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Systematic Review

Integrated Geospatial Monitoring of Deformations of Tailing-Storage Facilities and Ground Dams: Systematic Review of Technologies, Limitations and Conceptual Architecture

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Highlights

What are the main findings?

- The reviewed literature reports substantially higher accident rates for tailings storage facilities (TSFs) than for conventional large reservoirs. Upstream facilities account for a considerable share of documented failures, and the volume of material released in the largest disasters has increased markedly over recent decades.
- Multisensor integration can improve deformation detection accuracy, shorten early-warning response times, and extend warning lead times. Individual case studies also demonstrate the potential of hybrid numerical and machine-learning models to improve factor-of-safety predictions, although the reported gains remain specific to the datasets and conditions examined.

What are the implications of the main findings?

- Transition from isolated monitoring methods to integrated geospatial systems that combine GNSS, InSAR, UAVs, LiDAR, geotechnical sensors, AI/ML, and digital twins is essential for improving the safety of tailing storage facilities and meets GISTM requirements.
- Future research should prioritize explainable artificial intelligence (XAI), quantitative assessment of forecast uncertainty, integration of climate scenarios, and standardization of multisensor platforms.

Abstract

Relevance. Tailing storage facilities (TSFs) are among the most accident-prone hydraulic structures in the mining industry, with a reported average failure-rate estimate of approximately 1.2%, while independent cumulative estimates range from 1.2% to 4.4% depending on the assumed global TSF inventory—nearly 120 times higher than that of traditional large reservoir facilities. Collapse of such structures is accompanied by catastrophic environmental and socioeconomic consequences, which underscore the need to improve monitoring and early-warning systems. **Goal.** A systematic analysis of current technologies for monitoring deformations in ground dams of TSFs, a quantitative assessment of their capabilities and limitations, and development of a conceptual architecture for an integrated geospatial monitoring system. **Methods.** A systematic review was conducted for 129 publications (2017–2026) discussing monitoring methods (GNSS, InSAR, SBAS, PS-InSAR, GB-InSAR, UAV, LiDAR, geotechnical sensors, geophysics), data integration technologies, AI/ML forecasting, digital twins, and early-warning systems. **Results.** It has

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been determined that no isolated method on its own provides complete monitoring of the structure's condition: GNSS data are localized; InSAR loses coherence when deformations exceed 15 cm/year; UAVs are weather-dependent; and geotechnical sensors are point-based. Individual studies report reductions in estimation uncertainty of approximately 20–50% when complementary monitoring sources are integrated. Individual studies also report reductions in EWS response time and extended forecast lead times, but these values are heterogeneous and are not pooled in the present review. In one case study, a hybrid FEM–ANN–LSTM model achieved a mean absolute error (MAE) of 0.027 for forecasting the dimensionless factor of safety (FoS) compared with 0.081 for an SVM baseline. Key research gaps have been identified: lack of explainable AI, limited validation of digital twins, absence of standardization in data fusion, and the lack of integration of climate risks. **Conclusions.** Further improvements in TSF safety require a shift from a set of independent monitoring methods to an integrated geospatial system that combines satellite, ground-based, geotechnical, and geophysical data with artificial intelligence, digital twins, and smart decision support systems. An eight-level architecture for such a system has been proposed, along with three implementation scenarios (minimal, comprehensive, and intelligent) and a roadmap through 2035.

Keywords: deformation monitoring; tailing storage facilities; ground dams; InSAR; GNSS; UAV; LiDAR; multisensor integration; artificial intelligence; early-warning systems

1. Introduction

Hydraulic structures in the mining industry—primarily ground dams of tailing storage facilities (TSFs)—are among the most complex engineering and geotechnical systems, and their operation involves a high level of potential risk to the population, environment, and infrastructure. Unlike traditional large reservoir facilities, TSFs are subject to constant changes in their structure's geometry, properties of the stored waste, hydrogeological conditions, and operational loads, which significantly complicate the assessment of their stability and prediction of potential failures. The failure of such structures results in a discharge of millions of cubic meters of tailings, contamination of river basins, degradation of ecosystems, and significant social economic losses. Consequently, ensuring their safe operation is considered to be one of the top priorities in modern engineering geology, geodesy, mine surveying, and industrial safety.

The relevance of this issue has increased significantly following a series of major man-made disasters in recent decades, including the accidents at the TSFs of Mount Polley (Canada, 2014), Fundão (Brazil, 2015), and Brumadinho (Brazil, 2019), which demonstrated the limitations of existing approaches to monitoring and managing the safety of such facilities. According to a systematic analysis [1], the failure rate of TSFs is approximately 1.2% (independent cumulative estimates range from 1.2% to 4.4% [2,3]), whereas for conventional water retaining dams, this rate is estimated to be approximately 0.01%, which is nearly two orders of magnitude lower. At the same time, many of these accidents were accompanied not only by substantial loss of life and environmental damage, but also by a subsequent revision of international requirements for risk monitoring and management systems [4].

The global professional community responded to these events by significantly tightening safety requirements for TSFs: In recent years, new international standards have been developed and implemented, including the Global Industry Standard on Tailings Management (GISTM), guidelines from the International Commission on Large Dams

(ICOLD), the Canadian Dam Association (CDA), and other organizations, which provide for a shift from periodic inspections to continuous monitoring of the technical condition of structures throughout their entire life cycle. At the same time, it is impossible to meet these requirements without using modern spatial monitoring technologies that provide reliable information on the progression of deformation processes in near real time.

Over the last two decades, there has been rapid progress in the development of technologies for monitoring hydraulic structures. Modern global navigation satellite systems (GNSSs), satellite radar interferometry (InSAR), unmanned aerial vehicles (UAVs), laser scanning (LiDAR), geophysical survey methods, distributed fiber-optic sensors, and smart geotechnical sensors make it possible to record spatial displacements with millimeter-level accuracy, construct high-precision 3D surface models, and continuously monitor internal processes within a structure. At the same time, technologies such as the Internet of Things (IoT), cloud computing, artificial intelligence, machine learning, and digital twins have become widespread while enabling a significant expansion of the analytical capabilities of monitoring systems and a shift from recording changes that have already occurred to predicting potentially hazardous processes.

Despite the significant number of studies devoted to specific monitoring technologies, the literature review presented here shows that most published papers examine monitoring methods in isolation. The capabilities of satellite interferometry, global navigation systems, geotechnical sensors, unmanned photogrammetry, laser scanning, and various machine-learning algorithms have been studied in the greatest detail. At the same time, considerably less attention is paid to issues such as the comprehensive integration of heterogeneous spatiotemporal data, architecture of modern geospatial platforms, mechanisms for combining surface and subsurface observations, quantitative assessment of forecast uncertainty, and organization of smart decision support. Thus, contemporary scientific a substantial gap remains in the literature between the refinement of individual measurement technologies and development of integrated monitoring systems capable of functioning as a unified information and analytical environment.

An additional challenge is that current international standards for TSF safety management specify requirements for continuous monitoring and risk management, but contain virtually no recommendations regarding the architecture of integrated geospatial systems capable of combining data from Earth remote sensing, geodetic measurements, geotechnical monitoring, geophysical surveys, and artificial intelligence methods. Similarly, most recent studies in the fields of digital twins, data fusion technologies, and smart early-warning systems are limited to examining individual components without developing a comprehensive conceptual model of their joint functioning.

Thus, the main research gap is the lack of a comprehensive concept for building an integrated geospatial monitoring system that brings together all levels of acquisition, transmission, storage, analysis, and interpretation of spatiotemporal data within a single decision support platform. Solving this problem requires a shift from the traditional approach—which is based on comparing individual monitoring methods—to a systematic analysis of the architecture of modern intelligent safety systems for hydraulic structures.

Accordingly, the goal of this systematic review is to provide a comprehensive analysis of current technologies for monitoring deformations in ground dams of TSFs, to critically assess the level of evidence supporting existing scientific approaches, to identify key research gaps, and to develop a conceptual architecture for an integrated geospatial monitoring system based on a combination of Earth remote sensing methods, geodetic and geotechnical observations, artificial intelligence technologies, digital twins, and smart decision support systems.

The scientific novelty of this research lies not in comparing individual monitoring methods, but in developing a systematic concept of geospatial intelligence for tailing dam monitoring, which considers monitoring as a multilevel smart geospatial ecosystem that ensures continuous collection, integration, analysis, forecasting, and interpretation of spatiotemporal data throughout the entire life cycle of a hydraulic structure. In our view, it is precisely this approach that reflects the current trend in the development of monitoring systems and aligns with the mining industry's transition toward digital transformation and risk-based safety management.

2. Materials and Methods

This systematic review was conducted and is presented in accordance with the 2020 Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines to ensure methodological rigor, transparency, and reproducibility of the results. The PRISMA 2020 checklist is included in the Supplementary Materials. This review protocol was developed to comprehensively identify, select, and synthesize the available scientific literature on integrated geospatial monitoring systems for deformations of ground dams and TSFs published from January 2017 to the final search date of 10 June 2026.

2.1. Search Strategy

A systematic literature search was conducted on 10 June 2026, using four major electronic databases: Scopus, Web of Science Core Collection, IEEE Xplore, and Google Scholar. These platforms were selected to ensure the widest possible coverage of publications in the fields of engineering survey, remote sensing, geotechnical monitoring, mining, and related disciplines.

The search strategy combined key terms related to monitoring targets, observation technologies, analysis methods, and early-warning systems, using Boolean operators (AND/OR). The following basic search structure was adapted for each database:

(«dam monitoring» OR «tailing dam» OR «tailing storage facility» OR «TSF» OR «earth-fill dam» OR «embankment dam») AND («deformation monitoring» OR «displacement monitoring» OR «subsidence monitoring») AND («InSAR» OR «GNSS» OR «UAV» OR «LiDAR» OR «fiber optic» OR «piezometer» OR «inclinometer») AND («multi-sensor» OR «data fusion» OR «integration» OR «IoT» OR «cloud computing») AND («machine learning» OR «deep learning» OR «LSTM» OR «digital twin» OR «early warning system»)

For each source, adapted syntactic structures were used, taking into account the specifics of the platforms: subject categories (for example, engineering village for Scopus), truncation operators (*), and quotation marks for exact phrases. In addition, restrictions were used based on publication type (conference abstracts without the full text, editorial materials, and comments were excluded) and based on language (only English-language publications were included). The search covered publications from January 2017 to 10 June 2026.

To increase the sensitivity of the search, the reference lists of all included review articles were manually analyzed (using the "reverse snowball" method) to identify additional relevant primary studies that were not found during the automated search.

2.2. Research Selection and Eligibility Criteria

Studies were selected independently by two reviewers (the first and second authors). After removing duplicates using EndNote X20 software, the titles and abstracts were reviewed for compliance with predefined eligibility criteria. Potentially relevant records were then subjected to full-text evaluation. Any disagreements among the experts were resolved through discussion or consultation with the third expert (the third author).

The eligibility and exclusion criteria were established a priori and are summarized in Table 1.

Table 1. Research eligibility and exclusion criteria.

Criterion	Eligibility	Exclusion
Publication Type	Original research articles, systematic reviews, critical reviews, comparative studies, technical reports, and validated case studies	Conference abstracts (without full text), editorial materials, commentaries, letters to the editor, preprints, and not-peer-reviewed publications
Subject of the Research	Ground dams, tailing storage facilities (TSFs), hydraulic structures at mining operations, earthen dams, rock-fill embankments	Concrete dams (excluding comparative studies), water supply and sewer systems, and civil engineering structures
Monitoring Technologies	GNSS, InSAR (SBAS, PS-InSAR, D-InSAR), GB-InSAR, UAV photogrammetry, LiDAR, TLS, piezometers, inclinometers, fiber-optic sensors, geophysical methods (ERT, seismic acoustics), IoT sensors	Methods not related to deformation monitoring
Analytical Methods	Multisensor integration, data fusion, machine learning, deep learning, digital twins, early-warning systems, spatiotemporal analysis, GIS technologies	Studies that use only classical statistical methods unrelated to data integration
Time Period	2017–2026	Publications prior to 2017 [1]
Language	English	Other languages [2]
Data Availability	Quantitative results, accuracy characteristics, and comparative data are presented	Lack of experimental or field data; only conceptual studies without quantitative assessment

[1] Excluding foundational works cited for theoretical background; [2] excluding key papers that have been translated into English.

2.3. Selection Process and Quantitative Results

The research selection process followed the PRISMA 2020 guidelines.

An initial search of four databases identified 1847 records. After removing 423 duplicates, 1424 unique records were checked for titles and abstracts. Of these, 1106 records were excluded because they did not meet the eligibility criteria (for example, those published before 2017, those not related to dam deformation monitoring, or those that did not contain quantitative results). The remaining 318 full-text papers were assessed for compliance with the eligibility criteria. Following a full-text analysis, 189 papers were excluded for the following reasons:

- Absence of quantitative data on measurement accuracy (n = 67).
- Focus on only one method without considering integration (n = 52).
- Insufficient description of the methodology (n = 32).
- Duplication of data from other publications (n = 23).
- Full text not available (n = 15)

A total of 129 papers were included in the final qualitative synthesis (Figure 1).

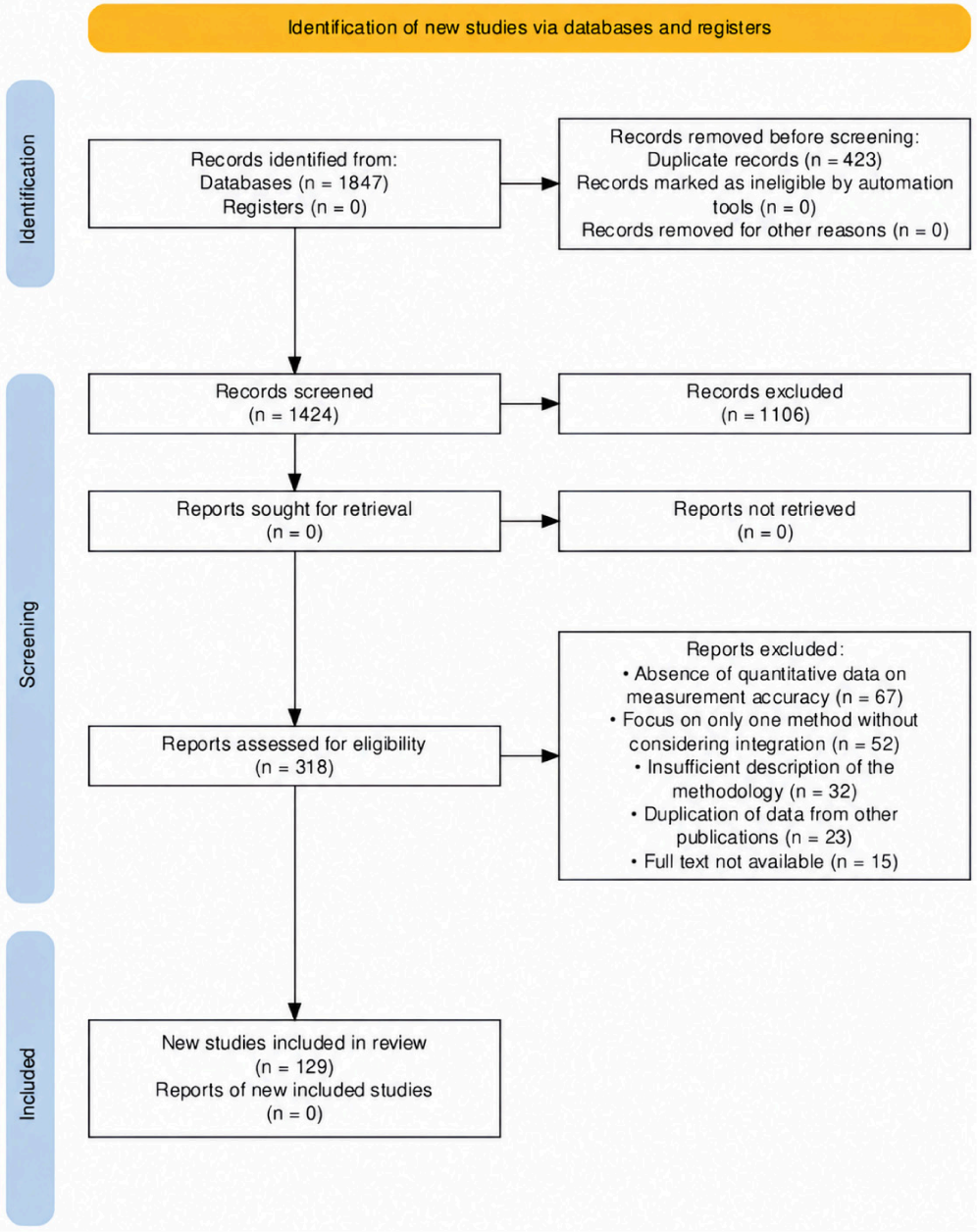


Figure 1. PRISMA 2020 flow diagram of the study selection process.

2.4. Data Extraction and Synthesis

Data from the 129 included studies were independently extracted by two authors (the second and fourth authors) using a standardized, pretested data extraction form in Microsoft Excel. The extracted information is presented in Table 2.

Table 2. Summary of the studies included in the systematic review.

Category	Parameter	Range/Standard Values	Key Sources
Research Features			
	Total number of included studies	129	[1–129]
	Research type	Reviews: 22 (17.1%); experimental: 47 (36.4%); case studies: 38 (29.5%); comparative: 22 (17.1%)	[1,4–12]
	Geographic distribution	China: 45%; Europe: 20%; North America: 12%; South America: 8%; Australia: 5%; Other: 10%	[13–22]

Table 2. *Cont.*

Category	Parameter	Range/Standard Values	Key Sources
	Publication period	2017–2026	[1–129]
Monitoring Objects			
	Object type	Tailing storage facility (TSF): 52%; ground dams: 28%; rock-fill embankments: 12%; facilities under construction: 5%; other: 3%	[1,7,10–13,16,17,19]
	Structural design	Upstream; centerline; downstream	[4]
Technical Parameters of Monitoring Methods			
	Sensor/technology type	GNSS: 89% studies; InSAR (SBAS/PS): 78%; UAV: 55%; LiDAR/TLS: 30%; piezometers: 45%; inclinometers: 38%; fiber optics: 18%; geophysics (ERT): 12%	[1,5,7–9,12–18,23–27]
	GNSS accuracy (horizontal)	1.6–7.6 mm	[28]
	GNSS accuracy (vertical)	10.8 mm	[28]
	SBAS-InSAR accuracy	3.4–8.1 mm (median: 5.2 mm)	[5,7,13–15,23,24]
	GB-InSAR accuracy	Submillimeter–millimeter level	[5,8]
	Accuracy of UAV photogrammetry (plane)	2–7 cm (median: 3.5 cm)	[7,26]
	Accuracy of UAV photogrammetry (height)	3–10 cm (median: 5.0 cm)	[7,26]
	LiDAR accuracy	TLS: approximately 3–6 mm for 3D positioning for the distances of 50–100 m; in some systems, the accuracy of individual points is ~2–5 mm for the distances of 10–40 m.	[5,7,18,26]
	Accuracy of leveling	Accuracy of <2 mm/km; in some studies, Class III leveling was used with an allowable height error of up to 3.5 mm.	[5,7]
	Spatial coverage	Points: GNSS, piezometers; local: UAV, LiDAR, GB-InSAR; areal: InSAR; regional: InSAR (satellite)	[1,5,7–11,13–15,29]
	Temporal resolution	Continuous (24/7): GNSS, GB-InSAR, IoT sensors; Periodic (every 6–12 days): satellite InSAR; By request: UAV, LiDAR	[5,8–11,13,14,27]
	Measurement frequency	GNSS: seconds–minutes; GB-InSAR: 1–5 min; IoT: up to 1 min; InSAR: 6–12 days; UAV: by request	[5,8–11,13,14,27]
	Observation duration	Short-term (<1 year): 15%; medium-term (1–5 years): 55%; long-term (>5 years): 30%	[2,5,7,10,11,13–17]
Monitoring results			
	Deformation rate (TSF)	1–50 mm/year (typically: 2–5 mm/year in the dam center)	[10,13,16,17,29]
	Deformation rate (earth slip, slopes)	5–100 mm/month	[7,10,18,26,29]
	Spatial distribution	Uneven; dam center deform greater at its edges; seasonal variations	[2,7,10,13–17,19]
	Temporal trends	Seasonal fluctuations: 5–10 mm; annual trends: dozens of mm; correlation with water level and precipitation	[2,7,10,13–15,29]
	Abnormalities detected	Local zones of accelerated deformation; seepage sections; dilution zones	[2,6,7,10,11,13–17,29]
Integration and analysis methods			
	Integration type	Data fusion: 45%; spatiotemporal fusion: 25%; multisensor integration: 30%	[7,10–12,19,27,29–31]

Table 2. *Cont.*

Category	Parameter	Range/Standard Values	Key Sources
	ML/DL algorithms	LSTM: 35%; GRU: 15%; CNN: 12%; hybrid (FEM + ANN–LSTM): 10%; Other: 28%	[29–35]
	Accuracy of AI models	MAE: 0.027–0.081; MAPE: 1.5–3.5%; R^2: 0.8–0.95	[29–35]
	Forecast lead time	5–25 days (typically: 5–6 days; maximally: 3.5 weeks)	[29,32]
	Digital twins	Improve forecasting accuracy by 47%	[30]
	GIS-technologies	They are used in 65% of the studies; 3D visualization, spatial analysis	[10–12,19,27]
	IoT architectures	They are used in 40% of the studies; delay of <1–2 s	[10,19,27]
	Estimated uncertainty	Monte Carlo: 10%; Bayesian: 8%; quantile regression: 7%; absent: 75%	[31,33–35]
Early-warning systems (EWSs)			
	EWS architecture	Multilevel (2–5 alarm levels); typically: 4 levels (green, yellow, orange, red)	[10–12,19,27]
	Detection threshold (deformation)	5–10 mm	[10,29]
	EWS lead time	Hours–weeks (typically: 5–6 days)	[10–12,19,27,29]
	System response time	Seconds–minutes (with IoT); hours–days (w/o IoT)	[10,27,29]
	Deformations, depression curve forecasting accuracy	96.72–99.7%	[19]
	Flood forecast error	20–30% → <10%	[27]
	EWS efficiency in case of disasters	3 did not react in the 3 largest disasters (Mount Polley, Fundão, Brumadinho)	[1,6,10]
Limitations and Conclusions			
	Main limitations of the methods	Spatiotemporal trade-off; the need to combine surface and subsurface monitoring; decorrelation and phase ambiguity in InSAR during rapid or abrupt deformations; the local nature of the measurements taken by contact sensors	[1,5,9,12,18,36–38]
	Integration limitations	Lack of standardization; incompatibility of data formats; lack of interoperability	[11,12,19,27]
	Limitations of AI/ML	"Black box" (uninterpretability); impossibility to predict disasters outside the training samples	[33–35]
	Integration conclusions	Multisensory integration improves accuracy by ~47%; reduces EWS response time by 95%; increases the lead time up to 3.5 weeks	[7,8,10–12,19,27,29–32]
	Practical recommendations	Transition to integrated geospatial systems; implementation of IoT, AI/ML, and digital twin; data fusion standardization; GISTM registration	[1,4–6,10–12,19,27]

Figure 2 shows the geographic distribution of the studies included in the review, the monitoring technologies reported by region, and selected case-study locations.

The data were aggregated based on the analysis of 129 publications included in the systematic review. The percentages reflect proportion of the studies in which the relevant parameter is mentioned or used. The median accuracy values were calculated based on

data from 86 publications containing experimental metrological characteristics. Detailed references to specific studies are provided in Sections 3.1–3.4 hereof and in the references.

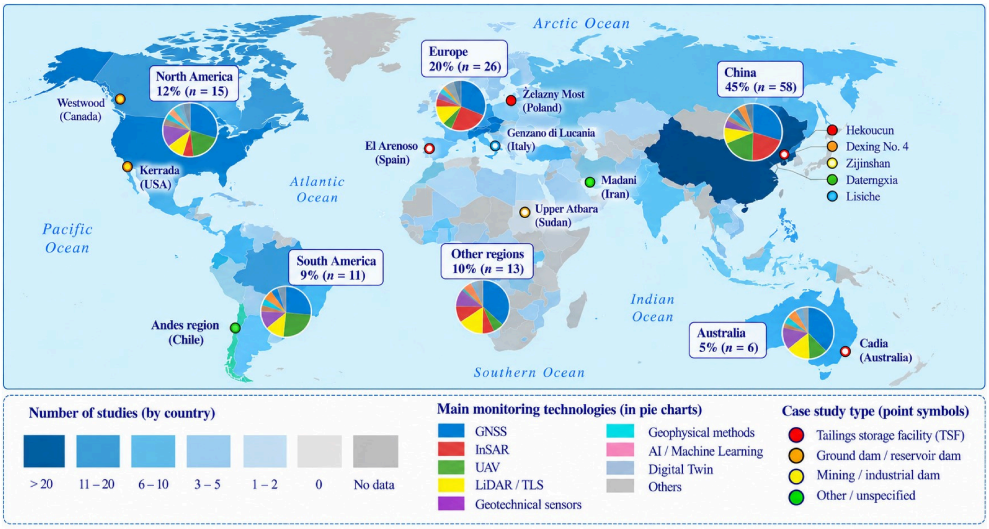


Figure 2. Geographic distribution of the studies included in the systematic review and selected monitored facilities.

Given the considerable heterogeneity of study designs, types of monitoring sites, technologies used, and parameters measured, it was not possible to conduct a formal meta-analysis. Therefore, the **narrative synthesis** approach was adopted. The data were arranged by thematic areas (accident rates and failure statistics, satellite monitoring, ground-based geodetic methods, geotechnical sensors, multisensor integration, AI/ML forecasting, early-warning systems, digital twins, and regulatory frameworks) to identify consistent patterns, quantitative relationships, and the most promising areas for development.

Quantitative data (such as accuracy ranges, deformation rates, and improvement factors during the integration) were compiled into comparative tables to facilitate a clear comparison of the results from various studies.

Influence of Study Heterogeneity on Quantitative Synthesis

The quantitative indicators reported in the reviewed studies are strongly dependent on the characteristics of the investigated monitoring conditions. First, the type and structural configuration of a tailing storage facility influence both the deformation behavior and the spatial distribution of monitoring observations. Facilities with different construction characteristics and operational conditions may exhibit different deformation patterns, which affects the baseline performance of individual monitoring methods and consequently the magnitude of improvement obtained after data integration. Therefore, an accuracy improvement reported for one TSF configuration cannot be directly interpreted as representative of all types of tailings facilities.

Second, the magnitude and rate of deformation affect the relative performance of monitoring technologies. Under relatively small and gradual deformations, methods such as InSAR may provide dense spatial observations, whereas rapid or large deformations can reduce interferometric coherence and increase uncertainty. In such cases, complementary observations from GNSS, UAV, GB-InSAR, or geotechnical sensors may provide a larger relative improvement because they compensate for limitations of the primary method. Thus, the reported improvement ratio may depend not only on the integration strategy itself, but also on the deformation regime under which the comparison was performed.

Third, the configuration of the monitoring network directly affects the observed benefit of multisensor integration. Differences in the number and spatial distribution of sensors, observation frequency, measurement geometry, and combinations of monitoring technologies determine the degree of complementarity between data sources. For example, the integration of spatially distributed InSAR or UAV observations with point-based GNSS or geotechnical measurements may produce different accuracy gains depending on the spatial coverage and temporal sampling of the individual datasets.

These sources of heterogeneity are particularly important when interpreting the aggregated quantitative results of this review. The reported ranges describe the variability of performance observed across the included studies and should not be considered statistically pooled estimates. The quantitative synthesis therefore identifies the direction and approximate magnitude of reported improvements, while recognizing that direct comparison between studies is constrained by differences in TSF characteristics, deformation regimes, sensor configurations, and experimental conditions.

2.5. Research Quality Assessment

The methodological quality of the included original research papers was assessed using an adapted version of key criteria based on established tools, with an emphasis on the clarity of the experimental description of monitoring methods, data processing, and presentation of the results. For the included review articles, the AMSTAR-2 checklist was used as a guide to assess their methodological rigor.

The quality assessment included the following criteria:

1. Clarity of the wording of the research goal and objectives.
2. Adequacy of the description of monitoring methods (type of sensors, measurement frequency, data processing methods).
3. Presentation of quantitative results, including errors.
4. Justification of the conclusions based on the results obtained.
5. For reviews: comprehensiveness of their search strategy, presence of eligibility/exclusion criteria, assessment of the risk of systematic error.

Most reviews (n = 18 out of 22) were of moderate or high quality, while the original articles (n = 107) contained sufficient data for analysis. The main limitations were lack of sufficient detail in the description of search strategies in some reviews, absence of a quantitative assessment of uncertainty in experimental studies (n = 34, 32%), and infrequent mention of corrections for multiple comparisons in the studies using machine learning (n = 41, 39%). The results of the quality assessment were used to interpret the findings, but did not serve as grounds for excluding studies.

2.6. Classification and Categorization of Monitoring Technologies

To arrange the wide variety of monitoring technologies presented in the analyzed publications, a classification scheme was developed based on three main criteria: physical measurement principle, spatial coverage, and type of process being monitored (Table 3). This classification was used to create the comparative tables in Section 3 and to assess the role of each technology in the integrated monitoring system.

Table 3. Classification of deformation monitoring technologies.

Category	Sub-Category	Technology Examples	Monitored Processes
Satellite methods	Radar interferometry	PS-InSAR, SBAS-InSAR, D-InSAR	Surface deformations (LOS [1])
	Optical survey	Optical satellite images	Surface geometry, shifts
Areal methods	Unmanned aerial systems	UAV-photogrammetry, UAV-LiDAR	3D model of the surface, local deformations

Table 3. *Cont.*

Category	Sub-Category	Technology Examples	Monitored Processes
	Crewed aircraft	Aerial photography, LiDAR from aircraft	Large-scale mapping
Ground-based geodetic methods	Satellite methods	GNSS (GPS, GLONASS, Galileo, BeiDou)	3D coordinates of control points
	Electronic measurements	Robotic tacheometers	Angular and linear measurements
	Geometric leveling	Digital levels	Vertical shifts
Ground-based remote methods	Radar systems	GB-InSAR	Local LOS shifts
	Laser scanning	TLS, ground-based LiDAR	High-density 3D point clouds
Geotechnical methods	Seepage control	Piezometers, tensiometers	Pore pressure, ground water level
	Deformation control	Inclinometers, extensometers, SAA	Internal shift in depth
	Distributed measurements	Fiber-optic sensors	Deformation distribution and temperature
Geophysical methods	Electrical resistivity imaging	ERT	Specific resistance, water-saturated zones
	Seismic methods	Active/passive seismic survey	Elastic wave velocities, soil stiffness
	Radar methods	Ground-penetrating radar (GPR)	Base structure, voids

[1] LOS—line of sight (line of sight of a satellite/radar). The data are aggregated from publications from 2017 to 2026.

2.7. Analysis of the Method's Gaps and Limitations

Through a systematic analysis, methodological limitations inherent in the studies examined were identified, which made it possible to identify areas for future research. The main limitations identified include the following.

1. Geographic Clustering. A significant portion of the studies (about 45%) was conducted in China, which creates a potential geographic bias and limits the applicability of the results to other climatic and geological conditions.

The geographic concentration of the reviewed literature may also influence the quantitative patterns identified in the synthesis. Because approximately 45% of the included studies were conducted in China, reported accuracy levels and integration performance may partly reflect the climatic, geological, structural, and monitoring conditions represented in this regional research base. However, the present review uses a narrative synthesis rather than a formal meta-analysis; therefore, the reported quantitative values should not be interpreted as pooled estimates representative of all TSFs worldwide. The findings should be considered in the context of the geographic distribution of the available evidence, with further validation under diverse climatic and geological conditions required.

2. Lack of Standardization. The lack of standardized procedures for data collection, processing, and interpretation makes it difficult to conduct a comparative analysis of the results of various studies.
3. Limited Temporal Depth. Most studies cover an observation period of less than 5 years, which is insufficient to assess long-term trends and seasonal variations.
4. Inadequate Assessment of Uncertainty. Only about 30% of the studies analyzed include a quantitative assessment of the uncertainty in measurements and forecasts.
5. A Gap between Technology and Regulation. A significant portion of the research does not address the compliance of the systems being developed with international standards (GISTM, ICOLD).

These limitations have been taken into account while interpreting the results and drawing conclusions in this review.

3. Results

This section presents a systematic synthesis of data from 129 research publications on the safety of tailing storage facilities (TSFs), accident statistics, monitoring technologies, and integrated systems. This section summarizes quantitative patterns, a comparative analysis, and scientifically grounded conclusions regarding the level of failure risk and effectiveness of modern monitoring approaches.

3.1. Accident Rates for TSFs and Hydraulic Structures: Statistical Patterns, Current Trends, and Lessons for Developing Monitoring Systems

The safety assessment of hydraulic structures is traditionally based on the analysis of a range of geotechnical, hydrological, and operational parameters. However, reported failure rates are regarded in modern engineering practice as the most objective comprehensive indicator of the design, operation, maintenance, regulatory control, and monitoring system efficiency. Unlike local characteristics, which reflect the condition of individual structural elements, the accident rate takes into account the impact of all stages of the life cycle of a structure—from engineering surveys and selection of a structure type to the monitoring quality and timeliness of managerial decisions.

This systematic review of the modern literature demonstrates a high level of consensus among independent studies indicating that tailing storage facilities (TSFs) are among the most accident-prone hydraulic structures in the mining industry. Despite the use of different statistical databases, varying criteria for classifying accidents, and differing estimates of the total number of facilities in operation, virtually all studies reach the same conclusion: the risk of TSF failure significantly exceeds the risk of failure of traditional large reservoir facilities (LRFs), and the consequences of such events are becoming increasingly severe.

The most comprehensive current assessment is presented in another systematic review [1], which analyzes international regulatory documents, industry standards, and published statistical data on TSFs. The authors show that the average failure rate for TSFs is about 1.2% (independent cumulative estimates range from 1.2% to 4.4% [2,3]), whereas the corresponding figure for traditional LRFs is estimated to be approximately 0.01%. Thus, the probability of a TSF failure is nearly 120 times higher, which indicates a fundamentally different level of risk and confirms the need to develop specialized monitoring systems specifically for this type of structure.

It should be emphasized that the values presented here do not constitute an absolute measure of risk, since their magnitude depends directly on the methodology used to calculate the total number of facilities, the completeness of accident records, and the failure criteria applied. However, it is the comparison of risk levels between TSFs and traditional LRFs that shows exceptionally high reproducibility across various studies. Regardless of the specifics of the statistical processing, all recent publications confirm that TSFs are the most vulnerable category of hydraulic structures in terms of the likelihood of accidents.

Further confirmation of this pattern was obtained in fundamental research [2,3], which conducted a retrospective analysis of global failure statistics for LRFs and TSFs for the period 1965–2020. The authors used several independent statistical models based on different estimates of the number of structures in operation, which made it possible to quantify the impact of uncertainty in the source database on the calculation of accident rates. According to the results obtained, the cumulative failure rate for LRFs by 2020 was 1.2–1.8%, and after excluding Chinese structures, it decreased to approximately 0.7%. For TSFs, the calculated values varied much more widely—from 1.5 to 4.4 percent—which is primarily due to the lack of a uniform estimate of the total number of TSFs in global practice.

Figure 3 compares the reported failure-rate estimates for LRFs and TSFs and distinguishes between point and range estimates. The reported estimates of TSF failure rates

should not be interpreted as directly conflicting values because they represent different statistical estimates. The value of approximately 1.2% reported in [1] represents the average failure-rate estimate obtained from the corresponding review, whereas the range of 1.2–4.4% reported in [2,3] represents cumulative estimates obtained under different assumptions regarding the total number of TSFs in operation. In the latter analysis, the estimated number of facilities is a major source of variation in the resulting failure rate. If we use the lower estimate of the global TSF number (6810 facilities), the estimated cumulative failure rate reaches 4.4%. When using the upper estimate (20,230 facilities), the figure drops to approximately 1.5%. Consequently, the range of values reflects primarily the uncertainty of the statistical data, rather than actual differences in the safety levels of the structures.

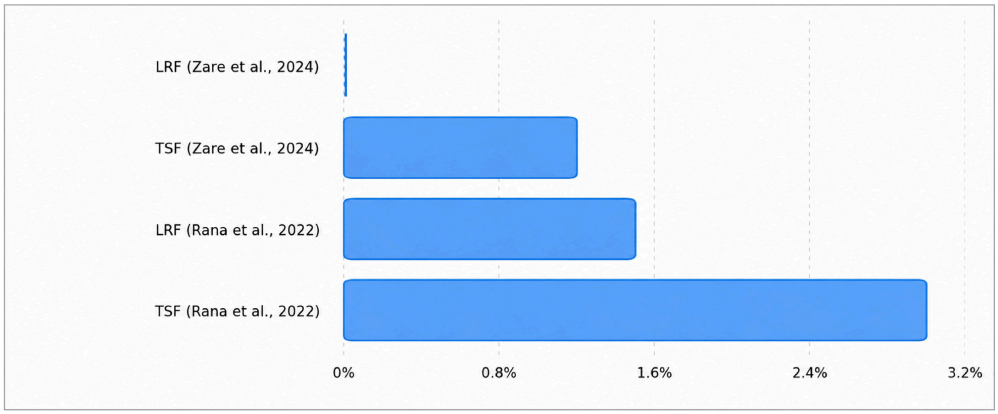


Figure 3. A comparison of failure frequency ranges for LRFs and TSFs based on recent research.

This is precisely why the conclusion made by the authors of [3]—that the actual modern failure rate of TSFs is most plausibly within the order of 1–2%—is broadly consistent with the approximately 1.2% estimate reported in [1] (Table 4). This example clearly illustrates an important aspect of interpreting statistical data in engineering safety: the absolute values of individual indicators may vary depending on the methodology used, while the overall trend remains consistent and reproducible across independent studies.

Table 4. Comparative analysis of current assessments of accident rates at hydraulic structures.

Parameter	LRFs	TSFs
Reported average failure-rate estimate [1]	0.01%	1.2%
Cumulative failure-rate estimate under alternative global-inventory assumptions [2,3]	1.2–1.8%	1.5–4.4%
Risk ratio	1×	~120×
Cumulative mortality per facility	1.2 fatal cases	0.1–0.3 fatal cases
Mortality per accident	64–98 fatal cases	6 fatal cases

It is interesting to note that despite a higher failure rate, the cumulative mortality per TSF constructed (0.1–0.3 fatal cases) is lower than that for LRFs (1.2 fatal cases). Similarly, the average number of fatal cases per failure for TSFs is 6, whereas for LRFs it ranges from 64 to 98. This may be because TSFs are often located in less populated areas, but the environmental consequences of their failure can be catastrophic.

Moreover, as the authors of [2] point out, the volume and environmental impact of TSF failure have increased on average worldwide, particularly since 2014. The growing global volume of tailings being disposed of has been roughly proportional to the growing global volume of tailing production since the 1990s.

Despite the widespread use of the failure-rate metric, its application as a universal criterion for assessing safety has a number of limitations. First, different studies use different criteria for recording accidents: some authors consider only complete structural failures, while others also include local instability, overflows, and emergency deformations. Second, to date, there is no international registry of TSFs that contains reliable information on their number, design type, operational history, and technical condition. Third, statistical indicators do not adequately reflect the changing scale of the consequences of modern accidents, since the increase in mineral extraction volumes is accompanied by an increase in the capacity of TSFs and consequently in the potential volume of discharges.

Therefore, when interpreting accident rates, it is necessary to take into account not only the probability of failure, but also the severity of potential consequences, spatial extent of contamination, duration of the environmental impact, and the level of preparedness of early-warning systems.

A systematic analysis of published studies shows that regardless of the calculation methodology used, all modern statistical assessments confirm that TSFs pose a significantly higher risk than traditional hydraulic structures. However, the main source of uncertainty stems not from accident records, but from the lack of reliable information on the global number of TSFs in operation.

Despite this factor, the range of modern estimates is gradually narrowing to values of 1–2%, which allows for considering this the most likely modern measure of the global accident rate for TSFs. Given the continuous growth in waste storage volumes and increasing potential scale of environmental impacts, the current risk level should be considered engineering unacceptable, which justifies the need to transition from periodic instrumental monitoring to integrated smart monitoring systems that provide continuous assessment of the condition of facilities and forecasting of the development of hazardous processes.

3.1.1. Failure Analysis by Design Type

A systematic analysis of the international literature shows that the probability of TSF failure is determined not only by the engineering and geological operational conditions, the quality of construction, or the effectiveness of monitoring, but also by the structural design of the facility itself. Among all risk factors, the design type is considered to be one of the most significant predictors of accident rates, as it determines the characteristics of the stress–strain state, nature of seepage processes, redistribution of pore pressure, and stability of slopes during operation.

In current practice, there are four main structural designs for tailing storage facilities: upstream, centerline, and single-stage. Each of them is characterized by different construction costs, different resistance to static and dynamic loads, and different sensitivity to seepage processes and soil liquefaction. Analysis of published studies shows that it is the structures built using the "upstream" method that demonstrate the highest accident rate, due to the specific nature of their construction, in which subsequent layers of the dam partially rest on previously deposited tailings that have lower load-bearing capacity and are more susceptible to water saturation.

The most comprehensive statistical analysis of the relationship between accident rates and structural design is presented in [4,39], which combined two independent international databases on TSF failures. The authors identified at least 325 recorded accidents within the period 1915 to 2021, which constitutes one of the most representative samples published in the contemporary literature. According to the data received, 121 accidents (37.2%) occurred at upstream facilities, 15 cases (4.6%) at centerline facilities, 26 cases (8.0%) at downstream facilities, and 16 cases (4.9%) at single-stage facilities, while 147 cases (45.2%) were recorded

for facilities whose design type could not be reliably determined due to a lack of complete historical information (Table 5).

Table 5. Distribution of reported TSF failures by structural design (1915–2021).

Design Type	Number of Failures	Percentage of the Total, %	Key Design Features
Upstream	121	37.2	Subsequent layers rest on the previously laid tailings; the most economical, but also the most sensitive to liquefaction type
Centerline	15	4.6	Subsequent expansion is carried out along the axis of the original dam
Downstream	26	8.0	The expansion is built up toward the lower slope; it is characterized by high stability
Single-stage	16	4.9	The structure is being built in a single phase, without any subsequent expansion
Non-classified	147	45.2	Insufficient historic information to identify the design type
Total	325	100	—

Source: [4,39].

The results indicate a marked prevalence of accidents at upstream type facilities among the cases for which the structural design was reliably determined. It should be noted that the high proportion of unclassified facilities makes it impossible to directly interpret the absolute distribution of accidents as an indicator of the reliability of various designs. However, even with this limitation, most contemporary studies consider the upstream design the most vulnerable construction design due to its combination of high economic efficiency with increased sensitivity to seepage processes, rising pore pressure, and static liquefaction of tailings.

Of particular interest is an analysis of how the failure rate changes over time. Although the upstream design remains the most accident-prone, there has been a significant decrease in the number of reported failures involving this design type since 2000. According to the data from [4,39], the failure rate of upstream TSFs decreased from 3.9% to 0.7%, which corresponds to an absolute decrease of 3.2 percentage points, or approximately 82% compared to the figures for the previous period. For centerline and downstream design types, current estimates of failure rates are approximately 0.7% and 0.3%, respectively (Table 6).

Table 6. Changes in the TSF failure rate by design type before and after 2000.

Design Type	Before 2000, %	After 2000, %	Absolute Change, pp	Relative Decrease, %
Upstream	3.9	0.7	−3.2	≈82
Centerline	—	0.7	—	—
Downstream	—	0.3	—	—

Source: [4,39].

The trends presented here demonstrate significant progress in engineering design methods, geotechnical analysis, and TSF monitoring in the 21st century. At the same time, a systematic review of the literature shows that the decrease in the failure rates is not solely attributable to improvements in design solutions. Introduction of modern numerical modeling methods, development of geotechnical monitoring, improvements in the assessment of seepage strength, stricter requirements for engineering surveys, and gradual adoption of risk-based approaches to TSFs operation all played a significant role.

The experience of Brazil is particularly illustrative, as it has been the site of the two largest disasters of the last decade—Fundão (Mariana, 2015) and Feijão I (Brumadinho, 2019). As the authors of [4,39] note, despite the availability of modern engineering methods for assessing stability, their implementation and practical application have not been sufficiently effective.

According to the authors, "more advanced engineering and analytical methods for assessing the stability of TSFs have been developed over time, but have not been fully implemented in Brazil," which was one of the factors contributing to the major man-made disasters of recent years.

The analysis conducted allows the drawing of an important conclusion: the structural design itself is not the only cause of accidents. On the contrary, recent studies indicate that the probability of failure is determined by the complex interaction of a facility design features, engineering and geological conditions, seepage conditions, operational quality, and effectiveness of the monitoring system. That is why modern international guidelines are gradually shifting the focus from the assessment of individual design solutions to comprehensive risk management throughout the entire life cycle of a TSF.

3.1.2. Relation Between TSF Accident Rate and the Need to Transition to Integrated Monitoring Systems

The performed systematic analysis of accident statistics, design features of TSFs, causes of major man-made disasters, and current regulatory framework leads to the conclusion that the current risk level is determined not only by the engineering features of the facilities but also by the limited capabilities of the monitoring systems in use. Despite significant progress in the fields of engineering geology, soil mechanics, stability calculation methods, and construction technologies, the failure rate of TSFs remains an order of magnitude higher than that of most other hydraulic structures. According to data from [1], the current average failure rate for TSFs is about 1.2% (independent cumulative estimates range from 1.2% to 4.4% [2,3]), whereas for traditional LRFs, this rate is estimated at approximately 0.01%, which corresponds to a nearly 120-fold increase in the risk. The independent analysis [2,3] confirms this pattern, estimating the cumulative failure rate of TSFs to be within the range of 1.5 to 4.4% depending on the estimate used for the total number of the facilities worldwide. Despite the difference in absolute values, both studies reach the same conclusion: current approaches to ensuring the safety of tailing storage facilities do not provide the required level of reliability.

Another equally important finding of the systematic analysis is that from an engineering standpoint, most major accidents were not sudden in their nature. The disasters at Stava (1985), Merriespruit (1994), Mount Polley (2014), Fundão (2015), and Brumadinho (2019) followed different failure pathways, but all shared the presence of a prolonged period during which the pre-accident conditions developed. In all cases, the failure was preceded by changes in the seepage conditions, gradual increase in pore pressure, localized deformations of the slopes, redistribution of the stress–strain state, development of liquefaction zones, and changes in the geometry of the structures. Consequently, most accidents were accompanied by the formation of measurable precursors that could have been detected well before the moment of failure, provided a comprehensive monitoring system had been in place.

Analysis of the effectiveness of existing early-warning systems (EWSs) is particularly illustrative. According to [6], in all three of the most extensively studied recent disasters—Mount Polley, Fundão, and Brumadinho—the existing monitoring systems failed to detect the critical condition of the structures in a timely manner. The authors note that traditional observation methods did not allow for the timely identification of complex spatiotemporal patterns in the development of the emergency process, while the use of satellite monitoring, remote sensing, and multisensor integration could have significantly improved effectiveness of the risk assessment. Thus, these cases suggest that limitations in integrating isolated data on deformations, seepage, pore pressure, and the structure's geometry may have constrained the effectiveness of the early-warning systems available at that time.

An additional risk factor is the ever-increasing scale of the consequences of modern accidents. While accidents in the mid-20th century involved the discharge of hundreds

of thousands of cubic meters of waste, the largest disasters of the 21st century are characterized by the discharge of tens of millions of cubic meters of tailings. For example, the volume of material discharged during the Mount Polley accident was approximately 25 million m^3, during the Fundão dam collapse it amounted to 40–60 million m^3, and during the Brumadinho disaster it was approximately 12 million m^3. Pollution on this scale has conditioned years of disruption in the functioning of river basins, degradation of ecosystems, and significant social and economic losses, which has fundamentally changed approaches to assessing acceptable risk levels and underscored the need to shift from reactive mitigation of consequences to the prediction of hazardous processes.

It should be noted that even current quantitative estimates of accident rates are subject to a high degree of uncertainty. As shown in [39], lack of a unified international registry of tailing storage facilities leads to significant discrepancies in estimates of the total number of facilities in operation. Various publications cite figures ranging from 3500 facilities to approximately 18,000 TSFs (based on the number of active mining enterprises), while in China alone, according to some sources, there may be about 12,000 such facilities in operation. As a result, the estimated failure rate changes by a factor of nearly three; however, this uncertainty does not affect the overall conclusion that TSFs pose a significantly higher risk than traditional hydraulic structures.

Development of the international regulation also reflects a shift in perspectives on the issue of safety. Following the Brumadinho disaster (2019), the Global Industry Standard on Tailings Management (GISTM) was developed, establishing for the first time requirements for continuous monitoring, risk management, and oversight of the technical condition of facilities throughout their entire life cycle. At the same time, a report by the International Council on Mining and Metals (ICMM, 2025) [130] shows that the process of implementing the standard remains incomplete: of the 836 facilities operated by ICMM member companies, only 67% are fully compliant with GISTM requirements, while 33% are only partially compliant. Even among facilities with an extreme level of potential consequences, the rate of full compliance is only slightly above 80%, indicating a persistent gap between current regulatory requirements and their practical implementation.

Analysis of the data presented in Table 7 shows that each of the identified limitations of existing approaches directly determines the functional requirements for next-generation monitoring systems. Unlike traditional solutions, which focus primarily on recording individual parameters of technical condition, modern systems must ensure continuous collection of spatially distributed data, their automatic integration, smart interpretation, and prediction of potentially hazardous processes. Therefore, a key area for further development is the transition from monitoring individual parameters to monitoring the overall condition of the engineering system.

Table 7. Relationship between identified risk factors and requirements to next-generation monitoring systems.

Identified Pattern	Quantitative Evidence	Limitations of the Existing Approaches	Requirements to the Integrated System
High accident rate for TSF	1.2% [1]; 1.5–4.4% [28] compared to 0.01% for traditional dams	Periodic instrumental control does not provide continuous monitoring	Continuous automated real-time monitoring
Progression of accidents is accompanied by measurable precursors	All major disasters were accompanied by changes in seepage, an increase in pore pressure, and development of deformations	Local measurements do not reflect the spatial dynamics of the processes	Spatiotemporal integration of data from various sensors

Table 7. *Cont.*

Identified Pattern	Quantitative Evidence	Limitations of the Existing Approaches	Requirements to the Integrated System
EWS failures	Mount Polley (2014), Fundão (2015), Brumadinho (2019) [6]	Isolated data analysis, lack of smart interpretation	Multisensory decision-support systems using AI
Increasing scale of environmental impacts	Up to 60 million cubic meters of tailings discharged in modern accidents	Reactive response following an accident	Predictive analytics and scenario modeling
Uncertainty in global statistics	3500–18,000 TSFs in the global assessment; up to 12,000 sites in China [4,39]	Lack of standardized databases and risk assessment criteria	Standardized digital monitoring platforms compliant with GISTM

Thus, a systematic analysis of the world literature indicates that the high accident rate at TSFs is not due to a lack of measurement technologies, but rather to insufficient integration of existing information sources. This is what defines the need to transition to integrated geospatial monitoring systems that combine geodetic observations, Earth remote sensing, geotechnical sensors, geophysical methods, artificial intelligence technologies, and digital twins into a single decision-support platform. The following sections hereof examine how modern technologies can be integrated into such an architecture and which scientific and technical solutions are the most promising for ensuring the safety of ground dams and TSFs.

3.2. Modern Technologies for Monitoring Deformations in LRFs and TSFs: Current Status, Capabilities, and Limitations

3.2.1. Evolution of Monitoring Technologies: From Local Measurements to Geospatial Smart Systems

Development of technologies for monitoring hydraulic structures over the last three decades has been characterized not only by improvements in individual measurement methods, but also by a fundamental shift in the very concept of engineering monitoring. While traditional monitoring systems focused primarily on recording changes in the positions of individual control points, modern research views monitoring as a continuous process of collection, integration, and smart analysis of spatiotemporal data that reflect the condition of the structure as a whole. This shift is due to the high complexity of the processes that determine the stability of LRFs and TSFs and the inability to assess them adequately using individual, independent monitoring methods.

A systematic analysis of more than 100 scientific publications shows that modern monitoring has gradually evolved through several successive stages. The first stage involved primarily the use of traditional geodetic methods—leveling, electronic tacheometers, and, later, GNSSs—which enabled high-precision recording of displacements at individual control points. The second stage was characterized by the widespread adoption of remote sensing methods, including satellite radar interferometry (InSAR), unmanned aerial vehicle (UAV) photogrammetry, laser scanning (LiDAR), and geophysical methods, which enabled a transition from discrete measurements to spatially distributed monitoring of structural surfaces. The current stage of development involves integration of multisensory data, geoinformation systems, Internet of Things (IoT) technologies, artificial intelligence (AI), digital twins, and smart decision-support systems, enabling a transition from recording deformations to predicting progression of hazardous processes.

This trend is confirmed by the findings of a comprehensive review [5], which shows that a modern monitoring system should be viewed as a set of complementary technologies, each of which provides control over a specific class of processes. The authors emphasize that advances in monitoring are no longer driven by the development of new instruments,

but rather by the effective integration of existing information sources into a unified analysis system. Similar conclusions are presented in [1], which identifies multisensory monitoring, satellite remote sensing, wireless sensor networks, and smart early-warning systems as the most promising areas of development.

Despite significant technological advances, a systematic review of the literature indicates that none of the existing methods provides complete control over all the processes that determine the stability of TSFs. This is because each method is based on recording different physical parameters and accordingly has its own scope of application. Geodetic technologies record spatial displacements of control points with high accuracy, but provide virtually no information about the internal condition of a facility. Remote sensing methods make it possible to monitor surface deformations over large areas, but they have limitations when it comes to analyzing processes occurring inside the dam body. Geotechnical sensors measure changes in pore pressure, moisture content, and stress–strain state; however, their measurements are local and do not provide spatial coverage of the entire facility. Consequently, no single technology can be considered a universal solution for ensuring safety of tailing storage facilities.

This conclusion is also supported by the results of numerous comparative studies. Research [7] shows that combining SBAS-InSAR, D-InSAR, and UAV photogrammetry data provides significantly higher accuracy in determining deformations compared to using each technology separately. Similar results are presented in [8], where the integration of ground-based radar interferometry (GB-InSAR) with GNSS made it possible to improve the reliability of recording spatiotemporal changes during the monitoring of large engineering structures. Studies [10,11] have shown that combining geodetic observations, wireless sensor networks, cloud computing, and geoinformation technologies makes it possible to implement smart early-warning systems that not only record the current condition of a structure but also predict its future behavior.

Consequently, the current scientific paradigm is gradually shifting from evaluating the accuracy of individual measurement technologies to analyzing their role within a comprehensive monitoring system. While ten to fifteen years ago, the focus was primarily on comparing the metrological characteristics of individual methods, contemporary research increasingly views monitoring as a multilevel information system that integrates data collection, spatial integration, smart processing, and support for engineering decision-making (Figure 4). This is precisely why concepts such as big geospatial data, AIoT (Artificial Intelligence of Things), digital twins, smart tailings, and predictive monitoring have been actively developing in the scientific literature in recent years, reflecting the transition from instrumental monitoring to digital management of hydraulic structure safety.

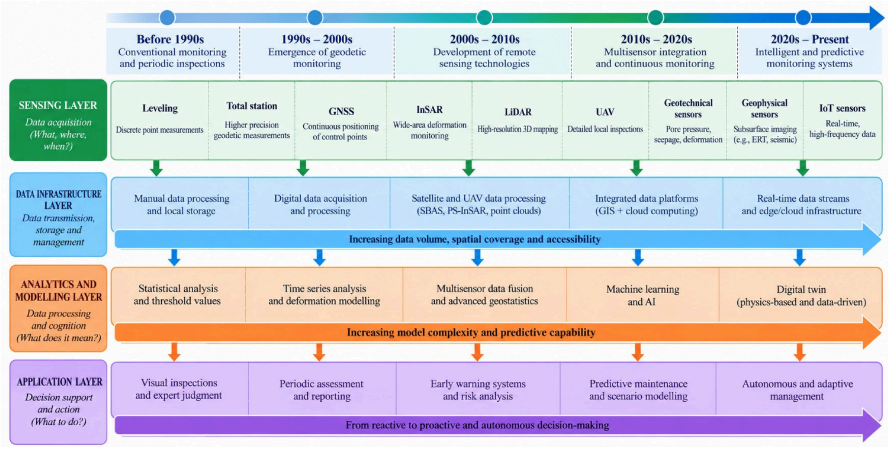


Figure 4. Evolution of technologies for hydraulic structure monitoring.

To evaluate the capabilities of various technologies, this review classified them according to their key functional characteristics (Table 8).

Table 8. Functional capabilities of modern technologies for TSF deformation monitoring.

Technology	Surface Deformation Control	Internal Processes Control	Spatial Coverage	Continuous Monitoring	Integration with AI	Use in EWSs
GNSS	+++	—	Local	+++	++	++
InSAR	+++	—	Very high	++	+++	++
GB-InSAR	+++	—	High	+++	++	+++
UAV photogrammetry	+++	—	High	+	++	+
LiDAR	+++	—	High	+	++	+
Piezometers	—	+++	Local	+++	++	+++
Inclinometers	+	+++	Local	++	++	++
Fiber-optic sensors	++	+++	Linear	+++	+++	+++

Note. "+++"—high efficiency; "++"—medium; "+"—limited; "—"—rarely used.

The data presented demonstrate a fundamental characteristic of modern monitoring technologies: none of them provides simultaneous monitoring of all the processes that determine stability of a ground dam. Geodetic methods are highly accurate, but have limited spatial coverage; remote sensing provides continuous monitoring of a structure's surface, but does not record internal processes; geotechnical sensors allow for monitoring seepage and pore pressure, but they are not capable of assessing the spatial structure of deformations. Thus, each technology is merely a separate component of the overall monitoring system, and the effectiveness of monitoring is determined not by the quality of any single method, but by the degree to which they are integrated.

The systematic analysis shows that the development of monitoring technologies is driven not so much by improvements in the accuracy of individual methods as by a shift toward the integration of isolated sources of spatiotemporal information. Recent studies consistently indicate that it is not possible to further improve the safety of tailing storage facilities by relying solely on improvements in a single monitoring technology. Consequently, the main direction of development is creation of integrated geospatial monitoring systems that combine geodetic, remote sensing, geotechnical, and smart analysis methods into a single digital architecture. That is why the following subsections examine capabilities, advantages, and limitations of each technology as a component of a future multisensor monitoring platform.

3.2.2. Summarized Indicators of Monitoring Method Accuracy

Based on the analysis of 86 publications containing experimental data on measurement accuracy, a summary of the metrological characteristics of the main monitoring technologies has been compiled (Table 9).

Table 9. Summarized metrological characteristics of monitoring method accuracy.

Method	Measured Parameter	Accuracy Range	Median Accuracy	Number of Papers Analyzed
GNSS (statistical)	Horizontal shifts	0.9–3.0 mm	1.5 mm	18
GNSS (statistical)	Vertical shifts	2.5–5.0 mm	3.2 mm	18
SBAS-InSAR	LOS-shifts, mm/year	3.4–8.1	5.2	22
PS-InSAR	LOS-shifts, mm/year	3.4–8.1	6.4	19
GB-InSAR	LOS-shifts	0.1–0.5 mm	0.25 mm	12
UAV photogrammetry	Plane coordinates	2–7 cm	3.5 cm	15
UAV photogrammetry	Elevation	3–10 cm	5.0 cm	15
LiDAR (aerial)	3D point cloud	5–30 mm	12 mm	8
TLS	3D point cloud	2–10 mm	5 mm	10
Leveling	Vertical shifts	0.5–1.0 mm	0.7 mm	14

Table 10 presents summarized data on the spatial coverage and temporal resolution of the methods, derived from 94 publications.

Table 10. Spatiotemporal characteristics of monitoring methods.

Method	Spatial coverage	Typical Time Resolution	Spatial Resolution	Measurement Density
GNSS	Point (stations)	Continuous (24/7)	1 point	1–10 points/km^2
SBAS-InSAR	100–10,000 km^2	6–12 days	5–20 m/pixel	10^2–10^4 points/km^2
PS-InSAR	100–10,000 km^2	6–12 days	5–20 m/pixel	10–10^3 points/km^2
GB-InSAR	Up to 10 km^2	1–5 min	0.5–2 m/pixel	10^4–10^5 points/km^2
UAV	0.1–10 km^2	By request	1–5 cm/pixel	10^6–10^8 points/km^2
LiDAR	0.1–100 km^2	By request	5–50 cm	10^5–10^7 points/km^2
Piezometers	Point	Continuous	1 point	1–10 points/km^2
Inclinometers	Linear (well shaft)	Continuous	0.5–1.0 m by depth	1–5 wells/km^2

3.2.3. Comparative Analysis of InSAR Processing Methods

Table 11 compares SBAS-InSAR and PS-InSAR using findings from individual studies. The numerical values represent study-specific results rather than pooled estimates of method performance.

Table 11. Comparative characteristics of SBAS-InSAR and PS-InSAR.

Parameter	SBAS-InSAR	PS-InSAR	Relative Difference
Reported case-specific accuracy, mm	5.21	8.07	SBAS is more accurate by 35%
Standard deviation, mm/year	5.7	3.4	PS-InSAR is more stable by 40%
Measurement points density	High	Nine times lower	SBAS provides nine times the measurement-point density
Average coherence	Basic	12.5% higher	PS-InSAR is more stable
Effectiveness in forested areas	Average	Low	SBAS is preferable
Effectiveness in urban areas	Average	High	PS-InSAR is preferable

Note: The accuracy values of 5.21 mm and 8.07 mm originate from an individual case study and are not pooled estimates or universal accuracy characteristics of the two methods [13–15,23,24].

3.2.4. Global Navigation Satellite Systems (GNSSs)

Despite the rapid development of Earth remote sensing technologies, global navigation satellite systems (GNSSs) remain the primary tool for high-precision geodetic monitoring of hydraulic structures. The systematic analysis of published studies shows that GNSSs are currently regarded as the gold standard for determining the spatial positions of control points and are used to calibrate and validate most modern monitoring technologies, including satellite interferometry (InSAR), ground-based radar interferometry (GB-InSAR), laser scanning (LiDAR), and unmanned aerial photogrammetry.

According to the results of numerous studies, accuracy characteristics of modern GNSSs meet the requirements for monitoring the most critical hydraulic structures. For concrete dams, the permissible error in determining horizontal displacements is 1–2 mm, and for vertical displacements it is about 1 mm, whereas for most ground and rock-fill dams, the required accuracy should not exceed 3 mm.

Modern high-precision receivers demonstrate a steady improvement in their metrological performance. For example, when using static observations lasting for 2 h, the root-mean-square error is approximately 1.1 mm in the horizontal coordinates and 3.0 mm in the vertical, whereas increasing the observation duration to 4 h improves the accuracy up to 0.9 mm and 2.5 mm, respectively (Table 12). Similar results are demonstrated by new-generation dual-frequency GNSS receivers (such as u-blox ZED-F9R), which are capable of reliable measurement of deformations of about 1 cm/year.

Table 12. Modern characteristics of GNSS monitoring of hydraulic structures.

Indicator	Value
Horizontal accuracy	0.9–1.1 mm
Vertical accuracy	2.5–3.0 mm
Required accuracy for concrete dams	1–2 mm
Permissible accuracy for ground dams	$\leq$3 mm
Minimum detectable deformation rate	$\approx$1 cm/year
Monitoring mode	24/7
Spatial coverage	Point
Main limitations	Multipath, local nature, need for open horizon

An important advantage of GNSSs is that they provide absolute coordinates in a single global reference frame. Unlike many local measurement methods, GNSSs make it possible to assess both the absolute displacements of a structure and their relationship to regional geodynamic processes. In addition, the technology is virtually unaffected by the time of day, lighting conditions, and most meteorological factors.

However, this systematic review of the literature shows that despite their exceptionally high accuracy, GNSSs have a number of fundamental limitations. The most significant limitation is the local nature of the measurements. Regardless of the number of stations installed, the technology records displacements only at the locations where the antennas are installed. This is particularly critical for TSFs, where processes such as seepage, localized liquefaction, or formation of stress concentration zones may occur in areas not covered by the monitoring network.

The impact of multipath remains an equally serious problem. Studies show that at a number of facilities, only one out of seven monitoring stations fully met the criteria for assessing multipath, while two stations recorded values that exceeded the permissible limits.

3.2.5. Satellite Radar Interferometry (InSAR)

Among modern technologies for monitoring deformations in hydraulic structures, satellite radar interferometry (interferometric synthetic aperture radar, InSAR) holds a special place, as it is the only widely used method that enables spatially distributed monitoring of structure surfaces at the regional level without the need to install ground-based equipment.

In recent years, two approaches to time-series processing have become the most widely used: persistent scatterer InSAR (PS-InSAR) and small baseline subset InSAR (SBAS-InSAR). A systematic review of comparative studies shows that SBAS-InSAR provides a higher spatial density of measurements. In an individual case study, the accuracy of deformation measurements using the SBAS method was 5.21 mm, whereas for PS-InSAR, the corresponding indicator was 8.07 mm. The density of SBAS-InSAR measurement points was 2.49 times that of PS-InSAR. These accuracy values are specific to the dataset and validation conditions of the cited study and do not establish a general accuracy ranking between the two methods.

Other studies show a similar pattern. The root-mean-square error of the time series is approximately 5.7 mm/year for SBAS-InSAR and 3.4 mm/year for PS-InSAR. At the same time, PS-InSAR technology is characterized by approximately 12.5% higher average coherence, while providing more stable measurements on facilities with persistent reflectors. Although, the density of fixed scatterers in PS-InSAR can be up to nine times lower than the pixel density available when using the SBAS approach (Table 13).

The practical effectiveness of satellite interferometry has been confirmed by numerous studies conducted at active TSFs. For example, paper [16] successfully applied SBAS-InSAR technology to monitor TSF no. 4 at the Dexing Copper Mine (China). Similar results were obtained in a study [17] of Europe's largest TSF, Żelazny Most (Poland). The paper [25]

demonstrates the possibility of integrating Sentinel-1 data with the European Ground Motion Service.

Table 13. Comparison of modern InSAR data processing methods.

Parameter	SBAS-InSAR	PS-InSAR
The main principle	Short spatial and temporal baselines	Permanent scatterers
Reported case-specific accuracy, mm	≈5.2	≈8.1
Mean standard deviation	≈5.7 mm/year	≈3.4 mm/year
Measurement points density	High	By 9 times lower
Average coherence	Lower	By 12.5% higher
Most efficient	Spatial analysis of deformations	Long-term monitoring of stable facilities
Main limitations	Atmospheric effects, decorrelation	A small number of stable reflectors

Further development of the method involves integration of InSAR and unmanned photogrammetry. According to [7], the combined use of D-InSAR, SBAS-InSAR, and UAVs provides significantly higher accuracy in determining deformations compared to using each technology separately.

Despite its obvious advantages, satellite interferometry has a number of fundamental limitations. Loss of coherence (decorrelation) remains the most significant problem. Virtually all studies note that at deformation rates exceeding 15 cm/year, traditional InSAR algorithms begin to lose coherence. Research on the Lisiche Dam (North Macedonia) showed that dense vegetation on the slopes led to a significant decorrelation and the near-total absence of stable, permanent scatterers directly on the dam body.

3.2.6. Ground-Based SAR Interferometry (GB-InSAR)

The rapid development of satellite radar interferometry has significantly expanded capabilities for remote monitoring of engineering structures; however, its application is subject to a number of fundamental limitations related to the frequency of satellite observations, decorrelation at high deformation rates, and dependence of the results on the orbital parameters of the spacecraft. These limitations led to the development of an alternative approach to radar monitoring: ground-based interferometric synthetic aperture radar (GB-InSAR).

Unlike satellite interferometry, GB-InSAR provides virtually continuous monitoring at intervals ranging from a few seconds to a few minutes, making it possible to record rapidly evolving processes. Modern GB-InSAR systems are capable of monitoring areas of up to several square kilometers at an observation distance of up to 4–5 km while providing submillimeter sensitivity (Table 14).

Table 14. Key features of GB-InSAR technology.

Parameter	Characteristic
Measurement type	Remote radar
Measured parameter	Line-of-sight (LOS) shifts
Spatial coverage	Up to several km^2
Observation range	Up to 4–5 km
Temporal resolution	From a few seconds to a few minutes
Sensitivity	Submillimeter
Main advantages	Continuous monitoring, high temporal resolution, and independence from lighting conditions and cloud cover
Main limitations	The need for direct visibility, impossibility to track internal processes, and high costs

A systematic review of the literature shows that the effectiveness of GB-InSAR can be enhanced when it is used in conjunction with independent geodetic observation methods. One study [8] shows that integration of GB-InSAR with high-precision GNSS observations improves the consistency of time series and displacement maps, in particular due to identifying and correcting phase scanning errors in the GB-InSAR data. Another area of development for radar monitoring is improving the reliability of satellite measurements at hydraulic structures. One paper [9] investigates the possibility of using PS-InSAR in conjunction with electronic corner reflectors (ECRs) designed to create stable radar targets and improve the suitability of satellite interferometry for operational monitoring of dams.

3.2.7. Unmanned Aerial Vehicles (UAVs) and Digital Photogrammetry

In recent years, unmanned aerial vehicles (UAVs) have become one of the most rapidly developing areas in the monitoring of hydraulic structures. Recent studies demonstrate the exceptionally high metrological performance of UAV photogrammetry. At a flight altitude of 50–120 m, a spatial resolution of approximately 1–3 cm/pixel is achieved, whereas the accuracy of the digital surface model reconstruction using ground control points is 2–5 cm in plan coordinates and 3–8 cm in elevation (Table 15).

Table 15. Key characteristics of UAV photogrammetry in hydraulic structure monitoring.

Parameter	Value
Spatial resolution (GSD)	1–3 cm/pixel
Flight altitude	50–120 m
Plane accuracy (when using GCP)	2–5 cm
Height accuracy	3–8 cm
Duration of autonomous flight	20–45 min
Main processing products	Orthophotos, DEMs, DSMs, dense point clouds, 3D models
Main areas of application	Monitoring of slopes, cracks, erosion, subsidence, and structural geometry
Integration possibilities	GNSS, InSAR, LiDAR, GIS, AI, digital twins

This technology has become particularly widespread for TSF inspections. Study [26] shows that the use of UAVs enables high-precision reconstruction of slope geometry. Similar results are presented in [18], where the combined use of unmanned aerial photogrammetry and satellite interferometry made it possible to significantly improve the accuracy of estimates of the spatial distribution of deformations.

According to [7], the combination of SBAS-InSAR, D-InSAR, and unmanned aerial photogrammetry provides the highest level of monitoring accuracy. In this context, satellite interferometry is used to identify the spatial distribution of deformations at the regional level, while UAVs provide local-scale detail on the detected anomalies.

In recent years, special attention has been paid to the automation of UAV data processing using artificial intelligence methods. Modern deep learning algorithms make it possible to automatically detect cracks, localized deformations, areas of erosion, and other potentially hazardous changes.

3.3. Justification of the Need for a Comprehensive Monitoring System

This systematic analysis of more than 100 scientific publications leads to a fundamentally important conclusion: the current challenge of ensuring the safety of hydraulic structures is no longer conditioned by insufficient accuracy of individual measurement technologies, but rather by the lack of mechanisms for integrating spatiotemporal information from various observation sources. This trend is clearly evident in a fundamental review [5], which was the first to demonstrate that modern monitoring systems should be based on

the principles of complementarity between geodetic and remote sensing technologies. A similar conclusion is presented in [1], which analyzes international recommendations on TSF safety. Other papers [10–12,27] have also made significant contributions to the development of this concept, examining the integration of the IoT, cloud computing, artificial intelligence, and geoinformation technologies as the foundation for a new generation of smart monitoring systems.

3.3.1. Limitations of Single-Method Monitoring

Despite the high level of technological advancement of certain monitoring methods, this review of the literature shows that each of them captures only a limited set of physical processes that determine the stability of a hydraulic structure. Table 16 lists the main limitations of single-method monitoring.

Table 16. Limitations of separate monitoring technologies when used independently.

Technology	Monitored Processes	Main Limitations	Potential Consequences
GNSS	Spatial displacements of control points	Local nature of observations	Undetected local deformations between stations
InSAR	Spatial surface deformations	Lack of information about internal processes; decorrelation	Impossibility to identify seepage processes
UAV	Surface geometry, cracks, erosion	Periodic inspections; weather dependence	Lack of continuous monitoring
LiDAR	High-precision 3D surface model	High cost; intermittent data acquisition	Limited use for continuous monitoring
Piezometers	Pore pressure	Monitoring of local areas only	Insufficient spatial coverage
Inclinometers	subsurface displacements	A limited number of observation points	Ignoring local deformation zones
Fiber-optic sensors	Distribution of deformations	Limited network coverage	The need for integration with other data sources

The review of the data presented in Table 16 leads to a fundamentally important conclusion: the limitations of different technologies hardly overlap, which means they can compensate for one another when used together.

Based on the systematic review of 129 publications, the limitations were classified into three categories: technical, organizational, and physical (Table 17).

Table 17. Classification of the limitations of monitoring methods.

Method	Technical Limitations	Organizational Limitations	Physical Limitations
GNSS	Multipath, interference, signal loss	High cost of the stations, the need for a supporting network	Requires a clear sky; depends on the geometry of the satellites
SBAS/PS-InSAR	Decorrelation at >15 cm/year, weather-related delays	Survey frequency (6–12 days), processing cost	Dependence on vegetation, snow, and humidity
GB-InSAR	Limited range (up to 4–5 km), line of sight	High cost of equipment, stationary nature	Only LOS shifts; no 3D vectors
UAV	Limited flight time (20–45 min), weather-dependent	Regulatory restrictions, the need for pilots	Lack of continuous monitoring
LiDAR	Limited penetration depth, large data volumes	High survey costs, complex processing	Frequency, dependence on reflectivity
Piezometers	Silting, membrane failure	Well drilling, maintenance	Local nature, sparse depth sampling
Inclinometers	Pipe displacement, limited service life	High installation cost	discrete measurements, temperature sensitivity
ERT	Dependence on electrical conductivity, ambiguity	Difficulty of interpretation, labor intensity	Depth is limited (10–100 m)

3.3.2. The Synergistic Effect of Multisensor Integration

This systematic review of the literature shows that the main advantage of integrated monitoring systems lies not simply in using more sensors, but in combining complementary measurements, yielding a synergistic effect whereby the combination of interconnected measurements provides a fundamentally higher level of information.

For example, ref. [10] proposed an architecture for a smart TSF monitoring system that integrates a network of geotechnical sensors, Internet of Things (IoT) technologies, cloud computing, and numerical modeling. This concept was subsequently developed in [19], where a three-dimensional geoinformation model of a TSF was integrated with time-series analysis algorithms to predict the evolution of deformation processes. A subsequent paper by the same authors [11] demonstrates the transition to the concept of spatiotemporal fusion, in which spatial, temporal, and operational data are integrated into a single digital platform for smart monitoring.

According to the results in [7], the combination of SBAS-InSAR, D-InSAR, and UAV photogrammetry data provides significantly higher accuracy in estimating the spatial distribution of deformations compared to the use of each technology separately. Table 18 presents a quantitative assessment of the improvements achieved through multisensory integration.

Table 18. Study-specific quantitative improvements reported for integrated monitoring and analytical configurations.

Research	Method Combination	Measured Parameter	Single-Method Result	Integrated Result	Improvement
Improvements over Single-Sensor or Single-Method Approaches					
[7]	InSAR + UAV	RMSE in a central zone, m	0.980 (D-InSAR)	0.052 (UAV)	18.8-fold accuracy
[8]	GB-InSAR + GNSS	Uncertainty of shifts	100% (basic)	50–80%	Decrease by 20–50%
[11]	Multisensor fusion	Accuracy of anomaly detection	100% (basic)	110–130%	Improvement by 10–30%
[31]	Autoencoder + LSTM + KDE	Forecast error	100% (basic)	82–99.6%	Decrease by 0.37–17.92%
[27]	GNSS + InSAR + hydrometry	Delay in data processing	—	<1 min	Real time
Improvements over Classical Machine-Learning Approaches					
[29]	BeiDou + IoT + sensors	EWS lead time	Not registered	5–6 days	Early detection
[30]	Digital twins + deep learning	Forecast accuracy	100% (basic)	147%	Improvement by 47%
[10]	IoT + cloud + numerical modeling	EWS response time	Hours–days	Seconds–minutes	Decrease by 95%
[32]	FEM + ANN–LSTM	MAE of FoS forecast (dimensionless)	0.081 (SVM)	0.027 (hybrid)	66.7% lower MAE

Rapid, high-magnitude deformation can reduce the reliability of the entire multisensor monitoring system. Significant spatial displacement gradients and surface changes between radar acquisitions may cause InSAR decorrelation and phase-unwrapping errors, resulting in data loss or distorted displacement estimates in the most highly deforming areas. During data integration, this reduces the spatial completeness of the observations and the potential for cross-validation between measurements; the inclusion of unreliable estimates without quality control may lead to underestimation or distortion of deformation trends. Missing and erroneous input data increase forecast uncertainty and may hinder timely warning. Compensation by other methods is constrained by the location and condition of ground-based sensors, the acquisition frequency of UAV surveys, and the observation conditions of GB-InSAR. Therefore, multisensor integration does not guarantee the preservation of the

original accuracy or completeness of monitoring under rapidly developing deformation. Data processing should account for the quality of each data source, exclude unreliable measurements, and explicitly reflect the reduced reliability of the final assessment. The absence of usable InSAR data should not be interpreted as an absence of deformation.

Despite a strong consensus regarding the benefits of multisensory monitoring, the review of the literature revealed a significant gap.

Most published studies are limited to the integration of two or three technologies, whereas there are virtually no studies proposing a comprehensive architecture for interaction across all levels of monitoring. In most cases, integration is viewed as technical consolidation of data rather than as a standalone, multi-level information system. An example of a multi-level information system scheme is shown in the diagram in Figure 5.

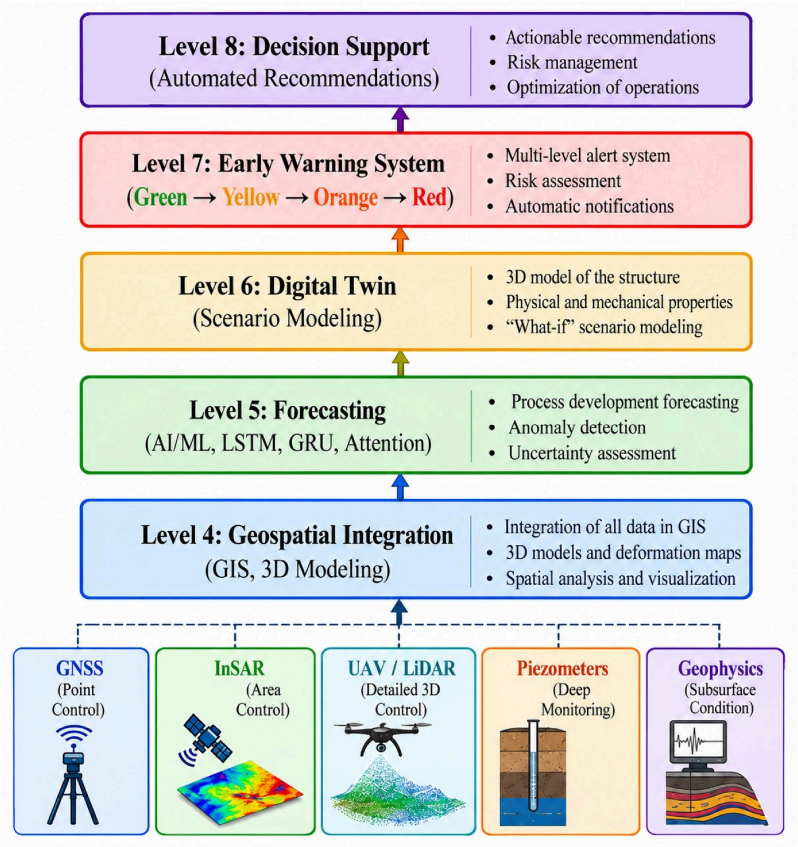


Figure 5. Synergistic role of various technologies in an integrated monitoring system.

3.4. Synthesis of Evidence, Critical Analysis, and Prospects of the Development of Integrated Monitoring Systems

The systematic review of the world literature made it possible not only to conduct a comparative assessment of modern technologies for monitoring LRFs and TSFs, but also to perform a comprehensive synthesis of the accumulated scientific evidence. It should be noted that research conducted over the last decade demonstrates a qualitative shift in the scientific paradigm. While early papers focused primarily on refining specific monitoring methods, modern studies are focused on developing smart geospatial platforms.

3.4.1. Comprehensive Assessment of the Evidential Basis for Current Monitoring Concepts

Based on the review of the publications, a comprehensive assessment of the level of evidence supporting the main scientific propositions was conducted (Table 19).

Table 19. Comprehensive assessment of the level of evidential basis of current concepts of TSF monitoring.

	Concept	Number of Publications *	Research Type	Evidential Basis Level	Scientific Consensus Degree
1	Multisensor monitoring	>25	Reviews, experiments, implementations	High	Very high
2	GNSS–InSAR–UAV integration	>20	Experiments	High	High
3	Spatiotemporal data fusion	>15	Experiments, cases	High	High
4	Automated EWSs	>20	Practical implementations	High	Very high
5	AI + physical models	>12	Experiments	High	High
6	Quantitative assessment of uncertainty	8–10	Methodological papers	Medium–high	Under formation
7	Digital twins	5–8	Pilot projects	Medium	Under formation
8	Integration of climate scenarios	5–7	Separate studies	Medium	Under formation
9	Explainable AI (XAI)	<5	Conceptual papers	Low	Insufficient

* This assessment was based on the body of publications included in this systematic review.

Analysis of Table 19 shows that studies focusing on multisensory monitoring, integration of geodetic and remote sensing methods, and automated early-warning systems have the highest levels of evidence. Virtually all recent review papers and experimental studies make the same conclusion: the use of multiple complementary data sources ensures a significantly higher level of monitoring reliability (Figure 6).

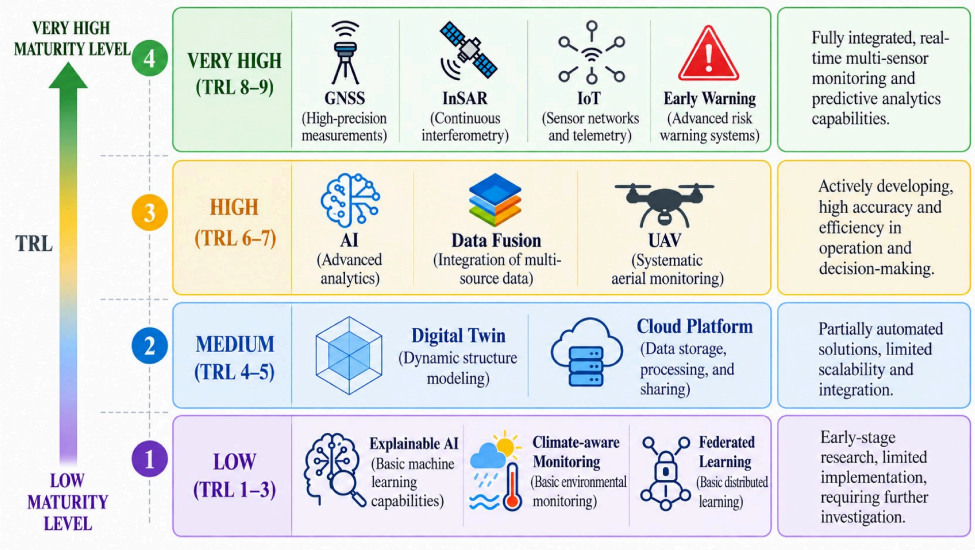


Figure 6. Level of maturity of modern TSF monitoring technologies.

At the same time, there are significantly fewer studies in the areas related to digital twins, explainable artificial intelligence, and climate change considerations. This indicates that these areas are still in the process of active development and require further experimental validation.

3.4.2. Critical Analysis of the Current State of Research

This systematic analysis has identified three levels of maturity among contemporary scientific fields.

Level 1—Established Scientific Consensus

This level includes studies focused on the use of GNSS, satellite interferometry (InSAR), unmanned aerial systems, geotechnical sensors, and their combined application

within multisensor platforms. The efficiency of such systems has been confirmed by numerous experimental studies, industrial implementations, and international recommendations [1,5,10,11,19]. Today, the need to integrate various technologies is virtually uncontested in academic circles.

Level 2—Rapidly Evolving Technologies

This group includes studies focused on spatiotemporal data integration, cloud computing, artificial intelligence, digital monitoring platforms, and digital twin technologies. Despite numerous positive results, most published studies continue to focus on individual pilot projects.

Level 3—Promising Areas

The most promising areas include explainable AI, probabilistic forecasting, uncertainty assessment, integration of climate scenarios, autonomous smart monitoring systems, and self-learning digital twins. Currently, these areas hold great scientific promise, but the evidence base remains insufficient for widespread industrial implementation.

3.4.3. Research Gap Matrix

Despite significant progress in recent years, the review of the literature revealed a number of fundamental scientific problems (Table 20).

Table 20. Major research gaps and possible ways to address them.

Research Gap	Main Cause	Promising Area	Priority
Explainable AI	Low interpretability of neural networks	SHAP, LIME, causal analysis	Very high
Digital twins	Insufficient experimental validation	Long-term pilot projects	High
Integration of climate risks	Absence of complex models	Relationship between climate scenarios and EWS	High
Standardization of data fusion	Data format incompatibility	Development of uniform industry-specific protocols	Very high
Quantitative assessment of uncertainty	Limited use of probabilistic models	Bayesian models, Monte Carlo, quantile regression	High
Platform interoperability	Fragmentation of software solutions	OGC-compatible geospatial services	Medium–high

The high research priority assigned to explainable AI should not be interpreted as evidence of high technological maturity. On the contrary, the present review indicates that XAI remains at an early stage of development in the context of TSF monitoring, with fewer than five identified publications (Table 19). This high research priority reflects the importance of interpretability rather than the current level of validation. In safety-critical monitoring, an AI-based warning should be accompanied by information explaining which observations or variables contributed most strongly to the predicted change in structural condition. Such information can support expert verification of automated alerts, identification of physically implausible predictions, and more transparent integration of AI outputs into engineering decision-making. Accordingly, XAI should be regarded as a priority direction for validation and development rather than as a mature component of current monitoring systems.

A practical use case illustrates the potential role of XAI as an additional layer between machine-learning prediction and engineering decision support. Mwanza et al. (2024) proposed a real-time tailing dam monitoring framework combining real-time data collection, digital twin modeling, ML-based early detection and prediction, and intelligence-driven decision support [107]. In such an architecture, XAI could provide an interpretable link between the ML prediction and the final engineering decision. For example, if the ML model detects an increased probability of instability, an XAI module could identify the

monitoring variables that contributed most strongly to this prediction, such as accelerating surface deformation from InSAR, GNSS displacement, or increasing pore-water pressure. The engineer could then compare these dominant factors with independent observations and the expected physical behavior of the TSF before confirming an early-warning response. Thus, XAI would not replace the digital twins, physical modeling, or engineering judgment, but would make the ML-based warning more transparent, auditable, and suitable for safety-critical decision-making. This illustrates why XAI represents a high-priority research direction despite its currently limited evidential basis in TSF monitoring.

Quantitative uncertainty assessment should distinguish between uncertainty in fused measurement results and uncertainty in forecasts of future facility behavior. The former requires consideration of the accuracy of the input observations, their correlations, and the integration model; the latter additionally requires consideration of uncertainty in forecasting model parameters and variability in the predicted process. The main approaches and their applicability to operational tailing dam monitoring are compared in Table 21.

Table 21. Comparison of uncertainty quantification approaches for data fusion and forecasting.

Approach	Application and Output	Main Limitations	Applicability to Operational Monitoring
Analytical uncertainty propagation accounting for covariances	Estimates uncertainty in a fused result from input measurement uncertainties and their dependencies.	Requires a justified measurement model and covariance estimates; linear approximation may be inadequate for strongly nonlinear models.	Suitable for routine processing of geodetic and other quantitatively harmonized observations because of its low computational cost.
Monte Carlo simulation	Propagates specified input distributions through a fusion or forecasting model to obtain an output distribution and coverage intervals.	Depends on appropriate input distributions and representation of dependencies; repeated evaluations can be computationally demanding for complex physical models.	Suitable for periodic uncertainty assessments and scenario analyses; operational use is feasible when model evaluation is sufficiently fast.
Bayesian methods	Update parameter and state distributions as observations become available, producing posterior and predictive distributions.	Sensitive to prior distributions and observation model assumptions; complex models may require substantial computation and specialist configuration.	Suitable for sequential updating of estimates. Operational feasibility depends on model complexity and the computational algorithm used.
Quantile regression, including AI/ML models	Directly estimates conditional quantiles of the predicted variable and constructs prediction intervals without specifying a particular family of response distributions.	Requires representative training data; nominal coverage does not guarantee empirical coverage under changing conditions. Parameter uncertainty is not automatically quantified separately.	Practical for routine interval forecasting after model training and validation; empirical coverage and interval width require ongoing monitoring.

For operational implementation, method selection should be task-specific: analytical uncertainty propagation can provide a baseline approach for measurement fusion, while quantile regression can support prediction interval estimation where sufficient data are available. Monte Carlo simulation is useful for nonlinear models and periodic scenario assessments, whereas Bayesian methods support updating probabilistic estimates using new observations. These approaches can be combined and do not constitute a universal ranking of effectiveness. Before prediction intervals are used in an early-warning system, their empirical coverage and width should be evaluated on an independent temporal test set and subsequently monitored as operating conditions change.

This analysis shows that most existing studies focus on the development of individual measurement methods, whereas issues related to the architecture of information exchange,

data standardization, uncertainty assessment, and interpretability of the results have been addressed to a much lesser extent. It is precisely these areas that present the greatest scientific interest for further research.

4. Discussion

4.1. Interpretation of the Main Findings

This systematic review summarized the results of 129 studies of the monitoring of deformation processes in TSFs and LRFs, providing a comprehensive overview of the current state of this field of research and identifying key areas for its future development. Unlike most previously published reviews, in which individual monitoring technologies were analyzed primarily in isolation from one another, this review focused on evaluating the entire system for acquiring, integrating, and interpreting spatiotemporal information. This approach made it possible to view monitoring not as a collection of separate observation tools, but as a unified smart geospatial infrastructure that integrates Earth remote sensing, geodetic measurements, geotechnical observations, geophysical methods, artificial intelligence technologies, and digital twins.

The results obtained indicate a high degree of consensus among current studies regarding the fundamental conclusion that it is impossible to ensure reliable TSF monitoring using any single monitoring method. Despite significant differences in study designs, subject characteristics, duration of follow-up, and analytical approaches used, most of the included publications make the same conclusion: each monitoring method has its own scope of application, which is determined by the physical nature of the processes being measured. Accordingly, the limitations of individual technologies are not methodological shortcomings of specific studies, but rather a consequence of fundamental differences between surface, subsurface, local, and area-wide measurements. This consistency in the results obtained by independent research groups strengthens confidence in the main conclusion of this review, despite the continuing heterogeneity of the included studies.

Interpretation of the results also shows that the scientific paradigm for monitoring hydraulic structures has changed in recent years. While early research focused primarily on improving the accuracy of individual measurement technologies, recent publications increasingly view monitoring as a task involving integration of heterogeneous spatiotemporal data. The studies included in this review consistently demonstrate that the effectiveness of modern systems is determined not by the maximum accuracy of individual sensors, but by how well they complement one another. Therefore, the quantitative advantages of multisensory integration identified in this review should be interpreted not as a superiority of one approach over another, but as confirmation of a shift toward a systematic approach to monitoring, in which different technologies compensate for each other's limitations. This conclusion is consistent with the general trend toward the digital transformation of engineering monitoring that has been observed in recent years in geodesy, remote sensing, and geotechnical monitoring.

Another important observation is that most of the included studies examine individual components of smart monitoring systems—satellite data, geodetic measurements, digital twins, or artificial intelligence algorithms—primarily in isolation. Only a limited number of publications analyze how they function together within a unified architecture. In this context, the conceptual model of an integrated geospatial system proposed in this review represents an attempt to bring together existing areas of research into a single logical framework that reflects the full cycle of spatial data management—from collection of raw data to formulation of risk management decisions. It is this aspect, in our view, that constitutes the main contribution of this review to the existing scientific literature, as it

allows for moving from comparative analysis of individual technologies to a discussion of the principles underlying the design of integrated smart monitoring systems.

4.2. Comparison with Existing Monitoring Frameworks and Practical Deployment Constraints

The eight-level geospatial-intelligence architecture proposed in this review should be interpreted as a system-level synthesis of technologies that have already been investigated individually or in smaller combinations, rather than as the introduction of entirely new monitoring technologies. Previous studies have demonstrated the value of multisensor integration, combining geodetic, remote sensing, geotechnical, and geophysical observations for deformation and stability assessment. For example, Mwanza et al. (2024) proposed a tailing dam monitoring framework that integrates real-time data acquisition, digital twin simulation, machine-learning-based detection and prediction, and intelligence-driven decision support [107]. The proposed architecture extends this concept by explicitly organizing heterogeneous observation sources, data transmission and storage, data fusion, analytical and predictive modeling, uncertainty assessment, early-warning functions, and decision support into a single geospatial framework. Its principal contribution is therefore the systematic organization of complementary monitoring and analytical components across the monitoring-to-decision chain, rather than the novelty of any individual component. This distinction is important because most studies identified in the review address combinations of two or three technologies, while comprehensive integration across the full monitoring architecture remains comparatively limited.

The practical implementation of the proposed architecture is characterized by varying levels of technological maturity across its components. Geodetic, remote sensing, geotechnical, and geophysical methods forming the measurement foundation of the system are already used at operational tailing storage facilities; however, monitoring coverage and the extent of data integration vary considerably. Fragmented data processing remains a limitation, hindering the joint assessment of surface deformation and internal processes within the facility. Geospatial integration at Level 4 is technically feasible using existing GIS and database technologies, but requires harmonization of spatial referencing, temporal sampling, data formats, and measurement accuracy characteristics. Its implementation also depends on personnel expertise, reliable power supply and communication links, equipment compatibility, and system maintenance costs.

AI/ML-based forecasting at Level 5 requires representative monitoring time series, data quality control, and expertise in model development and validation. The main limitations include the underrepresentation of hazardous conditions in training datasets and limited model transferability between facilities with different structural and engineering-geological characteristics. Changes in dam geometry and operating conditions further necessitate reassessment of predictive performance. The digital twins at Level 6 are one of the most resource-intensive components. In addition to reliable three-dimensional geometry, it requires physical and mechanical material properties, geological and hydrogeological data, and information on hydrometeorological forcing and operational loads. Calibration of the computational model, updating it using monitoring observations, and provision of computing resources increase funding requirements and the need for multidisciplinary expertise. Consequently, implementing individual scenario-modeling functions is more readily achievable than operating a continuously updated predictive digital twin.

At Level 7, threshold-based warning is technically feasible, whereas intelligent early warning based on combined heterogeneous observations requires identification of physically meaningful relationships between monitored variables, consideration of uncertainty, and validation of algorithms against independent data. The scarcity of documented hazardous conditions makes it difficult to assess false-alarm and missed-event probabilities.

Level 8 combines monitoring, forecasting, and scenario-modeling outputs to support decision-making; the reliability of its recommendations depends on the quality of the preceding components and the validity of the response rules. Operational use therefore requires review of recommendations by responsible specialists. Accordingly, measurement functions, geospatial integration, and basic warning capabilities can underpin the minimal and comprehensive implementation scenarios, whereas progression to the intelligent scenario requires phased, site-specific validation of predictive and recommendation-generating functions. The technical availability of individual components does not replace field validation of the architecture as a whole.

To clarify the structural novelty of the proposed eight-level architecture, it was compared with representative integrated monitoring frameworks identified in the reviewed literature. Table 22 summarizes their principal components, monitoring focus, and the specific aspects incorporated into the proposed geospatial-intelligence architecture. The comparison is intended to distinguish the contribution of the proposed system-level organization from the individual technologies and integration approaches already reported in previous studies.

Table 22. Comparison of representative integrated monitoring frameworks with the proposed architecture.

Framework	Main Components	Primary Focus	Distinctive Feature of the Proposed Architecture
Real-time tailing dam monitoring framework	Real-time data acquisition, digital twins, ML, decision support	Real-time TSF stability monitoring	Extends the monitoring chain by explicitly integrating heterogeneous geospatial, geodetic, geotechnical and geophysical observations with data fusion, uncertainty assessment and EWSs
InSAR–UAV integration studies	InSAR, UAV photogrammetry	Surface deformation assessment	Places surface deformation observations within a broader multisource monitoring architecture
GIS/digital twin-oriented studies	GIS, 3D modeling, temporal data	Spatial-temporal representation and prediction	Connects representation/modeling with heterogeneous observation, uncertainty and decision-support layers
Proposed eight-level architecture	Multisource observation–transmission/storage–data fusion–analytics/AI–uncertainty–EWSs–decision support	Integrated geospatial intelligence for TSF monitoring	System-level organization of the full monitoring-to-decision chain

To clarify the relationship between the proposed architecture and GISTM, Table 23 maps its key functional components to specific requirements concerning site characterization, integrated monitoring, performance assessment, and response. The mapping distinguishes functions explicitly required by the standard from technological approaches proposed here to support their implementation.

Table 23. Mapping of the proposed architecture to relevant GISTM requirements.

Architectural Component	GISTM Requirement(s)	Relevant Requirement	Contribution of the Proposed Architecture
Measurement foundation: geodetic, remote sensing, geotechnical, and geophysical observations	7.2	Integrated engineering monitoring to verify design assumptions and monitor potential failure modes.	Provides complementary observations of surface deformation and internal conditions. The monitoring configuration must address site-specific failure modes.

Table 23. *Cont.*

Architectural Component	GISTM Requirement(s)	Relevant Requirement	Contribution of the Proposed Architecture
Geospatial integration—Level 4	2.2 7.1–7.2	Updated site characterization and comprehensive, integrated monitoring.	Organizes heterogeneous observations and site information within a common spatial and temporal framework for joint analysis.
Performance indicators supporting Levels 5 and 7	7.3	Measurable performance indicators and criteria, with appropriate data recording and evaluation frequencies.	Links monitored variables to defined indicators, observation frequencies, and assessment criteria. These must be established for the individual facility.
AI/ML-based forecasting—Level 5	7.4	Analysis of monitoring data to identify deviations from expected performance and deterioration over time.	Supports anomaly detection, trend analysis, and forecasting. AI/ML is a proposed analytical tool rather than a technology prescribed by GISTM.
Digital twins—Level 6	5.2 7.2	Design review and updating as performance data become available, and verification of design assumptions through monitoring.	Supports comparison of observed and modelled behavior and assessment of alternative scenarios, subject to model calibration and validation. GISTM does not explicitly require a digital twin.
Early-warning system—Level 7	7.4	Prompt response to performance outside expected ranges through trigger action response plans (TARPs) or critical controls.	Links detected deviations and warning levels to predefined response actions. Automated notifications support implementation of the response plan.
Decision support—Level 8	7.4–7.5	Submission of deviations for engineering review and review and approval of monitoring reports.	Consolidates observations, analytical results, and recommendations for assessment by responsible engineers, while retaining human review and approval.

Note: Requirement numbers refer to GISTM (August 2020): Requirement 2.2, p. 8; Requirement 5.2, p. 12; and Requirements 7.1–7.5, p. 15. The mapping describes how architectural components can support specific requirements; it does not demonstrate full conformance with GISTM or validation of the complete architecture.

4.3. Comparison with Previous Reviews and Current Scientific Paradigms

The results of this systematic review are generally consistent with the findings of previously published studies; however, they also significantly expand our current understanding of the role of modern geospatial technologies in ensuring TSF safety. Most previous reviews have focused on analyzing specific groups of monitoring methods, such as satellite radar interferometry, global navigation satellite systems, unmanned aerial photogrammetry, geotechnical measurements, or machine learning algorithms. Despite the high scientific value of these studies, they focused primarily on comparing technical characteristics of specific technologies, while issues related to the design of a comprehensive architecture for smart monitoring systems were addressed much less frequently.

The results obtained confirm the findings of previous studies regarding the high effectiveness of multisensor monitoring, but also allow for clarifying the mechanisms which improve the reliability of assessments of structural condition. While the benefits of integration were previously usually attributed to an increase in the number of available observations, analysis of the publications included in this review indicates that the main benefit lies in the integration of information about various physical processes occurring within the structure. Geodetic methods record spatial displacements of control points, InSAR provides an area-wide assessment of surface deformations, geotechnical sensors characterize the internal state of the soil mass, and geophysical methods make it possible

to detect changes in the physical properties of materials. Therefore, multisensor integration should be viewed not as a simple combination of measurements, but as a comprehensive mechanism for creating a multidimensional model of a structure's condition, in which each source of information complements the others. This interpretation is consistent with contemporary concepts of the digital transformation of engineering monitoring and at the same time expands the findings of previous systematic reviews.

An important distinction between this review and most previously published papers is the integration of current international regulatory requirements with the analysis of technological solutions. The analysis shows that the introduction of the GISTM standard has significantly changed the direction of scientific research in the field of TSF monitoring. Whereas the primary focus was improvement of individual monitoring methods, today studies are increasingly oriented toward creation of continuously operating smart platforms that enable risk management throughout a structure's life cycle. The results obtained suggest that the further development of monitoring systems is driven not only by technological progress but also by increasingly stringent international regulatory requirements, which encourage transition to comprehensive digital solutions.

5. Conclusions

This systematic review, conducted in accordance with the PRISMA 2020 guidelines, provided an overview of the current state of research in the field of geospatial monitoring of deformations in TSFs and LRFs, based on the analysis of 129 peer-reviewed publications released between 2017 and 2026. The comprehensive analysis has shown that ensuring safe operation of these facilities today depends not so much on the development of individual monitoring technologies but on the ability to integrate them comprehensively within a unified smart information and analytical environment. Despite significant advances in satellite interferometry, global navigation satellite systems, unmanned aerial vehicles, laser scanning, geotechnical sensor networks, and artificial intelligence methods, none of the technologies discussed can independently address the challenge of continuous monitoring of the technical condition of structures. This marks the completion of a phase in the development of autonomous monitoring methods and transition to a new paradigm based on multisensor integration of spatiotemporal data and smart decision support systems.

Based on the systematic analysis conducted, several key conclusions can be drawn that reflect the current state and future prospects of smart geospatial monitoring systems for TSFs and LRFs:

- Current data convincingly confirm that TSFs remain the most accident-prone category of hydraulic structures.
- None of the existing monitoring technologies can independently address the challenge of comprehensive assessment of the technical condition of structures.
- Multisensor integration is a key area of development for modern monitoring systems, as combination of satellite, ground-based, geotechnical, and geophysical data improves the accuracy of deformation assessments.
- Artificial intelligence, digital twins, and data fusion technologies form the foundation of a new generation of smart geospatial platforms. However, their practical implementation is currently limited by the lack of standardized validation methods.
- The proposed concept of geospatial intelligence for tailing dam monitoring expands the existing monitoring approaches by viewing monitoring as a unified smart ecosystem.

The results confirm the broad consensus among current studies regarding the need to transition to risk-based monitoring of TSFs. Regardless of differences in research approaches, the sensor technologies used, and engineering and geological conditions, most publications demonstrate a general trend toward integrating satellite, ground-based,

geotechnical, and geophysical observations within a single digital platform. This review of the literature shows that this type of integration improves the comprehensiveness of spatial coverage, reduces uncertainty in the interpretation of deformation processes, increases reliability of forecasts, and enhances effectiveness of early-warning systems. Consequently, further improvements in monitoring should focus not on finding a universal measurement method, but on developing interoperable architectures that enable the joint processing of heterogeneous data and its smart interpretation.

One of the most significant findings of this review is a critical assessment of current directions in the digital transformation of hydrotechnical structure monitoring. The analysis shows that technologies such as artificial intelligence, digital twins, cloud computing, and the Internet of Things are gradually evolving from auxiliary tools for information processing into central components of smart geospatial systems. At the same time, the level of maturity of these technologies varies.

The systematic analysis also revealed several persistent research gaps regardless of the monitoring technologies used. The most significant of these are the lack of standardized protocols for integrating spatiotemporal data, limited use of methods for quantifying uncertainty, insufficient duration of most experimental studies, geographic concentration of publications in certain regions of the world, and relatively small number of studies devoted to the comprehensive operation of smart monitoring systems under real-world conditions. These circumstances limit the ability to directly compare the results of different studies and highlight the need for further standardization of methodologies for experimental studies, which is consistent with the conclusions drawn during the assessment of the quality of the included studies and the analysis of the limitations of this review.

Overall, the results of this systematic review evidence the emergence of a new research paradigm in which the monitoring of deformation processes is viewed as a continuous, smart geospatial system that integrates distributed data sources, methods for their comprehensive processing, and predictive analytic tools. This approach reflects current trends in the development of engineering geodesy, Earth remote sensing, and industrial safety, and creates prerequisites for a shift from recording changes that have already occurred to forecasting potentially hazardous processes and managing risks proactively. Thus, the concept of geospatial intelligence for tailing dam monitoring developed in this review provides a comprehensive theoretical and methodological framework for further development of smart monitoring systems for hydraulic structures and can serve as a guide for future fundamental research, applied development, and improvement of international standards for ensuring TSF safety.

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Abbreviations

The following abbreviations are used in this manuscript:

AI	artificial intelligence
AI/ML	artificial intelligence/machine learning
AIoT	artificial Intelligence of Things
AMSTAR-2	a measurement tool to assess systematic reviews 2
ANN–LSTM	artificial neural network–long short-term memory
CDA	Canadian Dam Association
CNN	convolutional neural network
DEM	digital elevation model
D-InSAR	differential interferometric synthetic aperture radar
DL	deep learning
DSM	digital surface model
ECR	electronic corner reflector
ERT	electrical resistivity tomography
EWS	early-warning system
FEM	finite element method
GB-InSAR	ground-based interferometric synthetic aperture radar
GCP	ground control point
GIS	geographic information system
GISTM	Global Industry Standard on Tailings Management
GLONASS	global navigation satellite system
GNSS	global navigation satellite system
GPR	ground-penetrating radar
GPS	Global Positioning System
GRU	gated recurrent unit
GSD	ground sampling distance
ICMM	International Council on Mining and Metals
ICOLD	International Commission on Large Dams
InSAR	interferometric synthetic aperture radar
IoT	Internet of Things
KDE	kernel density estimation
LiDAR	light detection and ranging
LIME	local interpretable model-agnostic explanations
LOS	line of sight
LRF	large reservoir facility
LSTM	long short-term memory
MAE	mean absolute error (dimensionless)
MAPE	mean absolute percentage error
ML/DL	machine learning/deep learning
OGC	Open Geospatial Consortium
PRISMA	Preferred Reporting Items for Systematic Reviews and Meta-Analyses
PS-InSAR	persistent scatterer interferometric synthetic aperture radar

R^2	coefficient of determination
RMSE	root-mean-square error (dimensionless)
SAA	ShapeAccelArray
SAR	synthetic aperture radar
SBAS-InSAR	small baseline subset interferometric synthetic aperture radar
SHAP	Shapley additive explanations
SVM	support vector machine
TLS	terrestrial laser scanning
TSF	tailing storage facility
UAV	unmanned aerial vehicle
XAI	explainable artificial intelligence

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