

AI and Remote Sensing for Resilient and Sustainable Built Environments: A Review of Current Methods, Open Data and Future Directions

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AI and Remote Sensing for Resilient and Sustainable Built Environments: A Review of Current Methods, Open Data and Future Directions

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Abstract - Critical infrastructures such as roads, bridges and buildings are increasingly exposed to damage from climate change, natural hazards and human-induced events, making rapid and reliable damage assessment essential for resilient infrastructure management. This review critically examines how artificial intelligence, combined with modern data acquisition technologies, is applied to damage assessment and monitoring across these three infrastructure classes. Following PRISMA 2020 guidelines, 244 peer-reviewed studies published between 2018 and 2026 are analysed for AI models, datasets, data sources and applications. Rather than cataloguing methods, the review interrogates why the field has converged on particular configurations. Three methodologically distinct ones emerge: detector-heavy pipelines on UAV road imagery, a split bridge literature between close-range visual inspection and InSAR-based long-term monitoring, and a satellite-based building literature focused on post-event change detection. The analysis shows that model choice is structurally constrained by sensing modality and data representation rather than architectural superiority, and that data availability is the binding constraint, not model capability: the literature remains concentrated on a small number of benchmark datasets, with limited cross-site validation and scarce satellite and SAR usage, despite their operational value. These same constraints help explain why operational adoption by the engineering sector remains limited. The review consolidates these findings into a conceptual taxonomy and a three-tier monitoring framework, and sets out a research agenda spanning foundation models, multimodal fusion, physics-informed AI, digital twins, edge AI, and explainable AI.

Keywords - machine learning, artificial intelligence, critical infrastructure, remote sensing , AI adoption, explainable AI.

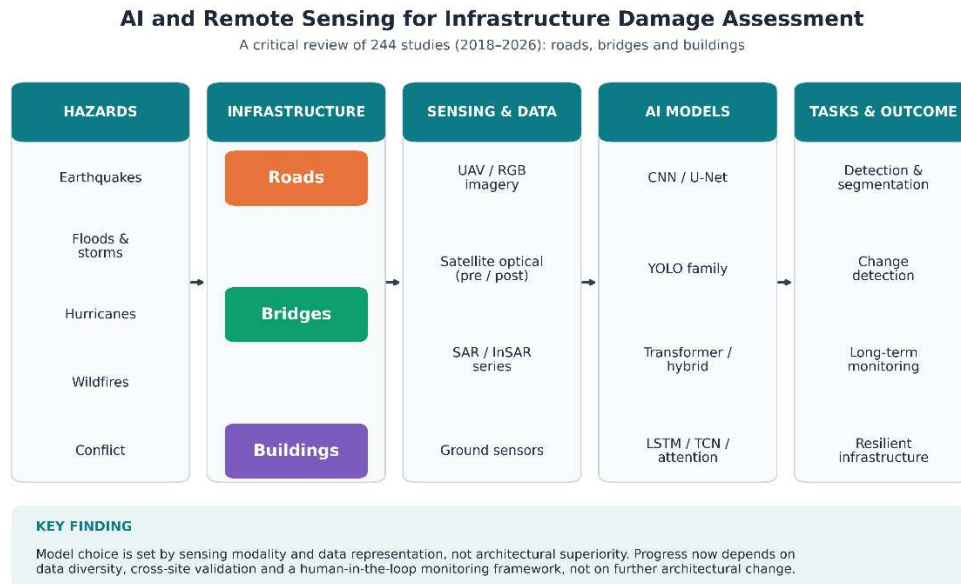


Figure 1. Graphical abstract summary

1. Introduction

Transport and building infrastructure underpin the economy, mobility and public safety of every region, which makes keeping them in serviceable condition a first-order priority. That task is becoming harder: climate change is intensifying the precipitation, heat and sea-level stressors that drive flooding, erosion and urban heat islands, eroding road safety and durability (de Abreu et al. 2022), while direct damage and cascading indirect damage compound across interdependent networks (Rebally et al. 2021). Consequently, fostering climate-resilient infrastructure is becoming essential for the economic prosperity and social coherence of any country (Argyroudis et al. 2022), aligning with the United Nations Sustainable Development Goals (SDGs) (United 2015).

Given these threats, critical infrastructures require quick damage assessment to enable informed decision making and on time restoration avoiding cascading impacts. This need is especially highlighted in challenging zones, such as areas under war or other disruptive events. The use of remote sensing technologies and satellites is crucial here, as data collection in these areas is often defined by security risks and restricted access making on-ground data hard to obtain (Zhao and Morikawa 2025).

Key methods to address this challenge involve damage assessment using satellite images, which can be sourced from open-access platforms or commercial providers. A prominent example is the ESA

(European Space Agency) Sentinel mission, which provides valuable data through radar imaging (Sentinel-1) and multispectral high-resolution imaging (Sentinel-2) (European Space Agency 2026). For instance, researchers have developed multi-scale approaches that integrate Sentinel-1 SAR images with high-resolution imagery and deep learning for rapid post-disaster infrastructure damage detection (Kopiika et al. 2025).

At the same time, AI is developing faster than the infrastructure can absorb it (RICS 2025). Certification processes, liability frameworks and workforce training in this field operate on timescales of years, yet the model families they must evaluate change within months, and the most widely used architectures offer no interpretable output by default, which sits uneasily with the professional accountability engineers carry for the decision they sign off (Nyokum and Tamut 2025; Byrd and Geheran 2026). Similar delays accompanied the adoption of the internet and of drone based inspection in engineering practice. To judge whether AI faces the same barriers, the literature needs to be read critically rather than descriptively: this review therefore examines not only which methods and datasets exist, but how far they can support operational use.

Previous work has tended to treat roads, bridges and buildings in isolation, and existing reviews are similarly partial: (Abedi et al. 2023) systematically reviewed machine learning for general civil-infrastructure damage, while (Abduljabbar et al. 2019) surveyed AI across the transport sector without a structural-damage focus. Two gaps follow. First, no review compares AI models and datasets across roads, bridges and buildings together. Second, although satellite radar such as SAR is established for monitoring, its integration with modern AI for holistic, cross-infrastructure damage assessment remains largely unexplored. This review addresses both from a critical standpoint: it synthesises 244 peer-reviewed studies (2018–2026) selected through a PRISMA 2020 search supplemented by targeted Google Scholar retrieval; characterises the field quantitatively by publication volume, infrastructure type, task framing, data source, dataset and AI model; identifies a structural split in bridge research between close-range visual inspection and InSAR-based long-term monitoring not previously made explicit; consolidates satellite and SAR work as a cross-cutting pathway that behaves differently across infrastructure classes; and critically assesses the readiness of these methods and datasets for operational practice, including what the corpus reveals about the factors limiting adoption. To our knowledge, this is the first integrated review of AI-based damage assessment to span roads, bridges and buildings together, the first to connect AI model families, sensing modality and operational scale

into a unifying conceptual taxonomy; and the first in this domain to propose a multi-tier, human-in-the-loop monitoring framework aligned with engineering accountability. The review identifies a transition under way from inspection-oriented AI towards predictive resilience AI, examines why operational adoption nevertheless remains limited (Nyokum and Tamut 2025; Plevris and Hosamo 2025; Byrd and Geheran 2026), and sets out a research roadmap towards continuous infrastructure digital twins. Because AI models for damage assessment inform decisions with operational, financial and humanitarian consequences, the ethical, transparency and policy implications of deploying them are discussed in Section 7.4.

The remainder of this paper is structured as follows. Section 2 describes the PRISMA-based search, screening and inclusion criteria. Section 3 presents a quantitative overview of the studies by publication year, infrastructure type and task distribution. Section 4 categorises the damage types and stressors covered in the literature. Section 5 analyses the data acquisition technologies, satellite and SAR methods, and benchmark datasets used across the reviewed studies. Section 6 examines the AI models themselves, first in aggregate and then by infrastructure class (roads, bridges, buildings) and by satellite. Section 7 synthesises the trends, research gaps and ethical and policy considerations. Section 8 concludes with priorities for future work.

2. Methodology

This review follows the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA 2020) guidelines (Page et al. 2021), to ensure a transparent and reproducible search and selection process. The objective is to identify, screen and synthesise peer-reviewed research on the application of AI models and datasets to the damage assessment and condition monitoring of transport infrastructure, specifically, roads, bridges and buildings, including studies that integrate satellite remote sensing and SAR technology.

A systematic database search was conducted across Scopus and Web of Science (WoS). To comprehensively cover the two main streams of the review, two complementary search queries were designed and applied independently to both databases, with results merged consequently. Search A targeted AI approaches for infrastructure damage detection, while search B targeted SAR and interferometric approaches combined with AI for bridge and road structural monitoring.

Search A: TITLE-ABS-KEY (
 ("Artificial Intelligence" OR "Deep Learning" OR "Computer Vision" OR "YOLO")
 AND ("Remote Sensing" OR "Satellite Imagery" OR "Optical Imagery" OR "UAV" OR "Drone")
 AND ("Damage Detection" OR "Crack Detection" OR "Pothole Detection")
 AND ("Transport Infrastructure" OR "Roads" OR "Bridges" OR "Pavements")
)
 AND PUBYEAR > 2017 AND PUBYEAR < 2027
 AND (LIMIT-TO (SRCTYPE, "j") OR LIMIT-TO (SRCTYPE, "p"))
 AND (LIMIT-TO (SUBJAREA, "ENGI") OR LIMIT-TO (SUBJAREA, "COMP")
 OR LIMIT-TO (SUBJAREA, "PHYS") OR LIMIT-TO (SUBJAREA, "MATH"))
 AND (LIMIT-TO (DOCTYPE, "ar") OR LIMIT-TO (DOCTYPE, "cp"))
 AND (LIMIT-TO (LANGUAGE, "English"))

Search B: TITLE-ABS-KEY (
 ("Artificial Intelligence" OR "Deep Learning" OR "Neural Network" OR "Computer Vision")
 AND ("SAR" OR "Synthetic Aperture Radar" OR "InSAR" OR "Interferometry")
 AND ("Bridge" OR "Road")
 AND ("Displacement" OR "Deformation" OR "Structural Health Monitoring")
)
 AND PUBYEAR > 2017 AND PUBYEAR < 2027
 AND (LIMIT-TO (SUBJAREA, "ENGI") OR LIMIT-TO (SUBJAREA, "EART")
 OR LIMIT-TO (SUBJAREA, "ENVI") OR LIMIT-TO (SUBJAREA, "PHYS")
 OR LIMIT-TO (SUBJAREA, "COMP") OR LIMIT-TO (SUBJAREA, "MATH"))
 AND (LIMIT-TO (DOCTYPE, "ar") OR LIMIT-TO (DOCTYPE, "cp"))
 AND (LIMIT-TO (SRCTYPE, "j") OR LIMIT-TO (SRCTYPE, "p"))
 AND (LIMIT-TO (LANGUAGE, "English"))

Both searches Were limited to journal articles and conference proceedings in English, across engineering, computer science, physics, mathematics, earth and environmental sciences subject areas. The merged results from searches A and B returned 346 records from Scopus and 98 from web of science giving 444 identified records prior to deduplication and screening. To supplement the systematic search and capture focused and recently published work not yet fully indexed by the major databases, a search was conducted also on Google Scholar using targeted keyword combinations aligned with the same thematic streams which identified 170 records.

2.1 Screening and selection

The overall selection process is summarised in the PRISMA 2020 flow diagram presented in Figure 2.

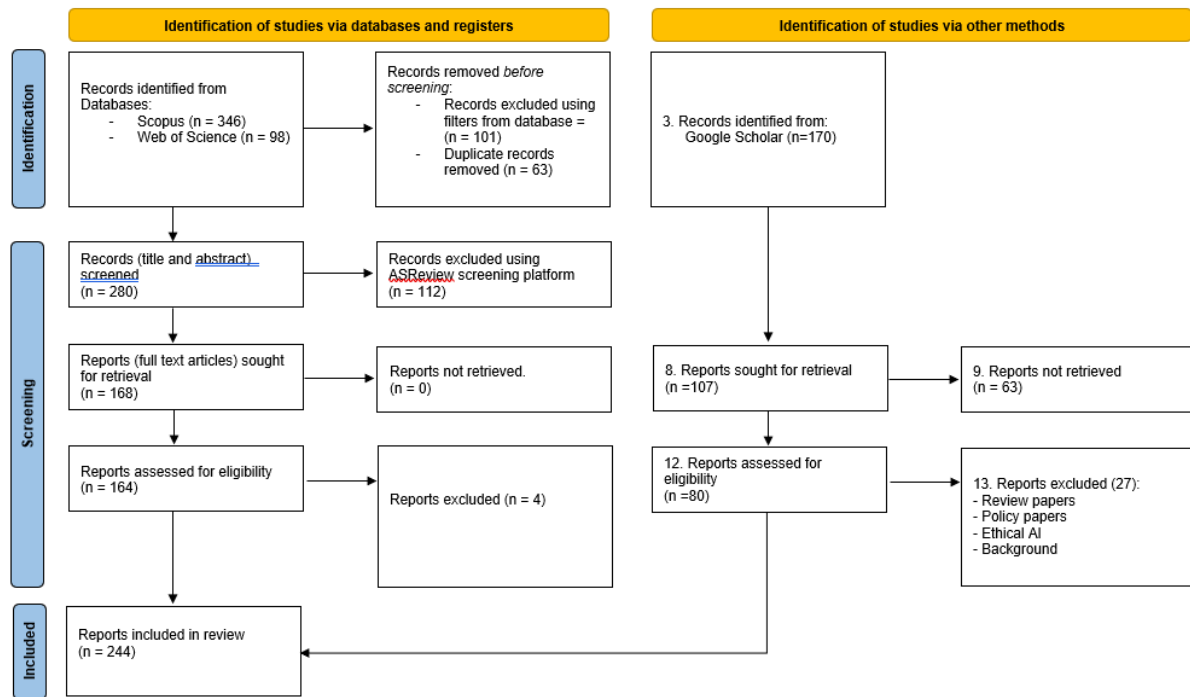


Fig. 2 PRISMA 2020 flow diagram review process

Abstract screening was performed using ASReview (van de Schoot et al. 2021), an open source active learning tool that uses machine learning to iteratively rank and prioritise records for human review. A seed set of confirmed relevant papers was used to initialise the active learning model, after which ASReview progressively surfaced the most relevant remaining abstracts for human assessment. Following the process, 112 records were excluded as not relevant to the review. The remaining 168 papers were successfully retrieved and assessed, with four papers excluded as they addressed geological or geophysical applications outside the scope of transport infrastructure assessment, resulting in 164 papers. On the identification of other studies via other methods, 80 papers have been included after screening and retrieval. The total set of studies for this review comprises of 244 papers, from 2018 to 2026.

Papers were included if they met all the following criteria:

- Applied AI or machine learning model to damage detection, damage assessment, condition monitoring, or structural health monitoring of transport infrastructures and civil structures.
- Published in English between 2018 and 2026.
- Peer-reviewed journal articles or conference proceedings.

Papers were excluded if:

- Addressed infrastructure types outside of review scope (i.e. geological formations, dams, pipelines).

- Were systematic or narrative reviews or policy documents without primarily experimental results.
- Did not apply a computational or AI based model.
- Could not be retrieved in full text.

Each criterion maps onto a specific stage of the PRISMA workflow in Figure 2: language, document-type and date filters were applied at identification; topical relevance (AI applied to road, bridge or building damage) was applied during ASReview-assisted screening; and full-text availability together with the exclusion of geological/geophysical applications outside transport scope was applied at eligibility, before the final included set of 244 studies.

3. Overview of the surveyed literature

This section provides a quantitative overview of the papers included in the review, characterising the body by publication year, infrastructure type and task distribution. The aim is to show the landscape of the field before the detailed analysis in the later sections.

Figure 3 shows the number of publications per year across the period 2018-2026. The trend reveals a clear and sustained growth trajectory, with a pronounced acceleration from 2021 onwards. Between 2018 and 2020 the publication volume remained stable at around 14-15 papers per year, reflecting a period of foundational work in which a relatively small research community was studying the use of deep learning to infrastructure monitoring. A first inflection point occurs in 2021, with output easing to 24 papers, followed by 26 papers in 2022. From 2023 onwards, the growth accelerates, with 39 papers published in 2023, 44 in 2024, and 61 in 2025, the highest annual count in the review period. In 2026 so far, six papers have been published.

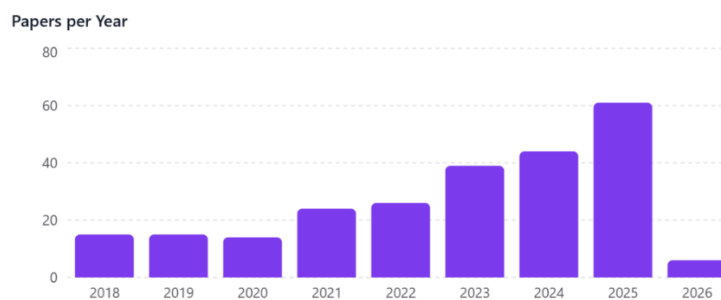


Fig. 3 Annual publications, 2018 - 2026. Output grows sharply from 2023, more than quadrupling over the review period

This more than four-fold increase in annual output (15 papers in 2018 to 61 in 2025) has not been matched by any equivalent growth in documented operational deployments or pilots within the reviewed

literature, suggesting that research productivity and institutional uptake are diverging rather than converging, a divergence this review returns to in Section 7.

Figure 4 presents the distribution of papers across infrastructure types. Road infrastructure is the most studied category, appearing in 114 papers (45% of the records), followed by the bridge infrastructure with 88 papers (35%). Buildings account for 23 papers (9%). Road infrastructure's dominant position reflects the relative ease of data collection: vehicle mounted cameras, UAVs, diverse road datasets and multiple international benchmarking competitions (i.e. GRDDC 2020 and GRDDC 2022). Bridge infrastructure, despite its structural complexity and specialised equipment needed for inspection, represents a substantial percentage.

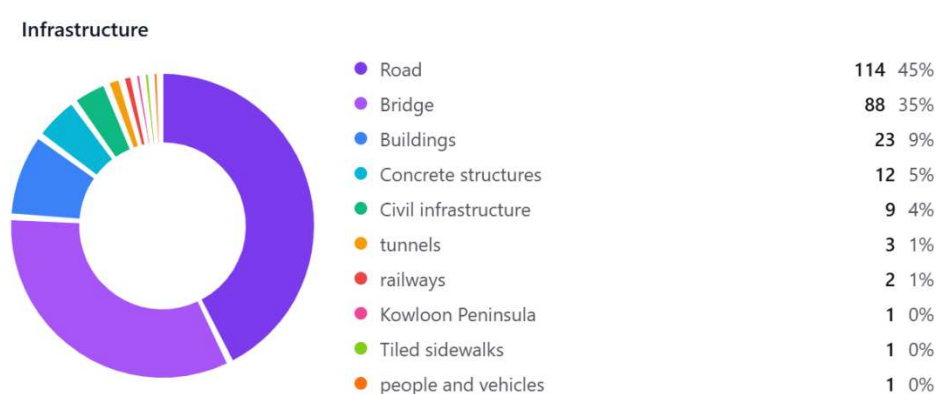


Fig. 4 Distribution of studies by infrastructure type. Roads (45%) and bridges (35%) dominate; buildings (9%) are markedly underrepresented relative to their real-world stakes

Here we present the distribution of computational tasks across the reviewed papers, in Figure 5. Object detection is the most common task, appearing in 82 papers (24% of all records), followed by classification with 75 papers (22%). Together these two tasks account for nearly half of all research output, reflecting a detection first approach. Crack detection and segmentation, which provides pixel level damage delineation, accounts for the other major portion of the studied records, at 14% each. The dominance of object detection and classification reflects both the increasing interest in computer vision for these tasks and the availability of labelled benchmark datasets that enable supervised training. The 14% share of segmentation task signals also a growing demand for finer spatial resolution in damage classification, particularly relevant for structural conditions where damage extent and size determine maintenance priority.

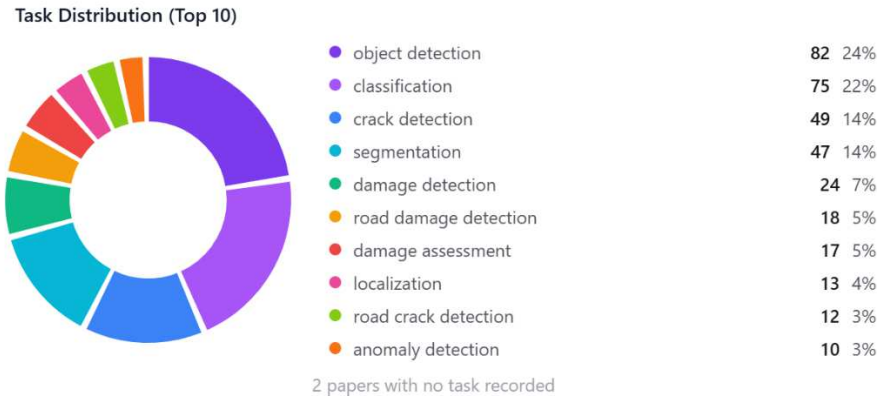


Fig. 5 Distribution of AI task framings across the 244 reviewed studies. Object detection dominates road infrastructure, segmentation is most common for buildings, and a monitoring - detection split characterises bridge work

Taken together, these distributions describe a field shaped more by data availability than by engineering priority. Road infrastructure leads (114 papers, 45%) not because it is the most safety-critical class but because vehicle-mounted cameras, UAVs and repeated benchmark competitions make road data the cheapest to obtain; buildings trail (23 papers, 9%) despite comparable real-world stakes; and the dominance of object detection and classification (together ~46% of records) reflects what benchmark datasets reward rather than what operators most need. The implication for the field is that the literature is optimising against the outlines of available data, not against the requirements of operational infrastructure management. Sections 4 to 6 examine this evidence in depth: damage types and stressors (Section 4), data sources and datasets (Section 5), and AI models by infrastructure class (Section 6).

4. Infrastructure damage types and stressors

4.1 Surface and structural damage in roads and buildings

Table 1 summarises the most common civil-infrastructure damage types identified across the reviewed studies, giving a structured taxonomy of the categories AI models have been applied to detect and classify. As established in Section 3, the research effort concentrates on road infrastructure, and this is reflected in the damage taxonomy: the most frequently targeted categories are lateral, longitudinal and alligator cracking, followed by potholes and surface deformation, mirroring the labels available in the dominant road benchmarks rather than an engineering ranking of severity.

Table 1. Common road and building damage categories targeted by AI approached in the reviewed studies

Author / Year		Roads			
	Longitudinal cracks	Lateral cracks	Alligator cracks	Cracks	Other road components
(Paramasivam et al. 2024)				x	Potholes
(Zeng and Zhong 2024)	x	x		x	Potholes, mesh cracks
(Guo and Zhang 2022)	x	x		x	Mesh cracks, pothole, longitudinal and lateral construction joint, crosswalk blur, white line blur.
(Stricker et al. 2021)	x	x	x	x	Patches, scratches, bleeding, manholes, curb, cobblestone, drill holes, vegetation, joints, water drains.
(Du et al. 2021)	x	x	x	x	Patches, nets, manholes
(Mei and Gül 2020)				x	
(Majidifard et al. 2020)	x	x	x	x	Reflective crack, block crack, sealed reflective crack, lane long. crack, sealed long. crack
(Hegde et al. 2020)	x	x	x		
(Angulo et al. 2019)	x		x	x	
(Stricker et al. 2019)			x	x	
(Weng et al. 2019)	x	x	x	x	
(Maeda et al. 2018)	x	x	x		
(Dorafshan et al. 2018)				x	
Buildings					
	Minor	Major	Destroyed	Ruin	Other
(Bhardwaj et al. 2025)					Damage, No damage
(Braik and Koliou 2024)	x	x	x		Undamaged
(V.V. et al. 2024)					Damaged, undamaged
(Kaur et al. 2023)	x	x	x		Undamaged
(Zhang et al. 2023)			x	x	
(Liu et al. 2022)			x		Debris, Spalling, Cracking
(Wang et al. 2022)	x	x	x		

(Wu et al. 2021)	X	X	X
(Weber et al. 2023)	X	X	X
(Gupta et al. 2019)	X	X	X

Regarding damage criteria for buildings, we can observe from Table 1 that it is common to classify the damages into the following: “Minor”, “Major” and “Destroyed”. Upon analysis of these papers, it was revealed that these classifications are used due to the widespread use of the “xBD” dataset (Gupta et al. 2019), which is a large-scale dataset of building damage assessment used for humanitarian relief and disaster rescue.

4.2 Bridge specific damage types

In the analysis of bridge damages, we identified the common terminology used in recent studies. The primary damage types found, which are detailed in the table below, include deflection, deformation, and displacement.

Table 2. types of bridge damage and location

Author/Year	Damage type	Component	Bridge studied	Country
(Xiong et al. 2026)	Displacement anomaly	Global structural behaviour	HK-Zhuhai-Macao Bridge	China
(Della Santa et al. 2026)	Structural deformation, displacement	Global structural behaviour	Tadcaster Bridge, Cantiano Bridge	UK, Italy
(Ren et al. 2025)	Deformation	Global structural behaviour	Sea crossing bridge	China
(Nettis et al. 2023)	Structural deformation	Global structural behaviour	Albiano Magra, Fossano	Italy
(Yunmei et al. 2023)	Deflection	Span	Custom	/
(Feng et al. 2023)	Displacement	Deck, Global structural behaviour	Nanjing bridge	China
(Markogiannaki et al. 2022)	Displacement, deformation	Global structural behaviour	Polyfyto	Greece
(Schlögl et al. 2021)	Deformation	Deck, Global structural behaviour	Seitenhafenbrücke	Austria
(Tian et al. 2021)	Deflection	Span	Southside of Jingtai Bridge	China
(Jung et al. 2019)	Deflection	Deck, Span, Global structural behaviour	Kimdaejung and Muyeong bridges	S. Korea

From Table 2, it can be observed that the reviewed studies focus on a range of structural response indicators, including deflection, deformation and displacement, measured across critical bridge components. The monitored responses primarily concern global bridge structural behaviour, including displacement and deformation of bridge decks, spans and load-bearing structural components. The diversity of case studies also indicates that these monitoring approaches are not limited to specific

geographical regions or bridge functions, as both highway and railway bridges are represented across multiple countries. More recent studies published between 2025 and 2026 reflect a shift towards satellite-based SAR monitoring for detecting minute structural displacements at large spatial scales. These approaches increasingly complement, and in some cases replace, traditional sensor-based structural health monitoring systems by enabling continuous and remote assessment of bridge behaviour. This trend includes the growing adoption of interferometric techniques such as InSAR (Wang et al. 2025; Della Santa et al. 2026; Xiong et al. 2026), MTInSAR (Nettis et al. 2023) or D-TomoSAR (Liu et al. 2018) which are discussed further in the next sections.

4.3 Natural hazards and human induced threats

Having detailed the specific damage types across road and bridge infrastructure, the focus now shifts to the broader context of casual events. The type of natural hazards, flood, earthquakes, wildfires and hurricanes, which directly influences the nature and scale of damage to transport infrastructure and consequently the most suitable remote sensing data and AI model design. The following table summarises a selection of studies that identify the specific hazard stressor investigated, illustrating the distribution of focus within the research area.

Table 3. Natural hazards stressors analysed for road, bridge and buildings

Author/Year	Wild-Fire	Flood	Land disaster	Nature disaster	Earthquake	Hurricane	Volcano	Human-induced	Tsunami
(Bhardwaj et al. 2025)						x			
(Cha et al. 2025)		x	x	x	x				
(Kopiika et al. 2025)								x	
(Braik and Koliou 2024)						x			
(Wang et al. 2024)						x			
(Weber et al. 2023)	x	x	x		x	x	x	x	
(Niloy et al. 2021)	x	x	x					x	x
(Arif et al. 2020)	x	x		x				x	

(Gupta et al. 2019)	x	x		x	x	x	x
(Rizk et al. 2019)			x				
(Barz et al. 2018)		x					
(Giannakeris et al. 2018)	x	x					

The hazards listed in Table 3 directly threaten the integrity of transport infrastructures, which are vital for economic and social connectivity. The table suggests that most of these natural hazards are floods and hurricanes, which can cause direct damage to roads and bridges, and as well as indirect impacts through cascading events like traffic disruptions. There are a range of methods that have been employed for damage quantification. In the context of natural disasters, methodologies such as StEER network (Wang et al. 2024) and HAZUS (developed by FEMA), presented in Table 4.

Specifically, HAZUS-FEMA has been applied for multi-hazard damage classification, encompassing events such as floods, hurricanes, and earthquakes (Gupta et al. 2019). These tools leverage geospatial data and standardized assessment protocols to support large-scale disaster impact evaluation.

Table 4. Damage quantification methods disasters

Author/Year	Damage quantification methods	Data source used	Infrastructure	Case study applications
(Wang et al. 2024)	StEER network	Visual survey, NOAA, Maxar, Copernicus	Natural disasters	Hurricane Ian
(Teopilus and Amrozi 2023)	PASER	Visual survey, Bina Marga	Roads	Dandels road, Java island
(Teopilus and Amrozi 2023)	PCI	Visual survey, Bina Marga	Roads	Dandels road, Java island
(Teopilus and Amrozi 2023)	SDI	Visual survey, Bina Marga	Roads	Dandels road, Java island
(Gupta et al. 2019)	Hazus Fema	Maxar	Natural disasters	xView2 competition

The table also includes entries for human-induced hazards, which connects to the discussion of using remote sensing in challenging situations such as warzones. Technologies such as Satellites and SAR can operate in these areas and are valuable for assessing infrastructure damage in these contexts, as in (Kopiika et al. 2025). The constraint here is the suitability of methodologies and data in these contexts,

i.e. the suitability of AI model for SAR based monitoring is limited by the slow acquisition and processing of SAR data, and therefore in the case of rapid-onset hazards like the ones above, timely damage assessment is critical.

5. Data acquisition and Datasets

5.1 Data collection technologies

In Figure 6, a comparison of the dominant data acquisition technologies across the three infrastructure classes is presented, after harmonising the original source labels into six sensing categories. The comparison shows that road studies are strongly dominated by UAV and mobile RGB imagery, reflecting the accessibility of pavement surfaces and the suitability of road damage detection for close-range visual inspection. Bridge studies show a more heterogeneous sensing profile, combining UAV inspection, satellite imagery, SAR/InSAR and sensor-based monitoring. This reflects the dual nature of bridge assessment, which includes both localized visual defect detection and long-term structural response monitoring (Achillopoulou et al. 2020). Building studies, in contrast, are dominated by optical satellite imagery, consistent with their frequent framing as post-disaster regional damage assessment rather than routine local inspection.

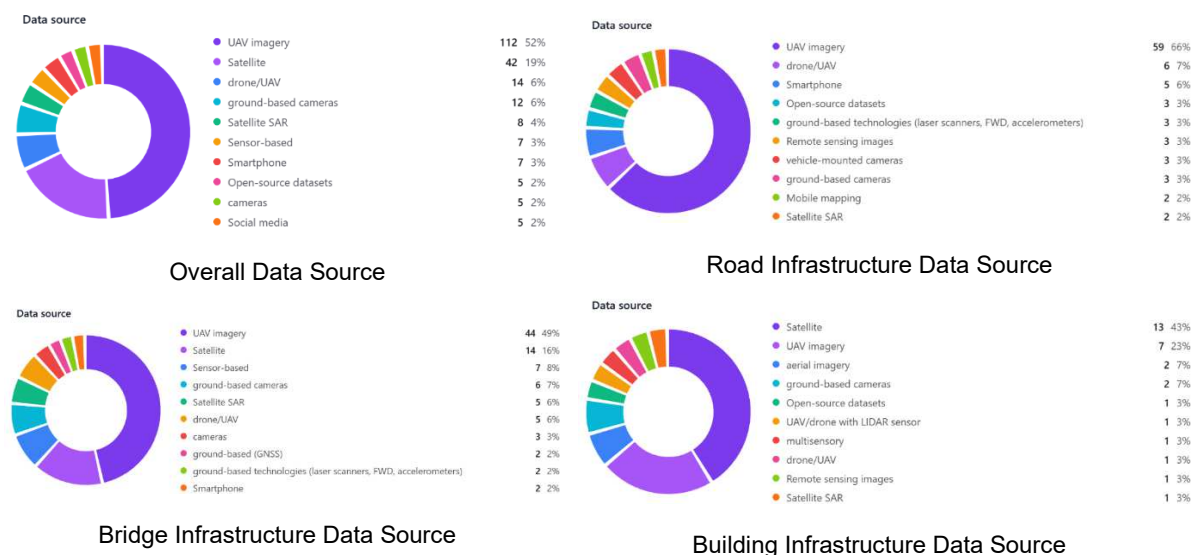


Fig. 6 Distribution of data-acquisition sources across the corpus per infrastructure. Top left: Overall view shows UAV imagery supplies over half of all studies; satellite and SAR together account for under a quarter. Top right: data sources used for road infrastructures. Bottom left: data sources for bridge infrastructures. Bottom right: data sources for building infrastructure

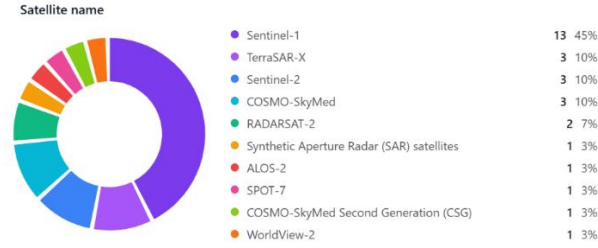


Fig. 7 Satellite names mainly used in the studies. Sentinel satellite dominates, being open-source. The other are commercial satellites such as TerraSAR-X, COSMO-SkyMed and RADARSAT-2

The underrepresentation of satellite and SAR methods, despite their unique capacity for continuous and network-scale monitoring, reflects institutional rather than technical constraints: processing expertise, dataset scarcity, and the absence of validated workflows for engineering applications.

5.2 Satellite imagery and SAR methods

Satellite imagery and Synthetic Aperture Radar (SAR) represent a distinct and growing acquisition pathway for infrastructure monitoring, appearing in 42 papers as optical satellite data and a further 8 as dedicated SAR (Figure 6). Table 5 summarises applications of SAR and the integration with AI across the reviewed literature.

Table 5. Applications of satellite SAR methods and uses of AI models

Author/Year	Application	AI	Satellite
(Xiong et al. 2026)	InSAR displacement anomaly detection, HK-Zhuhai-Macao Bridge	GAN/TadGAN	Sentinel-1
(Della Santa et al. 2026)	Pre-collapse risk prediction, Tadcaster Bridge (UK), Cantiano Bridge (Italy)	Multi-Head Attention NN	Sentinel-1
(Entezami et al. 2025)	Long-span bridge monitoring	Gaussian Process Regression, LSTM	Sentinel-1
(Ren et al. 2025)	Deformation-pattern classification for sea-crossing bridge	Temporal Convolutional Network, Transformer, Temporal Fusion Transformer, ROCKET	Sentinel-1
(Kopiika et al. 2025)	SAR-based assessment of bridges / critical infrastructure	Deep learning	Maxar Sentinel-1
(Entezami et al. 2024)	Long-span bridge monitoring	LSTM NN	/
(Wang et al. 2024)	Building damage assessment	Bayesian Networks	Maxar Sentinel-1
(Malinowska et al. 2024)	Persistent-scatterer deformation prediction	CNN, U-Net	Sentinel-1
(Feng et al. 2023)	Bridge displacement prediction, Nanjing bridge	Res-LSTM	Sentinel-1
(Entezami et al. 2023a)	Early damage detection, long-span steel arch bridge	Regression ANN	TerraSAR-X
(Entezami et al. 2022)	Displacement-based damage detection, Tadcaster Bridge	Hamiltonian Monte Carlo, sliced inverse regression	TerraSAR-X
(Nemni et al. 2020)	Rapid flood segmentation	FCNN	Sentinel-1
(Sun et al. 2020)	Ground displacement monitoring and prediction using InSAR	DeepInSAR	TerraSAR-X

As introduced in section 5.1, named satellite platforms in the dataset appear to be dominated by Sentinel-1, likely because ESA's open-access C-band SAR mission provides frequent revisits and versatile resolutions ranging from 5 x 5 m to 20 x 40 m. TerraSAR-X, Sentinel-2 and COSMO-SkyMed appear in 3 papers (10%) each, followed by RADARSAT-2 and ALOS-2.

The table demonstrated the versatility of SAR across a wide range of applications, from flood mapping and glacial monitoring to structural deformation tracking and pre-collapse prediction. A sustained line of research by Entezami and colleagues (Entezami et al. 2022; Entezami et al. 2023a; Entezami et al. 2023b; Entezami et al. 2023c; Entezami et al. 2024; Entezami et al. 2025) has progressively integrated Bayesian, regression, and recurrent networks into InSAR pipelines for bridge health monitoring. Most recent studies extend this further with attention networks, temporal convolutional networks and adversarial anomaly detection (Feng et al. 2023; Malinowska et al. 2024; Ren et al. 2025; Della Santa et al. 2026; Xiong et al. 2026), enabling automated pattern recognition and predictive structural health assessment from displacement time series. This represents a shift from passive observation to predictive monitoring. The key limitation is still latency in processing, as SAR acquisition is time-consuming and interferometric pipelines currently limit how quickly systems can respond to sudden hazards.

Table 6. Available satellite data for monitoring infrastructures. GSD: Ground Sample Distance

Author	Satellite data source	Data resolution in GSD	Features
(European Space Agency 2026)	Sentinel-1, ESA	5m - 40m	Radar imagery, dual polarization, short revisit times, fast product delivery. ESA.
(European Space Agency 2026)	Sentinel-2, ESA	10m	Wide-swath, high resolution and multi spectral imager for earth surface monitoring. ESA.
(Gupta et al. 2019)	Maxar	0.3m	Assessing building damages after natural disasters. MDA.
(Mari et al. 2018)	COSMO-SkyMed	1m - 100m	High resolution imagery, multi-mode operation and dual polarization capability. Italian Space Agency.
(Motohka et al. 2017)	JAXA ALOS-2	1m x 3m (spotlight), 3m, 6m, 10m (stripmap)	High resolution imagery, L-band SAR, Compact InfraRed Camera, Automatic Ship Identification System. Japanese Aerospace Exploration Agency.
(Chabot et al. 2014)	RADARSAT-2	3m – 100m	High resolution imaging, flexible polarization and left/right looking imaging capabilities. C-Band SAR. Canadian Space Agency.
(Roy et al. 2014)	Landsat 7/8	15/30m	Landsat 8 has narrower spectral bands, improved calibration and signal-to-noise characteristics, high radiometric resolution and more precise geometry compared to Landsat 7. NASA and US.
(Werninghaus and Buckreuss 2010)	TerraSAR-X	1m - 40m	Radar imagery, various imaging modes, high resolution, rapid switching between modes and polarizations. German Aerospace Centre and Airbus.

Some of the studies above have used damage quantification methods, which have been listed in Table 4, highlighting their application in real-world scenarios for assessing infrastructure damage, especially in the context of natural disasters.

5.3 Datasets for infrastructure damage detection

Having described the data acquisition technologies and satellite methods in the preceding subsections, this section provides a deeper analysis of the key datasets used for training and evaluating AI models.

Figure 8 shows the most frequently cited across the review. UAV-PDD2023 is the most referenced dataset, appearing in 9 papers, followed by xBD with 7 papers and RDD2022 with 5 papers. COSMO-SkyMed Second Generation (CSG) imagery appears in 4 papers as a bridge SAR monitoring source. UAPD and GRDDC2020 each appear in 3 papers. The dominance of UAV-PDD2023, a UAV captured pavement defect dataset used in papers across 2024-2026 (Chen and Liu 2025; Cheng et al. 2025a; Cheng et al. 2025b; Geng et al. 2025; Shang et al. 2025; Wang and Wei 2025; Yu and Li 2025; Zhou and Wang 2025; Li et al. 2026), reflects the surge in drone based road damage research in the latter part of the review period. xBD position as the second most cited dataset confirms its role as the central benchmark for building damage assessment, highlighting the majority of post disaster satellite classification studies in this review.

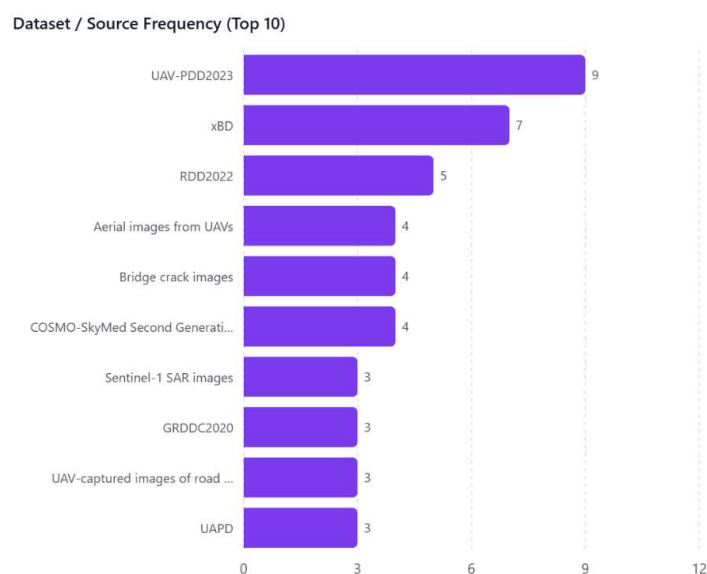


Fig. 8 Top 10 datasets used across the review. Road datasets dominate, followed by the big xBD dataset

In Table 7 presents the main datasets across all infrastructure types, restricted to papers published from 2018 onwards to keep the landscape aligned with the review period and with the deep learning era that rest of section 6 analyses. The road section is substantially larger than those for building and bridges, consistent with what analysed in section 3. Road datasets can be assembled using normal cameras and smartphones, enabling large scale collection efforts. The RDD competition series demonstrated this, in RDD2020 where data was collected from three countries (India, Japan, Czech republic) with 26,336 images, while RDD2022 expanded to six countries including Norway, United States, and China, with over 47,000 images.

Table 7. Datasets of damaged infrastructures used for detection

Authors/Year	Dataset	Classes	No. of Images	Images resolution
ROADS				
(Chu et al. 2026)	Custom	Crack	1600 + 80 + 100	256x256, 3840x2160
(Bafail et al. 2026)	Roboflow	Crack, Potholes, stone	4351	640x640
(Li et al. 2026)	UAV-PDD2023, RDD2022-China, Custom	Longitudinal cracks, transverse cracks, alligator cracks, mesh cracks, potholes.	2401 (RDD2022)	640x640
(He et al. 2025)	HighRPD	Longitudinal, transverse, irregular, block cracks; potholes	11696	640x640
(Taha et al. 2025)	DronePavSeg	Crack	1899	400x300
(Pan and Zhang 2025)	LCrack + RDD2022	Longitudinal, transverse, alligator cracks; potholes	5000+6000	630x630
(Arya et al. 2024)	RDD2022 CRDDC2022	Longitudinal, Transverse, Alligator cracks, Potholes.	47,420	512x512, 600x600, 720x720, 3,650x2044
(Du et al. 2021)	LIST	Crack, Pothole, Net, Patch-Crack, Patch-Pothole, Patch-Net, Manhole.	45,788	1,920x1080
(Arya et al. 2021)	RDD2020	Longitudinal cracks, Transverse cracks, Alligator cracks, and Potholes.	26,336	600x600, 720x720
(Stricker et al. 2021)	GAPs 10m	22 classes ¹ .	394	5,030x11,505
(Yang et al. 2020)	Crack500	Crack.	500	2,000x1500
(Mei and Gül 2020)	EdmCrack600	Crack.	600	1,920x1080
(Majidifard et al. 2020)	PID	Block, Lane longitudinal, Longitudinal, Sealed Longitudinal, Pothole, Alligator, Sealed reflective, Reflective, Transverse.	7,237	640x640
(Stricker et al. 2019)	GAPs v2	Intact, Cracks, Applied patches, Inlaid patches, Potholes, Open joints.	2,468	1,920x1080
(Angulo et al. 2019)	Modified RDD2018	Wheel mark, Construction joint long. , Equal interval, Construction joint lat., Partial/Overall pavement, Bump/Rutting, Crosswalk blur, White line blur.	18,034	600x600
(Weng et al. 2019)	G45	Transverse, Longitudinal, Block, Alligator	217	2,048x1,536
(Dorafshan et al. 2018)	SDNET2018	Cracked, Non-cracked	56,000	256x256

¹ Void, Inlaid patch, Applied patch, Scaled crack, Crack, Open joint, Pothole, Raveling, Scratch, Bleeding, Road marking, Surface water drain, Manhole, Expansion joint, Curb, Cobblestone, Drill hole, Object mobile, Object fixed, Joint, Road verge, Vegetation, Induction loop, Normal.

BUILDINGS				
(Chen et al. 2025)	BRIGHT	Intact, Damaged, Destroyed	4,246	1024x1024
(Yang et al. 2024)	Custom	Collapsed, Heavily damaged, Needs demolished, Slightly damaged	13	n/a
(Wang et al. 2024)	Custom	No Damage, Minor, Moderate, Severe, Destroyed	2,472	n/a
(Liu et al. 2022)	GDBDA	Debris, Collapse, Spalling, Crack.	8,340	800x800
(Gupta et al. 2019)	xBD	No damage, Minor damage, Major damage, Destroyed, Unclassified.	22,068	1,024x1,024
BRIDGES				
(Zhou and Wang 2025)	UAV-PDD2023, RDD2022-China-MotorBik	Longitudinal cracks, transverse cracks, mesh cracks, potholes, other.	2440 + 2477	640x640
(Dong et al. 2025)	Custom from Roboflow	Lateral, longitudinal, crocodile cracks	500	640x640
(Cui et al. 2025)	Custom	Concrete class	562	544x544
(Aisuwarya et al. 2025)	Custom from Roboflow	Crack	2944	640x640
(Flotzinger et al. 2024)	Dacl10k	12 classes ² .	9,920	Min: 336x245 Max: 6,000x5,152
(Santaniello and Russo 2023)	Z24	Undamaged, 20mm, 40mm, 80mm, 95mm displacement.	1,422	Time-series
(Xu et al. 2019)	Crack-detection	Crack, Non-crack.	6,069	224x224
(Mundt et al. 2019)	CODEBRIM	Crack, Spallation. Efflorescence, Exposed Bars, Corrosion.	1,590	2,592x1,944 to 6,000x4,000
(Dorafshan et al. 2018)	SDNET2018	Cracked, Non-cracked.	56,000	256x256

Across all infrastructure classes, the binding constraint is data availability, not model architecture. UAV imagery supplies over half of all studies (112 papers, 52%) because it is cheap, flexible and easy to label; satellite and SAR together appear in under a quarter despite being the only sensing modalities capable of continuous, network-scale assessment without physical access; and within each class the field has anchored on one or two datasets: UAV-PDD2023 and RDD2022 for roads, xBD for buildings, bespoke crack sets for bridges, and Sentinel-1 for satellite work. The consequence is a reproducibility environment in which performance is measured against a fixed distribution rather than the variable conditions of real deployment, which is the foundational reason high benchmark accuracy does not translate into engineering confidence.

² Crack, Alligator crack, Efflorescence, Rockpocket, Washouts concrete corrosion, Hollowareas, Spalling, Restformwork., Wetspot, Rust, Graffiti, Weathering, ExposedRebars, Bearing, Expansion joint, Drainage, Protective equipment, Joint tape.

6. AI models for infrastructure damage assessment

6.1 AI model families across infrastructure classes

Across the 244 papers reviewed, convolutional neural networks remain the single most common model family, appearing in 64 papers in their generic form (Figure 9). The next tier is split between Transformer based architectures (22), U-Net and its variants (21), and the YOLOv5 detector (20), followed by artificial neural networks (16). More recent YOLO releases, such as YOLOv8 (10), YOLOv7 (9), YOLOv8n (8), together account for a comparable share, and Generative Adversarial Networks appear in 7 papers.

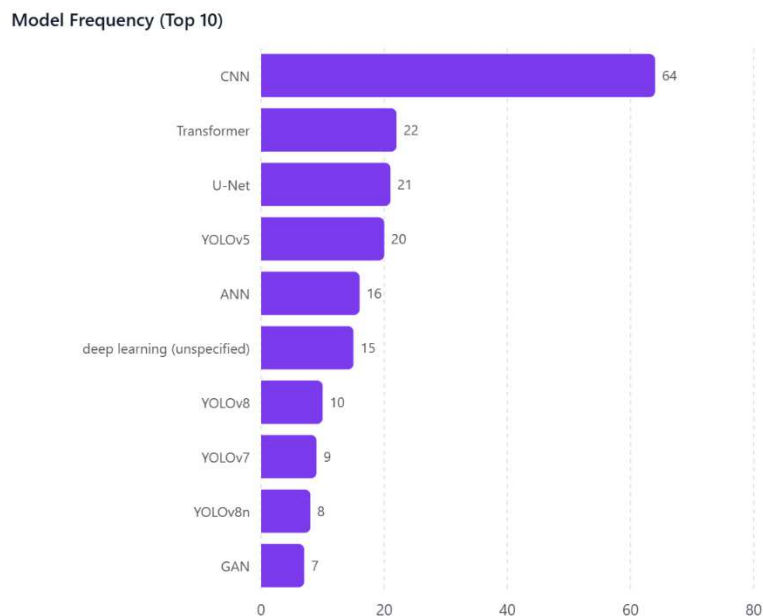


Fig. 9 Top AI models used. Most of the studies use CNN for multiple applications and infrastructures

The temporal distribution in Figure 10 mirrors the overall publication trend. From 2018 to 2020 the number of publications is minimal, to then accelerate from 2021 onwards. The rise is primarily driven by CNN and YOLO family detectors between 2021 and 2023, after which Transformer and hybrid Transformer-CNN models begin to appear more frequently. U-Net usage grows steadily throughout and tracks the growing fraction of studies framed as segmentation rather than classification. The remainder of this section examines how these general trends apply to each infrastructure class.

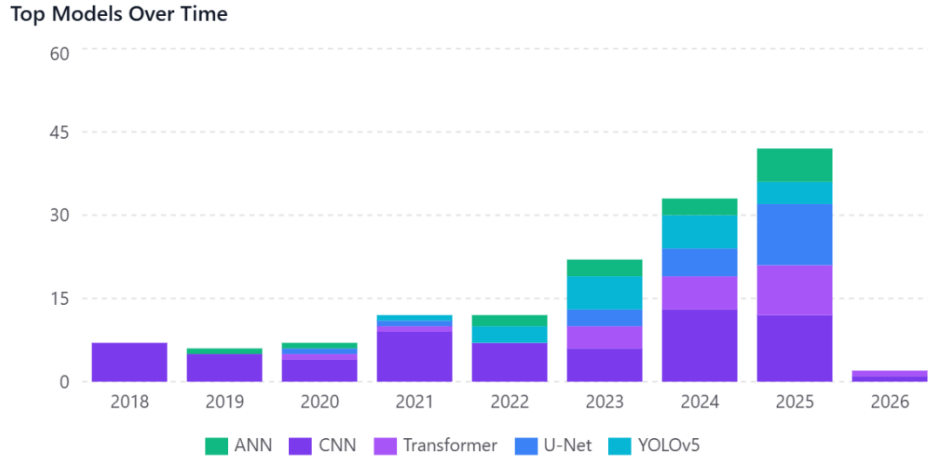


Fig. 10 Adoption trends of top AI models over time, illustrating the early dominance of CNNs and the recent diversification into Transformer, U-Net, and YOLOv5 architectures

Although CNNs, YOLO-family detectors, U-Net architectures and Transformer-based models dominate the reviewed literature, their suitability varies substantially depending on the sensing modality, computational constraints and infrastructure monitoring objective. Table 8 summarises the principal strengths, limitations and typical application domains of the main AI model families identified in this review. Some models used for each single infrastructure are presented in Table 9.

Table 8. Comparison of main models strengths and limitations

Model family	Strengths	Limitations	Typical infrastructure applications
CNN	Robust feature extraction, effective on moderate datasets	Limited long-range contextual understanding	Crack classification, defect recognition
YOLO	Real-time inference, efficient object detection	Reduced segmentation precision for fine defects	UAV road inspection, pothole detection
U-Net	High quality pixel level segmentation	Requires extensive annotated data	Building damage mapping, crack segmentation
Transformer	Strong spatial and temporal context modelling	Computationally intensive, large data requirements	Large-scale damage assessment, hybrid CNN-Transformer detection
RNN / LSTM / TCN	Captures temporal dependencies in sequential data; well suited to displacement and coherence time series	Requires long, regularly sampled time series and ineffective on single images. Limited spatial reasoning	InSAR/SBAS deformation monitoring, bridge pre-collapse prediction and anomaly detection

These corpus-wide totals, however, obscure a more informative pattern once studies are broken down by infrastructure class (Figure 11): the leading model for each class tracks its sensing modality and data representation rather than reflecting systematic architectural comparison.



Fig. 11 AI models, tasks and datasets by infrastructure class. Each row corresponds to one infrastructure class (roads, bridges, buildings); the columns show, left to right, the most frequent AI model families, the distribution of operational tasks, and the most reused datasets and data sources. Compiled from the 244-paper corpus

The largest and most standardised body of work addresses planar, repetitive defects in close-range RGB imagery, where single-stage detectors of the YOLO family and lightweight CNNs dominate. This is most pronounced for road surfaces, where UAV and vehicle-mounted capture aligns naturally with one-stage detection and a small set of shared benchmarks (UAV-PDD2023, RDD2022); close-range bridge-crack inspection and UAV-based building inspection follow the same recipe. Reported in-distribution accuracy is high (several 2024 - 2025 studies exceed mAP 0.9), but cross-domain performance tells a different story: (Jeong and Kim 2022) twelve-model YOLOv5 ensemble reached only $F1 = 0.67$ on the cross-country RDD2022 split. Combined with the heavy reuse of a few datasets,

this image-detection literature is approaching benchmark saturation, in which incremental architectural tweaks yield small in-distribution gains that may not survive a change of site, country or sensor.

Where the input shifts from close-range capture to satellite pre- and post-event optical imagery, the task reframes from object detection to change detection and segmentation, and the dominant architectures shift accordingly to encoder–decoder and Siamese designs. Building damage assessment is the clearest case: a single benchmark, xBD, underpins the majority of studies, feeding pre/post image pairs to CNN or U-Net classifiers in Siamese or two-branch configurations that jointly localise buildings and grade damage (Bai et al. 2020; Wu et al. 2021; Wang et al. 2022). The few non-xBD studies do not replicate this recipe but migrate to neighbouring framings, such as ground-level or UAV capture with YOLO-family detectors (Liu et al. 2022; Martinelli et al. 2023), which again shows how directly the input modality dictates the model family rather than the reverse.

A structurally distinct path abandons imagery altogether in favour of displacement time series derived from satellite SAR and InSAR products. Here the problem is sequential rather than spatial, and recurrent, temporal-convolutional, attention-based and adversarial models take over: LSTM on SBAS-InSAR (Feng et al. 2023), TCN/ROCKET on PS-InSAR (Ren et al. 2025), a multi-head attention network for pre-collapse prediction (Della Santa et al. 2026) and TadGAN anomaly detection (Xiong et al. 2026). In some cases, for roads, SAR-based subgrade work (Karimzadeh et al. 2022; Wang et al. 2025) shifts the task from surface defects to sub-surface deformation monitoring.

The satellite-based studies form a cross-cutting case, treated separately in Section 6.2.

Table 9. AI models for infrastructure damage assessment across the reviewed corpus

Roads			
Author/Year	Model	Dataset	Task
(Sim et al. 2026)	StyleSPADE	Custom	Segmentation
(Li et al. 2026)	MFD-YOLO	RDD2022-China, UAV-PDD2023	Road damage detection
(Bafail et al. 2026)	YOLOv8	Roboflow dataset	Object detection
(Wang et al. 2025)	SDR-TabTransformer	Sentinel-1 SAR	Regression/deformation
(Elhence et al. 2025)	HARP-UNet	UAV pothole imagery	Segmentation
(Wu et al. 2025)	YOLOv8s-D	UAV dataset	Segmentation
(Pan and Zhang 2025)	CrackLite-Net	LCrack dataset, RDD2022	Crack detection
(Cheng et al. 2025a)	RLD-NET	UAV road surface images	Object detection
(Alzamzami et al. 2024)	YOLOv8	UAV pothole dataset	Pothole detection
(Khan et al. 2024)	Faster R-CNN	RDD2022	Object detection

(Zeng and Zhong 2024)	YOLOv8-PD	RDD2022	Road damage detection
(Karimzadeh et al. 2022)	Multi-Layer Perceptron (MLP)	Sentinel-1 SAR	Classification
(Jeong and Kim 2022)	YOLOv5x	RDD2022 (6 countries)	Road damage detection
(Samma et al. 2021)	VGG-19	Drone captured road damage images	Classification
Bridge			
Author/Year	Model	Dataset	Task
(Sim et al. 2026)	StyleSPADE	Custom	Segmentation
(Xiong et al. 2026)	GAN / TadGAN	InSAR displacement time series HK-Zhuhai-Macao bridge	Anomaly detection
(Della Santa et al. 2026)	Multi Head Attention NN	InSAR displacement time series Tadcaster bridge, Cantiano bridge	Pre-collapse prediction
(Ren et al. 2025)	TCN / ROCKET	PS-InSAR time series, sea crossing bridge	Classification
(Zhou et al. 2025)	DBE-YOLO	Concrete beam + urban bridge dataset	Crack detection
(Yang et al. 2025)	Vision Transformer + YOLO	Concrete bridge damage dataset	Damage detection
(Aisuwarya et al. 2025)	YOLOv8x	Bridge damage dataset	Crack detection
(Yin et al. 2024)	YOLOv8 + Transformer	Bridge damage dataset	Object detection
(Song et al. 2024)	ResNet-18 (CNN)	UAV collected bridge crack dataset	Crack segmentation
(Abubakr et al. 2024)	Xception	CODEBRIM	Classification
(Liu et al. 2023)	YOLOv5	Concrete bridge crack images	Object detection
(Feng et al. 2023)	LSTM / SBAS-InSAR	Sentinel-1 SAR Nanjing Bridge	Displacement prediction
(Yu et al. 2021)	YOLOv4-FPM	Bridge crack images	Crack detection
(Kang and Cha 2018)	CNN	UAV concrete bridge data	Damage detection localisation
Buildings			
Author/Year	Model	Dataset	Task
(Bhardwaj et al. 2025)	ResNet-U-Net	Post hurricane satellite images	Damage assessment
(Wang et al. 2024)	Causal Bayesian Network	InSAR imagery of hurricane Ian	Damage detection and classification
(V.V. et al. 2024)	U-Net	Google earth images Mariupol 2022	Segmentation
(Martinelli et al. 2023)	YOLO	UAV building images	Damage detection
(Munawar et al. 2022)	Deep CNN + Cycle GAN	Sydney building UAV images	Crack detection and segmentation
(Wang et al. 2022)	Two-step CNN	xBD Mexico earthquake, Midwest flood	Damage detection and localisation
(Liu et al. 2022)	LA-YOLOv5	GDBDA	Object detection
(Wu et al. 2021)	Attention U-Net / SEresNeXt	xBD + Maxar open data	Classification and segmentation
(Bai et al. 2020)	PPM-SSNet	xBD Tohoku 2011	Classification and segmentation

6.2 Satellite based methods across infrastructure classes

Satellite and SAR work cuts across all three infrastructure classes, highlighted in Table 10. This table is best read as a cross-section of how the same sensing platforms have been used across different applications. Sentinel-1 supplies the imagery for roughly half of the satellite-based studies in the review, with TerraSAR-X, Sentinel-2 and COSMO-SkyMed each contributing a smaller but comparable share.

CNN and U-Net variants lead, followed by Transformer and ANN architectures at roughly equal number, and fewer papers using LSTM, SVM, Random Forest, native InSAR processing and a Multi-Head Attention network. Image based change detection on pre and post event scenes (Bai et al. 2020; Wu et al. 2021; Bhardwaj et al. 2025) is a fit for encoder-decoder architectures, while long term displacement monitoring on PS-InSAR or SBAS-InSAR time series is structurally a sequence problem and is accordingly addressed with LSTM (Feng et al. 2023), temporal convolution and classical time-series methods (Ren et al. 2025), attention networks (Della Santa et al. 2026) and adversarial anomaly detectors (Xiong et al. 2026). The two paths use the same satellites but different products: an image pair in the first case and a deformation time series in the second.

The building papers are exclusively image-based and concentrate on change detection between pre- and post-event scenes. The road papers split between static classification on SAR features (Karimzadeh et al. 2022) and time-series regression on deformation (Wang et al. 2025). The bridge entries are almost entirely time-series based, such as InSAR displacement series which is consistent with the long-term monitoring application identified earlier in this section.

Table 10. SAR and Satellite based methods

Author/Year	Model	Source/Dataset	Task
(Xiong et al. 2026)	GAN / TadGAN	InSAR	Anomaly detection
(Della Santa et al. 2026)	Multi-head Attention NN	InSAR	Pre collapse prediction
(Bhardwaj et al. 2025)	ResNet-U-Net	Post hurricane satellite images	Damage assessment
(Cha et al. 2025)	Difference based segmentation	Pre/post satellite images	Change detection
(Ren et al. 2025)	TCN / ROCKET	PS-InSAR	Bridge condition classification
(Wang et al. 2024)	Causal Bayesian Network	InSAR	Damage detection
(Malinowska et al. 2024)	CNN + U-Net	Sentinel-1	PS deformation prediction
(Feng et al. 2023)	LSTM / SBAS-InSAR	Sentinel-1	Displacement prediction
(Karimzadeh et al. 2022)	MLP	Sentinel-1	Road condition classification
(Wu et al. 2021)	Attention U-Net	xBD, Maxar	Building damage segmentation
(Bai et al. 2020)	PPM-SSNet	xBD, Maxar	Building damage segmentation

The patterns identified across the three infrastructures are consolidated below and in the conceptual taxonomy of Figure 12. Across all three infrastructure classes, the dominance of particular AI model families is not driven primarily by architectural superiority, but by structural constraints imposed by sensing modality and data representation. For road infrastructure, the prevalence of UAV and vehicle-

mounted RGB imagery naturally favours single-stage object detectors such as the YOLO family and lightweight CNNs, which align with real-time operational requirements and large annotated image datasets such as RDD and UAV-PDD. This reflects road assessment being framed as real-time object detection under constrained computational budgets; by contrast, Transformer architectures appear in SAR and long-term monitoring, where spatial context and temporal dependencies outweigh inference speed. Bridge monitoring exhibits a bifurcated methodological structure: close-range UAV imagery supports CNN and YOLO-based crack detection and segmentation, while satellite SAR and InSAR products generate displacement time series that necessitate temporal models, including LSTM, temporal convolutional networks, attention-based architectures, and adversarial anomaly detectors. Building damage assessment is largely constrained to satellite-based pre- and post-event optical imagery, where change detection and segmentation tasks dominate and encoder-decoder architectures such as U-Net, Siamese CNNs, because the task is delineating damaged structures across wide areas rather than detecting localized defects. These patterns indicate that model choice across the literature is largely endogenous to data availability, spatial resolution, and temporal structure, rather than reflective of a systematic exploration of architectural optimality. This structural coupling between infrastructure type, sensing technology, and AI model family explains the observed convergence of methodologies and highlights that future progress is more likely to be driven by advances in dataset diversity and sensing integration than by incremental architectural modification alone.

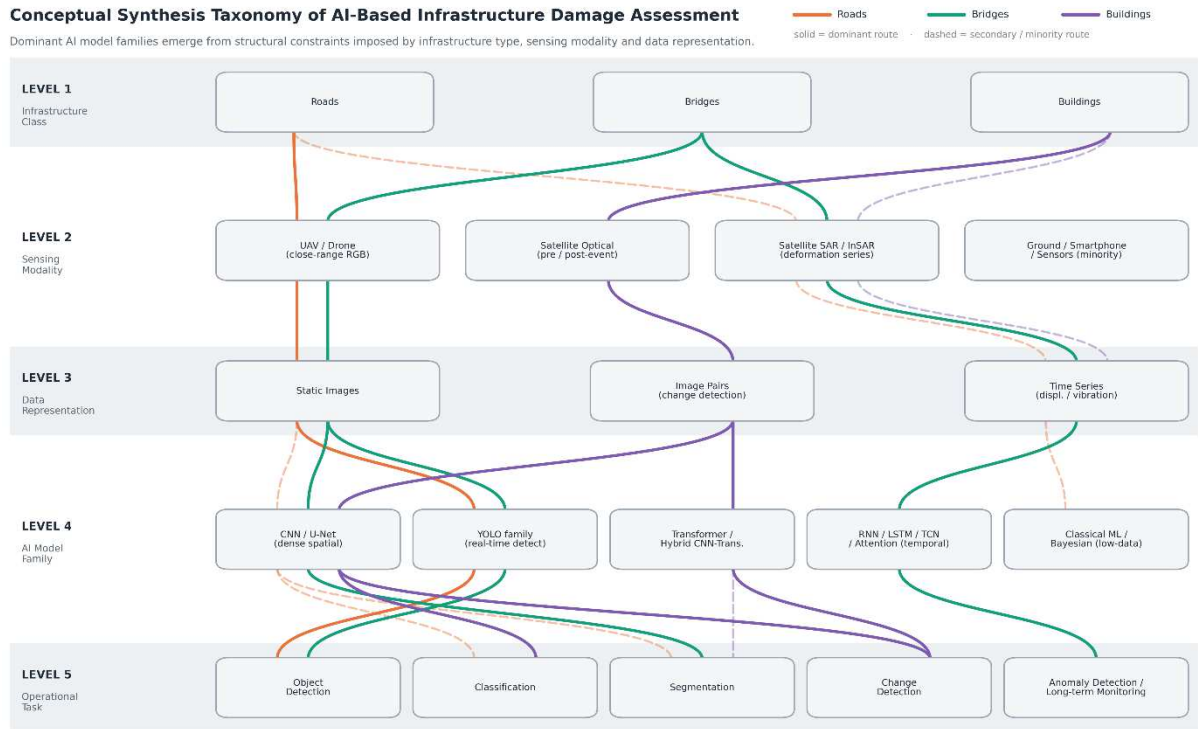


Fig. 12 Conceptual synthesis taxonomy of AI-based infrastructure damage assessment

7. Discussion

Building on the cross-infrastructure synthesis presented in Section 6 and the conceptual taxonomy in Figure 12, the following discussion highlights the structural limitations and implications of current approaches. The synthesis of the reviewed literature indicates that current limitations in AI-based infrastructure damage assessment are driven less by deficiencies in model capability and more by structural constraints related to data availability, evaluation practice, and deployment context. Across roads, bridges, and buildings, the overwhelming reliance on a small number of benchmark datasets, such as RDD variants for roads, xBD for buildings, and bespoke crack or InSAR time-series datasets for bridges, has resulted in methodological convergence and limited evidence of cross-domain generalisation. Therefore, reported performance gains are often dataset-specific and difficult to transfer across geographic regions, hazard types, or sensing conditions. This is particularly evident in satellite and SAR-based studies, where sophisticated temporal and attention-based models are increasingly employed, yet progress remains constrained by sparse labelled data, processing latency, and the absence of standardised validation protocols. The findings therefore suggest that future advances will depend primarily on the development of diverse, multi-sensor, and longitudinal datasets, together with

evaluation frameworks that explicitly account for uncertainty, bias, and deployment risk. Without such advances, further architectural innovation alone is unlikely to yield proportional improvements in operational reliability or decision-making value. The discussion develops these findings as follows: it first proposes a multi-scale framework that organises the literature by sensing modality and operational scale (7.1); it then sets out the research gaps and structural limitations the review identifies (7.2); it considers what these imply for operational adoption and engineering practice (7.3); and it closes with the ethical and professional-accountability implications of deploying these models (7.4).

7.1 Towards a multi-scale AI framework for infrastructure damage assessment and monitoring

The reviewed literature can be organised into three operational tiers, distinguished by sensing modality, spatial scale, dominant model family and, critically, where the human sits in the decision loop.

Tier 1: Local visual inspection. The first layer concerns localized visual inspection using UAVs, smartphones and ground-based RGB imagery. Studies in this category predominantly frame infrastructure assessment as a real-time object detection or crack segmentation problem, explaining the dominance of CNN- and YOLO-based architectures. Applications mainly include pothole detection, pavement distress assessment and concrete crack identification in bridges and buildings. The primary advantage of this layer is its high spatial resolution and operational flexibility, although scalability remains limited because data collection requires physical proximity and repeated field deployment. At this tier the engineer reviews the detection output before scheduling a physical inspection: AI flags, the human decides.

Tier 2: Regional event assessment. The second layer operates at regional scale and is primarily driven by optical satellite imagery and pre-/post-disaster change detection workflows. Here, infrastructure assessment shifts from localized defect recognition to scene-level interpretation and damage-state classification. Consequently, segmentation architectures such as U-Net and Transformer-based encoder-decoder models become more prevalent. Typical applications include earthquake damage assessment, flood mapping and conflict-zone destruction analysis. This layer enables large-area coverage and rapid situational awareness, although temporal resolution is constrained by satellite revisit frequency and environmental conditions such as cloud cover. A damage

analyst reviews the change map and damage classification before any response is triggered, therefore the AI maps and the human interprets.

Tier 3: Continuous structural monitoring. The third layer concerns continuous structural monitoring using SAR/InSAR displacement time series and temporal AI models. Unlike the first two layers, which primarily analyse static imagery, this tier treats infrastructure as a dynamic system whose behaviour evolves over time. Recurrent neural networks, attention-based architectures and temporal convolutional models are therefore increasingly adopted for bridge displacement prediction, deformation monitoring and pre-collapse risk assessment. The main advantage of this layer lies in its predictive capability and network-scale coverage, although processing latency, computational complexity and limited availability of SAR-ready datasets remain significant challenges. Here, the structural engineer reviews the deformation trend and receives an explainable alert before any action is authorised, this AI monitors, the human authorises.

The three layers differ substantially in sensing scale, temporal frequency, computational requirements and operational objectives. Tier 1 systems prioritise rapid and high-resolution inspection but operate at limited spatial scale. Tier 2 approaches maximise geographic coverage for disaster response, while Tier 3 systems emphasise long-term resilience and predictive structural monitoring. Together, these layers illustrate a broader transition within the literature from isolated defect detection towards integrated and continuous infrastructure intelligence systems. Future infrastructure monitoring systems are likely to integrate these layers into unified digital resilience platforms combining UAV inspection, satellite-based situational awareness and continuous SAR-enabled structural monitoring. Such integration could support AI-assisted digital twins, predictive maintenance and climate-resilient infrastructure management at network scale. Crucially, every tier places a qualified engineer at the point of decision, which is what makes the framework compatible with the accountability and liability requirements of infrastructure practice.

Drawing these trends together, we propose a three-tier monitoring framework (Figure 13) that organises the reviewed methods by operational scale and by the human role at each level: localised UAV inspection, regional satellite-based assessment, and long-term SAR and InSAR monitoring.

Three-Tier AI Monitoring Framework for Resilient Infrastructure

Three complementary layers of one monitoring system, with the human role shown at each tier. Increasing spatial scale and time horizon

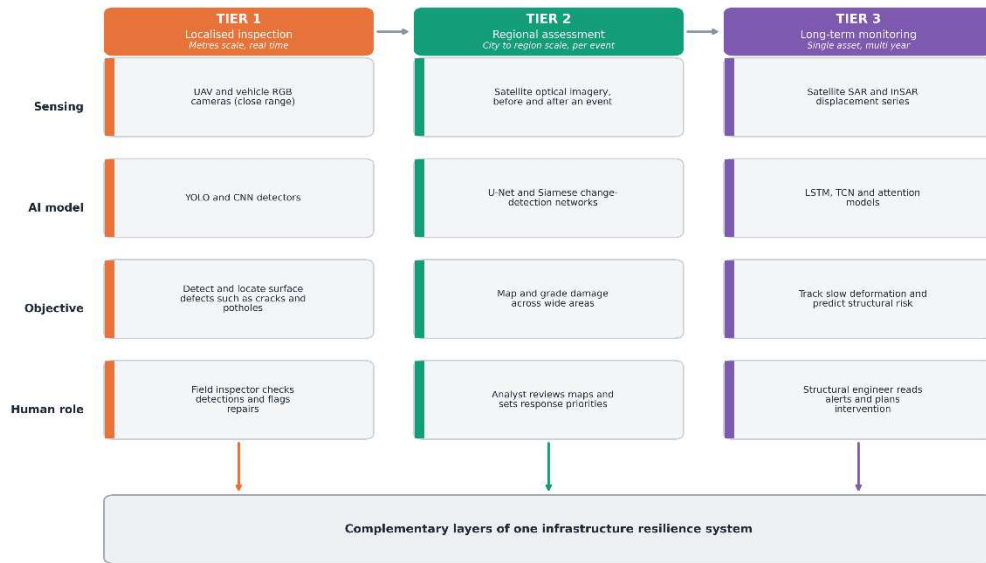


Fig. 13 Three-tier AI monitoring framework for resilient infrastructure. The framework synthesises the reviewed literature into a multi-scale structure integrating sensing modality, AI architecture, operational objective and the human-in-the-loop role at each

Building on this framework, Table 11 summarises the sensing and AI model configuration best suited to each common deployment scenario, together with its main advantages and limitations.

Table 11. Recommended sensing and AI model configurations by deployment scenario

Scenario	Recommended sensing	AI model type	Advantages	Limitations
Road potholes / surface cracks	UAV / mobile RGB	YOLO family	Real time, low cost	Weather/light sensitivity, weak cross domain transfer
Road deformations	Sentinel-1 SAR	MLP / TabTransformer	Sub surface signal, wide coverage	Coarse resolution, indirect (consider commercial satellites)
Flooded infrastructure	Sentinel-1 SAR	U-Net / CNN	Cloud & night penetration	Coarse resolution (consider commercial satellites)
Regional building damage	Satellite optical pre/post	U-Net / CNN	Rapid wide-area mapping	Needs pre-event imagery, cloud cover
Bridge crack inspection	UAV RGB	YOLO / CNN	Fine defect localisation	Accessible surfaces only
Bridge structural displacement	InSAR time series	LSTM / TCN / Attention	Predictive long-term monitoring	Slow processing, needs long coherent series

While this framework shows how the methods fit together operationally, it also makes clear where the evidence base is still thin, which the next section addresses.

7.2 Research gaps and structural limitations

Many of the research gaps identified in this review are better understood not as isolated shortfalls but as connected symptoms: the literature is structured to produce benchmark performance rather than

operationally validated systems. Five limitations appear, each following the pattern of an observed trend, its implication, and the resulting gap.

- No validation or certification standards: models are evaluated almost exclusively on in-distribution benchmark splits; cross-site or cross-event testing is rare in the road and building subsets, and multiple evaluations across different countries produce divergent results. Without sector-specific validation standards, a high reported accuracy carries no guarantee of operational reliability (Byrd and Geheran 2026)
- Black-box models: CNN and YOLO families dominate the corpus, and neither produces interpretable outputs by default. For an engineer professionally responsible for a decision, deploying a model whose reasoning cannot be audited is fundamentally unjustifiable (Nyokum and Tamut 2025; Byrd and Geheran 2026).
- Reproducibility gap: The field's reliance on only few benchmarks means most models are never tested outside their training conditions. If the data behind a model cannot be identified, a third party cannot reproduce, validate or certify it.
- Privacy and data governance: UAV and satellite imagery of infrastructure raises sovereignty and commercial-sensitivity questions that no reviewed paper addresses, leaving a governance vacuum around the very data the field depends on (Plevris and Hosamo 2025).
- Pace of change outrunning institutions. The four-fold growth in output over seven years has no counterpart in deployment. Procurement, certification and training cycles operate on timescales of years while model families evolve on timescales of months, so guidance is outdated almost as soon as it is written (RICS 2025).

These barriers are reinforced by methodological limitations within the literature itself. Dataset concentration around benchmarks such as xBD, RDD2022 and UAV-PDD2023 creates geographic and infrastructural bias, as models are repeatedly evaluated on similar visual environments and damage typologies. Cross-region and cross-event validation remains limited, making generalisability difficult to assess. Reporting practices are inconsistent, with several papers omitting preprocessing pipelines, uncertainty estimation or computational requirements. Together these factors complicate direct comparison between approaches and may overestimate real-world deployment readiness.

7.3 From research to practice: enabling operational adoption

If the limitations above are structural, so are the remedies. The path from research to practice runs from open data, through reproducibility, validation and trust, to deployment; intervening at any one point without the others, changes little.

- Open data and open models: research groups should publish training data and model weights, not only headline accuracy, so that third parties can reproduce and validate results. Reproducibility is the precondition for every subsequent step
- Sector-specific validation standards: minimum requirements for cross-site testing, dataset diversity and uncertainty reporting should be defined before a model informs an infrastructure decision, closing the evaluation gap identified in Section 7.2.
- Explainable AI by default: for Tier 3 applications, structural monitoring and pre-collapse prediction, explainability is a precondition, and regulation should reflect this.
- Human-in-the-loop frameworks: the role of the engineer in the AI decision chain should be codified, which simultaneously resolves the liability question: the AI recommends, the engineer decides, and the engineer remains accountable.
- Deployments with embedded evaluation: research groups should partner with infrastructure operators on real-world pilots with rigorous outcome tracking, rather than further benchmark-only studies (RICS 2025). Practical adoption also turns on factors the literature rarely reports: the cost of each sensing tier (UAV and ground imagery being cheapest, SAR and InSAR most expensive in expertise and processing), whether the underlying datasets and platforms are open-access or commercial (Sentinel data is open, high-resolution optical and several SAR products are not), and the specialist skills each approach demands. Surfacing these practical considerations is itself a precondition for adoption.

7.4 Ethical AI and policy considerations

Damage assessment models inform which bridges get inspected, which roads are closed after a flood, and which buildings are declared safe or unsafe. Three issues deserve attention.

The first is fairness, as UAV-PDD2023, RDD2022 and xBD were each collected in a specific set of countries, and models calibrated on them carry the road types, building and damage patterns of those

regions with them. Deploying into a setting that does not match the training distribution, it will under or over predict in ways that cause humanitarian and financial consequences.

The second is transparency, where studies that do not name a model or datasets becomes an accountability problem when outputs inform real decisions. For an AI-based recommendation to be valid and defensible, the model, training data and evaluation protocol need to be documented carefully, as this has not yet become a standard practice in infrastructure applications specifically (Díaz-Rodríguez et al. 2023; Radanliev 2025).

The third is policy. Current regulations were written before AI based damage assessment was operationally feasible and do not yet specify validation, uncertainty reporting and liability (RICS 2025). A universal framework is unlikely to work across multiple jurisdictions, but sector specific guidance is a realistic near term target that would address the evaluation gap identified in section 7.2.

These concerns converge on a question of professional accountability. Engineers carry a legal and ethical obligation to understand the basis of any technical recommendation they make, which is why explainability cannot be treated as an optional feature in this domain. As (Byrd and Geheran 2026) argue, AI tools "need to undergo verification and validation processes, just as our computational models do, to ensure that AI processes are in conformance with accepted engineering practice." The dominance of CNN and YOLO architectures places the accountable engineer in an untenable position: a recommendation that cannot be audited exposes the engineer, the operating organisation and the public to liability without accountability. The absence of any explainability evaluation across the reviewed literature is therefore not a gap in research ambition but a systematic mismatch between what research measures and what deployment requires.

8. Conclusion

Transport infrastructures underpin the functioning of modern economies and remain highly exposed to climate driven and disaster driven damage. This review has critically examined the AI models, datasets and acquisition technologies applied to damage assessment of roads, bridges and buildings, with particular attention to satellite and SAR-based methods. The evidence points to a consistent conclusion: progress is now constrained less by model architecture than by data availability, evaluation practice and the conditions for operational use. Satellite sensing, the only modality that scales to continuous network-

wide monitoring, remains underused and limited by data preparation rather than model availability; time-series approaches are established only for bridges and largely absent for roads and buildings; and cross-site evaluation is rare across all three classes. The conceptual taxonomy (Figure 12, Section 6) explains why: model choice is structurally coupled to sensing modality and data representation, so the time-series gap for roads and buildings and the SAR bottleneck are data problems, not model problems. The three-tier, human-in-the-loop framework proposed in Section 7 is offered as a structure for organising future work against these gaps.

Six priorities follow:

- Foundation models for infrastructure: multimodal vision-language models, geospatial foundation models and self-supervised learning on remote-sensing data, to reduce dependence on small labelled benchmarks.
- Multimodal AI: principled fusion of SAR, optical imagery, LiDAR, vibration sensors and IoT streams for a complete picture of infrastructure health.
- Physics-informed AI: integrating structural mechanics and finite-element models with data-driven methods, which is especially important for acceptance in engineering practice.
- Digital twins: AI-integrated infrastructure twins for predictive maintenance, resilience simulation and climate adaptation.
- Real-time edge AI: TinyML and on-device inference on UAVs and low-power platforms for monitoring at network scale.
- Explainable and trustworthy AI: explainability, uncertainty quantification and validation suited to professional accountability, treated as a precondition for deployment rather than an add-on.
- Adaptive governance for a fast-moving field: regulatory frameworks, procurement cycles and workforce training are calibrated to technologies whose capabilities are stable or predictably improving, whereas AI model families evolve on timescales of months, rendering fixed guidance outdated almost as soon as it is written. Future strategies should build in adaptive governance, frameworks that establish principles and validation criteria rather than prescribing specific architectures.

Realising these priorities will require not only technical progress on model architectures and processing pipelines, but also standardised metrics for data readiness in the infrastructure domain (Hiniduma et al.

2025), together with the sector specific validation, documentation and uncertainty reporting as identified in Section 7.4. Initiatives like AI4SAR demonstrate progress in leveraging SAR effectively, yet future research must prioritize not only technological advancement, but also robust and standardized metrics for evaluating data readiness specific to transport infrastructures. This will ensure AI driven solutions deliver efficient, reliable and sustainable outcomes.

The evidence reviewed here suggests that incremental architectural improvement is no longer the binding constraint on AI-based infrastructure damage assessment. The field's next advances depend on open datasets that reflect the geographic and hazard diversity of real infrastructure networks, validation standards that require cross-site and cross-condition testing, explainability frameworks suited to professional accountability in engineering practice, and human-in-the-loop deployment architectures that position AI as decision support rather than autonomous decision-making. Models capable of detecting a bridge crack or mapping a flood already exist; converting that capability into routine engineering practice, through the data, validation and trust conditions identified in this review, is now the field's defining challenge and its most consequential research frontier.

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