Resolving Data Conflicts in Multi-Source Landslide Monitoring: A Critical Review Towards Trustworthy Early Warning

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Abstract: Multi-source monitoring has become the default configuration for landslide early warning, yet inter-sensor divergence is often treated primarily as measurement uncertainty or noise to be reduced, while its potential diagnostic value receives comparatively less attention. This review examines the transition from data fusion to conflict-aware monitoring through a bibliometric analysis of 264 Web of Science records (2015–2026) and a critical appraisal of methodological advances. The bibliometric results reveal a three-stage evolution—from instrument-driven to data-driven and now to fusion-driven research—and expose a structural blind spot: the literature concentrates on how to fuse data successfully while largely neglecting how to diagnose and resolve conflicts when sensors disagree. To address this gap, we propose a conflict typology that distinguishes datum conflicts, scale conflicts, and response conflicts according to their physical origins rather than their numerical symptoms. Unlike traditional uncertainty inventories, sensor fault classification schemes, and fusion-stage taxonomies, the classification system proposed in this paper links each type of discrepancy to a falsifiable physical cause, the necessary metadata, and a corresponding resolution pathway. We further argue that conflict detection should move beyond cross-sensor threshold comparison toward physics-informed consistency checks, because the divergence of trend and phase among monitoring quantities often encodes mechanistic transitions that statistical smoothing would discard. A critical comparison of five resolution paradigms—mathematical weighting, adaptive deep learning, physics-informed neural networks, Dempster–Shafer evidence fusion, and knowledge-graph-based reasoning—shows that no single approach dominates; rather, the choice depends on the match between data endowment, theoretical reserve, and site complexity. Finally, we outline an auditable closed-loop framework in which every conflict is recorded with its sensor metadata, environmental driver, resolution paradigm, and verification outcome, converting disagreement from an operational nuisance into a reusable knowledge asset. These findings suggest that trustworthy early warning does not require the elimination of inter-sensor divergence, but rather transparent, traceable, and physically grounded interpretation of such divergence.

Keywords: Multi-source monitoring, data conflict, landslide early warning, conflict resolution, trustworthy decision-making, bibliometric analysis, knowledge graph.

1. INTRODUCTION

Landslides rank among the most common and destructive geological hazards worldwide [1]. As global climate change intensifies, landslide crises triggered by extreme weather occur with increasing frequency, inflicting damage on infrastructure, loss of life, and economic harm. The reliability of landslide defense and mitigation strategies hinges on the timeliness and efficacy of early warning systems (EWS). At its core, the quality and interpretability of monitoring data constitute a decisive factor in disaster risk prevention [2]. Over the past two decades, monitoring methods have diversified, shifting slope monitoring from a sensor-scarce environment to a multi-sensor collaborative framework. However, as the central bottleneck of warning systems reveals, the abundance of monitoring data itself introduces new challenges to coherent interpretation and trustworthy decision-making [3]. Figure **1** schematically summarizes the typical configuration of a multi-source slope monitoring system and the principal factors contributing to cross-source data conflict.

Due to the complexity of geological conditions and disaster causation, contemporary landslide monitoring employs multiple complementary sensing technologies [4]. These technologies differ in physical principles, observation geometries, and spatiotemporal coverage, ensuring comprehensive extraction of disaster characteristics. For instance, satellite interferometric synthetic aperture radar (InSAR) provides wide-area surface deformation fields with millimetre-level precision, but its displacement observations are confined to the radar line-of-sight (LOS) direction and averaged within each resolution cell [5]. The global navigation satellite system (GNSS) furnishes three-dimensional position information relative to an absolute geodetic reference frame, with centimetre-to-millimetre-level accuracy, though its signal quality is susceptible to degradation in densely vegetated, topographically occluded, or multipath-prone environments [6]. Ground-based interferometric synthetic aperture radar (GB-InSAR) delivers high-temporal-resolution LOS displacement measurements from fixed stations, with flexible revisit intervals, but its spatial coverage and geometric configuration are constrained [7]. In addition, point sensors such as acoustic emission (AE) sensors, piezometers, inclinometers, and tensiometers capture

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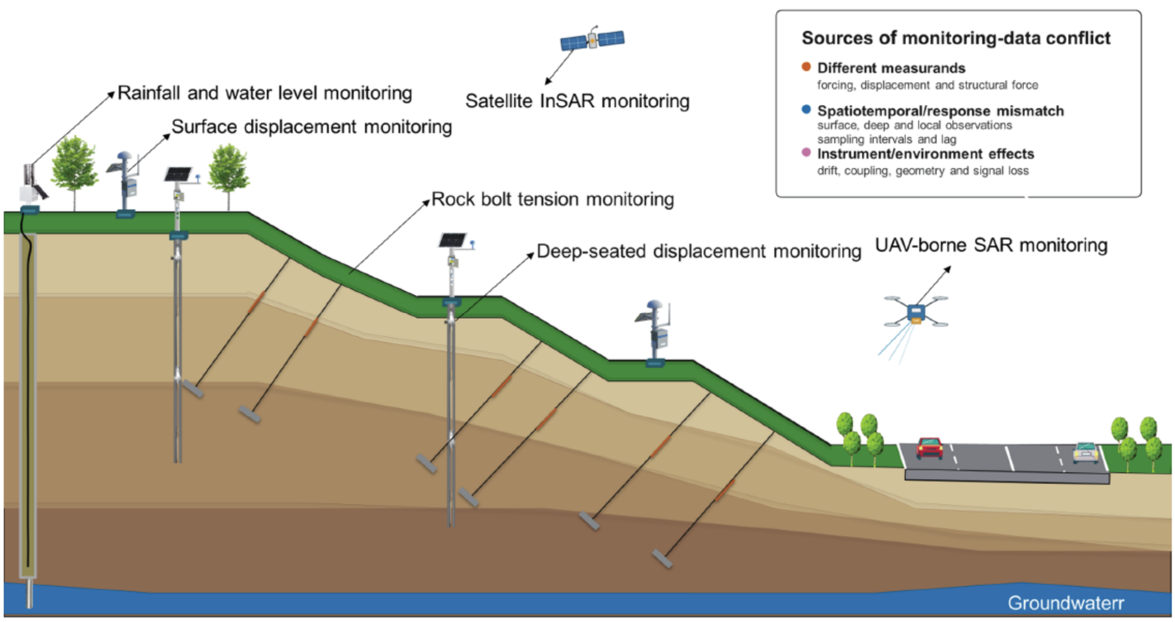

Figure 1: Schematic of multi-source slope monitoring and sources of data conflict.

local physical processes within the slope, including internal micro-fracturing, pore-water pressure fluctuations, and subsurface shear deformation. However, these instruments are costly [8], limiting the number of points that can be instrumented on a single slope; consequently, data reliability decays rapidly with distance from the installation point [9]. The sensing range, position, physical quantity, and measurement precision of these technologies differ fundamentally [10]. No single method can capture the full kinematic state of a slope, and the complementarity among these techniques is the principal driver for integrating multi-source landslide warning systems [11, 12]. For example, satellite InSAR is used for mountain reconnaissance and susceptibility assessment, GNSS stations provide datum control and surface displacement monitoring, and in-situ sensors monitor landslide triggering factors. An increasing number of field deployments and operational monitoring projects adopt such integrated configurations. Engineers generally assume that these redundant and diverse monitoring modes collectively enhance the robustness of slope failure characterization and the reliability of warning decisions [13]. However, in practice multi-source monitoring faces a major challenge: different sensors deployed on the same landslide body often yield numerically divergent or even qualitatively contradictory assessments of the same deformation phenomenon [14].

This divergence in the multi-source monitoring of slope is evident at various levels [15]. Displacement magnitudes at nominally identical locations differ; temporal trends are inconsistent; stability classifications from different sensors are opposite. This phenomenon is termed data conflict. It is not an incidental by-product of instrument malfunction or measurement noise, but an inherent consequence of fundamental differences in the physical object measured, the spatial averaging kernel, the temporal sampling scheme, and the sensitivity to site-specific environmental and geometric factors of each sensor [16]. The causes of data conflict can be traced to three interrelated aspects. First, geometric projection differences between InSAR and GNSS solutions [17]. InSAR and GB-InSAR measure only the projection of the true three-dimensional displacement vector onto a specific LOS direction, whereas GNSS resolves the full displacement vector. Conversion between the two requires kinematic assumptions about the deformation, which are rarely validated; the same slope movement can produce markedly different observational signatures under different viewing geometries. Second, spatiotemporal scale mismatch between satellite and ground-based sensors [18]. Satellite InSAR, for example, Sentinel-1 with a typical revisit cycle of 6–12 days, whereas some commercial constellations can reach hourly intervals. Moreover, InSAR results usually average deformation over tens of meters per pixel, whereas ground-based radar may sample the same area at sub-minute intervals but with a different spatial footprint. These differences in data interpretation can cause the same slope to appear simultaneously in a state of local acceleration and overall apparent stability. Third, confounding factors arising from the monitoring environment and operation. These error sources, including atmospheric delay in InSAR [19], ionospheric and tropospheric effects in GNSS [20], temperature drift in ground-based radar [21], and sensor coupling degradation in inclinometers [22], each have specific error budgets, are difficult to model precisely, and perturb the final monitoring results.

Although these conflicts are inherently predictable, current operational practice tends to treat inter-sensor differences as measurement noise, suppressing them through averaging, smoothing, or selective filtering. This conventional approach simplifies the interpretation workflow, but it exerts a concrete and non-abstract impact on the reliability of early warning. When the analysis pipeline smooths or discards divergent observations, it inevitably attenuates signals that may indicate the onset of local instability. Documented cases in the literature illustrate this consequence. Carlà, Farina [6] recorded an unexpected failure of an open-pit slope in which satellite InSAR time-series, interpreted in isolation, indicated slope stability, whereas contemporaneous ground-based radar detected local acceleration motion masked by the satellite geometry. Post-failure reconciliation of the two datasets revealed that the apparent conflict was precisely the critical warning signal. Similarly, multiple landslide warning operations report that reliance on satellite InSAR alone yields significantly shorter warning lead times than multi-source joint interpretation, because the satellite geometry's insensitivity to certain motion components delays anomaly detection [23]. These are not isolated incidents; they reflect a pervasive pattern. When conflict is treated as interference to be eliminated, the informational content embedded in the divergence is discarded along with the noise, and warning opportunities are lost before failure occurs. Recognition of this pattern has prompted a gradual but definite shift in the academic attitude toward data conflict. An increasing body of research no longer seeks to eliminate conflict but instead treats inter-sensor differences as diagnostic information. Multi-source data conflicts can locate active deformation zones, reveal three-dimensional kinematic geometries inaccessible to single observation geometries, and compel analysts to articulate the uncertainty of each instrument [24, 25]. This perspective reframes the problem of multi-source integration in slope monitoring: the objective is no longer to produce a single averaged deformation value that masks disagreement, but to preserve, characterize, and transparently report the full distribution of sensor observations and their divergence, thereby enabling warning thresholds to be defined on the basis of convergence or divergence patterns rather than absolute displacement magnitudes.

Therefore, this paper reviews advances, technical methods, and limitations in the field of multi-source landslide monitoring through bibliometric analysis and critical methodological assessment. The bibliometric component is based on a systematic search of the Web of Science Core Collection (2015–2026), yielding 264 screened records comprising peer-reviewed English journal articles and reviews on landslide or slope monitoring studies involving heterogeneous sensor combinations or comparisons. Building on the bibliometric results, the paper further reviews data conflict typologies, detection rule frameworks based on measurement uncertainty characterization, and a comparative evaluation of three solution approaches.

The remainder of the paper is structured as follows. Section 2 describes the literature search and bibliometric methods. Section 3 presents the bibliometric results, including temporal trends, citation networks, keyword clusters, and core literature identification. Section 4 constructs a systematic typology of data conflicts and reviews detection methods based on uncertainty characterization. Section 5 evaluates three principal solution approaches, comparing their applicable domains and performance evidence. Section 6 discusses implications for trustworthy warning practice, proposes a monitoring–decision framework, and identifies outstanding open questions. Section 7 summarizes the principal findings and outlines prospects for integrating data-conflict-aware methods into operational warning systems.

2. DATA AND METHODS

The literature search was conducted in the Web of Science (WoS) Core Collection, with the final search performed on 15 July 2026. The publication period was restricted to 2015–2026, with records published up to the search date included. The search strategy employed a topic-field (TS) combined query, constructed from four term groups joined by the Boolean operator AND: Group 1 comprised landslide-related terms (landslide*, slope failure, slope deformation, slope stability); Group 2 comprised monitoring and early-warning terms (monitoring, early warning, early detection, real-time monitoring); Group 3 comprised data-fusion terms (fusion, integration, data integration, information fusion, multi-source, multi-sensor, multisource, multi sensor); Group 4 comprised uncertainty and decision-support terms (uncertainty, uncertainty quantification, reliability, decision making, decision support, risk assessment). This query was submitted three times within the same session to capture records arising from database update lags.

After export, the retrieved records underwent the following cleaning steps in sequence: (1) the three retrieval results were merged and deduplicated using the WoS unique identifier (UT); for the few records with missing UT fields, a fallback mechanism based on title–year–source was used to assist deduplication; (2) document types were limited to articles and reviews;

(3) publication years were restricted to 2015–2026; (4) non-English records were excluded by detecting non-Latin characters in titles; (5) a subject screening was performed, requiring that at least one landslide-related term and one monitoring-related term appear in the title, abstract, keywords, or author keywords, while excluding off-topic records such as pure glacier flow, structural health monitoring of buildings and bridges, and image classification without a landslide context. Each step was logged to ensure the screening process is fully reproducible. The final cleaned corpus contains 264 records. A manual spot-check of 30 retained and 30 excluded records confirmed that the subject filter accurately distinguished landslide monitoring data-fusion studies from off-topic literature. No citation count or citation threshold was set; the corpus therefore reflects the actual publication profile of the field within the window, rather than a subset of highly cited papers. All references cited in this review were cross-checked against the WoS export dataset to verify that each record exists and is traceable via DOI.

3. BIBLIOMETRIC LANDSCAPE

3.1. Publication and Citation Trends

Figure **2** presents the annual publication output and citation counts of the 264 records in the Web of Science Core Collection from 2015 to 2026. The publication volume grew from 2 papers in 2015 to 81 in 2026. The growth rate accelerated markedly after 2021, with a leap in 2024 (from 14 to 32 papers) and a sustained surge through 2025–2026. Total citations formed a first minor peak in 2019 (569) and reached a maximum of 599 in 2023, remaining at a high level in 2024. This bimodal structure may reflect two waves of knowledge diffusion experienced by the field. The 2017–2019 interval corresponds to the initial penetration of InSAR technology into landslide monitoring, whereas the post-2021 period marks the maturation of multi-source data fusion from methodological exploration to engineering application.

The annual publication curve is not a simple linear increase; the growth from 2015 to 2026 is roughly forty-fold, a rate that ranks among the highest in engineering geology research directions. Based on the slope of growth, the evolution can be summarized in three phases.

(1) Incubation (2015–2019): The average annual output during this period was fewer than 7 papers. InSAR and GNSS monitoring technologies were applied as independent tools in separate case studies; no systematic data-fusion methodology had but taken shape. The total citation count surged to 569 in 2019, with a per-paper average of 71.1, indicating that the sparse literature of this phase consisted largely of seminal works. For example, the PS-InSAR framework proposed by Ferretti *et al*. (2002) was rediscovered and applied in landslide monitoring during this period, producing a knowledge-diffusion pattern characterized by small volume and high impact.

(2) Transition (2020–2023): The total citation count dropped sharply to 186 in 2020, with a per-paper average of only 26.6. This does not signal a decline in academic influence; rather, it marks a shift in the research community from citing classics to producing new knowledge. During this phase, a large influx of papers on emerging methods diluted the average citation per paper. The publication volume stabilized at 14 papers during 2021–2023, forming a plateau. SBAS-InSAR, GNSS real-time processing, and distributed fibre-optic sensing technologies matured progressively, providing the data

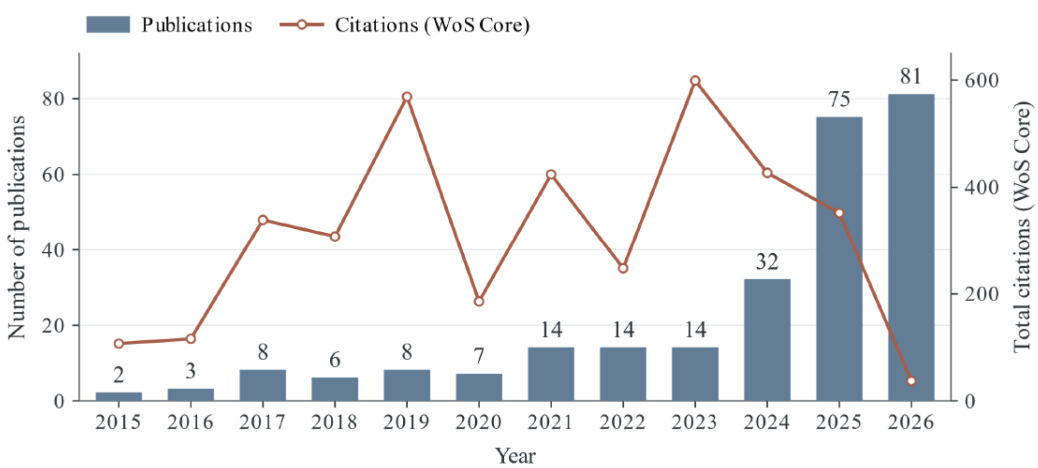

Figure 2: Annual publications (bars) and total Web of Science Core citations (line) for the 264 records, 2015–2026. 2026 is a partial year at export.

foundation for multi-source fusion. But the fusion algorithms themselves had not achieved a breakthrough, preventing further growth in publication volume.

(3) Surge (2024–2026): The publication volume leaped to 32 papers in 2024, a 128% increase over the plateau; it reached 75 in 2025 and 81 in the first half of 2026 alone. This surge is closely linked to the maturation of three technical conditions. First, the global coverage of open satellite data from Sentinel-1 made InSAR a routine monitoring tool. Second, deep-learning frameworks (Transformer, GNN) provided nonlinear modelling tools for heterogeneous data fusion. Third, the migration of digital-twin and knowledge-graph concepts into the geohazard domain spawned new research directions such as semantic fusion. In addition, the per-paper citation average dropped sharply after 2024, as the flood of publications in the emerging field diluted the visibility of older literature—a phenomenon consistent with the transition phase.

A comparison of the publication and citation curves reveals a pronounced lag between publication peaks and citation peaks. The 2019 citation peak corresponds to foundational papers published in 2015–2017; the 2023 citation peak corresponds to methodological extension papers from 2018–2021. From a bibliometric standpoint, this two-tier structure constitutes a technology-readiness roadmap: engineering practitioners should prioritize core-layer, highly cited papers to build a technical foundation, then selectively track extension-layer developments to anticipate future directions, rather than investing equal effort in every new methodological paper. The above assessment excludes the data in 2026, as citations for that year have not but accumulated and the publication count is distorted by the incomplete calendar year.

The year 2021 is the most informative inflection point in this curve. Prior to this, annual output remained below 15 papers; the field presented as a scattered collection of methodological papers. In the four subsequent years, publication volume increased more than five-fold. A closer inspection of the data shows, however, that output during 2021–2023 actually remained at the 14-paper plateau; the true leap began in 2024. Therefore, 2021 is better interpreted as a signal that technical preparation was complete, rather than the starting point of a research explosion. That year, the open-source release of SBAS-InSAR processing chains (e.g., SNAP, MintPy) lowered the technical barrier; the commercialization of GNSS real-time precise point positioning (PPP) services made centimeter-level displacement monitoring a routine service; and the migration of distributed acoustic sensing (DAS) from petroleum exploration to geohazard monitoring entered the pilot stage. The convergence of these technical conditions laid the groundwork for the post-2024 surge, but innovations in fusion methodology itself lagged behind advances in sensor technology. The burst-detection analysis in Section 3.2 will provide further evidence for this interpretation.

3.2. Keyword Structure and Research Fronts

Keyword co-occurrence analysis partitions the corpus into three clusters, shown in Figure **3**. The fusion cluster contains terms such as fusion, multi-sensor, and data assimilation, addressing methods for integrating multi-source data. The instrument cluster contains terms such as InSAR, GNSS, GB-InSAR, and SBAS, reflecting the various monitoring technologies. The learning cluster contains terms such as machine learning, deep learning, and model, representing data-driven modelling approaches. The three clusters contain 16, 14, and 12 nodes respectively. Cross-cluster terms such as integration and monitoring serve as bridging nodes—they appear in both instrument and learning literature, indicating that multi-source fusion sits at the intersection of two research traditions.

During network construction, both author keywords (DE) and Keywords Plus (ID) were included, as they capture different information dimensions: the former reflects the authors' perceived contribution focus, the latter reflects how papers are indexed and retrieved. Terms appearing in both DE and ID carry higher weight in the co-occurrence network. Generic terms such as remote sensing and analysis were excluded a priori; otherwise, they would dominate all clusters and obscure structural boundaries. Edge weights are defined as the number of records in which two terms co-occur; thick edges therefore represent genuine thematic co-occurrence relations, not merely accidental superposition of high-frequency words. The three clusters map the space of practice: the fusion cluster connects methods for combining instruments, the instrument cluster connects the technologies themselves, and the learning cluster connects models applied to data. The separation between instrument and learning clusters aligns precisely with the disciplinary boundaries revealed in the subsequent journal-source analysis. This explains why associations that a single narrative review struggles to capture become clearly visible in the co-word map.

This map reveals the deep knowledge structure of the field. The separation between instrument and

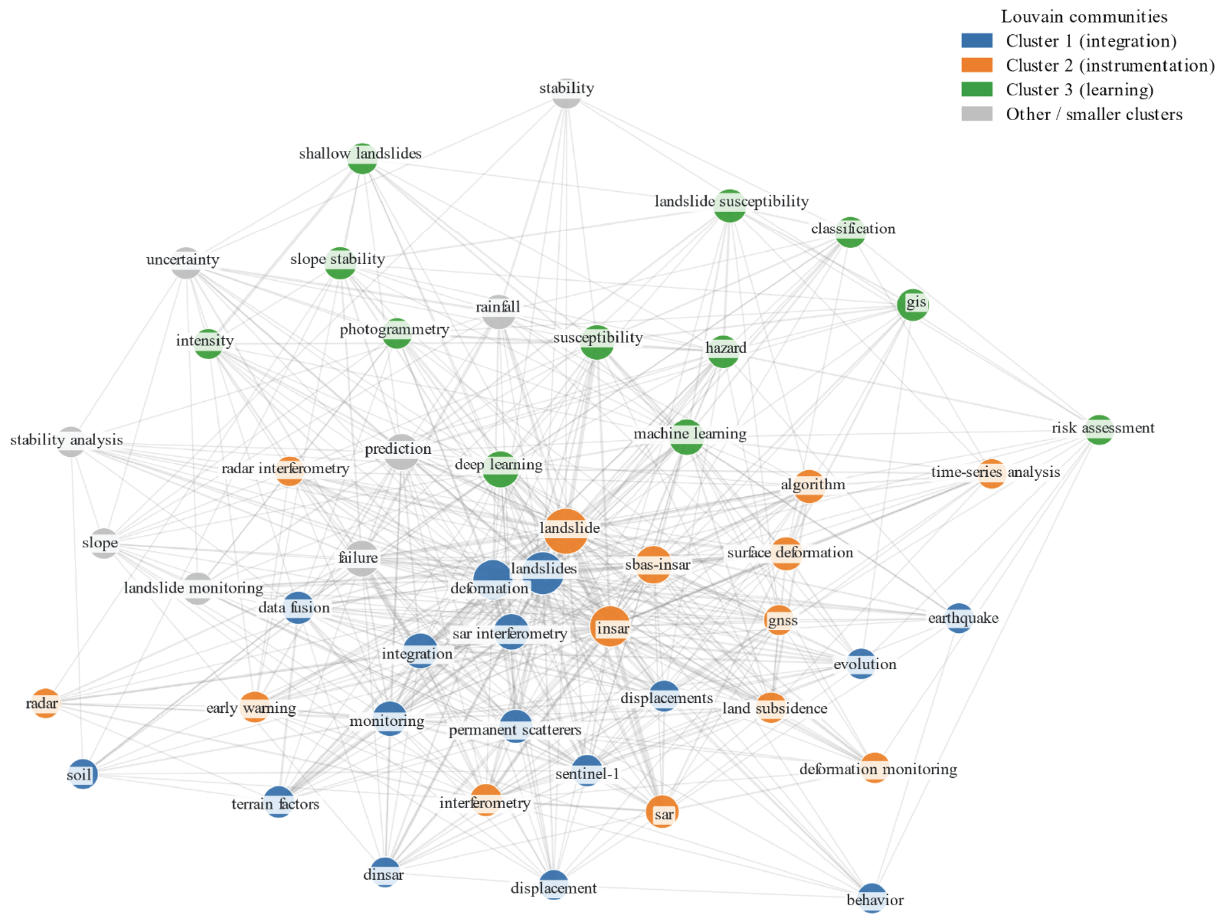

Figure 3: Keyword co-occurrence network of the 264 records (top 50 keywords; edge weight = co-occurrence count).

learning clusters reflects a disciplinary barrier between data producers and data consumers: the former originates from surveying, remote sensing, and geophysics, focusing on sensor precision, signal processing, and error correction; the latter originate from computer science and statistics, focusing on model architecture, training strategy, and generalization performance. The fusion cluster lies at the boundary between the two; its researchers' core task is to transform the heterogeneous data output by the instrument cluster into a unified representation processable by the learning cluster. This is precisely the root of data conflict, and the problem this review seeks to address systematically. The bridge terms integration and monitoring, with frequencies of 17 and 16 respectively, fall below landslide (44) or insar (31), but may carry higher betweenness centrality in the network. They are not the most popular research objects, but they are critical nodes for information flow. For researchers entering the field, prioritizing papers containing these bridge terms over chasing high-frequency keywords offers a faster route to grasping the full picture.

Burst detection analysis, shown in Figure **4**, identifies terms that accelerated after 2023. The detection employs transparent rules rather than black-box algorithms: for each keyword, the annual frequency is divided by the mean of the preceding three years; a ratio ≥ 2 that persists into the following year is flagged as a burst. Lowering the threshold to 1.5 in a sensitivity test leaves the ranking of leading terms unchanged, confirming that the conclusion does not depend on precise threshold setting. This rule favors terms that burst after a period of quiescence; hence high-steady-frequency terms from Figure **2** (e.g., InSAR, GNSS) do not appear in the burst list. The results show that SBAS-InSAR, deep learning, machine learning, failure, and deformation all achieved burst ratios above 3 during 2024–2025, with the leading bursts concentrated in 2025. This pattern indicates that the research frontier has shifted from single-technology description toward the fusion of multi-source data with learning-based methods.

It should be stressed that burst terms reveal recent accelerators, not the most important terms. Already high-frequency terms lack the velocity to produce high ratios, while single-year spikes may mask steadily rising trends. The frequency data in Figure **2** provides a corrective perspective. The leading bursts of 2025 (SBAS-InSAR, deep learning, machine learning) carry two messages. (1) Deepening of the learning cluster: the shift from direct application of off-the-shelf models

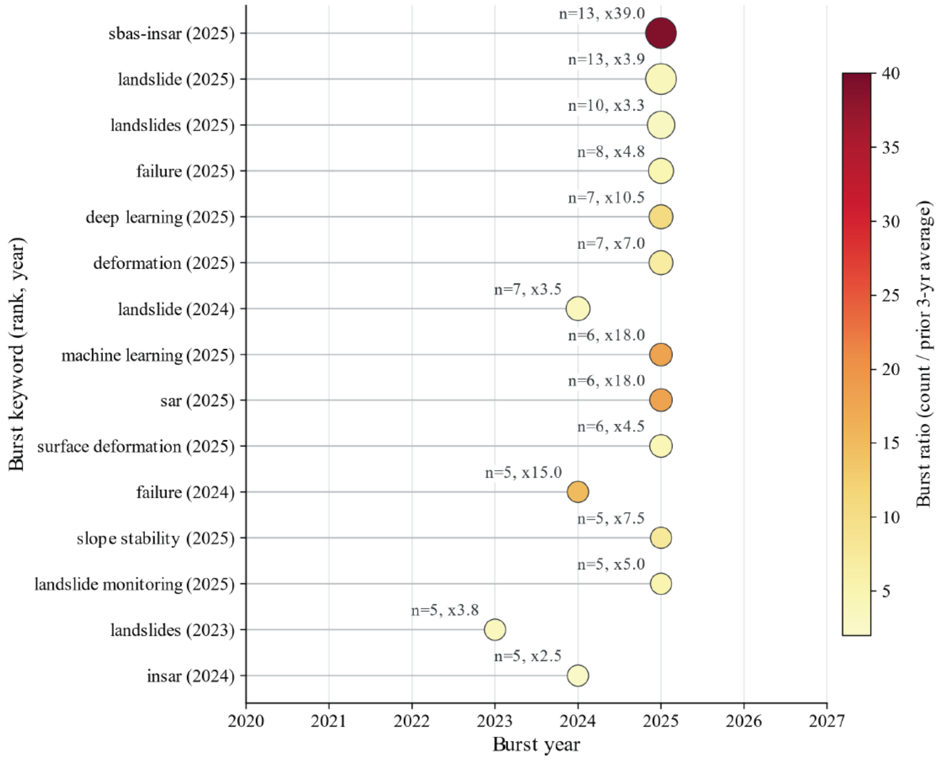

Figure 4: Emergent keywords plotted by burst year. Burst strength is the count; colour shows the burst ratio.

(e.g., random forest, support vector machine) toward methods purpose-built for deformation data (e.g., spatiotemporal graph neural networks, physics-informed neural networks) marks domain adaptation rather than tool transplantation as the new paradigm. (2) Refinement of the instrument cluster: the burst of SBAS-InSAR records the diffusion of small-baseline technology as the default processing workflow for slope InSAR, driven by the open availability of Sentinel-1 data and the maturation of open-source processing chains (e.g., MintPy, SNAP).

From the perspective of cluster evolution, the field has undergone a three-stage transition from instrument-driven to data-driven to fusion-driven:

(1) 2015–2018 (instrument-driven): Dominated by precision improvement and applicability extension of single technologies such as InSAR and GNSS; keywords concentrated in the instrument cluster.

(2) 2019–2022 (data-driven): Machine learning penetrated landslide monitoring, but mostly as off-the-shelf applications (e.g., using random forest for susceptibility assessment); the learning and instrument clusters developed independently.

(3) 2023–2026 (fusion-driven): The synchronous maturation of deep learning and InSAR processing technology made multi-source + learning a research direction scalable to implementation; cross-density among the three clusters increased markedly.

This evolutionary logic, however, exposes a structural blind spot: fusion-cluster research focuses on how to achieve successful fusion, with insufficient attention to how to diagnose and handle fusion failure. The absence of terms such as conflict, uncertainty, and trustworthiness from the burst list confirms the observation of this review—data conflict resolution has not but become an independent research frontier, but is implicitly assumed to be naturally solvable through better algorithms. This blind spot is precisely the gap this review seeks to fill.

3.3. Source Titles and Most-Cited Contributions

The 264 records are distributed across 90 source titles. Figure **5** presents top 12 of 90 journals in the corpus. Remote Sensing leads with 44 records, followed by Engineering Geology (18), Applied Sciences (16), and Landslides (16). The concentration in remote-sensing and engineering-geology outlets reflects the dual instrumentation and geotechnical audience of the field.

The source-title distribution is explained by the structure of the two communities rather than by journal quality. Remote Sensing leads because it is an open-access, broad-scope outlet where the InSAR community consolidates method and application

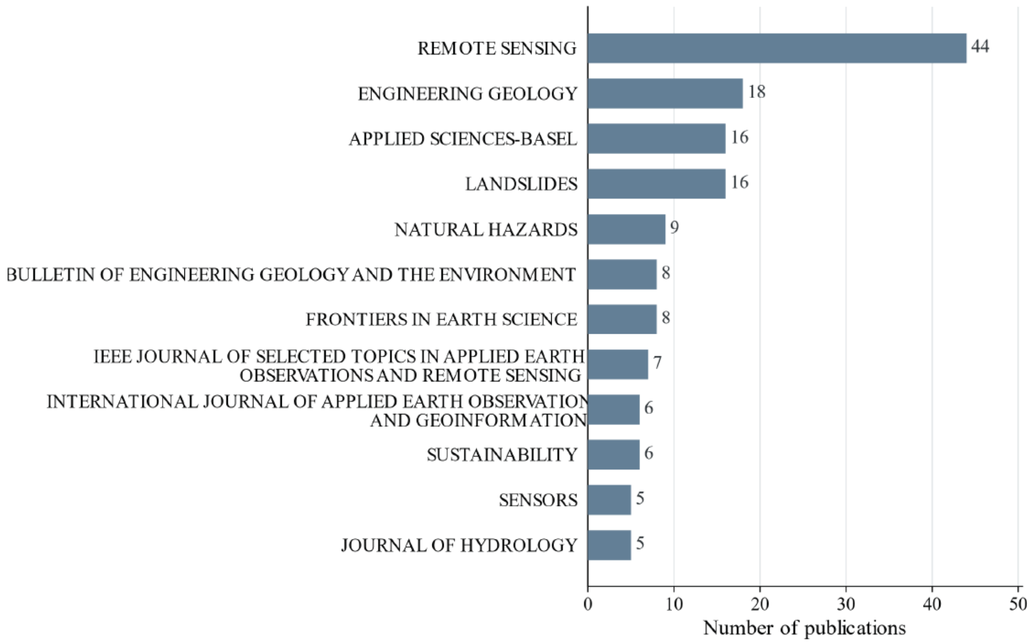

Figure 5: Source-title productivity, top 12 of 90 journals in the corpus.

papers; its 44 records are a direct count of how often InSAR work is published and how often it is open access. Engineering Geology and Landslides carry the geotechnical and hazard-angle work, where the same combination problem is studied from the slope-mechanics side. The presence of a remote-sensing outlet and a geotechnical outlet among the leaders is the same divide seen in the keyword clusters, and it explains why a single narrative review struggles to cover the field: the instrumentation papers and the mechanics papers rarely cite one another, which is exactly the gap a co-word map can expose.

The 90 source titles hide a long tail. The top four journals account for just under half of the 264 records, and the remaining records are spread thinly across dozens of outlets from general geoscience to civil engineering and remote sensing. That spread means the field has no single home journal, which slows the accumulation of a shared method vocabulary; a contribution can be read by the InSAR community, the geotechnical community or neither, depending on where it lands. For an agency scanning the literature, the practical implication is to watch Remote Sensing, Engineering Geology, Applied Sciences and Landslides first, because they carry the bulk of the fusion work, and to treat the long tail as a source of occasional method papers rather than a routine read.

The most-cited contributions are dominated by studies that combine or reconcile multiple sources. As shown in Figure **6**, Casagli, Intrieri [4], at 440 citations, sets the remote-sensing frame; Carlà and co-workers contribute four of the top six papers through work on satellite InSAR prediction, inverse-velocity thresholds, GNSS–InSAR–GB-InSAR combination and an unexpected open-pit failure. Moretto, Bozzano [26] is the most-cited explicit statement of InSAR limitations and openings. The citation core therefore supports the thesis of this review: the field values the papers that confront inter-sensor disagreement directly.

The most-cited list is dominated by review and perspective pieces [4, 26, 27] and by case studies that combine instruments on a single slope [5, 6]. The balance is the bibliometric expression of the review's main claim: the field cites the papers that show how to combine sources more than the papers that report a single instrument. Casagli, Intrieri [4] sets the frame at 440 citations, and four of the top six papers are by Carlà and co-workers, which concentrates the citation core in one research group and one method lineage. That concentration helps a new research plan because the decisive papers are few and well known, but it also means the evidence base for fusion rests on a narrow set of authors; the knowledge graph proposed in Section 5 is one way to keep that core from narrowing further as the field grows.

3.4. Author Productivity

Author productivity is concentrated in a core group. Casagli (10 papers) and Zhang L.L. (7) lead, followed by a group of five authors with four or five papers each. The same names appear among the most-cited contributions, indicating that the citation core and the productivity core overlap. Figure **7** shows the top 15 authors by paper count in the corpus.

The concentration of output in a small group of authors implies that the field's methods are carried by a few laboratories. Casagli (10 papers) and Zhang L.L.

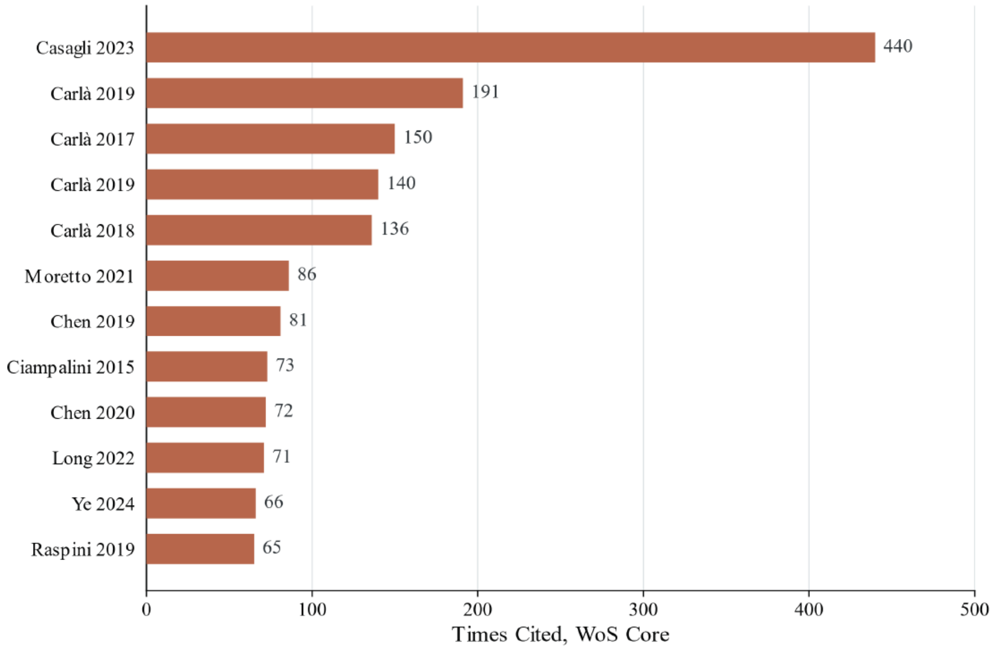

Figure 6: Most-cited papers, top 12 by Times Cited (Web of Science Core).

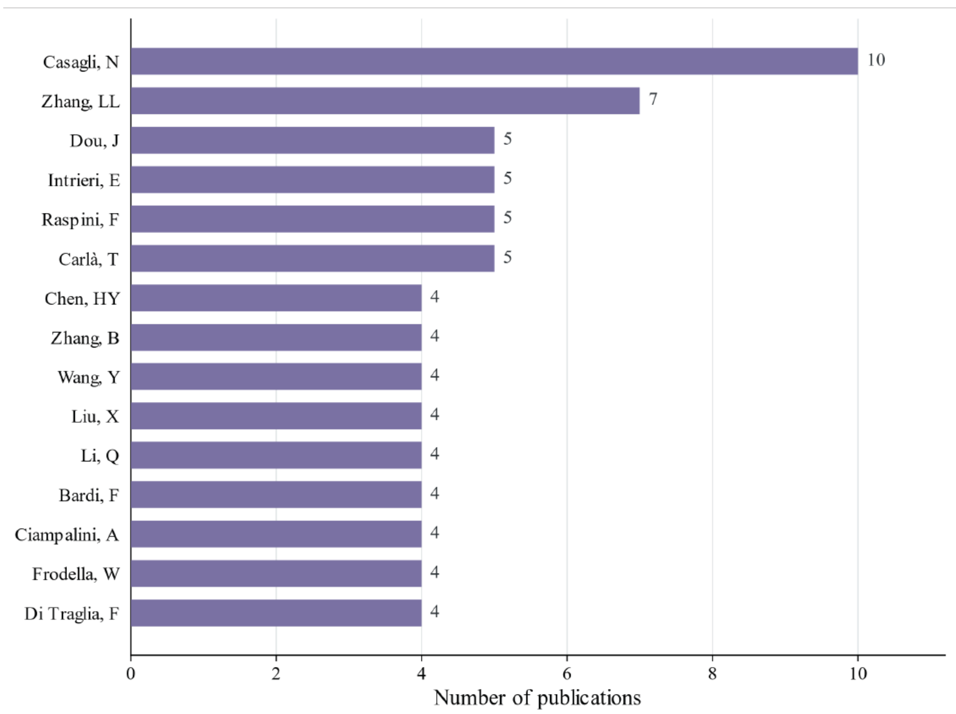

Figure 7: Author productivity, top 15 by number of papers in the 264-record corpus.

(7) lead, and a second tier of four-to-five-paper authors (Carlà, Intrieri, Dou, and others) supplies most of the rest. That concentration helps reproducibility because the same groups provide the software and the case data, but it also means the citation core is narrow and the same names are likely to appear among the reviewers of a new submission. A new research plan should read the leading authors' methods papers directly rather than rely on secondary summaries, and should expect the field's center of gravity to shift only slowly.

The author list also shows the international structure of the field. The most productive authors are based in Italy and China, and several of the top-cited papers are co-authored across those groups, consistent with the strong European and Chinese research plans in slope monitoring. The conflict problem is therefore addressed by a connected community, which raises the chance that a local solution is shared quickly; the knowledge graph in Section 5 is a machine-readable way to keep that sharing explicit. A corpus with country and institution fields would make this collaboration structure measurable rather than inferred, and its absence is a stated limitation of the present data.

4. CONFLICT TYPOLOGY AND DETECTION

4.1. Conflict Typology

Existing classifications of multisource monitoring mainly concern uncertainty sources and propagation, sensor reliability, or the level at which heterogeneous data are fused. In contrast, the present study focuses on cross-source disagreements that persist after individual data sources are considered reliable. Such discrepancies cannot all be attributed to observational noise, but may arise from differences in geometric reference, spatiotemporal sampling, or mechanical response. Accordingly, the conflicts reported in the literature are classified into three types: datum conflict, scale conflict, and response conflict, according to their physical origins and corresponding interpretation pathways.

Datum conflict is the most readily identifiable discrepancy type in multi-source joint analysis [5]. It typically manifests as systematic deviations between InSAR LOS displacement and the projected component of GNSS three-dimensional displacement onto the same LOS direction, or as inconsistent magnitude trends even after geometric projection conversion [28]. For example, when the GNSS-derived displacement vector projected onto the InSAR LOS direction still shows a persistent offset or an opposite trend relative to the InSAR measurement, the discrepancy cannot be resolved by geometric transformation alone and indicates a datum-level misalignment between the two observation systems [29, 30]. Attributing such discrepancies simplistically to data error and discarding them directly, or assuming a constant offset and subtracting it retrospectively, both risk introducing new systematic errors. When the slope is in a state of continuous creep, the offset estimate from a so-called quiescent period is unreliable [6].

Once the datum framework is properly addressed, scale conflict becomes the pertinent concern. Unlike datum conflict, scale conflict does not involve data validity per se; it is a mismatch between the spatiotemporal sampling characteristics of different monitoring technologies and the characteristic scales of landslide evolution [31]. InSAR provides areal displacement fields at meter-to-decameter resolution, reflecting the average behavior of the slope. GNSS delivers millimeter-accurate displacement at isolated points. AE or distributed fiber optics capture micro-fracturing or strain signals along linear survey lines [32]. When the slope exhibits non-uniform deformation—such as multi-stage sliding or coexisting slip surfaces—the areal average from InSAR may indicate overall stability, while a GNSS point happens to lie at the rear scarp of a locally reactivated old landslide, and AE sensors register dense release along a deep-seated shear band. The three appear contradictory on the surface, but each reflects deformation information at a different spatial scale [5]. In the temporal dimension, InSAR with its revisit cycle of days to weeks is sensitive to cumulative displacement; AE samples at millisecond-level frequency; groundwater level responds to short-term rainfall infiltration [33]. Requiring multi-source data to match strictly at a single moment while ignoring these temporal-scale differences risks obscuring the intrinsic multi-temporal-scale nature of landslide processes [34]. Resolution of scale conflict is therefore achieved through multi-scale mechanical modelling: using the areal constraint from InSAR to invert the overall movement trend, correcting local non-uniformity with GNSS points, and constraining the constitutive parameters of the shear band with high-frequency AE data. Information fusion is realized at the model level, rather than through forced spatiotemporal registration at the data level.

At a deeper level, conflict manifests as response conflict: a trend divergence among different monitoring quantities in response to the same mechanical process [35]. The physical root of this type lies in the fact that each sensor captures deformation mechanisms at different links in the slope's response chain [36]. During the acceleration phase of a creep-type landslide, the surface displacement rate may rise continuously while the energy recorded at existing AE sensors declines [32]. This does not indicate that the slope is stabilizing; it may reflect a shift in the stress concentration zone after fractures have coalesced to form a main slip surface. In addition, after rainfall infiltration raises the groundwater level, surface displacement may decelerate in the short term [37]. This phenomenon may relate to phase lag in the hydro-mechanical coupling process—while elevated pore-water pressure reduces effective stress, volumetric compression during the drainage-consolidation-dominated stage may temporarily mask the growth of shear displacement. Identifying response conflict requires knowledge of the specific geological conditions and sensor layout of the slope. Averaging the data or discarding outliers is not appropriate. Table **1** summarizes the three conflict types, their underlying physical mechanisms, representative examples from the literature, and the resolution paradigms suited to each.

The three conflict types may coexist in engineering practice, but their identification and treatment follow a

Table 1: Conflict Typology: Definition, Physical Mechanism, Typical Example, and Appropriate Resolution Paradigm

Type	Definition	Physical mechanism	Typical example	Suited paradigm
Datum Conflict	Systematic offset in absolute level or displacement at the same point	Differences in reference frames, projection geometry, atmospheric/orbital residual phases	Carlà, Farina [6] open-pit failure; Carlà, Tofani [5] GNSS+InSAR+GB-InSAR	Establishment of joint geometric benchmarks, co-located calibration
Scale Conflict	Agreement on level but disagreement on rate or trend	Variations in spatial resolution, sampling frequency, and support structures	Zeng, Feng [31] InSAR early-warning limits; Cai, Liu [38] Kalman fusion	Multi-scale mechanical modeling, cross-scale parameter transfer
Response Conflict	Disagreement from scale or timing mismatch	Distinct deformation mechanisms of the slope leading to heterogeneous responses and phase lag	Chen, Prishchepov [35] urban multi-source	Verification of constitutive models, analysis of mechanical response chains

clear logical hierarchy. Datum conflict points to external differences in the geometric observation system; it is mitigated through reference-frame unification and systematic error correction. Scale conflict points to inherent differences between observation modality and process scale; it requires multi-scale modelling to achieve cross-scale information transfer. Response conflict points to divergence in the slope's internal mechanical mechanisms; it demands comprehensive assessment integrating constitutive relationships and deformation stages. This classification also imposes specific requirements on metadata recording for monitoring data: datum conflict calls for attention to reference-point coordinates and correction parameters; scale conflict requires explicit documentation of sensor spatial coverage and sampling frequency; response conflict necessitates recording the temporal relationships between monitoring quantities and external triggers such as rainfall and water level. Complete metadata records help link isolated discrepancy events into interpretable mechanical processes, providing the foundation for subsequent knowledge-graph construction and intelligent diagnosis.

4.2. Detection Principle

Conventional practice sets a threshold to validate discrepancies among multi-source data [39]. Experience reported in the literature suggests this approach is itself questionable [40]. InSAR measures cumulative line-of-sight displacement; GNSS measures three-dimensional positional change; acoustic emission reflects internal micro-fracturing within the rock mass; pore-water pressure gauges reflect the seepage field. These sensors differ in physical dimension, spatial averaging scheme, and the time window in which they are sensitive to deformation. Computing relative errors from multi-source monitoring data and comparing them against a fixed threshold lacks physical justification [41]. The primary task of conflict detection is therefore not to label a particular data source as erroneous, but to determine whether the inconsistency stems from instrument or environmental interference, or from the intrinsic complexity of the slope deformation mechanism.

In terms of data quality, each sensor has its inherent precision bandwidth and error sources. Sentinel-1 SBAS-InSAR in complex terrain exhibits an RMSE of approximately 4–5 mm and an MAE of about 2 mm; its accuracy is affected by atmospheric phase residuals, orbital error, and decorrelation [42]. PS-InSAR can identify millimeter-level deformation trends, but it demands high spatial density of monitoring points; precision degrades when point density is insufficient [43]. GNSS-RTK achieves an RMS error of about 3 mm in the horizontal direction and about 5 mm in the vertical after optimization, but in slope environments multipath effects and satellite signal occlusion can amplify errors to the centimeter level [44]. AE sensitivity reaches the micro-strain level, but environmental noise from rainfall, traffic, and mechanical vibration often mixes with the target signal; signal-to-noise separation remains a practical challenge [45]. Pore-water pressure sensors themselves offer reliable measurement accuracy, but disturbance around the borehole and the representativeness of measurement points are often harder to control. Consequently, when fluctuations in a given data source exceed its own precision bandwidth, the priority is to examine the quality of that single source, rather than submitting it prematurely to multi-source conflict analysis.

Multi-source consistency checking begins only after each data source has been confirmed as independently reliable. The focus is not on numerical discrepancy, but on whether the trend and phase relationship of each monitoring quantity still conform to the mechanical laws of that slope [46]. For example, both InSAR and GNSS may show continuously accelerating displacement while AE energy decays. This is not necessarily a data anomaly; it may correspond to the process of fracture coalescence and the subsequent shift of the stress concentration zone after the main slip surface has formed [47]. In addition, after a heavy rainfall event, the groundwater level has risen markedly, but surface displacement decelerates in the short term [48]. This phenomenon may relate to phase lag in the seepage-deformation coupling process. While elevated pore-water pressure reduces effective stress, volumetric compression during the drainage-consolidation stage may temporarily mask the growth of shear displacement. Such judgements depend on understanding the hydro-mechanical processes of the slope, not on numerical thresholds that span different physical dimensions [49].

Furthermore, certain inconsistencies themselves may be precursor signals of a transition in the slope deformation mechanism. During the creep stage, displacement rate and AE event rate are usually positively correlated; if the two suddenly decouple—displacement continues to increase while AE becomes quiet—this may indicate that the slope is shifting from distributed micro-fracturing to localized shear, a sign of impending failure [50]. If statistical smoothing is applied to this pair of contradictory data, the key warning signal is lost [51]. The underlying logic of conflict detection is therefore to test whether the monitoring data still present a self-consistent physical picture against known mechanical laws [52]. When the data begin to present an inconsistent physical picture, the objective is not to force consistency, but to investigate the mechanical cause behind the inconsistency [53].

In engineering practice, threshold setting remains necessary, but the values should adapt to site conditions and the deformation stage, rather than being copied across sites [54]. During stable periods, historical data can be used to calibrate the natural fluctuation range of each sensor, forming a site-specific baseline [55]. Once the slope enters an acceleration stage, numerical consistency should no longer be demanded; attention should shift to whether the phase relationship and trend coherence among monitoring quantities still conform to mechanical laws. Each cross-source inconsistency should be recorded as an event with timestamp, environmental parameters, and mechanical criteria. Long-term accumulation of such records builds a site archive, providing reference for subsequent judgements under similar conditions and avoiding the need to build understanding from scratch each time.

5. CONFLICT RESOLUTION PARADIGMS AND CLOSED-LOOP FRAMEWORK

The literature on handling multi-source data conflicts has developed along three technical paths—mathematical weighting and evidence theory, adaptive machine learning, and physics-informed modelling. The recent trend is to combine these into hybrid architectures, with knowledge graphs providing auditable closed-loop management. The suitability of each paradigm at field sites varies; the choice is not a matter of technical preference, but is constrained by the match among data foundation, theoretical reserve, and monitoring objective.

5.1. Mathematical Weighting and Evidence Theory

Dempster-Shafer evidence theory has a long record in landslide susceptibility assessment. Milaghardan, Delavar [56] combined D-S theory with the certainty factor, using belief functions to integrate predisposing factors such as slope gradient, terrain roughness index, and rainfall. Their study in Cao Bang Province, Vietnam, reported an overall accuracy of 74.5%, above that of the traditional certainty-factor model. This demonstrates that D-S theory offers verifiable advantages in synthesizing uncertainty from multi-source evidence. Its limitations under high-conflict conditions have also been documented: when the mass-function assignments of different evidence sources diverge markedly, the classical Dempster combination rule can yield counter-intuitive results—the Zadeh paradox. In landslide monitoring, this means that when InSAR and GNSS provide opposing evidence on the deformation trend of the same slope, simple multiplication of mass functions may not reflect the field state.

Kalman filtering is another mathematical weighting method, demonstrating real-time capability in multi-platform InSAR data fusion. Cai, Liu [38] dynamically integrated ascending and descending Sentinel-1 data with ALOS-2 PALSAR-2 data through a Kalman filter, shortening the monitoring temporal resolution from 12 days for a single orbit to 1 day, while enabling subsequent displacement prediction. These methods are transparent in process, computationally economical, and auditable. Their implicit premise is that the uncertainty of each sensor has been fully calibrated; for newly deployed stations or slopes with complex geology, this premise is often difficult to satisfy.

5.2. Adaptive Machine Learning

Deep learning has expanded into landslide displacement prediction. Ge, Li [57] proposed LiteTransNet, introducing the Transformer architecture and attention mechanism to landslide displacement prediction. Self-attention layers capture long-range dependencies in time series, and the model outperformed traditional recurrent neural networks on multiple datasets. Han, Miao [58] used deep convolutional autoencoders to integrate rainfall, surface displacement, and vertical displacement data for slope failure mode identification, demonstrating the utility of nonlinear feature extraction in fusing multi-source heterogeneous data. Graph convolutional networks (GCN) have also been applied to landslide displacement prediction and susceptibility assessment, explicitly modelling the spatial adjacency among monitoring points.

Transfer learning offers a route to address data scarcity. Recent studies have explored strategies to leverage pre-trained models or cross-site knowledge transfer, reducing the dependence on large labelled datasets at a single site. For instance, domain-adaptive approaches have been investigated to align the feature distributions between source and target slopes, though the robustness of such transfer under geologically heterogeneous conditions remains to be fully validated. The limitations of adaptive machine learning are marked in landslide monitoring: the dependence on labelled data is heavy, but high-quality, long-duration landslide monitoring labels are scarce in the field; the inference process is opaque, rendering it difficult for engineers to explain why a given sensor receives higher weight at a specific moment; when the data distribution shifts due to external events such as rainfall or earthquakes, the model may drift without self-correction capability.

5.3. Physics-Informed Modelling

Physics-informed neural networks (PINN) provide a path to link data-driven methods with mechanical mechanisms. Dahal and Lombardo [59] embedded the permanent-deformation constraint of the Newmark slope-stability method into a standard data-driven architecture. The network extracts geotechnical parameters from proxy variables while minimizing the residual loss against physical laws, yielding high susceptibility prediction accuracy and generating regional-scale geotechnical parameter distribution maps. Moeineddin, Seguí [60] incorporated creep mechanisms into a PINN framework, using the finite-element method to solve stress-deformation relations for catastrophic creep-landslide stability estimation. Cao and Gong [61] introduced transfer learning to develop the TL-PINN model, freezing specific hidden layers to improve capture of rainfall-induced landslide dynamics. The model handles discontinuous top-boundary conditions and steep gradients more effectively than conventional PINN.

The core value of PINN lies in embedding control equations as soft constraints in the loss function, allowing the model to respect physical laws such as seepage-deformation coupling even when data are sparse. The bottleneck in engineering application is also evident: the mechanical model of the local site must be identified and encoded as partial differential equations or constitutive relations. This demands deep geomechanical knowledge and explicitly injects the modeller's prior assumptions into the solution. When site geology is complex and shear-zone mechanical parameters vary markedly in space, simplified physical equations may become an overly rigid constraint, preventing the model from capturing the true complexity of the field.

5.4. Hybrid Strategies and Knowledge Fusion

A single paradigm is often inadequate for compound conflicts in the field. Consider a case with datum offset between satellite data and ground beacons, together with a rate gap in the acoustic channel. The physics-informed layer can correct the datum and describe the creep law, but it cannot capture local rate anomalies outside the equations. The data-driven model can learn this residual, but it offers no guarantee of physical plausibility under extrapolation. Recent research tends to combine the two: the physics-informed layer constrains the solution space, the adaptive layer fits the residual, and the evidence-fusion layer explicitly handles conflicts between their outputs.

Evidence fusion shows its value when different paradigms point to opposite conclusions. It is not a fourth independent method, but a meta-layer for handling inter-paradigm disagreement. Its purpose is to make divergence explicit rather than mask it through mathematical averaging. Knowledge graphs serve a central function in this process. Wu, Xie [62] integrated knowledge graphs with machine learning for landslide susceptibility assessment, using knowledge-graph representation learning to recommend feature factors. In the Three Gorges Reservoir area, this raised the random-forest model accuracy to 87.2%, demonstrating that domain knowledge can offset the subjectivity of pure data-driven feature selection. In multi-source monitoring conflict resolution, knowledge graphs can encode “monitoring data—physical mechanism—warning rule” as a queryable semantic network, enabling structured reuse of historical conflict-resolution experience.

5.5. Applicable Boundaries and Selection Logic of the Paradigms

The five conflict-resolution paradigms are compared using five common criteria: transparency and auditability, data dependence and adaptability, physical

Table 2: Comparison of Conflict Resolution Techniques

Technical Approach	Core Advantages	Major Limitations	Applicable Contexts
Mathematical Weighting and Kalman Filtering [38, 56]	Transparent processes, low computational cost, auditable results	Assumes known uncertainties, limited applicability for newly established stations	Calibration of uncertainties required, necessitating real-time integration
Adaptive Deep Learning [57, 58]	Captures nonlinear sensor discrepancies, adapts to local environments	Relies on labeled data, opaque inference, risk of data drift	Availability of a historical case library for similar sites
Physics-Informed Neural Networ [59-61]	Respects governing equations, can extrapolate with sparse data	Requires identification and encoding of local mechanical models, explicit prior assumptions	Known mechanical mechanisms with sparse monitoring data
D-S Evidence Fusion [56]	Explicitly addresses belief conflicts, tolerates cognitive uncertainty	Subjectivity in quality function allocation	Significant discrepancies in outputs across different paradigms
Knowledge-graph-based fusion [62]	Auditable tracking, reuses historical conflict experiences	Requires long-term maintenance and investment in knowledge curation	Long-term monitoring projects or multi-institutional collaborations

consistency, robustness and reliability, and engineering applicability. These criteria respectively evaluate the traceability of the decision process, dependence on data and prior information, conformity with physical mechanisms, stability under uncertain or changing conditions, and feasibility for operational deployment. Together, they provide a consistent basis for assessing the strengths, limitations, and applicable conditions of different approaches.

The five technical paths present different trade-offs among transparency, adaptability, physical consistency, and data demand (Table **2**). Mathematical weighting offers process transparency and low computational cost, but its validity rests on the premise that uncertainty has been fully calibrated. For newly deployed stations or slopes with complex geology, this premise is often unsatisfied, limiting its utility in the early project stage. Adaptive machine learning captures nonlinear response differences among sensors, but its dependence on labelled data and its opaque inference render warning decisions difficult to validate against physical plausibility; drift risk also arises when the data distribution shifts. Physics-informed modelling guarantees physical consistency under extrapolation by embedding control equations, but identifying and encoding the local mechanical model demands deep geo-mechanical knowledge, and the modeler's prior assumptions are explicitly injected into the results. In geologically complex sites, this may become an overly rigid constraint. Dempster-Shafer evidence fusion can explicitly handle belief conflicts among different paradigms, but the subjective assignment of mass functions remains an open issue. Knowledge graphs and digital-twin frameworks suit long-term monitoring projects or multi-institutional collaboration; their value lies not in real-time computation speed, but in converting conflict-resolution experience into auditable, reusable knowledge assets.

From an engineering standpoint, the choice of resolution strategy should respond to the data foundation and theoretical reserve at hand, not to technical novelty. When sensor uncertainty has been recorded over a long period and the covariance structure is clear, mathematical weighting remains the most economical and auditable starting point. When uncertainty calibration is lacking but a historical case library from similar sites exists, adaptive learning serves as a supplementary tool, but its output must be checked against physical plausibility. When the site mechanical mechanism is largely understood and monitoring data are relatively sparse, physics-informed modelling is advantageous, though its results will inevitably encode the modeler's prior assumptions. When different paradigms diverge, the combination of evidence fusion and knowledge graphs provides a framework for explicit handling of the disagreement, turning the conflict itself into an auditable, reusable knowledge asset rather than noise to be smoothed away.

6. DISCUSSION

6.1. From Bibliometric Findings to Operational Framework

Bibliometric results and the conflict typology together point to one conclusion: discrepancies in multi-source data should not be treated as noise to be filtered, but as independent information carriers to be recorded and analyzed. Based on the technical paths reviewed above, monitoring agencies can establish a phased operational framework. The initial investment focuses on data-management protocols and staff training, not hardware expansion.

The framework comprises four steps that can be advanced progressively. First, at the data-display level, annotate the uncertainty bandwidth of each sensor and identify conflict events according to the joint-uncertainty rules described in Section 4.2; this step requires no new hardware. Second, establish paired validation between satellite products and ground beacons at specific slopes, turning cross-source divergence into interpretable mechanical evidence rather than mere visual alerts. Third, record metadata at the sensor-installation stage—identifier, datum frame, epoch, support conditions, nominal uncertainty, and raw-data stream pointer—providing a structured relational basis for the knowledge graph and avoiding manual matching later. Fourth, include conflict interpretation in analyst training, so that cross-source divergence triggers a search for mechanical explanation before smoothing is applied.

For practical implementation, the framework requires three basic categories of information: monitoring observations, sensor metadata, and external driving factors. Monitoring observations include deformation, pore-water pressure, acoustic emission, rainfall, and other available measurements; sensor metadata record the reference frame, sampling interval, spatial support, installation condition, and nominal uncertainty; environmental information provides the context for interpreting rainfall-, reservoir-, or temperature-related responses. Decision making follows a hierarchical logic. Each data source is first checked against its own uncertainty range and quality-control criteria. Cross-source consistency is then evaluated in terms of reference compatibility, spatiotemporal scale, and physically expected trend or phase relationships. When disagreement exceeds the expected range, it is classified as datum, scale, or response conflict, and the corresponding correction, scale reconciliation, or mechanism-based interpretation is applied before the warning decision is updated.

The bibliometric results indicate that fusion-method papers constitute the core nodes of the current citation network. New monitoring projects can therefore build directly on published methodological frameworks and apply them to local data, without repeating methodological exploration. The practical value of the conflict-aware workflow is illustrated by the 2017 Mud Creek landslide in California [23]. InSAR characterized the long-term slow movement, whereas optical pixel tracking captured rapid acceleration about one month before failure, supporting failure forecasting several days in advance. Rather than indicating unreliable data, this divergence reflected the different sensitivities of monitoring techniques during the slow-to-fast transition. The case shows that conflict-aware monitoring can improve sensor complementarity, support mechanism-based interpretation of cross-source disagreement, and preserve critical acceleration signals for early-warning decisions.

6.2. Temporal Dimension and Environmental Drivers of Conflict

Cases of reservoir-bank slopes and rainfall-induced landslides show that multi-source data conflicts are time-dependent. Under extreme weather or reservoir-level fluctuation, different sensors respond to the same driving factor with phase differences: groundwater change may precede surface displacement by hours to days, while InSAR, constrained by its revisit cycle, captures only cumulative effects. If conflict records are analyzed in isolation from environmental drivers—rainfall, reservoir level, temperature—they may be misjudged as instrument malfunction or local anomaly.

Conflict records must therefore preserve trigger-condition information, so that subsequent analysis can interpret divergence within its specific environmental context. The combination of MT-InSAR and machine learning has been used to separate reservoir-level-driven signals from local deformation; a similar separation logic applies to conflict resolution. Incorporating driving factors into conflict metadata is a necessary step toward improving the interpretability of warnings.

6.3. Auditability Check and knowledge Accumulation

The credibility of an early-warning system depends not only on prediction accuracy, but on the traceability of the decision process. To this end, an audit mechanism based on historical cases can be established: for any closed warning event, the record is checked for four items—the sensors that produced the divergence, their respective uncertainty bandwidths, the resolution paradigm adopted, and the decision rule triggered. Cases with complete records provide reference for subsequent similar conflicts; even if the warning result is incorrect, the reasoning process can be reproduced and evaluated. Cases with missing records resist post-hoc review; even if the result is correct, chance cannot be ruled out. Validation is conducted at both data and decision levels. Conflict-resolution results are checked against independent or subsequent observations, while warning outcomes are verified against the actual slope response. The validated conflict type, resolution strategy, and decision outcome are then fed back into the site archive or knowledge graph to refine subsequent interpretation and warning rules.

Knowledge graphs serve a structural function in this process. By storing conflict type, resolution strategy, and validation result in linked form, the system can retrieve historical cases for analogical reasoning when a new divergence pattern appears, giving the closed-loop framework a self-improvement capability.

6.4. Limitations and Future Directions

This review has two limitations. First, the literature source is restricted to English papers in the Web of Science Core Collection; Chinese-language literature and grey literature are excluded. This may bias the publication-trend curve, especially given the research volume on landslide monitoring in China. Second, the exported data lack country and institution fields, preventing national productivity or collaboration-network analysis; this awaits a more complete dataset.

Future work can expand in three directions. First, extend the corpus to Chinese databases to correct regional bias in current publication trends. Second, supplement citation-relationship fields to enable true co-citation analysis rather than keyword-based bibliographic coupling. Third, establish a labelled benchmark dataset of multi-source monitoring conflicts, containing instrument configuration, datum frame, environmental drivers, and validation results, so that different resolution paradigms can be compared against a uniform standard rather than relying solely on expert judgement.

7. CONCLUSIONS

The shift from single-sensor to multi-sensor landslide monitoring has generated an abundance of data, but it has not automatically produced an abundance of trustworthy warnings. This review demonstrates that the central bottleneck in current early-warning practice is not the shortage of fusion algorithms, but the absence of a systematic discipline for handling the conflicts that inevitably arise when heterogeneous sensors observe the same slope. Through bibliometric analysis of 264 records and critical methodological review, three principal conclusions emerge.

(1) Data conflict is not an instrumental malfunction to be filtered out; it is an inherent consequence of the differences in physical observables, spatial averaging, temporal sampling, and environmental sensitivity among sensors. Treating conflict as noise simplifies the workflow but discards mechanistic information. The typology of datum, scale, and response conflicts proposed here provides a basis for interpreting divergence according to its physical origin rather than its numerical magnitude, thereby preserving the diagnostic content that smoothing operations would otherwise attenuate.

(2) The five resolution paradigms surveyed—mathematical weighting, adaptive machine learning, physics-informed modelling, evidence fusion, and knowledge-graph reasoning—each carry distinct trade-offs among transparency, adaptability, physical consistency, and data demand. None is universally superior; the appropriate choice depends on whether sensor uncertainties have been calibrated, whether labelled historical cases exist, whether the site mechanics have been characterized, and whether the project horizon justifies the curation effort for knowledge formalization. The critical insight is that paradigm selection should be treated as a resource-allocation decision constrained by site conditions, not as a technology-adoption decision driven by algorithmic novelty.

(3) Trustworthy warning requires more than accurate prediction; it requires traceable justification. The closed-loop framework outlined here—detect, resolve, decide, verify, and feed back—converts each conflict event into an auditable record that links sensor disagreement, environmental driver, resolution paradigm, and verification outcome. This record is the raw material from which knowledge graphs learn, and it is the documentation that makes a warning defensible after the fact, whether the warning was right or wrong.

The bibliometric trajectory suggests that the field is still in a rapid-growth phase, with the fusion-driven surge of 2024–2026 likely to continue. Yet the keyword and citation structure reveals that the intellectual core of the field remains anchored in integration methods rather than in conflict diagnostics. Closing this gap will require benchmark datasets that contain labelled sensor disagreements with known physical causes, so that resolution paradigms can be compared on evidence rather than on expert judgment. It will also require greater engagement with the Chinese-language and grey literature that the present English-only corpus necessarily excludes. Future reviews that incorporate these extensions will be able to test whether the fusion front continues to accelerate or settles into a steady state, and whether conflict-aware monitoring matures from a critical perspective into an operational standard. This provides geotechnical engineers with a more transparent basis for stability assessment, risk prioritization, and warning escalation.

CREDIT AUTHORSHIP CONTRIBUTION STATEMENT

Yizheng Su: Investigation, Writing – review & editing, Writing – original draft, Project administration. Jue Li: Writing – original draft, Writing – review & editing, Project administration, Funding acquisition. Chao Wang: Investigation, Writing – original draft

DECLARATION OF COMPETING INTEREST

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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