railways mostly adopts a single observation such as InSAR or GNSS, which cannot adequately support hazard-chain analysis [8]. Key components such as railway subgrade settlement, cutting slopes, tunnel portals, bridge–culvert valley sections and bridge–tunnel transition zones largely rely on empirical formulas or local

experiments, and lack dynamic assimilation and closed-loop warning strategies [4]. A warning system that integrates multi-source observation, data assimilation and the PAD closed loop is therefore of great practical significance for improving geohazard prevention and control along railways [12].

Building on this comparison, this paper reviews railway geohazard identification, monitoring, assimilation and early warning and develops an integrated framework for these tasks rather than another technology-specific catalogue. The main contributions are as follows. (1) Starting from the linear extent, engineering coupling and operational sensitivity of railways, the distribution characteristics, evolution patterns and warning requirements of typical hazards such as landslides, rockfalls, debris flows and settlement are summarised, with emphasis on the essential differences between plastic and brittle failure in evolution rhythm, precursory information and assimilation strategy. (2) In view of the practical needs of corridor-scale screening, the focused verification of key sections, and dynamic state tracking, the characteristics and applicable boundaries of multi-source monitoring data—including remote sensing, ground sensing, track geometry, inspection trains, GPR, DFOS and train-induced vibration—are reviewed, and a hierarchical monitoring-to-assimilation organisation tailored to railway applications is proposed. (3) Recent advances in data assimilation in related studies are critically reviewed, highlighting the roles of sequential updating, uncertainty representation and mechanism–data dual-driven dynamic coupling. (4) Focusing on the connection among monitoring data, hazard states, track-geometry response and engineering response, a PAD closed-loop warning framework tailored to railway applications is established, providing a reference for building geohazard early-warning systems and risk management along railways.

Review Methodology

This article is a structured narrative review. To improve the transparency and coverage of literature identification, a supplementary search was conducted using Semantic Scholar Academic Graph and OpenAlex for publications from 2000 to August 2026. The search focused on four themes: railway geohazards; multi-source monitoring; data assimilation and state updating; and early warning, risk assessment and operational decision-making. Journal and review articles, substantive conference papers and research reports directly relevant to these themes were considered, while duplicate records and studies unrelated to railway geohazards, ground or earthwork deformation, monitoring, data assimilation or engineering risk were excluded. Retrieved records were screened by title, abstract and bibliographic information, and relevant studies were compared with the existing bibliography to identify gaps in the thematic coverage of the review. This supplementary search was intended to check thematic coverage and identify representative gaps in the existing bibliography, rather than to provide an exhaustive systematic retrieval of all eligible studies.

2. Characteristics of Geohazards Along Railways and Early-Warning Requirements

2.1. Hazard Types and Spatial Distribution

Geohazards along railways differ from site-specific risks: the risk usually extends continuously along the line and varies with geomorphological zoning, stratigraphic structure, hydrological conditions and engineering disturbance [13]. Railway lines often cross mountains, hills, valleys and soft-soil plains, and the geological background differs greatly between sections, so that several hazard types frequently coexist along the same line [11]. Considering the actual service environment along railways, the main hazards can be grouped into four categories: landslides, debris flows, rockfalls and settlement [14]. These

four categories are not only the most common objects in current monitoring and early-warning research but also the engineering-geological problems with the most direct impact on railway operational safety.

As shown in Figure 2, the spatial distribution of these hazards is controlled by geomorphological units, geotechnical structure and engineering disturbance, exhibiting clear sectional differentiation. Mountainous and hilly areas are dominated by landslides, rockfalls and debris flows: landslides occur mostly in zones of overall slope deformation, rockfalls concentrate in high and steep rocky slopes, cutting slopes and tunnel-portal sections, while debris flows are controlled by gullies and their outlets. Plains and soft-soil areas are more prone to settlement, especially in soft foundations, backfill zones and bridge–tunnel transition zones, where long-term slow-varying risks readily develop. In addition, culvert-crossing sections, portal areas, river-crossing sections and slope-toe cut sections are often sensitive locations where several hazards act together. For instance, some piedmont sections may be affected by an upper landslide and may also develop into a debris-flow channel under heavy rainfall; some portal slopes face local rockfall risk while lying within a background of overall deformation [15]. The risk along the line shows clear spatial differentiation and risk amplification at key nodes, so monitoring must go beyond detecting isolated hazard points and identify high-risk sections and their controlling factors.

Overall, landslides, rockfalls, debris flows and settlement represent the main slope deformation, local rock-mass instability, gully hazards and long-term foundation deformation along railways, respectively. They differ in their distribution environment, controlling factors and engineering interaction mode, but share one feature: their hazard process is highly coupled with the spatial layout of the line and with operational safety. Subsequent monitoring and warning research should therefore abandon the single-site or single-hazard analysis paradigm and establish an integrated understanding from the perspective of “sectional zoning–focused identification–dynamic tracking–engineering response”.

It should be noted that the classification into landslides, rockfalls, debris flows and settlement mainly defines the hazard objects, whereas railway warning must further answer how a hazard affects the railway structure and translates into engineering-response needs. Therefore, without replacing the traditional hazard-type classification or the analysis of plastic and brittle failure mechanisms, as shown in Table 2, the engineering interaction modes of geohazards along railways can be summarised—from the interaction between the hazard body and the railway structure—by intrusion type, foundation-deformation type, scour/undermining type and dynamic-response type. This complementary classification helps to translate geohazard impacts into railway engineering-response problems and provides a link for the subsequent selection of monitoring techniques, the setting of assimilation variables and the PAD decision output.

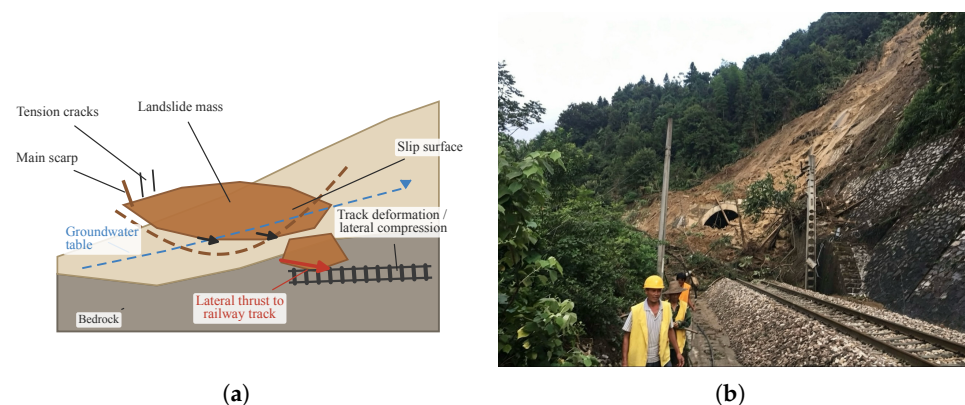


Figure 2. Cont.

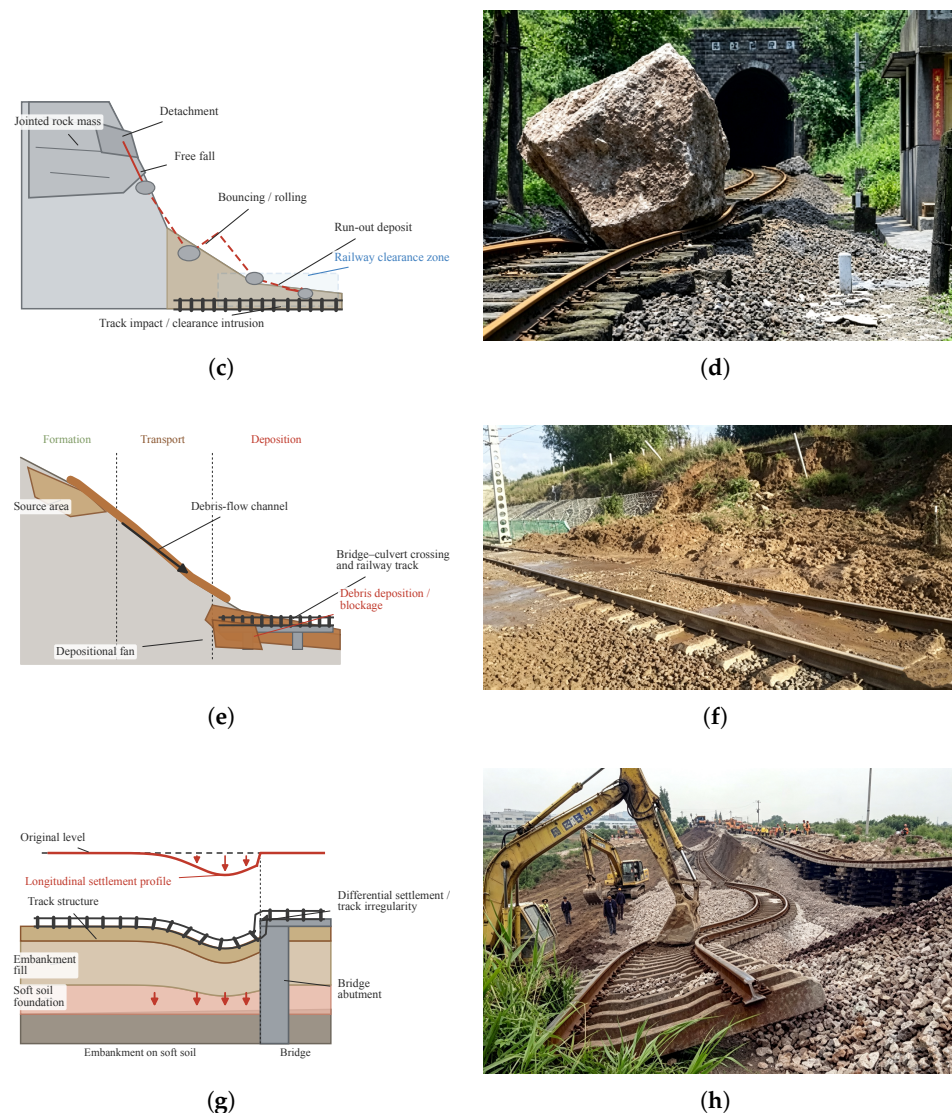


Figure 2. Typical geohazards along a railway corridor and their damage to the track: (a) schematic of landslide action; (b) field photo of track damage by landslide; (c) schematic of rockfall action; (d) field photo of track damage by rockfall; (e) schematic of debris-flow action; (f) field photo of track damage by debris flow; (g) schematic of settlement action; (h) field photo of track damage by settlement.

Table 2. Engineering interaction types of geohazards along railways and their operational-response implications.

Interaction Type	Main Hazards	Main Affected Objects	Typical Railway Consequences	Main Monitoring Information	PAD Response
Intrusion type	Rockfall, falling rocks, debris flow, lateral squeezing by landslide	Clearance, track, catenary, railway clearance envelope	Clearance intrusion by rockfall, ballast burial, train-collision risk, line interruption	Video, LiDAR, microseismic/acoustic emission, cracks, rainfall	Emergency inspection, speed restriction, line closure, hazard removal

Table 2. Cont.

Interaction Type	Main Hazards	Main Affected Objects	Typical Railway Consequences	Main Monitoring Information	PAD Response
Foundation-deformation type	Soft-soil settlement, mining collapse, subgrade deformation, freeze–thaw settlement	Subgrade, track structure, bridge–tunnel transition zone	Differential settlement, track irregularity, increased maintenance pressure	InSAR, GNSS, levelling, track geometry	Targeted re-survey, maintenance planning, speed restriction, reinforcement
Scour/undermining type	Pier scour, subgrade void, tunnel-invert cavity, karst collapse	Bridge–culvert foundation, subgrade base, tunnel invert	Weakened support, structural instability, sudden collapse	GPR, water level, flow velocity, vibration response	GPR re-survey, defect detection, reinforcement, closure inspection
Dynamic-response type	Ballast stiffness anomaly, abrupt transition-zone stiffness change, foundation degradation	Wheel–rail system, ballast, track foundation	Abnormal vibration, increased wheel–rail force, accelerated fatigue	Axle-box/car-body acceleration, track geometry, wheel–rail force	Maintenance window, condition-based maintenance, temporary speed restriction

2.2. Evolution Patterns and Early-Warning Requirements

The monitoring and early warning of geohazards along railways depend not only on identifying the spatial location of a hazard but, more importantly, on grasping its evolution. Although landslides, debris flows, rockfalls and settlement all belong to the main hazard types along the line, they differ markedly in failure mechanism, precursory information and imminent-failure response [16]. In terms of failure mode, the instability of soil landslides and settlement mostly manifests as a progressive deterioration of the soil–rock mass under hydro-mechanical coupling, showing clear plastic-failure characteristics. By contrast, rockfalls manifest more as the continuous accumulation of hidden damage in key load-bearing structures, with sudden brittle fracture and through-going failure at a critical state, a typical brittle-failure process [17]. As shown in Table 3, the differences in evolution between the two determine that the warning system cannot adopt a uniform mode in monitoring indicators, identification logic and response timeliness.

Table 3. Mechanism-based differentiation of geohazards and corresponding early-warning strategies along railways.

Failure Mode	Mechanism	Sensitive Indicators	Typical Case
Plastic failure	Progressive shear failure dominated by plastic rheology	Displacement, inclination, stress, etc.	Mentougou landslide, Beijing [18]
Brittle failure	Sudden fracture failure dominated by crack propagation and coalescence	Natural frequency, spectral centroid frequency, damping ratio, etc.	Hongyanshan rockfall [19]

The plastic–brittle distinction is used here to identify the dominant evolution mechanism and warning evidence at a given stage, rather than to assign every hazard to an immutable binary class. Mixed and transitional behaviour is accommodated by changing the observation emphasis and assimilation configuration as the governing process changes. Debris flows are treated separately as rapid-onset gully hazards because rainfall triggering,

source availability and channel transport do not fit naturally into displacement-dominated plastic or fracture-dominated brittle warning.

In railway scenarios, the essential feature of plastic failure is that the strength of the hazard body is not lost instantaneously but gradually weakens under sustained external disturbance, eventually evolving into overall instability. The failure process typically comprises three stages: initial deformation, relatively stable creep development, and later accelerated failure. Throughout this process, quasi-static monitoring indicators such as displacement growth, settlement rate, pore-pressure change, crack propagation and local stress adjustment provide good indication [19]. Plastic failure is therefore better identified through the process-based monitoring of its stage transitions [20], and its warning logic can be summarised as “continuous tracking–stage identification–dynamic correction of risk level”, as shown in Figure 3b.

Unlike plastic-failure hazards, rockfall failure is more typically brittle. Its essential feature is not gradual instability after the long-term accumulation of macroscopic deformation, but the hidden development of micro-damage inside the key load-bearing structure over a long period, followed by sudden fracture once the limit state is reached [21]. As the rock bridge deteriorates under rainfall, freeze–thaw or vibration, the macroscopic displacement may not be significant, yet internal damage keeps accumulating. Once the damage reaches a critical level, the structural plane may coalesce within a short time, leading to the detachment, sliding or fall of the unstable rock mass [22]. Rockfall warning therefore cannot rely on the displacement-threshold logic used for plastic-failure hazards. Instead, it requires dynamic indicators of internal damage, such as natural-frequency drift and changes in damping, to detect the critical state before brittle fracture [23]. Its warning logic can be summarised as “damage-anomaly capture–critical-state identification–rapid emergency response”, as shown in Figure 3d.

For plastic-failure hazards, the warning objective is to track the evolving state continuously, identify transitions between stages and update the risk level dynamically; process-based warning is therefore appropriate [24]. For brittle-failure hazards, the priority is to detect damage in key load-bearing structures as early as possible and shorten the interval between detection and emergency action, which calls for critical-state warning [25]. These differences in warning lead time, sensitive indicators and required actions call for failure-specific system configurations and tiered response protocols.

Along a railway corridor, plastic and brittle failure may occur in different sections of the same line and may be sequentially linked at individual sites. Plastic and brittle failure are not entirely separate: some complex landslides or rocky slopes may exhibit staged features of brittle initiation, plastic evolution and local sudden change, as illustrated in Figure 3e. During brittle initiation, the update should give greater weight to high-frequency damage-sensitive evidence such as frequency drift, damping change and acoustic-emission or microseismic activity. When progressive creep becomes dominant, sequential updating should shift toward displacement, pore pressure and strain while retaining damage observations as supporting evidence. Local collapse requires the event-driven updating of the affected range and railway response, followed by rapid operational action. During transitions, both evidence groups should be retained until the governing process is supported by consistent observations; the assimilation configuration therefore changes with the evolution stage rather than with a fixed hazard label. Geohazard warning along railways cannot remain at the level of a single hazard, a single indicator or a static threshold, but should establish a differentiated identification framework tailored to the governing failure mechanism.

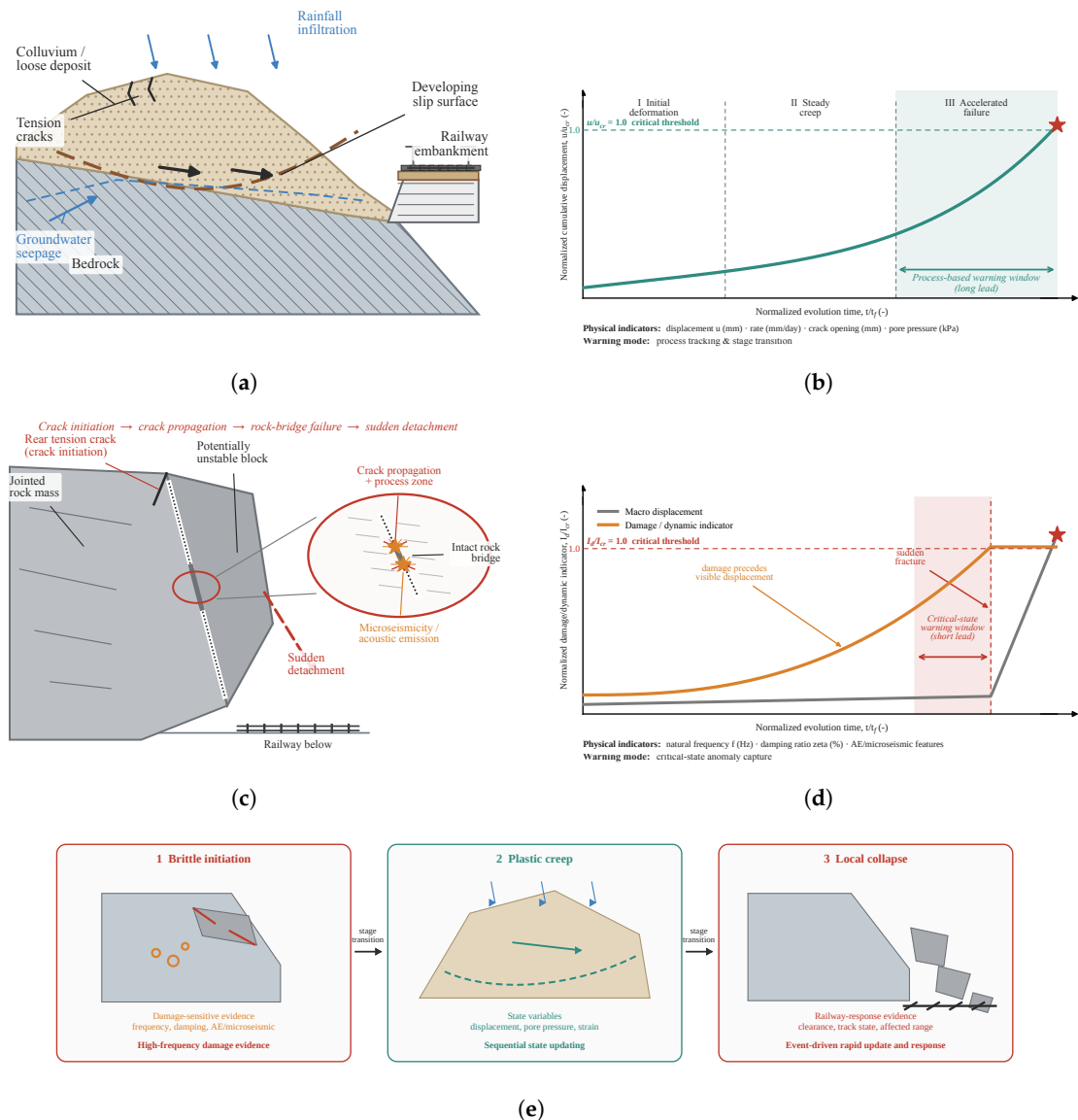


Figure 3. Evolutionary patterns and differentiated early-warning requirements of plastic, brittle and composite geohazard processes along railways: (a) progressive plastic-failure mechanism; (b) process-based warning logic; (c) brittle rapid-onset failure mechanism; (d) critical-state warning logic; (e) composite sequence of brittle initiation, plastic creep and local collapse, with stage-dependent assimilation adjustment. Panels (b,d) use the normalized ratios u/u_{cr} and I_d/I_{cr} , respectively, against normalized evolution time t/t_f , where t_f denotes the time at which the local critical state is attained. The value 1.0 therefore marks the attainment of the site-specific critical displacement u_{cr} or critical damage/dynamic indicator I_{cr} ; it is not a universal physical threshold. Actual thresholds must be calibrated according to hazard type, geological conditions, monitored quantity and railway operating context using site models, historical observations or field calibration.

3. Multi-Source Monitoring Techniques and Data Characteristics for Geohazards Along Railways

Railways are characterised by continuous extension, the crossing of many geomorphological units and the concentration of risk at local key nodes. Monitoring along the line must both cover the long-distance corridor and obtain finer data at locations such as bridge-tunnel transition zones, cutting slopes, valley-crossing sections, soft-soil settlement areas and high-fill or deep-cut sections. A single monitoring technique cannot adequately satisfy these spatial-coverage and temporal-response requirements simultaneously. Therefore,

the evaluation of multi-source monitoring techniques does not lie in whether a particular device is advanced, but in what kind of information in the hazard-evolution chain each monitoring technique can capture, whether such information can serve decisions for railway operational safety, and whether the required coverage can be sustained over the asset life [7]. As shown in Figure 4, satellite remote sensing can identify a large-scale deformation background, UAVs and LiDAR can depict the geometric details of key sections, ground sensors can track the internal or surface state of the hazard body, and railway-specific monitoring such as track-geometry inspection, comprehensive inspection trains, GPR, DFOS and train vibration directly reflects the response of the engineering structure [26]. Only when these data complement one another in space and time, within feasible deployment and maintenance arrangements, can the perception component of the PAD loop continuously update the risk state.

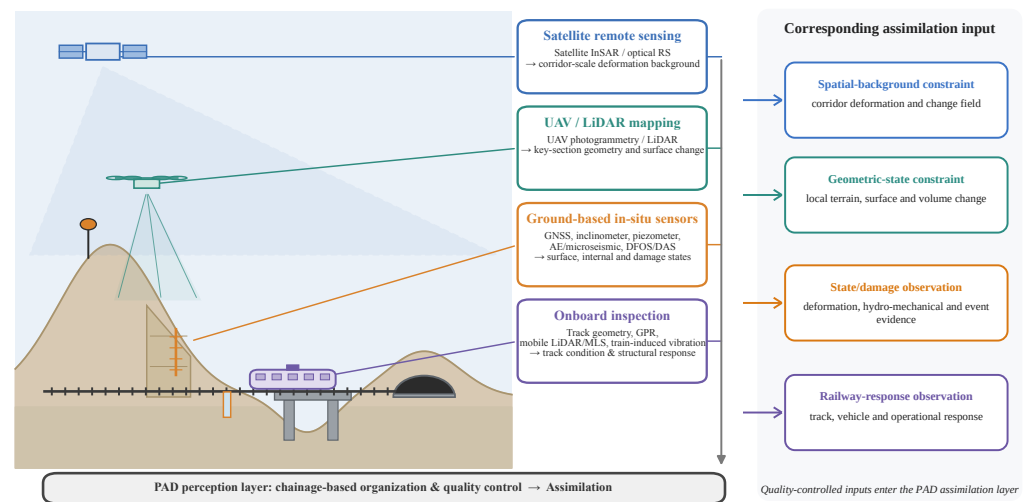


Figure 4. Integrated spaceborne–airborne–ground–onboard monitoring and the organisation of the PAD perception layer for geohazards along railways. Directional arrows map satellite, UAV / LiDAR, ground-sensor and onboard observations to spatial-background constraints, geometric-state constraints, state/damage observations and railway-response observations, respectively. Solid arrows indicate forward information, state or decision transfer; dashed arrows, where present, indicate feedback or iterative updating; and colours distinguish process stages or functional groups rather than universal risk thresholds.

3.1. Satellite Remote Sensing

Along long-distance railways, some hidden dangers may be distributed beyond existing hazard points. Soft-soil settlement, mining-area influence, the reactivation of ancient landslides and slow river-bank deformation may all gradually affect line safety over years of operation. Conventional manual inspection and single-point instruments are better suited to known key sections and are clearly insufficient for identifying slow deformation at the whole-line scale. Interferometric Synthetic Aperture Radar (InSAR) can retrieve surface deformation from multi-temporal radar images and has high application value in identifying railway subgrade settlement and slow landslide activity [27–29]. For railways, InSAR results need to be further analysed in conjunction with line mileage, structure type and engineering-segmentation information. The impact of uniform settlement on operational safety differs from that of differential settlement. High-speed railways are especially concerned with track smoothness, the deformation of bridge–tunnel transition zones and the longitudinal differential settlement of the subgrade. Overlaying the InSAR deformation field with line mileage, track structure and engineering-segmentation information allows the extraction of settlement gradient, curvature change and abnormal deformation sections

along the line. Compared with the single maximum settlement, indicators such as settlement gradient, curvature change and abnormal sections better reflect track smoothness and structural service state in railway maintenance, and thus better support risk grading and maintenance decisions [27,28].

For components such as the railway subgrade, bridges, culverts and tunnel portals, surface deformation must be interpreted together with structure type and engineering location. Soft-soil settlement, slow slope deformation, river-bank scour and the uneven deformation of bridge–tunnel transition zones may affect operational safety through subgrade cracking, track irregularity, abutment differential settlement or portal-slope instability. In railway scenarios, remote-sensing deformation results mainly help to identify abnormal sections that may affect line safety and structural service state; whether ground monitoring devices should be deployed or field re-survey should be carried out is then judged in combination with line grade, subgrade structure, bridge–tunnel location, drainage conditions and historical inspection records [30].

Optical remote sensing is less direct than InSAR in measuring deformation, but has high value for image interpretation. Slope cracks, vegetation anomalies, bank erosion and construction disturbance are often more easily interpreted from high-resolution optical images. For debris-flow gullies, tunnel portals and culvert valley-crossing sections, optical images can supplement geomorphological and source information that InSAR cannot adequately express. Compared with historical images, they can also reflect long-term changes such as channel-deposit variation, the expansion of bare slope areas and anthropogenic disturbance [31].

InSAR is affected by vegetation cover, surface scattering conditions, slope-aspect geometry and revisit period, and cannot adequately capture short-duration processes such as rockfalls and debris-flow outbursts. Optical images are limited by cloud and rain weather and illumination conditions, and cannot adequately achieve continuous dynamic warning. Satellite remote sensing is therefore better suited to identifying suspected risk sections, building a long-term deformation background and guiding the deployment of focused monitoring, and cannot replace high-frequency ground monitoring.

3.2. UAV, LiDAR and Three-Dimensional Surveying

When remote-sensing results show persistent deformation in a section, or field inspection finds slope cracks or abnormal subgrade deformation, the monitoring scale needs to shift from whole-line screening to local refined identification. Unmanned Aerial Vehicle (UAV) photogrammetry, Light Detection and Ranging (LiDAR) and terrestrial three-dimensional laser scanning can acquire high-resolution images and point clouds, suitable for verifying railway cutting slopes, tunnel portals, culvert valley-crossing sections, high-fill or deep-cut sections and bridge–tunnel transition zones [32].

Multi-temporal UAV images can reconstruct orthophotos and digital surface models to extract slope-crack propagation, changes in slump boundaries and changes in the outline of unstable rock masses. LiDAR is more sensitive to three-dimensional morphological changes and has advantages in identifying unstable rock blocks and computing slope-volume change. Terrestrial three-dimensional laser scanning is suitable for close-range targets such as high and steep slopes, tunnel-portal back slopes, retaining walls and protective structures, providing denser geometric information [33]. The value of these techniques along railways lies more in detailed site investigation following corridor-scale screening. For example, after InSAR finds slow displacement in a cutting slope, UAVs can further identify whether the trailing-edge crack is developing, and LiDAR can compute the volume change between multi-temporal point clouds. If the section is adjacent to an abutment, culvert or tunnel portal, it is also necessary to judge whether the deformation

may affect the structural foundation and line clearance. If point clouds and images are used only to display the field situation, they cannot adequately support subsequent data assimilation. Geometric information should be converted into computable state quantities, such as slope deformation rate, the displacement of unstable rock blocks and change in line clearance. These quantities can be related to ground-sensor results and jointly analysed with rainfall, groundwater, track geometry and engineering-structure response [34].

3.3. Ground Geotechnical Monitoring

Key high-risk sections along railways usually require ground monitoring devices. GNSS, inclinometers, crack meters, tiltmeters, pore-pressure gauges and rain gauges provide data with higher temporal resolution. Compared with remote sensing and three-dimensional surveying, these instruments have limited coverage but more directly reflect the internal or surface state of the hazard body [35]. For engineering applications, monitoring locations and indicators should be selected according to the governing hazard-evolution mechanism. As shown in Table 4, different monitoring techniques differ markedly in accuracy, temporal response and spatial coverage, and their perception roles point to different information types such as environmental triggering, hazard state or damage anomaly. Ground monitoring is therefore not merely a collection of instruments: it is a monitoring configuration designed for subsequent assimilation and tailored to the differences between plastic and brittle failure.

Table 4. Spatiotemporal resolution of multi-source monitoring techniques and their roles in PAD perception [14].

Level	Technique	Accuracy/Resolution	Temporal Response	Data Form	Role in PAD Perception
Satellite remote sensing	InSAR	mm–cm deformation	Day–week	Deformation-rate field, cumulative deformation	Corridor deformation screening
	Optical remote sensing	Sub-metre–metre image	Day–month	Orthophoto, hazard interpretation patches	Hidden-danger patch identification
Low-altitude and close-range surveying	UAV photogrammetry	cm-level image	Task-based, periodic	Orthophoto, DSM, 3D point cloud	Verification of abnormal sections
	LiDAR	cm-level point cloud	Task-based, periodic	Point cloud, DEM, slope profile	Micro-topography change identification
	Terrestrial 3D laser scanning	mm–cm surface change	Periodic, intensified re-survey	High-density point cloud, multi-temporal differencing	Refined slope identification
Ground geotechnical monitoring	GNSS	mm–cm displacement	Continuous, high-frequency	3D displacement time series	Displacement-trend updating
	Hydrostatic levelling	mm settlement	Periodic, continuous	Settlement, differential-settlement series	Settlement-state updating
	Inclinometer	$\pm 1\text{--}3\text{ mm}/30\text{ m}$	Periodic, continuous	Deep horizontal-displacement profile	Deep-deformation identification
	Crack meter	$\pm 0.2\%$ FS	Continuous, high-frequency	Crack opening, propagation rate	Crack-propagation identification
	Pore-pressure gauge	$\pm 0.1\%$ FS	Continuous, high-frequency	Pore pressure, water level, infiltration response	Hydrological-trigger constraint
	Rain gauge, weather station	0.1–0.5 mm rainfall	Real-time, high-frequency	Rainfall, intensity, temperature/humidity	Triggering-condition input

Table 4. Cont.

Level	Technique	Accuracy/Resolution	Temporal Response	Data Form	Role in PAD Perception
	Acoustic emission, microseismic	Not by displacement	Real-time, high-frequency	Event count, energy, spectrum, location	Brittle-damage identification
Railway operation monitoring	Track-geometry inspection	mm-level geometric state	Day-month or inspection-train cycle	Gauge, cross-level, longitudinal level, alignment, twist	Linking ground deformation with operational safety
	Comprehensive inspection train/onboard inspection	Continuous along mileage	Periodic or task-based	Video, laser point cloud, clearance and defect records	Risk archive along mileage
	GPR	cm–dm subsurface identification	Task-based	Ballast thickness, voids, moisture anomaly, weak interlayer	Identifying internal subgrade defects
	Train-induced vibration (opportunistic sensing)	Depends on sensor and speed	High-frequency/operational	Axle-box/car-body acceleration, DAS vibration, wheel–rail response	Assisting identification of stiffness anomaly and support degradation

Engineering selection must consider life-cycle burden in addition to sensing performance. Satellite remote sensing has a low field-deployment burden but requires recurring data acquisition and specialist processing; UAV/LiDAR and GPR require task-based access, trained operators and repeated surveys; permanent ground, acoustic-emission, microseismic and distributed-fibre systems add civil works, power, communications, calibration and sensor-maintenance demands. Track-geometry and onboard measurements can reduce additional deployment where existing inspection assets are available. Across these techniques, terrain, safe railway access and possession windows affect installation, while data storage, interpretation, equipment replacement and false-alarm review affect long-term operation and maintenance. A practical hierarchy is therefore to use low-site-footprint methods for corridor screening, reuse inspection or communication-fibre assets where data quality is adequate, and reserve dense permanent arrays for high-consequence sections. Because actual costs depend on corridor length, site access, existing assets, procurement and local labour, no universal price or fixed cost ranking is assigned [7,26,36,37].

3.4. Railway-Specific Monitoring Techniques

3.4.1. Track Geometry, Onboard Inspection and GPR Monitoring

Geohazard monitoring along railways has a distinct operational dimension. Landslides may cause a lateral squeezing of the subgrade and abnormal track alignment, settlement changes the longitudinal level and smoothness of the track, and rockfalls and debris flows may cause clearance intrusion, ballast burial and culvert blockage. Monitoring along railways therefore includes not only slope and foundation monitoring but also track-geometry inspection, onboard inspection, trackside video, clearance detection, ground-penetrating radar (GPR) and train-vibration-response monitoring [7].

As shown in Figure 5, a track-geometry inspection vehicle or comprehensive inspection train can acquire parameters such as gauge, cross-level, twist and track distortion during operation. Although these indicators are not traditional geohazard monitoring parameters, they directly reflect the response state of the railway structure under geohazard action. In some soft-soil settlement sections, subgrade deformation may not yet have caused visible damage, but the longitudinal level irregularity has begun to increase. Landslide-affected sections may also first manifest as local alignment offset or cross-level anomaly. Combining track-geometry data with hidden dangers along the line, rainfall and the InSAR deformation background can improve the accuracy of judging the degree of hazard impact [8].

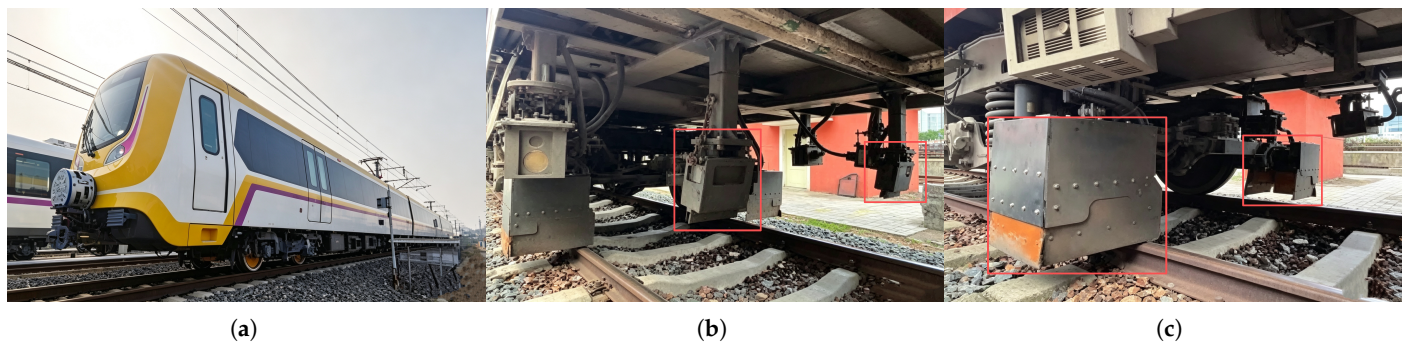


Figure 5. Track-geometry inspection vehicle and the layout of onboard inspection equipment [38]: (a) track-geometry inspection vehicle; (b) installation position of the inspection camera; (c) installation position of the rail-profile inspection assembly. The red frames in (b,c) indicate the locations of the inspection camera and rail-profile inspection assembly, respectively.

Onboard laser scanning and video inspection can repeatedly acquire information on cutting slopes, tunnel portals and line clearance along the railway. Their advantage is consistency with the operational space of the line: data can be organised by mileage and matched with track defects, inspection records and maintenance logs. The upper parts of high and steep slopes, deep-cut valleys and distant slopes on the outer side of the line cannot always be fully observed by onboard equipment, which requires supplementation by UAVs, remote sensing and manual survey. External-environment monitoring along railways should not be split into several unrelated data types, but should form a risk archive that unfolds continuously along the mileage [39].

GPR is highly applicable to internal hidden dangers of the railway ballast and subgrade. The impact of geohazards on railways sometimes does not appear directly on the slope surface, but is gradually reflected through subgrade moisture anomalies, weak interlayers and changes in structural-layer thickness. GPR can detect the state of the substructure beneath the track and, combined with track-geometry inspection and settlement monitoring, can distinguish the relationship among surface track irregularity, internal subgrade defects and external geohazard disturbance [40].

3.4.2. Distributed Optical-Fibre and Train-Induced Vibration-Response Monitoring

Distributed optical-fibre sensing (DFOS) is highly compatible with railways and is an important part of the ground in situ sensing and continuous sensing in Figure 4. Optical fibres can be laid along the subgrade, slope, tunnel, bridge and transition zone, acquiring continuous strain, temperature or vibration information through Brillouin optical time-domain reflectometry, Rayleigh scattering or DAS [36]. For the railway subgrade, optical fibres can monitor settlement deformation, internal strain concentration and dynamic response under train loading. With DAS, train-running vibration, rockfall impact, construction disturbance and some abnormal acoustic-vibration events can also be sensed [37]. Slope-laid fibres can record the deformation process of landslides or slopes, while embedded fibres help to identify internal differential deformation and local weak zones of the subgrade [41].

Train-induced vibration-response monitoring can serve as an important supplement for state identification along railways. As operating trains pass, they exert repeated dynamic actions on the track, ballast, subgrade, culverts and tunnel structures; the vibration responses recorded by axle-box, car-body or trackside sensors can reflect local stiffness change, support degradation and abnormal dynamic response. Compared with traditional static monitoring, such data are closer to the railway operational state, but are also easily affected by train speed, vehicle type, wheel–rail condition and environmental noise. Their

results should therefore not serve as a sole warning basis, but be combined with track geometry, GPR, DFOS, field inspection and geological data to assist in identifying problems such as subgrade voids, pier-foundation scour, abrupt transition-zone stiffness change and abnormal ballast state.

For repeatable comparison, each passage should retain speed, mileage, running direction, vehicle class and configuration, load state and wheel-condition metadata. After sensor synchronisation, invalid-sample and outlier removal, de-meaning/detrending, and anti-alias filtering, the time record is converted to the distance domain using

$$x(t) = x_0 + \int_{t_0}^t v(\tau) d\tau, \quad (1)$$

and resampled to a common mileage interval before wavelength-band filtering and feature extraction [42]. For the peak-decomposed Hilbert-amplitude feature examined by Malek-jafarian et al. [43], the published first-order speed scaling can be written in the present notation as

$$A_j^{(v)}(x) = \frac{v_{\text{ref}}}{v(x)} A_j(x), \quad (2)$$

where $v(x)$ is the measured passage speed and v_{ref} is a reference speed common to the compared passages. In the cited experiment, the baseline was an arbitrary average speed and the scaling was applied only after low-speed segments had been removed. This linear correction is therefore a case-specific empirical option rather than a universal vehicle-track law: its adequacy and valid speed range must be established from repeated healthy passages for the line, sensor and extracted feature concerned; otherwise, passages should be stratified by speed or a calibrated speed-feature relation should be used.

Vehicle-type effects should be removed after speed correction rather than by pooling unlike trains. For feature j and vehicle/configuration class c , including a comparable load state and running direction, a class-conditioned normalized residual can be defined as

$$Z_{j,c}(x) = \frac{A_j^{(v)}(x) - \mu_{j,c}(x)}{\sigma_{j,c}(x)}, \quad (3)$$

where $\mu_{j,c}(x)$ and $\sigma_{j,c}(x)$ are the mean and standard deviation obtained from repeated healthy-baseline passages of the same class. Only speed- and vehicle-conditioned residuals, together with their baseline uncertainty and quality flags, should enter anomaly comparison or assimilation; raw vibration amplitudes should not be compared directly across heterogeneous passages. Wheel-condition-sensitive features should be retained as covariates or exclusion flags so that a vehicle defect is not misidentified as a local track or foundation anomaly.

High-frequency fibre monitoring such as DAS produces large volumes of data; for example, train vibration, construction activity, wind and rain disturbance, and geological anomaly signals may be superimposed. Without a signal-identification model and field calibration, fibre anomalies are easily misjudged. DFOS is better understood as an important supplement to the perception component along railways rather than a single solution replacing all sensors. It provides continuous spatial information, point-type instruments provide physical interpretation of key components, remote sensing and UAVs provide the external-environment background, and track geometry and onboard inspection provide operational-response evidence [26].

In summary, multi-source monitoring data play different roles within the PAD framework according to spatial coverage, temporal resolution and physical-characterisation features. Wide-area remote sensing and low-altitude surveying data are mainly used to

build the deformation background along the line, detect abnormal sections and support risk zoning; these operations belong to perception, data fusion or screening unless the observations are used to update an explicit spatial-state model. Ground deformation, hydrological response and engineering-structure monitoring data can continuously characterise the state evolution of key components and are the main basis for site-scale assimilation that updates variables such as displacement, pore pressure and strain. Acoustic-emission, microseismic and dynamic-response information is more sensitive to brittle-failure processes and can serve as damage evidence for targeted model updating. Thus, the perception component supplies spatial-background constraints, state observations and damage evidence, but only their formal incorporation into a model-state or parameter update is termed data assimilation.

4. Data Assimilation and PAD Closed-Loop Early Warning

With the rapid development of multi-source monitoring techniques, the focus of geohazard warning along railways has gradually shifted from data acquisition to the effective fusion of observation information, dynamic state updating and engineering-decision support. Railway lines often cross complex geological environments, and different sections differ markedly in topography, engineering structure and operating conditions. The distribution and evolution of landslides, rockfalls, debris flows and ground settlement along the line have clear spatial continuity and may also produce risk accumulation and amplification at key nodes such as the subgrade, track, bridges, culverts, tunnel portals and bridge–tunnel transition zones. Relying on a single monitoring indicator, even if local anomalies can be identified, cannot adequately characterise the hazard-evolution process and its potential impact on engineering and operational safety [5].

The core of PAD closed-loop warning is therefore not simply to add monitoring data, but to transform discrete observations, through the assimilation process, into continuously updatable risk-state information [44]. Data assimilation plays a key role here: on the one hand, by fusing multi-source observations, it continuously corrects the hazard-evolution model and the engineering-response model, improving the accuracy of state estimation; on the other hand, with model constraints, it maintains the physical consistency and engineering rationality of the updated results, providing a more reliable dynamic basis for subsequent risk assessment and decision response. Related railway-earthwork research has also used Bayesian updating to revise slope-failure likelihood while representing uncertainty explicitly [45].

4.1. Conceptual Basis and Recent Progress of Data Assimilation

In railway geohazard warning, data assimilation does more than aggregate multi-source monitoring results. It continuously incorporates observations into hazard-evolution and railway-response models so that the estimated risk state is updated whenever new data become available. As shown in Figure 6, mileage-referenced quality control and an observation operator first relate the observations to the model forecast and quantify the innovation. The assimilation algorithm then updates the hazard state, model parameters and associated uncertainty sequentially, before mapping the updated state to railway indicators such as settlement, stability, track irregularity, clearance risk, vibration response and structural damage. The resulting estimates can therefore support risk classification, operation and maintenance decisions, and subsequent feedback updates.

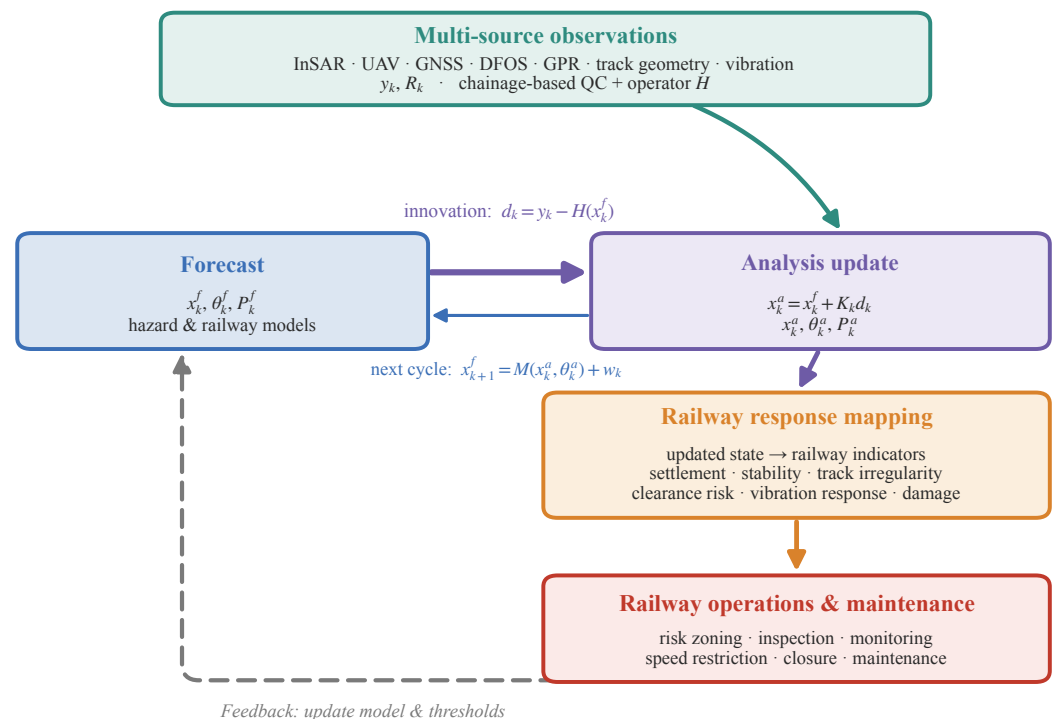


Figure 6. Sequential state-updating and railway-response mapping mechanism of data assimilation for geohazards along railways. Solid arrows indicate forward information, state or decision transfer; dashed arrows indicate feedback or iterative updating; and colours distinguish process stages or functional groups rather than universal risk thresholds.

In this review, the term data assimilation is used only when observations are combined with an explicit dynamic, physical, statistical or hybrid model to update state variables and/or model parameters, with the observation operator and uncertainty or error treatment stated or at least identifiable. Multi-source data fusion denotes registration, harmonisation or joint feature/evidence combination without such a model-state update. Anomaly detection identifies departures from a baseline or learned pattern, while risk zoning assigns sections to spatial categories using susceptibility, exposure, consequence or evidence rules. These processes can supply observations, priors or candidate sections to an assimilation cycle, but they are not themselves data assimilation. Likewise, a map created by overlaying InSAR, inventory and engineering layers remains corridor screening unless new observations formally revise a spatial model state, parameters or their uncertainty.

Mileage–Time Registration and Multi-Source Quality Control

Before assimilation, each observation should retain its value and unit, acquisition time and support interval, railway chainage, line/track/direction and component identifiers, coordinate reference, quality flag, observation-error estimate, and processing provenance. Time stamps should use a common time base with synchronisation uncertainty recorded. Fixed sensors are linked to surveyed chainage, mobile observations are map-matched to the correct track and direction, and remote-sensing or UAV/LiDAR observations are projected to the declared coordinate system and associated with corridor sections while retaining their acquisition epoch and spatial support. Asynchronous observations are matched to the model state at their actual acquisition time or through a time-aware observation operator. Quality control should check identifiers and units, timing and duplicates, spatial registration, instrument status and calibration, spikes, drift and dropout, and consistency with nearby observations or engineering records. Raw data are retained and corrected, or rejected values are flagged. Usable observations enter with their estimated uncertainty,

questionable observations require uncertainty inflation, and failed observations are excluded but remain auditable. Numerical screening limits remain sensor- and site-specific.

Railway PAD nevertheless requires a two-scale organisation. The line first needs corridor-scale screening to identify candidate sections and provide spatial priors; warning performance and operational response then depend on the evolving state of key hazard bodies, cross-sections or engineering nodes. As shown in Table 5, corridor screening covers the railway line, engineering segments and geomorphological units, using InSAR, optical remote sensing, UAV, LiDAR and historical inventories to construct the deformation background, anomaly map and preliminary risk zoning. These are perception outputs, not assimilated states by default. Site-scale assimilation focuses on major hazard bodies, cutting slopes, subgrade, transition zones, tunnel portals and culvert valley-crossing sections, using an observation operator to update displacement, pore pressure, strain, damage, stability or track-response states and their uncertainty. A corridor product becomes data assimilation only when it performs the same formal state/parameter update for an explicit spatial model. The two scales therefore form a progressive PAD relationship—wide-area screening and prior identification, focused model-based state updating, and engineering-response assessment—rather than two processes that are both labelled assimilation [46].

Table 5. Distinct roles of corridor screening and site-scale data assimilation in railway PAD.

PAD Role	Target Objects	Main Observation Sources	Principal Outputs/Updated Variables	Update Frequency	Model Requirement
Corridor perception and screening	Railway line, engineering segments, risk sections, geomorphological units along the line	InSAR, optical remote sensing, UAV, LiDAR, historical hazard inventory	Deformation background, settlement rate, anomalous patches, spatial priors and preliminary risk zoning	Weekly/monthly or task-based	Registration, baseline and zoning rules; not data assimilation unless an explicit spatial state/parameter model is updated
Site-scale data assimilation	Major hazard bodies, cutting slopes, subgrade, transition zones, tunnel portals, culvert valley sections	GNSS, inclinometer, pore pressure, optical fibre, strain gauge, acoustic emission, microseismic	Updated displacement, pore pressure, strain, frequency, damage and stability states/parameters with uncertainty	Hourly/daily, with higher frequency during imminent-failure conditions	Explicit evolution model, observation operator and observation/model-error treatment

In recent years, data-assimilation methods have gradually been introduced into geotechnical problems such as settlement prediction, landslide-displacement updating, slope-stability analysis and the prediction of the construction-induced deformation of underground structures. Unlike traditional monitoring analysis, these methods emphasise combining observation data with physical or numerical models and, through parameter inversion, state updating and uncertainty constraint, improve the model's ability to dynamically characterise the hazard-evolution process. Table 6 summarises representative data-assimilation studies in recent years for geohazards along railways and related geotechnical scenarios.

Table 6. Recent advances in data assimilation for railway-related geohazards and relevant geotechnical applications.

Algorithm	Improvement	Application Field	Model	Data Type	Performance
Variational data assimilation (VDA)	Back-calculating settlement-model parameters from DInSAR deformation	Railway embankment settlement [47]	Embankment settlement-prediction model	DInSAR displacement	Identifying settlement-sensitive sections
PIDA, PF	Introducing landslide physical constraints	Hydrodynamic-pressure-driven landslide [12]	Slip-zone degradation model	Displacement monitoring	Improving displacement-prediction accuracy
PF-based simultaneous state-parameter estimation (SSPE)	Simultaneously estimating landslide state and model parameters	Rainfall-induced landslide [48]	Displacement time-series model	Displacement, rainfall	Improving short-term prediction
Improved PF	Improving particle propagation and resampling	Rainfall-induced landslide stability [49]	TRIGRS model	Factor of safety, groundwater pressure	Correcting model bias
ES-MDA	Fusing InSAR, CPT and 3D geological model	Settlement along roads [50]	Settlement forward model	InSAR, CPT, GeoTOP	Characterising settlement heterogeneity
Ensemble-based DA (EBDA)	Fusing surface deformation and construction observation	Construction deformation of underground structures [51]	Elastic, elasto-plastic numerical models	Surface deformation, face observation	Improving construction-prediction reliability
Maximum a posteriori (MAP)	Joint calibration of settlement model with routine monitoring and satellite DInSAR	Bridge-embankment transition-zone settlement [52]	Geotechnical settlement model	Settlement plate, DInSAR displacement	Supporting maintenance decisions
MAP	—	Road bridge-embankment transition zone [53]	Simplified geotechnical settlement model	Settlement monitoring, DInSAR displacement	Evaluating maintenance scenarios
Ensemble Kalman filter (EnKF)	Bayesian assimilation update based on PS-InSAR deformation and FEM	Frozen-soil subgrade deformation of high-speed railway [54]	Frost-heave model (FHM)	PS-InSAR vertical deformation	Improving frost-heave prediction
EnKF	—	Soft-soil foundation embankment [55]	Hydro-mechanical coupled FEM	Embankment monitoring	Reducing prediction uncertainty
Kalman filter (KF)	Multi-platform time-series, ascending/descending InSAR slope-aspect reconstruction	Dynamic landslide monitoring [56]	Multi-platform InSAR estimation model	Multi-platform InSAR	Improving temporal resolution
KF	—	Landslide slope-aspect deformation [57]	Time-series InSAR state-reconstruction model	Sentinel-1 SAR	Reconstructing slope-aspect deformation
EnKF	Multi-model, multi-scheme comparison and FEM-SAR-hydrological coupled updating	Slope-stability analysis [58]	Hydro-mechanical coupled FEM	Slope deformation	Updating factor of safety
EnKF	—	Hydro-mechanical slope stability [59]	Slope-stability FEM	Synthetic deformation	Comparing algorithm applicability
EnKF	—	Geotechnical stability analysis [60]	ABAQUS FEM	Geotechnical parameters, staged observation	Updating spatial parameter field
KF	—	Landslide deformation analysis [61]	Deformation-hydrological response model	SAR deformation, hydrological factors	Revealing hydrological-response mechanism

The above studies show that the key to mechanism–data dual-driven assimilation is not simply stacking monitoring data on a mechanism model, but determining observation evidence, state variables and model constraints according to the failure mechanism. As shown in Table 7, for plastic failure such as landslides and settlement, the hazard process usually features continuous deformation and progressive deterioration, and observations such as displacement, pore pressure, settlement and strain can reflect the state evolution well. Therefore, data such as InSAR, GNSS, inclinometer, pore pressure, settlement plate, track geometry or subgrade-structure response can be introduced into creep models, Biot consolidation models, hydro-mechanical coupled models or empirical–physical hybrid models, and methods such as EnKF, PF, ES-MDA or MAP can update the displacement field, pore-pressure field, strength parameters, factor of safety and engineering-response quantities.

For brittle failure such as rockfalls, rock-mass instability and locked-segment rocky landslides, macroscopic displacement precursors are often insufficient, and the hidden damage of key load-bearing structures better reflects the critical state of instability. Railway field studies also show that seismic arrays can support near-real-time rockfall detection, localisation and characterisation [62]. The assimilation object for such hazards should not still focus mainly on displacement updating, but should take dynamic information such as natural frequency, damping ratio, frequency-drift rate, acoustic emission or microseismic energy as damage evidence, and, combined with simplified fracture-mechanics models, rock-bridge degradation models or block-stability models, update the equivalent stiffness, damage degree and instability probability.

For the rapid-onset gully-hazard row in Table 7, gauge/radar rainfall and nowcasts define the forcing ensemble, while antecedent wetness, source availability and transport parameters define the state/parameter ensemble [63–65]. Quality-controlled hydrological and debris-front or deposition evidence can update member states or weights through EnKF, PF or likelihood weighting as appropriate [49,59]. The retained members are propagated through initiation, run-out and blockage models to estimate initiation probability, arrival time, affected chainage and culvert/track blockage. The cycle is refreshed with each valid observation or nowcast, while thresholds and ensemble perturbations require catchment-specific calibration.

Algorithm choice also depends on the required update latency and the degree of nonlinearity, rather than on hazard name alone. Table 8 therefore gives a qualitative engineering comparison; the relative computational demand depends on model dimension, ensemble or particle size and the observation operator, so the ratings are intended for method selection rather than as fixed performance rankings.

Table 7. Assimilation strategies, observation cadence and engineering implications for different failure processes.

Failure Process	Mechanism Constraint and Observation Focus	State-Updating Method	Observation and Update Cadence	Engineering Implication
Plastic-dominant	Hydro-mechanical coupling and progressive deformation; displacement, pore pressure, settlement and strain	Creep, consolidation or hydro-mechanical coupled models; EnKF, PF, ES-MDA or MAP	Periodic or data-arrival updates, intensified after rainfall or accelerating deformation	Risk-level updating, intensified monitoring, speed restriction, line closure, maintenance and reinforcement
Brittle-dominant	Crack propagation and rock-bridge degradation; frequency drift, damping change, acoustic emission and microseismicity	Fracture or block-stability models; Bayesian updating, evidence fusion or parameter inversion	Continuous high-frequency dynamic sensing; event-driven updates when damage anomalies emerge	Rapid re-survey, imminent-failure warning, line closure, hazard removal and reinforcement

Table 7. Cont.

Failure Process	Mechanism Constraint and Observation Focus	State-Updating Method	Observation and Update Cadence	Engineering Implication
Rapid-onset gully hazard	Rainfall triggering, antecedent wetness, source availability and channel transport; gauge/radar rainfall, soil moisture or pore pressure, channel water level, flow/debris-front evidence and depositional change	Ensemble members perturb rainfall forcing, initial wetness/source state and hydrodynamic/rheological parameters; sequential likelihood, PF or EnKF updating is followed by member-wise initiation/run-out/blockage propagation	Continuous rainfall and channel ingestion during an event; update on each quality-controlled observation/nowcast cycle and after debris-front or blockage evidence	Probability of initiation, arrival-time/impact-range distribution and culvert/track blockage probability; speed restriction or line closure, inspection, preventive hazard removal and emergency response

Table 8. Qualitative comparison of assimilation algorithms for railway geohazard warning [49,59,66].

Algorithm	Suitable Updating Task	Relative Computational Demand	Nonlinear/Non-Gaussian Adaptability	Real-Time Suitability
KF	Low-dimensional sequential state updating with an approximately linear model	Low	Limited	High when the state and observation models remain approximately linear
EnKF	Sequential state-parameter updating with nonlinear forward models	Moderate; repeated ensemble runs	Moderate; nonlinear propagation but Gaussian update	Moderate-high with a reduced ensemble or simplified model
PF	Strongly nonlinear or non-Gaussian updating in a limited state space	High; many particles and resampling may be required	High	Limited for high-dimensional models; feasible after state reduction
ES-MDA	Windowed parameter inversion and retrospective state correction	Moderate-high; repeated forward runs	Moderate-high for nonlinear inverse problems	Low for observation-by-observation streaming; suitable for periodic recalibration
MAP/VDA	Model calibration or state estimation with an explicit objective function	Model- and optimiser-dependent	Depends on the forward model and optimisation scheme	Low-moderate; more suitable for scheduled updates than emergency cycles
Bayesian/evidence fusion	Combining sparse heterogeneous damage evidence and expert constraints	Low-moderate	Moderate; flexible evidence representation but indirect state dynamics	High for rapid screening, but it does not replace state evolution models

Compared with landslides and settlement, data-assimilation research on rapid-onset hazards such as rockfalls and debris flows remains limited. Most studies focus on parameter inversion, event back-analysis or model calibration—for example, calibrating run-out models against observations of debris-flow motion and deposition [67], or updating rock-mass parameters to improve the reliability of unstable-block stability analyses [68]. These studies provide a methodological basis for identifying gully and unstable-rock-mass hazards, but remain some distance from real-time warning and operational response. Current applications nevertheless show a clear shift from correcting individual monitoring variables to coupling multi-source observations with physical models. Most studies still address a single hazard or engineering setting, however, and no unified assimilation framework yet accommodates the multiple hazards, exposed railway assets and response requirements encountered along railway corridors [12].

The key constraint on data assimilation entering PAD closed-loop warning lies not purely in algorithm accuracy, but in the still-insufficient connection between assimilation results and engineering response. Many studies can update displacement, pore pressure or settlement states, yet do not translate these estimates into engineering problems such as speed restriction, line closure, maintenance or emergency reinforcement. Some models improve prediction accuracy but inadequately consider data gaps, error propagation and evidence-chain tracing, making the results difficult to stably enter the actual operation-and-maintenance workflow [69]. Subsequent research should therefore shift from single-hazard prediction toward closed-loop warning along railways, focusing on establishing the mapping among hazard state, track/engineering response and response measures, and forming a verifiable and transferable assimilation framework based on unified data standards and error representation.

4.2. PAD Closed-Loop Early-Warning Framework Oriented to Railways

Based on the sequential state-updating and railway-response mapping mechanism shown in Figure 6, the PAD closed-loop warning tailored to railway applications must further address the organisation among multi-source observations, hazard state and engineering response. After multi-source observations enter the warning system, they must first be interpreted within a unified engineering coordinate and physical context. InSAR deformation reflects surface displacement at a certain spatial resolution, GNSS and crack meters reflect local point changes, pore-pressure gauges reflect hydrological triggering conditions, and distributed optical fibre and engineering-inspection data are closer to structural response. Without a unified time datum, mileage stake number and error annotation, these data cannot be mapped into a common state space for updating [70].

Considering the spatial-extension feature of railways, the perception stage should cover both corridor-scale screening and intensified observation at key nodes. At the corridor scale, InSAR, optical remote sensing and historical hazard records can identify key locations such as slow-deformation zones, gully source areas and settlement-sensitive zones. After entering key sections, means such as UAVs, ground sensors, track-geometry inspection, GPR, DFOS and onboard inspection can provide higher-frequency local information. After quality control and mileage-based organisation, the data must be linked with the hazard state and engineering response through an observation operator. InSAR can constrain the regional slow-deformation background, but its result cannot be directly equated with slip-surface displacement or actual structural deformation; pore-water pressure can reflect the hydrological triggering process, but its hazard significance is affected by stratigraphic structure and drainage conditions [71]; railway engineering monitoring information such as track geometry, clearance detection, GPR and onboard inspection can reflect the impact of geohazards on the service state of the line, but still needs to be interpreted together with line-structure features and operational-control standards.

After the risk-state updating is completed, the warning result must enter a specific engineering-response workflow. The railway system needs to transform the risk level, evidence quality, impact range and uncertainty range into executable actions, including routine inspection, intensified monitoring, field re-survey, speed restriction, line closure, temporary repair, maintenance, reinforcement, and post-event re-survey and model updating. The PAD closed-loop output should not stop at a single colour level or a fixed-threshold result, but should clarify how the risk state affects key components such as the subgrade, track, bridges, culverts, tunnel portals and bridge–tunnel transition zones, and give corresponding railway operation-and-maintenance response recommendations.

4.3. Stage-Based Operation Mechanism of the PAD Closed Loop

Geohazard warning along railways usually passes through stages of normal operation, risk development, emergency response and post-event recovery, and different stages correspond to different data requirements, model complexity and decision timeliness. If the same update frequency and model configuration were always used, the normal stage might incur unnecessary computational burden, while the imminent-failure stage might fail to meet rapid-response needs. The PAD closed loop therefore needs to adjust data invocation, assimilation frequency and engineering-response strategy with the risk stage, and the operation mechanism is shown in Figure 7.

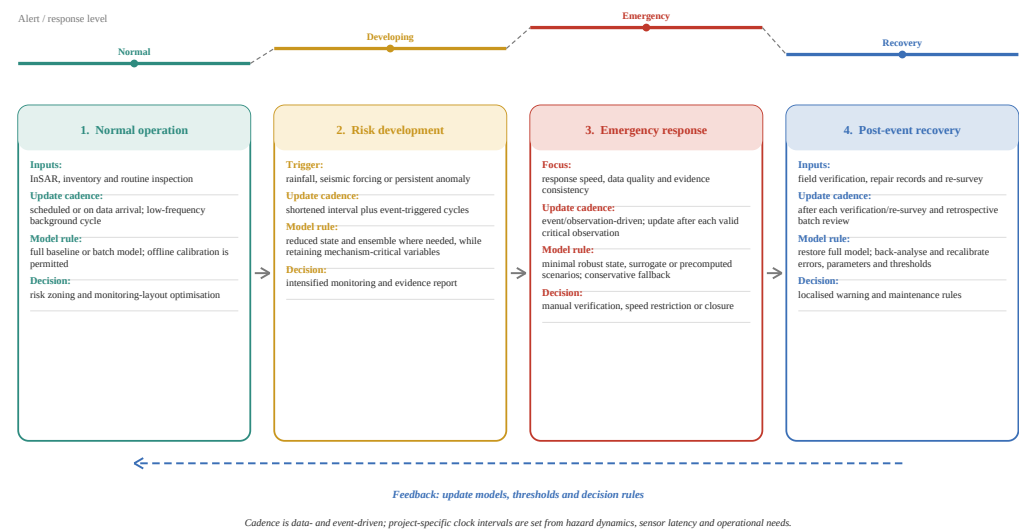


Figure 7. Stage-based operation mechanism of the PAD closed-loop early-warning framework for geohazards along railways. Each block states its data- or event-driven update cadence and the corresponding model-simplification rule; project-specific clock intervals are determined from hazard dynamics, sensor latency and railway operational needs. Solid arrows indicate forward information, state or decision transfer; dashed arrows indicate feedback or iterative updating; and colours distinguish process stages or functional groups rather than universal risk thresholds.

In the normal-operation stage, InSAR, historical hazard records and routine inspection data can jointly form a corridor-scale risk basemap to identify key sections and objects for intensified monitoring [72]. This stage should not pursue an overly high update frequency; more important is to establish a long-term stable background field and distinguish typical sections such as landslide-controlled sections, gully-hazard-sensitive sections and settlement-prone sections. Scheduled or data-arrival updates may therefore use the full baseline or batch model. The output can be used for monitoring-layout optimisation, annual maintenance planning and risk-zoning management. Continuous rainfall, seismic disturbance or the sustained enhancement of monitoring anomalies all drive the system from normal screening into the focused tracking of key sections. The update interval should then be shortened and supplemented by event-triggered cycles; if computation becomes restrictive, state dimension or ensemble size may be reduced while retaining the variables required by the governing mechanism. The update object should shift from background parameters to dynamic states: landslides should focus on updating displacement rate and pore-pressure response, debris flows on source state and channel response, rockfalls on cracks and dynamic response, and settlement on differential deformation. When the warning level changes, the evidence source, data-quality grade and uncertainty range should be provided simultaneously, so that engineers can judge the basis for the risk change [73].

The emergency-response and post-event recovery stages place greater emphasis on response speed and evidence reliability. During heavy rainfall, rockfall or sudden settlement, communications may be interrupted, sensors may fail and data may be missing, and complex models are also more susceptible to error amplification in the strongly nonlinear evolution stage [73]. Emergency updating should therefore be driven by each valid critical observation or event and use a minimal robust state, validated surrogate or precomputed scenario when the full model cannot meet the response time; conservative fallback and manual verification remain mandatory when data quality declines or sources disagree. When multi-source evidence is consistent in direction and the data quality is reliable, the automated warnings may be assigned greater weight. Railway operators may take measures such as speed restriction, line closure, intensified inspection, temporary repair, emergency reinforcement or hazard removal according to the risk level and affected component. After the emergency response, field verification, repair records and re-survey results should flow back to the database and the assimilation model rather than being kept only as archives. Recovery updates occur after verification and re-survey and may restore the full model for retrospective back-analysis, parameter/error recalibration and threshold review. Through post-event review, model parameters, error structures and response rules can be gradually corrected, forming a localised warning capability suited to a specific line, geological environment and operational organisation. For railways with long service periods and wide cross-regional coverage, post-event feedback determines the long-term reliability of the warning system more than the accuracy of a single prediction [10].

Overall, the data-assimilation and PAD closed-loop warning framework connects multi-source monitoring techniques with engineering-oriented warning applications. In geohazard prevention and control along railways, multi-source perception provides the data basis, data assimilation completes state updating and parameter correction, and the decision stage transforms the risk state into railway operational-response measures. Because landslides, rockfalls, debris flows and settlement have different evolution mechanisms, their impact paths on the subgrade, track, bridges, culverts, tunnel portals and bridge-tunnel transition zones also differ, so the warning system must simultaneously consider hazard type, failure mechanism and engineering interaction mode. By constructing the mapping among hazard state, engineering response and response measures, the PAD closed loop can drive geohazard warning along railways from single-point monitoring, empirical thresholds and post-event intervention toward multi-source perception, dynamic assimilation and closed-loop decision-making.

5. Challenges, Trends and Engineering Application Prospects for Railways

Existing research and engineering practice have formed a solid foundation in remote-sensing identification, ground monitoring, risk assessment and emergency response, but the connection from multi-source perception to state updating and then to railway engineering decisions remains insufficiently tight. The engineering application of geohazard warning along railways depends not only on the monitoring techniques and modelling methods themselves, but also on whether they can be connected with specific affected components, operation-and-maintenance workflows and response measures. In long-distance railways in particular, geological conditions change rapidly along the line, hazard-type combinations are complex, and monitoring data come from scattered sources, so how warning results translate into executable inspection, speed restriction, closure, maintenance and reinforcement measures still warrants further discussion.

5.1. Challenges and Development Trends

5.1.1. Perception: Comparable Evidence and Sustainable Coverage

The main perception challenge is not a shortage of sensors but the lack of comparable evidence over a long, heterogeneous asset. Remote sensing, UAVs, onboard and track-geometry inspection, GPR, DFOS, GNSS, pore-water pressure, crack and stress measurements differ in spatial support, sampling frequency, error source and relation to the hazard state. Direct stacking can therefore create a false impression of agreement: a remote-sensing pixel may indicate persistent regional settlement, a point sensor may represent only a local layer, and track inspection may show an engineering response without identifying its subsurface cause. The immediate priority is a railway data model that preserves time, chainage, track, component, footprint, processing provenance and uncertainty, combined with the registration and quality-control procedure defined in Section 4.1. Coverage must also be sustainable. Corridor sensing should reduce the number of locations requiring permanent instrumentation, while existing inspection trains, telecommunications fibre and maintenance visits should be reused where their data quality is adequate. Otherwise, a nominally comprehensive perception layer may deteriorate through power, communications, calibration and access failures before it provides a useful warning record.

Artificial intelligence can assist this component through image interpretation, cross-sensor anomaly detection, automated quality flags and the prioritisation of field verification. Its limitation is that rare hazardous events, sensor replacement and environmental change create distribution shift: a classifier trained on normal operation may be confident precisely when the site enters an unseen state. AI outputs should therefore remain traceable to source observations, carry out-of-distribution or confidence information and trigger human verification when evidence is novel or conflicting. In PAD, AI-assisted detection is a perception output unless it is subsequently linked to a formal model-state update; this boundary prevents an accurate classifier from being mistaken for an assimilated hazard state.

5.1.2. Assimilation: Model Inadequacy, Nonlinearity and Advanced Updating

The principal assimilation challenge is joint uncertainty in observations and models. Vegetation, viewing geometry, surface-cover change, rainfall, groundwater and construction disturbance produce source-dependent errors, while simplified hazard models omit local stratigraphy, drainage, fracture geometry or source availability. If these errors are represented poorly, an update may interpret observation noise as hazard evolution or force a biased model toward an apparently precise but incorrect state. Model discrepancy, observation error, registration uncertainty and parameter non-identifiability must therefore be separated where possible, and posterior predictive checks should accompany the updated state. The different warning rhythms also matter: progressive landslides and settlement permit sequential trend updating, whereas debris flows and rockfalls may produce non-Gaussian, multimodal or threshold-dominated states for which a Gaussian update is inadequate.

Advanced data-assimilation research should consequently be selected by failure mechanism and decision latency rather than by algorithm novelty. Ensemble Kalman methods are efficient for moderately nonlinear continuous states but can suffer from limited-ensemble covariance and Gaussian assumptions; particle filters can represent non-Gaussian posteriors but may degenerate in high-dimensional systems; variational and smoother methods exploit time windows but introduce optimisation cost and can delay event response; multi-model or model-averaging approaches expose structural uncertainty but require defensible model weights [49,59,66]. Promising directions include adaptive ensemble design, localisation and inflation for spatial railway states, Rao–Blackwellised or hybrid ensemble–particle schemes for mixed continuous/event variables, moving-window

smoothers for retrospective calibration, and explicit model-discrepancy terms. These methods should be benchmarked not only by prediction error but also by calibration, robustness to missing or conflicting sensors, computational latency and stability under rare-event conditions.

Physics-informed machine learning and learned surrogates can reduce model cost or supply observation operators when full numerical models are too slow. However, a surrogate should be trained and tested over the operational envelope, constrained by conservation or stability relations where appropriate, and accompanied by uncertainty and fallback rules. Online learning from post-event feedback is valuable only if model and data versions are controlled; otherwise, silent model drift can change warning behaviour without engineering review. The credible frontier is therefore not an autonomous black-box warning system, but a hybrid assimilation architecture in which physical constraints, probabilistic updating and AI components have explicit roles and auditable failure modes.

5.1.3. Decision and Feedback: Railway Consequences, Governance and Learning

The decision gap is the translation of a posterior hazard state into consequences for a specific railway asset. The same surface displacement can have different implications for a uniform embankment section, a transition zone, a tunnel portal or a clearance-sensitive cutting. Generic geohazard thresholds should therefore not be transferred directly. The posterior distribution must first be mapped to track level/alignment, clearance intrusion, culvert capacity, structural response or affected chainage, and then combined with lead time, traffic exposure, evidence quality and uncertainty. Decision rules require railway-specific calibration, accountable approval and conservative fallback when the state estimate and engineering observations disagree.

Cloud–edge computing can shorten this chain: the cloud can maintain historical records, regional models, model training and cross-section comparison, while the edge handles quality screening, reduced-order updating and rapid alerts when communications are constrained. Speed alone is insufficient, however. Every warning should retain the observation set, software and model version, posterior uncertainty, threshold version, operator decision and subsequent field outcome. False alarms, missed detections, inspections, maintenance and post-event surveys must feed back separately to perception quality rules, assimilation error models and decision thresholds. This governance closes the PAD loop and provides the evidence needed to determine whether additional sensing or model complexity produces a real operational benefit rather than only a better retrospective fit.

5.2. Engineering Application Prospects for Risk Warning Along Railways

High-speed railways have high requirements for track smoothness and operational continuity. Although settlement and differential settlement develop relatively slowly, their long-term accumulation affects the track-geometry state and further increases maintenance pressure. For soft-soil areas, cut–fill boundary sections, bridge–tunnel transition zones and existing settlement-anomaly areas, a single inspection captures only a snapshot and cannot adequately describe the evolution of settlement. Therefore, as shown in Figure 8, railway settlement warning can build a PAD closed loop following the logic of “remote-sensing identification–ground verification–state updating–operation and maintenance response”.

InSAR is mainly used to obtain long-term settlement trends across an extended railway corridor and to identify sections with high settlement rate or marked spatial difference. Precise levelling, GNSS and track-geometry inspection can correct the deformation magnitude of key components and judge whether settlement has already affected the service state of the line. Field-inspection data can supplement engineering information on the ballast, subgrade, bridge–tunnel transition zones and drainage facilities. Different data

have different emphases in the closed loop: remote-sensing data provide corridor-scale background identification, ground monitoring data provide local continuous constraints, and track-inspection data directly connect settlement deformation with operational safety. Within the assimilation component, settlement magnitude, settlement rate and foundation parameters are the principal state and parameter variables to be updated. Historical settlement series, engineering-geological zoning and existing maintenance records can serve as background information to establish the initial prediction field of settlement development, and subsequent InSAR, GNSS, levelling and track-inspection data are used to correct the prediction. For sections where settlement develops stably, a lower update frequency can be adopted, focusing on whether they deviate from the long-term consolidation trend; sections with accelerating settlement, increasing differential settlement or abnormal track geometry require more frequent assimilation and targeted monitoring. Thus, railway settlement warning can gradually shift from single-point threshold judgement to sectional state updating.

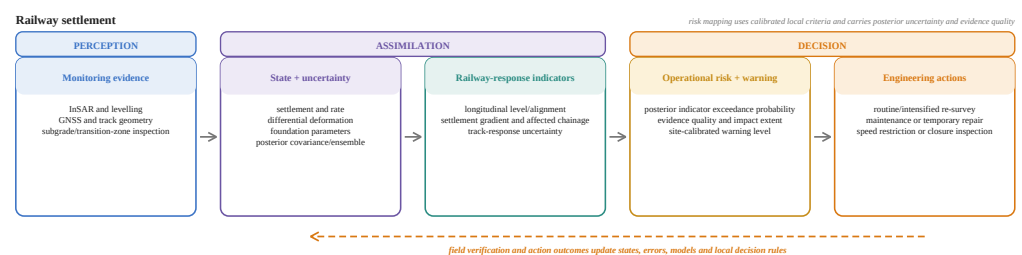


Figure 8. PAD-based closed-loop workflow for railway settlement early warning. The workflow explicitly separates monitoring evidence, updated state and uncertainty, railway-response indicators, operational risk/warning level and engineering actions. Solid arrows indicate forward information, state or decision transfer; dashed arrows indicate feedback or iterative updating; and colours distinguish process stages or functional groups rather than universal risk thresholds.

At the decision end, settlement-warning results can be transformed into operation-and-maintenance measures at different levels. Sections where settlement is slow and has not yet affected the track state can be included in routine re-survey and maintenance plans. Sections with accelerating settlement or increasing differential settlement require more frequent inspection and advance maintenance planning. When a settlement anomaly has already affected the track-geometry state or is approaching the operational-control standard, measures such as speed restriction, temporary repair or focused closure inspection can be taken. In this way, the PAD closed loop does not simply add a prediction model, but connects remote-sensing identification, ground monitoring, state updating and railway operation and maintenance.

The same explicit decision chain is required for landslides, rockfalls and debris flows, but their state variables, railway-response indicators and warning lead times differ, as shown in Figure 9. For a landslide, the posterior displacement, pore-pressure and stability state is mapped to lateral subgrade deformation, track alignment/level response, clearance risk and affected chainage. For an unstable rock block, damage, crack connectivity and detachment probability are mapped to the probability and location of track or catenary intrusion. For a debris flow, the initiation and run-out ensemble is mapped to arrival time, affected chainage, burial/impact range and culvert or track blockage probability. The operational warning level is then determined from the posterior probability of these railway-response indicators, the estimated impact extent and lead time, and the quality and consistency of the supporting evidence. The mapping criteria are calibrated for the site and railway asset; the posterior mean alone is not treated as a decision. High uncertainty or inconsistent evidence triggers conservative restrictions and rapid verification rather than

an unsupported automatic downgrade, consistent with uncertainty-aware railway-slope risk assessment [74].

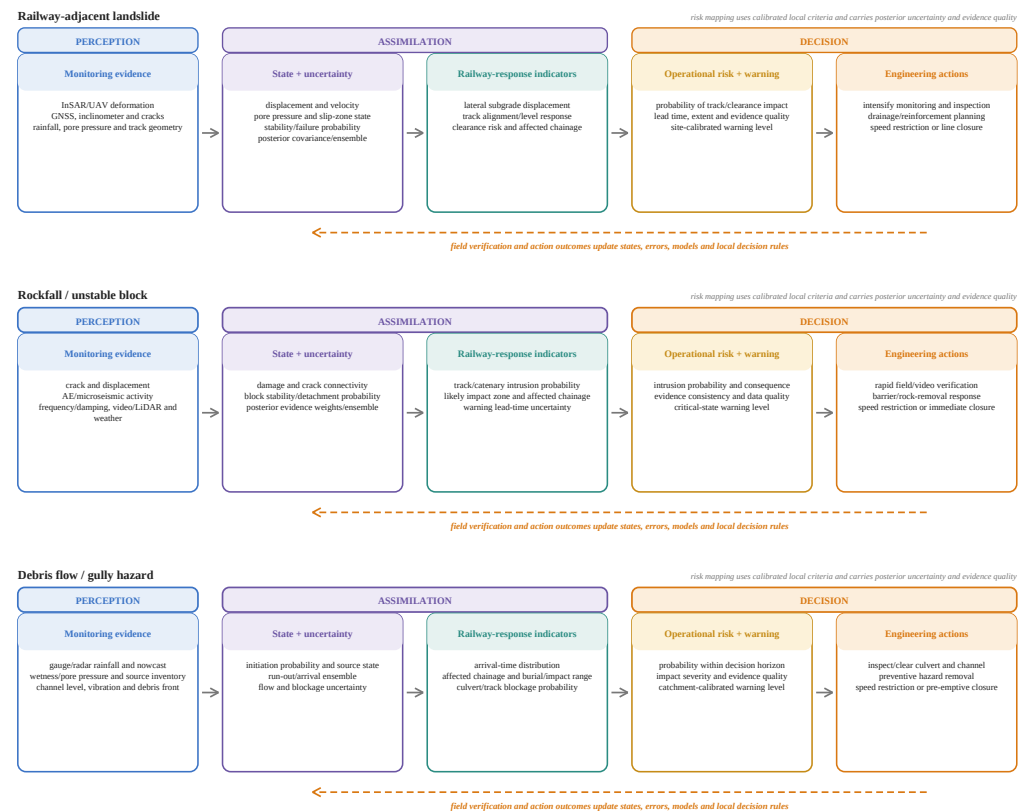


Figure 9. Complete PAD closed-loop workflows for, from top to bottom, a railway-adjacent landslide, an unstable rock block and a debris-flow/gully hazard. Each workflow follows the explicit chain “monitoring evidence–state and uncertainty–railway-response indicators–operational risk and warning level–engineering actions”, with field verification and action outcomes fed back to update states, error models and local decision rules. Solid arrows indicate forward transfer, dashed arrows indicate feedback, and colours distinguish functional groups rather than universal risk thresholds.

5.3. Case-Based Demonstration of the PAD Framework Using Published Railway Measurements

5.3.1. Case and Measured Data

A case-based demonstration was conducted using published measured InSAR and Optram observations from the Malmbanan railway in northern Sweden. The purpose is not to claim a new experimental validation, but to retrospectively organise an existing railway study according to the PAD workflow and demonstrate how its published outputs can support engineering interpretation. Palmqvist et al. [75] investigated the single-track Kiruna-Riksgränsen section of Malmbanan using Sentinel-1A/B C-band imagery and Optram survey-train measurements. Ascending and descending Sentinel-1 Single Look Complex data acquired between 27 September 2015 and 26 June 2020 were processed with Persistent Scatterer Interferometry (PSI). The report generated vertical and horizontal surface-motion time series and compared railway-adjacent PS observations with Optram track-geometry measurements. Both datasets included spatial positions, enabling nearest-point matching and section-based comparison. These processing, matching and classification operations were performed in the published project; the present review did not obtain or reprocess the proprietary raw measurements and did not rerun a data-assimilation algorithm.

5.3.2. Corridor-Scale Screening

In PAD terms, the published InSAR product represents wide-area perception and spatial-prior identification rather than strict data assimilation. Palmqvist et al. [75] examined vertical and horizontal motion within an approximately 800 m wide corridor centred on the Kiruna–Riksgränsen railway. The dominant mean vertical-velocity range was approximately -10 to $+10$ mm/year, while marked subsidence of about -25 mm/year occurred around Kirunavaara, Björkliden and Riksgränsen. The observations therefore supported corridor-level hotspot screening and indicated where railway-specific evidence should be examined more closely. One published hotspot, KM Tavla 1513/802 near Björkliden, had a mean vertical velocity of -23.4 mm/year over 2015–2020 and a cumulative vertical displacement of -118.6 mm. These values are retained as published annotations in Figure 10; they are not recomputed results or universal railway risk thresholds.

Malmbanan (Kiruna–Riksgränsen): published measurements organized as a retrospective PAD demonstration

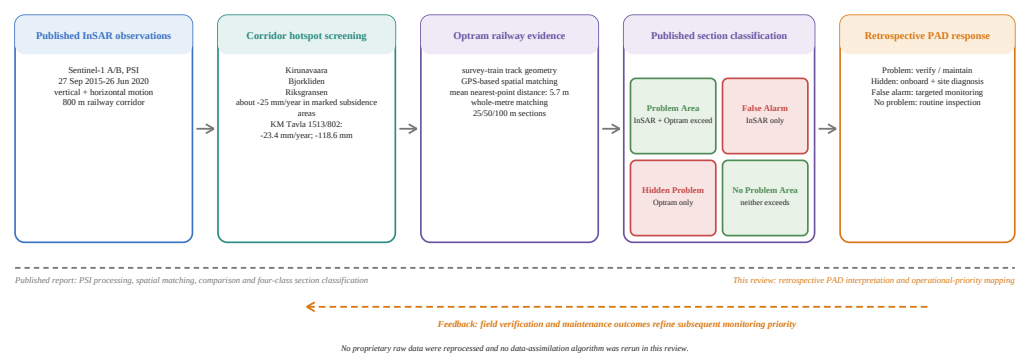


Figure 10. Retrospective PAD interpretation of published measured InSAR and Optram observations from the Malmbanan Kiruna–Riksgränsen case [75]. The first four blocks summarise the published PSI observations, hotspot screening, spatial matching and four-class section classification; the operational-priority mapping and feedback block are the interpretation introduced in this review. No proprietary raw data were reprocessed and no assimilation algorithm was rerun.

5.3.3. Site-Level Evidence Integration and Zoning

The report then provided the railway-condition evidence needed to interpret the InSAR hotspots. Optram records track geometry from survey trains, whereas InSAR measures ground-surface motion over a spatial cell; the two sources are therefore complementary rather than interchangeable. The published matching procedure related Optram locations to their nearest InSAR PS points, with a reported mean nearest-point distance of approximately 5.7 m, reduced the matched measurements to whole-metre positions, and grouped threshold exceedances into 25, 50 and 100 m sections [75]. Thirty-one sensitivity tests varied time period, section length and one- or two-standard-deviation thresholds. The report classified each section as a Problem Area when both InSAR and Optram exceeded their thresholds, a Hidden Problem when only Optram exceeded, a False Alarm when only InSAR exceeded, or a No Problem Area when neither exceeded. This was a published comparison/classification exercise, not a posterior state update. The report also cautioned that Optram measured railway height at 0.25 m intervals while the InSAR product represented approximately 15×15 m ground cells, and that low-coherence filtering removed a large proportion of candidate InSAR points. These scale and quality differences limit any claim of direct equivalence.

5.3.4. PAD Interpretation and Operational Implication

Figure 10 reorganises the published evidence as a retrospective PAD demonstration without reproducing the report's geographic classification map. In this interpretation, a Problem Area provides mutually supporting ground-motion and track-condition evidence and should receive priority field verification, intensified monitoring and maintenance assessment. A Hidden Problem shows that the railway measurement is abnormal although the InSAR screening has not identified the section; onboard and site monitoring should therefore remain decisive and the cause should be diagnosed locally. A False Alarm indicates marked surrounding ground motion without a contemporaneous Optram threshold exceedance; it should be retained as a targeted monitoring section rather than automatically treated as either a railway failure or an irrelevant signal. A No Problem Area remains in routine inspection unless subsequent observations change its evidence state. Field verification, maintenance findings and later monitoring should feed back to the section classification and local decision rules. The case thus illustrates the railway-oriented chain “corridor screening–local railway-condition evidence–section classification/risk zoning–operational priority–monitoring feedback”. The final operational-priority mapping is the interpretation proposed by this review, whereas PSI processing, spatial matching, threshold comparison and the four published section categories belong to Palmqvist et al. [75]. This demonstrates engineering applicability at a scale appropriate for a review article, but it does not present a new PAD validation or a reanalysis of the Malmaban dataset.

5.4. Extended Application to Other Engineering Interaction Types Along Railways

In addition to settlement-type risks, intrusion-type, scour/undermining-type and dynamic-response-type problems can also be incorporated into the PAD closed loop along railways. Intrusion-type risks can combine video, LiDAR, microseismic, acoustic-emission, crack and rainfall data to support rapid responses to rockfall clearance intrusion, ballast burial and portal blockage; scour/undermining-type risks can combine GPR, water level, flow velocity, culvert inspection and vibration response for the verification and reinforcement of bridge–culvert foundations, subgrade bases and tunnel-invert cavities; dynamic-response-type risks can use track geometry, axle-box or car-body acceleration, wheel–rail force and DFOS/DAS vibration information to identify abnormal ballast stiffness, abrupt transition-zone stiffness change and foundation degradation. It should be noted that the dynamic-response type is not a traditional independent geohazard, but the dynamic-response manifestation of an abnormal railway–foundation state under train loading. Including it in the engineering interaction types is intended to serve railway operation monitoring and PAD decision mapping.

Overall, the above extended applications should still follow the chain of “multi-source perception–state assimilation–track-geometry and engineering-response mapping–railway operational-response output–feedback updating”. Other transportation geotechnical scenarios, such as pipelines crossing landslide-prone slopes [76–78], can draw on this framework in future research, but the engineering-application focus of this paper remains on geohazard warning along railways.

6. Conclusions

This review yields four main conclusions:

(1) Railway geohazard warning should be organised by the evolving failure mechanism and railway interaction, not by a fixed hazard label alone. Progressive deformation, damage accumulation and rapid-onset gully processes require different observations, update rhythms and decision lead times, while mixed sites may move between these regimes. The plastic–brittle distinction is therefore useful as a pair of mechanism end

members, provided that transitional behaviour and debris-flow triggering/transport are represented explicitly.

(2) Corridor screening and data assimilation solve different problems. InSAR, inventories and engineering layers can identify spatial anomalies and priorities across a long line, but fusion, anomaly detection and zoning are not data assimilation unless observations formally update an explicit model state or parameters with uncertainty treatment. The defensible two-scale organisation is consequently “corridor perception and prior identification–site-scale state/parameter updating–railway-response mapping”. This distinction is essential for comparing methods and for avoiding unsupported claims of assimilation performance.

(3) The practical contribution of PAD is the closed engineering chain rather than the names of its three components. Monitoring evidence is registered by time, chainage and asset; mechanism-conditioned assimilation produces a state estimate and uncertainty; the result is mapped to track geometry, clearance, blockage, structural response or affected chainage; and the railway operator selects verification, intensified monitoring, maintenance, speed restriction or closure, with outcomes returned to the data, model and decision rules. The Malmaban demonstration shows that published InSAR screening and track-geometry evidence can be retrospectively organised along this chain, while also showing the present limit: it is an engineering illustration, not a new validation of PAD or a reanalysis of proprietary data.

(4) The principal research gaps are now implementation gaps. They include durable multi-source data governance; observation and model-error separation; calibrated local thresholds; non-Gaussian and mixed-process assimilation; robust mapping from posterior hazard state to railway consequence; life-cycle affordability; and prospective validation using shared measured datasets and recorded operational outcomes. AI, hybrid ensemble-particle methods, smoothers and learned surrogates are promising only when uncertainty, distribution shift, latency, traceability and conservative fallback are evaluated. Future studies should therefore compare complete warning chains by calibration, missed-event and false-alarm behaviour, decision lead time, operational benefit and long-term maintainability, rather than by prediction accuracy alone.

Author Contributions: Conceptualisation, Yan Du and Mowen Xie; methodology, Yan Du and Anqi Zhang; investigation, Anqi Zhang, Hongda Zhang and Jingnan Liu; writing—original draft preparation, Yan Du and Anqi Zhang; writing—review and editing, Yan Du, Mowen Xie and Yujing Jiang; visualisation, Anqi Zhang and Hongda Zhang; supervision, Mowen Xie and Yujing Jiang; funding acquisition, Yan Du and Jingnan Liu. All authors have read and agreed to the published version of the manuscript.

Funding: This research was funded by the National Key R&D Program of China (2023YFC3081400), the National Natural Science Foundation of China (41702371), the Open Fund Project of State Key Laboratory of Mining Response and Disaster Prevention in Deep Coal Mines (SKLMRDPC22KF13), the Open Fund Research Project Supported by State Key Laboratory of Strata Intelligent Control and Green Mining Co-founded by Shandong Province and the Ministry of Science and Technology (SICGM202503), and the Fund of Chongqing Key Laboratory of Facility Damage Mechanism and Protection in Highland Mountain Environment (LQ24KFJJ09).

Data Availability Statement: No new raw monitoring data were generated or reprocessed in this review. The case-based demonstration relies on published measured observations reported by Palmqvist et al. [75]; access to the underlying data is governed by the original project and data owners.

Conflicts of Interest: The authors declare no conflicts of interest.

Glossary

Variable glossary for Figure 6. Note: all vectors, matrices and operators are application-dependent; the schematic update denotes the common forecast–observation–analysis structure rather than a single mandatory assimilation algorithm.

Symbol	Physical/statistical meaning	Symbol	Physical/statistical meaning
k	Analysis epoch; $k + 1$ denotes the next forecast/update cycle.	f, a	Superscripts denoting forecast (prior) and analysis (posterior) quantities.
$\mathbf{y}_k$	Quality-controlled multi-source observation vector at epoch k , after mileage/time registration. Forecast and updated state vectors; application-dependent entries may include displacement, pore pressure, damage state, settlement or railway-response variables.	$\mathbf{R}_k$	Observation-error covariance, including measurement and registration uncertainty.
$\mathbf{x}_k^f, \mathbf{x}_k^a$	Forecast and updated estimation-error covariance (or ensemble-derived uncertainty representation) for the estimated state/parameters.	$\boldsymbol{\theta}_k^f, \boldsymbol{\theta}_k^a$	Forecast and updated model-parameter vectors for the hazard and railway-response models.
$\mathbf{P}_k^f, \mathbf{P}_k^a$	Innovation, $\mathbf{d}_k = \mathbf{y}_k - \mathcal{H}_k(\mathbf{x}_k^f)$, i.e., the observation-minus-forecast residual.	$\mathcal{H}_k(\cdot)$	Observation operator mapping the forecast state into the measurement space at the observation support and epoch.
$\mathbf{d}_k$	Hazard/railway evolution model propagating the updated state and parameters to the next epoch.	$\mathbf{K}_k$	Gain or algorithm-specific update operator that maps the innovation to a state/parameter correction.
$\mathcal{M}_k(\cdot)$		$\mathbf{w}_k$	Process/model-error term representing unresolved forcing and model inadequacy during propagation.

References

1. Liu, C. Research on the prevention and response of geological hazards along linear engineering. *Chin. J. Geol. Hazard Control* **2024**, *35*, 1–4. (In Chinese)
2. Liu, Y.; Xu, C.; Huang, B.; Ren, X.; Liu, C.; Hu, B.; Chen, Z. Landslide displacement prediction based on multi-source data fusion and sensitivity states. *Eng. Geol.* **2020**, *271*, 105608. [CrossRef]
3. Zhang, K. Review on geological disaster monitoring and early warning system based on “3S” technology in China. *Chin. J. Geol. Hazard Control* **2020**, *31*, 1–11. (In Chinese)
4. Wu, S.; Qi, D.; Li, H.; Lan, Y.; Li, J.; Sun, M. A multifactor coupled early-warning model for pipeline landslide hazards based on the dynamic evolutionary process of disaster. *Hydrogeol. Eng. Geol.* **2024**, *51*, 182–189. (In Chinese)
5. Liu, H.; Bai, M.; Li, Y.; Yang, L.; Shi, H.; Gao, X.; Qi, Y. Landslide displacement prediction model based on multisource monitoring data fusion. *Measurement* **2024**, *236*, 115055. [CrossRef]
6. Kostrzewski, M.; Melnik, R. Condition monitoring of rail transport systems: A bibliometric performance analysis and systematic literature review. *Sensors* **2021**, *21*, 4710. [CrossRef] [PubMed]
7. Zschiesche, K.; Reiterer, A. Optical measurement system for monitoring railway infrastructure—A review. *Appl. Sci.* **2024**, *14*, 8801. [CrossRef]
8. Koohmishi, M.; Kaewunruen, S.; Chang, L.; Guo, Y. Advancing railway track health monitoring: Integrating GPR, InSAR and machine learning for enhanced asset management. *Autom. Constr.* **2024**, *162*, 105378. [CrossRef]
9. Banic, M.; Ristic-Durrant, D.; Madic, M.; Klapper, A.; Trifunovic, M.; Simonovic, M.; Fischer, S. The use of Earth observation data for railway infrastructure monitoring—A review. *Infrastructures* **2025**, *10*, 66. [CrossRef]
10. Piciullo, L.; Tiranti, D.; Pecoraro, G.; Cepeda, J.M.; Calvello, M. Standards for the performance assessment of territorial landslide early warning systems. *Landslides* **2020**, *17*, 2533–2546. [CrossRef]

11. Liu, G.; Mao, W.; Wang, X.; Zhang, R.; Jia, H. A review of key technologies for fine-scale InSAR monitoring of geological hazards along high-speed railways. *J. Southwest Jiaotong Univ.* **2026**, *61*, 785–805. (In Chinese)
12. Liu, Y.; Long, J.; Li, C.; Zhan, W. Physics-informed data assimilation model for displacement prediction of hydrodynamic pressure-driven landslide. *Comput. Geotech.* **2024**, *167*, 106085. [[CrossRef](#)]
13. Zhang, H.; Tang, M.; Tang, M.; Zhang, W. Risk assessment method for landslide disasters of oil and gas pipelines in mountainous areas. *J. Geol. Hazards Environ. Preserv.* **2022**, *33*, 90–95. (In Chinese)
14. Du, Y.; Li, R.; Xie, M.; Jiang, Y.; Zhang, H.; Liu, J. Mechanism differentiation of geological hazards with plastic and brittle failure and data assimilation early warning paradigm. *J. China Univ. Min. Technol.* **2026**, 1–21. (In Chinese). [[CrossRef](#)]
15. Feng, L.; Intrieri, E.; Pazzi, V.; Gigli, G.; Tucci, G. A framework for temporal and spatial rockfall early warning using micro-seismic monitoring. *Landslides* **2021**, *18*, 1059–1070. [[CrossRef](#)]
16. Zhang, J.; Tang, H.; Li, C.; Gong, W.; Zhou, B.; Zhang, Y. Deformation stage division and early warning of landslides based on the statistical characteristics of landslide kinematic features. *Landslides* **2024**, *21*, 717–735. [[CrossRef](#)]
17. Yang, Y.R.; Lee, T.-T.; Wang, T.-T. Spatiotemporal characteristics of ground microtremor in advance of rockfalls. *Sci. Rep.* **2022**, *12*, 7038. [[CrossRef](#)] [[PubMed](#)]
18. Liu, X. Analysis of shallow landslide induced by “23·7” heavy rainstorm: Taking Mentougou District in Beijing as an example. *Urban Geol.* **2025**, *20*, 143–149. (In Chinese)
19. Chen, H.; Qin, X. Status quo and trend of unstable rock stability analysis. *J. Chongqing Jiaotong Univ. (Nat. Sci.)* **2018**, *37*, 49–60. (In Chinese)
20. Chen, M.; Huang, D.; Jiang, Q. Slope movement classification and new insights into failure prediction based on landslide deformation evolution. *Int. J. Rock Mech. Min. Sci.* **2021**, *141*, 104733. [[CrossRef](#)]
21. Du, Y.; Huo, L.; Xie, M.; Jiang, Y.; Jia, B.; Cong, X. Monitoring and early warning experiment of rock collapse. *Chin. J. Theor. Appl. Mech.* **2021**, *53*, 1212–1221. (In Chinese)
22. Bottelin, P.; Méric, O.; Baillet, L.; Beniamine, D.; Lescurier, A. Mapping rockfall hazard and detecting precursory damage in rock slopes with passive seismic: Lessons from the La Praz case-study. *Eng. Geol.* **2024**, *338*, 107627. [[CrossRef](#)]
23. D’Angiò, D.; Lenti, L.; Martino, S. Microseismic monitoring to assess rock mass damaging through a novel damping ratio-based approach. *Int. J. Rock Mech. Min. Sci.* **2021**, *146*, 104883. [[CrossRef](#)]
24. Wang, X.; Diao, M.; Guo, H.; Wang, L.; Guo, H.; Li, D. Landslide deformation prediction and automatic warning by coupling machine learning and physical models. *Earth Space Sci.* **2024**, *11*, e2023EA003238. [[CrossRef](#)]
25. Feng, L.; Zhang, Z. Seismic monitoring in rockfall: A literature review. *J. Eng. Geol.* **2024**, *32*, 545–564. (In Chinese)
26. Ragnoli, M.; Scarsella, M.; Leoni, A.; Ferri, G.; Stornelli, V. Wireless sensor network-based rockfall and landslide monitoring systems: A review. *Sensors* **2023**, *23*, 7278. [[CrossRef](#)] [[PubMed](#)]
27. Kizilirmak, G.; Cakir, Z. Application of PS-InSAR and diagnostic train measurement techniques for monitoring subsidence in high-speed railway in Konya, Türkiye. *Infrastructures* **2024**, *9*, 152. [[CrossRef](#)]
28. Chang, L.; Sakpal, N.P.; Oude Elberink, S.; Wang, H. Railway infrastructure classification and instability identification using Sentinel-1 SAR and laser scanning data. *Sensors* **2020**, *20*, 7108. [[CrossRef](#)] [[PubMed](#)]
29. Huntley, D.; Rotheram-Clarke, D.; Pon, A.; Tomaszewicz, A.; Leighton, J.; Cocking, R.; Joseph, J. Benchmarked RADARSAT-2, Sentinel-1 and RADARSAT Constellation Mission change-detection monitoring at North Slide, Thompson River Valley, British Columbia: Ensuring a landslide-resilient national railway network. *Can. J. Remote Sens.* **2021**, *47*, 635–656. [[CrossRef](#)]
30. Xu, Q.; Song, K.; Liu, H.; Zheng, W.; Dong, S.; Zhang, L. Remote real-time monitoring and early warning of pipeline status under landslide conditions based on stress–strain analysis. *ASCE-ASME J. Risk Uncertain. Eng. Syst. A Civ. Eng.* **2024**, *10*, 04023060. [[CrossRef](#)]
31. Hou, H.; Chen, M.; Tie, Y.; Li, W. A Universal Landslide Detection Method in Optical Remote Sensing Images Based on Improved YOLOX. *Remote Sens.* **2022**, *14*, 4939. [[CrossRef](#)]
32. Chen, Y.; Liu, X.; Zhu, B.; Zhu, D.; Zuo, X.; Li, Q. UAV Image-Based 3D Reconstruction Technology in Landslide Disasters: A Review. *Remote Sens.* **2025**, *17*, 3117. [[CrossRef](#)]
33. Zhao, L.; Ma, X.; Xiang, Z.; Zhang, S.; Hu, C.; Zhou, Y.; Chen, G. Landslide Deformation Extraction from Terrestrial Laser Scanning Data with Weighted Least Squares Regularization Iteration Solution. *Remote Sens.* **2022**, *14*, 2897. [[CrossRef](#)]
34. Li, Z.H.; Jiang, N.; Shi, A.C.; Zhao, L.-Y.; Xian, Z.; Luo, X.-L.; Li, H.-B.; Zhou, J.-W. Reservoir landslide monitoring and mechanism analysis based on UAV photogrammetry and sub-pixel offset tracking: A case study of Wulipo landslide. *Front. Earth Sci.* **2024**, *11*, 1333815. [[CrossRef](#)]
35. Hu, M.; Ren, Y.; Xiao, L.; Liu, X.; Tan, Q.; Han, H.; Guo, J. Landslide monitoring based on GNSS and automated inclinometer systems and dynamic modeling using SPH: A case study in Qinghai, China. *Environ. Earth Sci.* **2024**, *83*, 170. [[CrossRef](#)]
36. Anjana, K.; Herath, M.; Epaarachchi, J. Optical fibre sensors for geohazard monitoring: A review. *Measurement* **2024**, *235*, 114846. [[CrossRef](#)]

37. Zhu, H.H.; Liu, W.; Wang, T.; Su, J.W.; Shi, B. Distributed acoustic sensing for monitoring linear infrastructures: Current status and trends. *Sensors* **2022**, *22*, 7550. [\[CrossRef\]](#) [\[PubMed\]](#)
38. Cao, Y.; Li, J.; Sun, Y.; Su, S.; Yang, W.; Wang, W. Design of comprehensive inspection vehicle for heavy-haul railway lines. *China Saf. Sci. J.* **2026**, *36*, 57–62. (In Chinese)
39. Kononen, A.; Kaartinen, H.; Kukko, A.; Lehtomäki, M.; Taher, J.; Hyypä, J. Fully automated extraction of railtop centerline from mobile laser scanning data. *Autom. Constr.* **2024**, *168*, 105812. [\[CrossRef\]](#)
40. Wang, S.; Liu, G.; Jing, G.; Feng, Q.; Liu, H.; Guo, Y. State-of-the-art review of ground penetrating radar (GPR) applications for railway ballast inspection. *Sensors* **2022**, *22*, 2450. [\[CrossRef\]](#) [\[PubMed\]](#)
41. Yin, J.; Li, Z.W.; Liu, Y.; Liu, K.; Chen, J.-S.; Xie, T.; Zhang, S.-S.; Wang, Z.; Jia, L.-X.; Zhang, C.-C.; et al. Toward establishing a multiparameter approach for monitoring pipeline geohazards via accompanying telecommunications dark fiber. *Opt. Fiber Technol.* **2022**, *68*, 102765. [\[CrossRef\]](#)
42. Baasch, B.; Heusel, J.; Roth, M.H.; Neumann, T. Train wheel condition monitoring via cepstral analysis of axle box accelerations. *Appl. Sci.* **2021**, *11*, 1432. [\[CrossRef\]](#)
43. Malekjafarian, A.; O'Brien, E.; Quirke, P.; Bowe, C. Railway track monitoring using train measurements: An experimental case study. *Appl. Sci.* **2019**, *9*, 4859. [\[CrossRef\]](#)
44. Yan, Y.; Xiong, G.; Zhou, J.; Wang, R.; Huang, W.; Yang, M.; Wang, R.; Geng, D. A whole process risk management system for the monitoring and early warning of slope hazards affecting gas and oil pipelines. *Front. Earth Sci.* **2022**, *9*, 812527. [\[CrossRef\]](#)
45. González, Y.T.; Briggs, K.M.; Svalova, A.; Glendinning, S. Evaluating the likelihood of slope failure in ageing earthworks using Bayesian updating. *Infrastruct. Asset Manag.* **2023**, *10*, 207–222. [\[CrossRef\]](#)
46. Tian, H.M.; Wang, Y.; Phoon, K.K. Real-time fusion of multi-source monitoring data with geotechnical numerical model results using data-driven and physics-informed sparse dictionary learning. *Can. Geotech. J.* **2024**, *61*, 2535–2552. [\[CrossRef\]](#)
47. Peduto, D.; Huber, M.; Speranza, G.; van Ruijven, J.; Cascini, L. DInSAR data assimilation for settlement prediction: Case study of a railway embankment in the Netherlands. *Can. Geotech. J.* **2017**, *54*, 502–517. [\[CrossRef\]](#)
48. Wang, J.; Nie, G.; Gao, S.; Xue, C. Simultaneous state–parameter estimation of rainfall-induced landslide displacement using data assimilation. *Nat. Hazards Earth Syst. Sci.* **2019**, *19*, 1387–1398. [\[CrossRef\]](#)
49. Xue, C.; Nie, G.; Li, H.; Wang, J. Data assimilation with an improved particle filter and its application in the TRIGRS landslide model. *Nat. Hazards Earth Syst. Sci.* **2018**, *18*, 2801–2807. [\[CrossRef\]](#)
50. Verberne, M.; Koster, K.; Fokker, P.A. Multi-data settlement prediction along a road section integrating InSAR and coastal subsurface information with data assimilation. *Front. Earth Sci.* **2024**, *11*, 1323874. [\[CrossRef\]](#)
51. Aono, Y.; Yamamoto, S.; Sakurai, H.; Tada, H.; Okuno, T.; Kikumoto, M. Fundamental studies on data assimilation for prediction of ground deformation during construction of underground structures. *Jpn. J. JSCE* **2024**, *80*, 24-19002. [\[CrossRef\]](#)
52. Giangreco, C.; Venmans, A.A.M.; Peduto, D. DInSAR data assimilation for optimising maintenance at transition zones between bridges and road embankments: A numerical study. *Proc. Int. Assoc. Hydrol. Sci.* **2020**, *382*, 469–474. [\[CrossRef\]](#)
53. Peduto, D.; Giangreco, C.; Venmans, A.A.M. Differential settlements affecting transition zones between bridges and road embankments on soft soils: Numerical analysis of maintenance scenarios by multi-source monitoring data assimilation. *Transp. Geotech.* **2020**, *24*, 100369. [\[CrossRef\]](#)
54. Wei, G.; Lei, C.; Gao, M.; Zhou, H.; Li, X.; Zhang, C. Data assimilation of PS-InSAR vertical deformation into a frost heave model to analyze subgrade deformation of high-speed railway in northwest China. *Cold Reg. Sci. Technol.* **2024**, *218*, 104059. [\[CrossRef\]](#)
55. Amavasai, A.; Tahershamsi, H.; Wood, T.; Dijkstra, J. Data assimilation for Bayesian updating of predicted embankment response using monitoring data. *Comput. Geotech.* **2024**, *165*, 105936. [\[CrossRef\]](#)
56. Cai, J.; Liu, G.; Jia, H.; Zhang, B.; Wu, R.; Fu, Y.; Xiang, W.; Mao, W.; Wang, X.; Zhang, R. A new algorithm for landslide dynamic monitoring with high temporal resolution by Kalman filter integration of multiplatform time-series InSAR processing. *Int. J. Appl. Earth Obs. Geoinf.* **2022**, *110*, 102812. [\[CrossRef\]](#)
57. Yao, J.; Zhan, R.; Guo, J.; Wang, W.; Yuan, M.; Li, G.; Zhang, B.; Zhang, R. Evolutionary analysis of slope direction deformation in the Gaojiawan landslide based on time-series InSAR and Kalman filtering. *PLoS ONE* **2024**, *19*, e0316100. [\[CrossRef\]](#) [\[PubMed\]](#)
58. Mohsan, M.; Vardon, P.J.; Vossepoel, F.C. On the use of different constitutive models in data assimilation for slope stability. *Comput. Geotech.* **2021**, *138*, 104332. [\[CrossRef\]](#)
59. Mohsan, M.; Vossepoel, F.C.; Vardon, P.J. On the use of different data assimilation schemes in a fully coupled hydro-mechanical slope stability analysis. *Georisk* **2024**, *18*, 121–137. [\[CrossRef\]](#)
60. Wang, D.; Wang, C.; Pu, X.; Song, H.; Wan, J.; Cao, Z. Data assimilation by combining ABAQUS with ensemble Kalman filter and its application to geotechnical engineering. *Front. Earth Sci.* **2024**, *12*, 1456186. [\[CrossRef\]](#)
61. Jiang, Y.; Liao, M.; Zhou, Z.; Shi, X.; Zhang, L.; Balz, T. Landslide deformation analysis by coupling deformation time series from SAR data with hydrological factors through data assimilation. *Remote Sens.* **2016**, *8*, 179. [\[CrossRef\]](#)
62. Rebert, T.; Cai, C.; Hallier, A.; Bardainne, T. Rockfall alarm system for railway monitoring: Integrating seismic detection, localization, and characterization. *Geophysics* **2024**, *89*, KS13–KS23. [\[CrossRef\]](#)

63. Berenguer, M.; Sempere-Torres, D.; Hürlimann, M. Debris-flow forecasting at regional scale by combining susceptibility mapping and radar rainfall. *Nat. Hazards Earth Syst. Sci.* **2015**, *15*, 587–602. [\[CrossRef\]](#)
64. Huang, J.; van Asch, T.W.J.; Wang, C.; Li, Q. Study on the combined threshold for gully-type debris flow early warning. *Nat. Hazards Earth Syst. Sci.* **2019**, *19*, 41–51. [\[CrossRef\]](#)
65. Dixit, S.; Siva Subramanian, S.; Srivastava, P.; Yunus, A.P.; Martha, T.R.; Sen, S. Numerical-model-derived intensity–duration thresholds for early warning of rainfall-induced debris flows in a Himalayan catchment. *Nat. Hazards Earth Syst. Sci.* **2024**, *24*, 465–480. [\[CrossRef\]](#)
66. Emerick, A.A.; Reynolds, A.C. Ensemble smoother with multiple data assimilation. *Comput. Geosci.* **2013**, *55*, 3–15. [\[CrossRef\]](#)
67. Pasculli, A.; Zito, C.; Sciarra, N.; Mangifesta, M. Back analysis of a real debris flow, the Morino-Rendinara test case (Italy), using RAMMS software. *Land* **2024**, *13*, 2078. [\[CrossRef\]](#)
68. Li, D.Q.; Zang, H.H.; Tang, X.S.; Guan, R. Efficient Bayesian updating for deformation prediction of high rock slopes induced by excavation with monitoring data. *Eng. Geol.* **2024**, *342*, 107772. [\[CrossRef\]](#)
69. Huang, F.; Mao, D.; Jiang, S.H.; Zhou, C.; Fan, X.; Zeng, Z.; Catani, F.; Yu, C.; Chang, Z.; Huang, J.; et al. Uncertainties in landslide susceptibility prediction modeling: A review on the incompleteness of landslide inventory and its influence rules. *Geosci. Front.* **2024**, *15*, 101886. [\[CrossRef\]](#)
70. Lee, S.J.; Yun, H.S.; Kim, T.Y. Monitoring of high-speed railway ground deformation using interferometric synthetic aperture radar image analysis. *Appl. Sci.* **2025**, *15*, 4318. [\[CrossRef\]](#)
71. Ning, P.; Jiang, Y.J.; Tang, J.J.; Xie, Q.J. Research on the early warning model for pipelines due to landslide geohazards under multiple influencing factors. *Water* **2023**, *15*, 693. [\[CrossRef\]](#)
72. Liang, J.; Qi, W.; Xu, C.; Wang, P.; Sun, J.; Zhang, X.; Xue, Z.; Chen, J.; Cui, Y.; Pan, J.; et al. Evaluation of geological hazards susceptibility along a key railway based on machine learning. *Sci. Rep.* **2025**, *15*, 42497. [\[CrossRef\]](#) [\[PubMed\]](#)
73. Zhu, W.; Zhang, G.; Chen, J.; Chen, G.; Liu, W. Problems and reflections on professional monitoring and early warning of geological hazards: A case study of Shiyang City. *Chin. J. Geol. Hazard Control* **2026**, *37*, 98–109. (In Chinese)
74. Macciotta, R.; Martin, C.D.; Morgenstern, N.R.; Cruden, D.M. Quantitative risk assessment of slope hazards along a section of railway in the Canadian Cordillera—A methodology considering the uncertainty in the results. *Landslides* **2016**, *13*, 115–127. [\[CrossRef\]](#)
75. Palmqvist, C.-W.; Ochsner, M.; Jamali, S.; Åmerbilly, K.; Hashemi, H.; Nilfouroushan, F.; Bagherbandi, M.; Karim, R.; Kour, R.; Åldstedt, R.; et al. *Satellite Monitoring of Railways Using Interferometric Synthetic Aperture Radar (InSAR)*; Report to Trafikverket, Grant 7194; Lund University: Lund, Sweden, 2021.
76. Zhang, P.; Wang, X.; Tang, X.; Liu, S. Limit displacement of a landslide for an X80 buried pipeline crossing it. *Chin. J. Geol. Hazard Control* **2023**, *34*, 21–29. (In Chinese)
77. Jia, H.; Yang, M.; Dai, L.; Que, Y.; Wang, D.; Yu, Z.; Zhao, Y.; Hu, W.; Xu, J.; Tang, J. Centrifuge tests on the deformation law of pipelines crossing slopes with different water contents. *Sci. Rep.* **2024**, *14*, 19466. [\[CrossRef\]](#) [\[PubMed\]](#)
78. Li, R.; Wang, Z.; Chen, P. Development of the method of pipeline bending strain measurement based on microelectromechanical systems inertial measurement unit. *Sci. Prog.* **2020**, *103*, 0036850420925231. [\[CrossRef\]](#) [\[PubMed\]](#)

Disclaimer/Publisher’s Note: The statements, opinions and data contained in all publications are solely those of the individual author(s) and contributor(s) and not of MDPI and/or the editor(s). MDPI and/or the editor(s) disclaim responsibility for any injury to people or property resulting from any ideas, methods, instructions or products referred to in the content.