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TIERED MULTI-SCALE DAMAGE ASSESSMENT OF CRITICAL INFRASTRUCTURE USING COHERENCE CHANGE DETECTION AND SAM-BASED DEEP LEARNING

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Abstract

Critical infrastructure like bridges supports transportation, accessibility, and economic flow by enabling movement. However, during conflicts and natural disasters, these vital assets are often targeted due to their strategic importance, causing major disruptions and costly recovery efforts. Traditional damage assessment methods, rely on manual inspection and on-site surveys, facing limitations in accessibility, especially in conflict zones, where safety risks and restricted access complicate evaluations. In these contexts, rapid, automated damage assessments are crucial to enable remote restoration planning and decision-making, ultimately fostering resilience. This research presents a multi-scale framework for the rapid assessment of damaged infrastructure assets, addressing the challenges of accessibility and timeliness in high-risk or remote areas. Leveraging diverse digital tools, including satellite imagery, crowdsourced data, and geospatial datasets, the framework enables scalable damage characterization by integrating Sentinel-1 SAR data, coherence change detection (CCD), and deep learning-based image segmentation for automated infrastructure damage assessment. A case study in Ukraine, involving 17 bridges damaged during conflict, demonstrates the framework's adaptability to challenging environments. This approach enhances the speed and reliability of the initial damage assessments, supporting data-driven decision making for infrastructure restoration prioritization and investment, which are essential to resilience-building efforts in post-disaster recovery.

Keywords: critical infrastructure, automated damage assessment, remote sensing, data fusion, deep learning, coherence change detection

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1 INTRODUCTION

Critical infrastructure, such as bridges, is vital for connectivity, economic flow, and accessibility, enabling the movement of people and goods, promoting social cohesion, and ensuring access to essential services, including emergency facilities [1],[2]. Maintaining and monitoring their condition is crucial for uninterrupted operation. In conflict situations, bridges are often targeted due to their strategic importance, and damage can severely affect functionality, leading to high restoration costs and traffic disruptions [3],[4].

Preliminary damage assessment is necessary to facilitate informed decision-making and recovery planning [5]. Traditional infrastructure inspections rely on costly, time-consuming, and often risky manual surveys, which become impractical in inaccessible areas after major disasters (e.g. in conflict- affected regions) [6]. Moreover, large-scale damage requires regional assessments, but conventional methods fail to account for asset interdependencies, delaying recovery [7],[8]. To address this, integrating digital tools, such as GPS, InSAR, IoT, UaV, DIC, and others, enables multi-scale assessments, bridging gaps between macro-level regional evaluations and micro-level asset inspections [9],[10],[11],[12]. Satellite imagery has emerged as a key tool for remote damage assessment, but its integration across different scales remains limited. In the case of bridges, remote sensing and computer vision-based methods aid in assessing structural deflections, soil settlements, cracks, and corrosion, enhancing decision-making for restoration [13],[14].

Earth Observation (EO) technologies, particularly Synthetic-Aperture Radar (SAR), offer non-invasive monitoring for post-disaster damage characterization [15]. InSAR data, combined with Coherent Change Detection (CCD), detects structural changes by comparing pre- and post-event images [16],[17],[19]. While existing studies focus on natural disasters, conflict-related damage presents unique challenges due to scattered destruction in dense urban environments, making automated damage identification difficult [18]. High-resolution satellite data, often unavailable in conflict zones due to security concerns, further complicates assessments. Low-resolution imagery and open data sources, such as crowdsourcing and OpenStreetMap, can help mitigate these limitations [19],[20].

Deep learning and computer vision enable automated infrastructure assessments, reducing reliance on manual inspections [21]. Convolutional neural networks (CNNs) facilitate damage classification and detection, while techniques like Grad-CAM improve localization [22]. Social media and crowdsourced images provide real-time insights, complementing satellite and UAV-based assessments [23]. Advanced semantic segmentation models, such as Segment Anything Model (SAM), enhance image preprocessing for damage identification. Deep learning-based approaches, including Bidirectional Feature Pyramid Networks and Mask R-CNN, achieve high accuracy in structural health monitoring, improving efficiency in post-disaster decision-making [24].

Despite advancements in remote sensing and AI-driven damage assessment, a unified framework integrating multi-scale damage characterization remains absent. Traditional methods struggle to assess extensive bridge damage, particularly in conflict zones where accessibility is severely limited [6]. Effective assessment must consider multiple factors, including damage type, extent, accessibility, interdependencies with other assets, and resource availability, all of which influence recovery strategies. However, current research is often fragmented, focusing on either regional (macro-) or asset-level (meso-) assessments without integrating these perspectives into a cohesive engineering framework. This gap hinders a comprehensive understanding of how infrastructure damage impacts regional operability and vice versa.

In order to fill this gap, we propose a multi-scale framework for rapid, automatic damage characterization of critical infrastructure in conflict-prone regions, which is in more detail described in recent publication [16]. The approach combines InSAR CCD to evaluate damage levels with open-source satellite imagery, crowdsourced images, and records from open access databases for validation. Demonstrated in a post-conflict Ukrainian case study, this framework enhances accuracy and efficiency in bridge damage assessment, supporting timely, data-driven restoration efforts.

2 TIERED APPROACH FOR DAMAGE ASSESSMENT

2.1 General multi-scale framework and data

Figure 1 presents a tiered framework for multi-scale damage characterisation, integrating disparate open-access data sources to enable rapid and informed decisions for infrastructure restoration. This approach combines **regional (R)**, **asset (A)**, and **component (C)** scale assessments to address the challenges of damage detection in conflict-affected regions. By leveraging multiple data sources, including remote sensing technologies, satellite imagery, records from open access databases, and crowdsourced information, the framework offers a comprehensive understanding of damage across different scales.

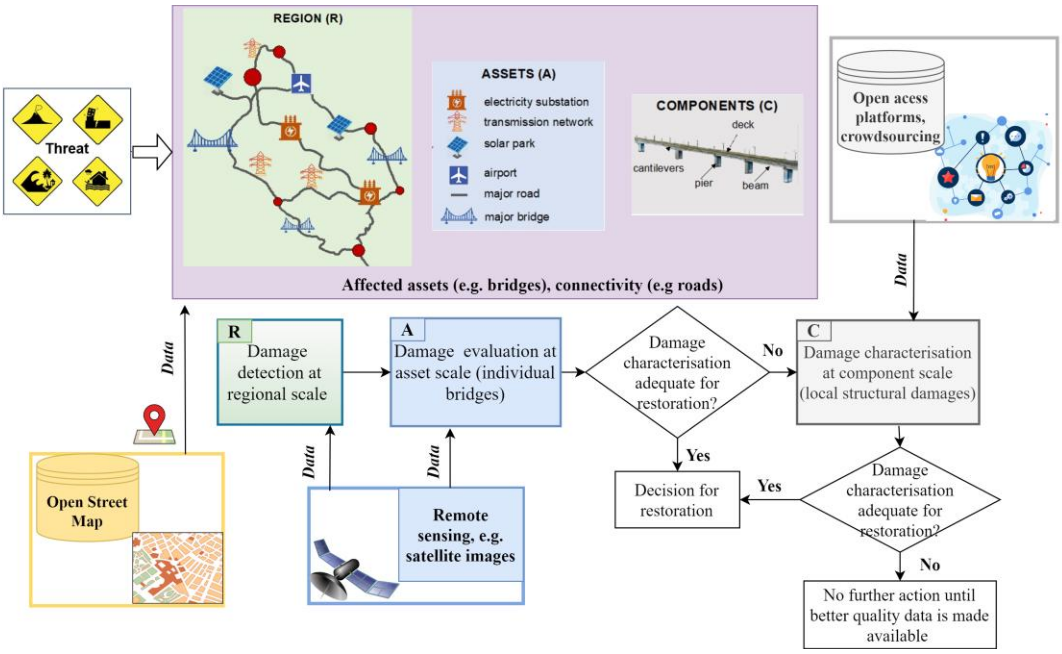


Figure 1: Framework for damage assessment at different scales: regional (R), asset (A) and component (C) toward decisions for restoration.

Each data source plays a distinct but complementary role in the damage characterisation process. Regional-scale assessments provide a broad overview of affected areas, which is refined and validated using asset-level data to capture more detailed information. When necessary, component-scale data offers high-resolution insights into specific structural elements, filling critical gaps left by broader-scale assessments. In this way, the proposed multi-scale integration enhances the accuracy and reliability of damage detection, which is of crucial importance to facilitate decision-making for restoration strategies. By integrating regional, asset, and component-level information this research ensures that both broad network-level vulnerabilities and detailed structural damage are captured, enabling a robust and scalable approach for post-disaster recovery planning [16].

2.2 Damage assessment at regional and asset scales

Damage characterisation at the regional and asset scale involves a multi-phase approach using open-access data and remote sensing technologies (See Figure 2). The primary data sources include Sentinel-1 Single Look Complex (SLC) imagery [25],[26] and crowdsourced data, such as OpenStreetMap (OSM) [27], to indicate the particular timeframe of the disaster, which led to infrastructure damage in the area.

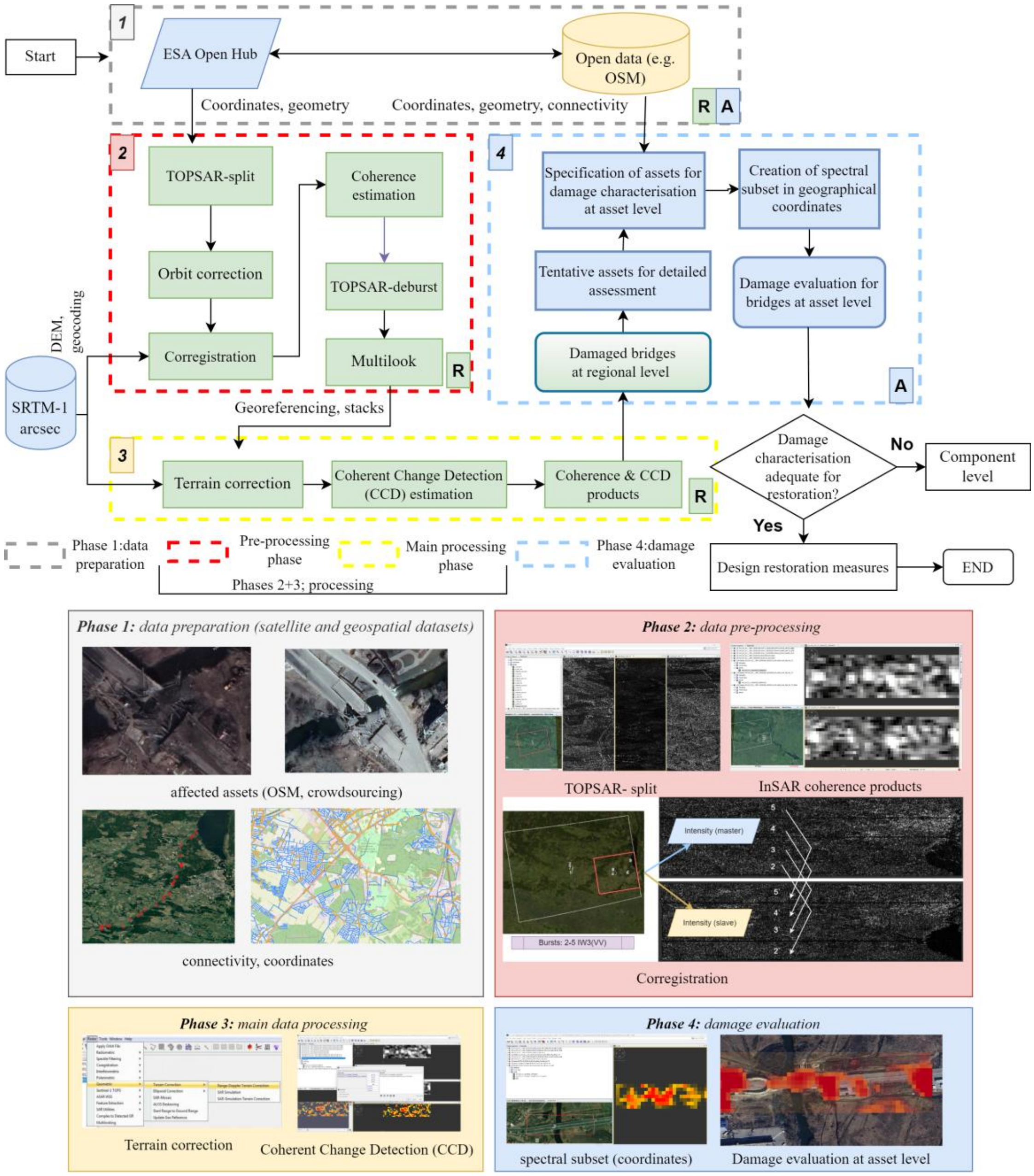


Figure 2: Workflow for damage evaluation at regional (R) and asset (A) scale based on four phases

The process begins with **Phase 1**, where Sentinel-1 SAR images are acquired in both ascending and descending geometries from open-access platforms like ESA Open Hub [25]. Concurrently, preliminary geographic coordinates of affected assets are identified using OSM [27] and crowdsourcing platforms [28],[29], which report disruptions in transport routes and asset damage. Crowdsourced data address potential limitations of OSM by providing up-to-date information during hazard events. In **Phase 2**, Sentinel-1 SAR images undergo preprocessing using the Sentinel Application Platform (SNAP). This involves splitting images into sub-swaths, applying orbit correction using precise orbit files, and co-registering the images with the Digital Elevation Model (DEM) [30] of the Shuttle Radar Topography Mission (SRTM-1 arcsec)[31]. Interferometric pairs are generated from images taken before and after the hazard, followed by coherence (γ) estimation to assess changes in radar reflections, which serve as an indicator of structural stability (see Equation 1).

$$\gamma = \frac{E\left\lfloor u_1 u_2^* \right\rfloor}{\sqrt{E\left[\left|u_1\right|^2\right]}\sqrt{E\left[\left|u_2\right|^2\right]}}, \tag{1}$$

where u_1 and u_2 indicate the complex correlation coefficient between two SAR scenes, *E{}* represents the mathematical expectation and * is the complex conjugate operator.

Phase 3 focuses on Coherent Change Detection (CCD) to identify damage. CCD involves calculating coherence values for two pairs of SAR images, —one pair taken before the event,— $\gamma(pre)$ and another before and after the event,—$\gamma(post)$ (Equation 2).

$$CCD = \gamma(pre) - \gamma(post)\,. \tag{2}$$

Coherence values range from 0 (low stability) to 1 (high stability). A decrease in coherence between pre- and post-event images indicates significant changes in the built environment, suggesting damage [34]. CCD values, which range from -1 to 1, are used to quantify these changes. Positive CCD values indicate substantial differences and potential damage, while values near zero represent stable areas.

Finally, in **Phase 4**, coherence and CCD products are integrated into Geographic Information Systems (GIS) such as ArcGIS or QGIS. This integration visualises areas with potential damage, providing a semi-automatic means of identifying and prioritising locations for further inspection and repair. Assets of interest are further cross-validated using open data sources like Google Maps and Sentinel-1 imagery. The results are exported in Well-Known Text (WKT) format for GIS-based illustration and damage classification. Different CCD ranges correspond to varying damage levels, which are classified according to engineering criteria to support restoration planning.

2.3 Damage assessment at component scale

When regional or asset-scale assessments are insufficient for making restoration decisions, a more detailed component-scale assessment becomes essential. This involves detecting, localising, and classifying damage at the structural component level using advanced semantic segmentation methods (See Figure 3).

For selected assets additional visual information is gathered from open platforms such as The Eyes on Russia [28] and UADamage [29]. These images, showing visible structural damage, are processed using selected computer vision (CV) techniques for automatic damage detection. The process consists of two main steps:

- Component Segmentation – Identifying specific structural components (e.g., bridge deck, pier).
- Instance Segmentation – Classifying and localising the type of damage (e.g., cracks or deformations).

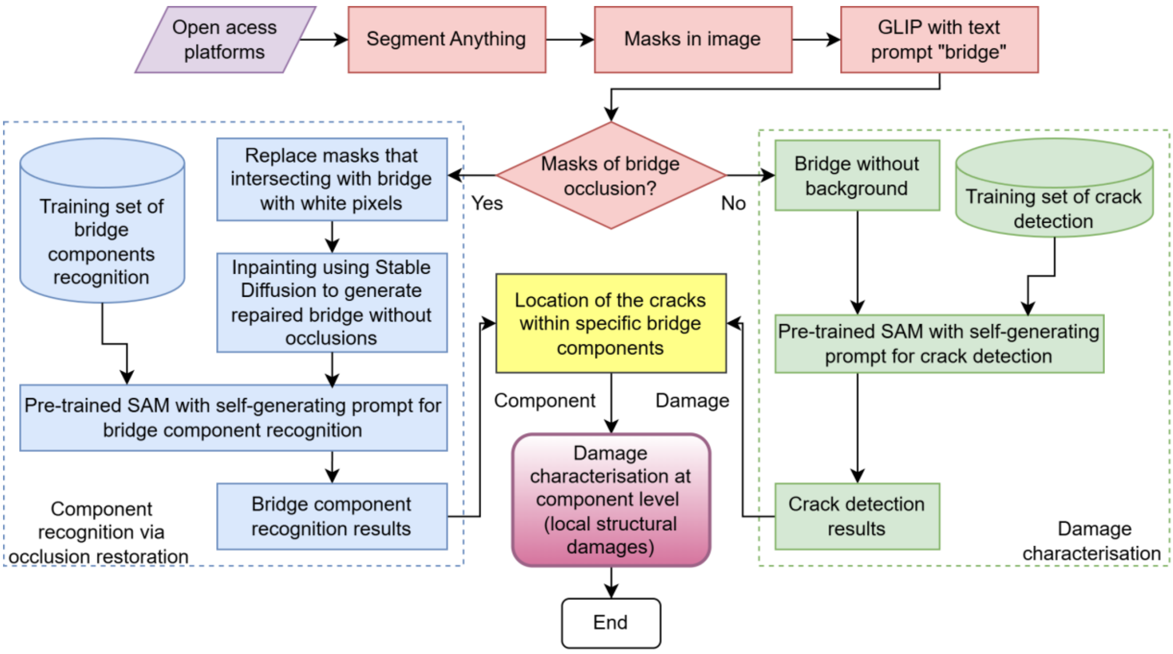


Figure 3: Flowchart, illustrating the damage characterisation method at component scale

Since some images may have limited resolution or obstructions, image pre-processing is employed to enhance quality and remove occlusions. Large pre-trained models, such as Grounded Language-Image Pre-training (GLIP) [35],[36] and Contrastive Language-Image Pre-Training (CLIP)[37], improve image clarity and facilitate more accurate detection. For instance segmentation, the Segment Anything Model (SAM)[38] is used to generate precise masks for the detected components.

In this automated workflow, SAM's "anything mode" detects all potential masks in an image, with labels assigned to each mask. Masks labeled as "bridge" by GLIP are isolated for further analysis. If occlusions are detected, the stable diffusion model is applied for image inpainting to restore hidden sections of the structure. This process generates context-consistent repair content and reconstructs the missing parts of the bridge or other components.

Damage Characterisation follows once occlusions are resolved. SAM, enhanced with a self-generating prompt mechanism, automatically detects damage such as cracks or deformations. The final output integrates component recognition and damage characterisation to pinpoint the exact location and extent of the damage within each structural component.

3 APPLICATION: CONFLICT CASE STUDY

Assessing infrastructure damage in inaccessible regions like Ukraine presents significant challenges, particularly due to ongoing hostilities. Missile strikes and artillery fire have caused widespread destruction, severely damaging over 345 bridges across the region, with the Kyiv region being one of the most affected [39]. Bridges along the Irpin River, crucial for logistics, supply routes, and evacuation corridors, have sustained substantial damage, disrupting critical connections such as Bucha-Kyiv, Hostomel-Kyiv, and Irpin-Kyiv routes [40]. This case study focuses on validating the proposed framework by identifying and characterising damage to selected bridges along the Irpin River. Given the inaccessibility of these areas, the framework enables remote damage detection and classification, accelerating decision-making for restoration efforts and enhancing the region's resilience.

The assessment is conducted at both regional, asset and component scales, following the methodology outlined in Section 2. At the regional scale, open geospatial data from OpenStreetMap (OSM) is used to identify critical river-crossing bridges essential for maintaining connectivity. These bridges are geometrically validated using Google Satellite Imagery and high-resolution optical images, resulting in 17 bridges selected for further evaluation.

At the asset scale, damage detection is performed using Sentinel-1 SAR Single Look Complex (SLC) images during the period of extensive destruction between February and March 2022. The Coherent Change Detection (CCD) method is employed to assess damage, with coherence values from image pairs analyzed to determine damage severity. Each asset is classified according to the Level of Knowledge (LoK), which reflects the reliability of results based on coherence values (see Figure 4). Assets with coherence in the first image pair below 0.5 ($\gamma(pre)<0.5$), indicated low-resolution data and unreliable results, are excluded from the evaluation. High coherence values (above 0.7) indicate high reliability and allow for a more accurate damage assessment.

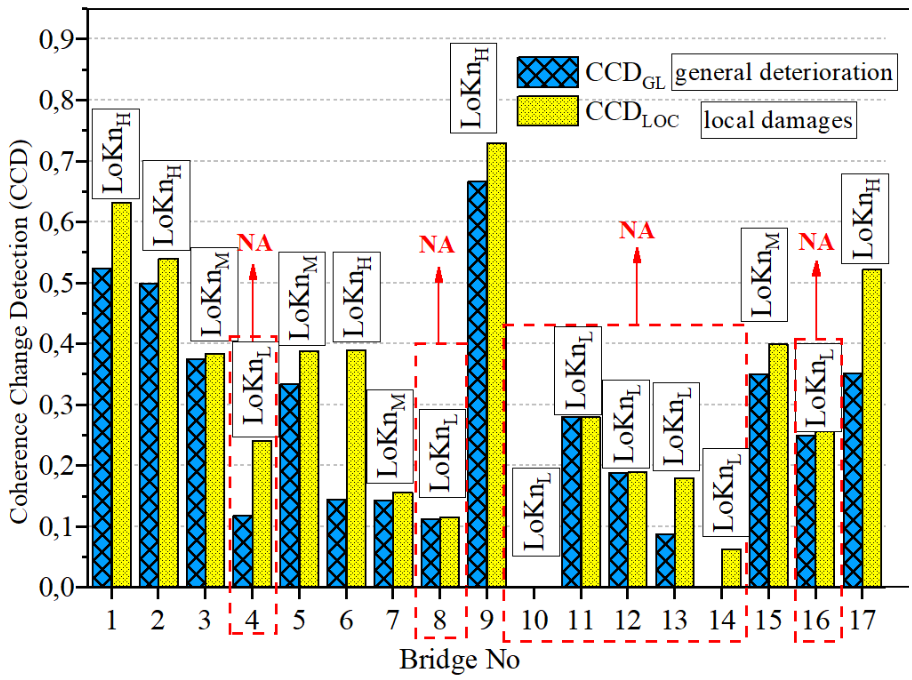


Figure 4: Coherent Change Detection (CCD) and Level of Knowledge (LoK) for the analyzed bridges. CCD_{LOC} indicates local damage within the asset area (maximum CCD); CCD_{GL} indicates mean deterioration (average CCD).

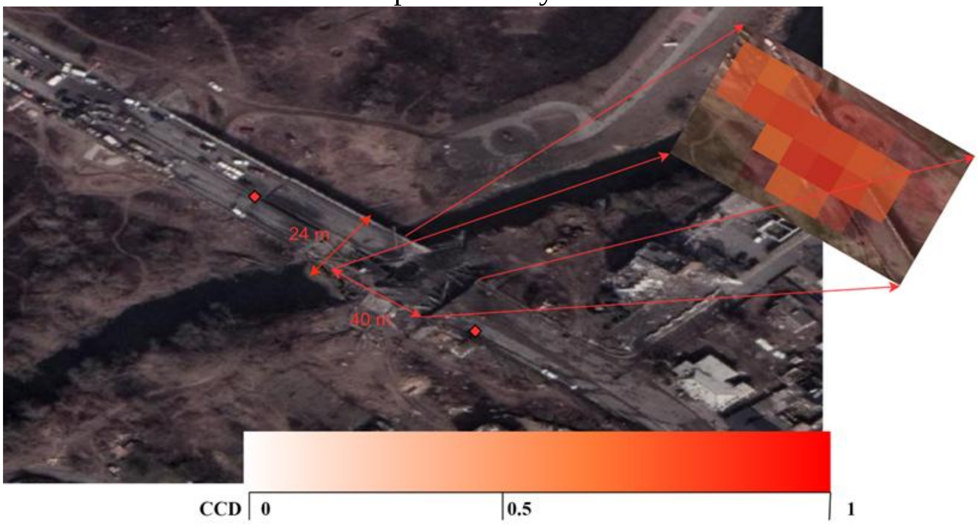
Damage levels are categorized as low (DL_L), moderate (DL_M), or high (DL_H) based on CCD values at both local (CCD_{LOC}) and global (CCD_{GL}) scales (see Table 1).

DL	CCD_{LOC} (Max)	CCD_{GL}	Description
DL_H (High)	0.5-1.0	0.4-1.0	Severe/Complete damage: Complete destruction of the structure or some of its components.
DL_M (Moderate)	0.35-0.5	0.3-0.4	Moderate/Extensive damage: Considerable damage in some of the components.
DL_L (Low)	0.0-0.35	0.0-0.3	No/Minor damage: General deterioration, signs of slight damage.

Table 1: Damage characterisation of infrastructure assets (bridges) based on CCD.

Assets are assigned an index corresponding to their damage level, based on approximate CCD value ranges. Despite limitations related to satellite spatial resolution, line of sight, and event sequence, the methodology proves effective for damage evaluation when access to the affected area is restricted.

Figure 5 illustrates an example of damage assessment at asset scale for Bridge No 1 (high reliability of data, -LoK_H and high level of damage, -DL_H). Alignment of the CCD results integrated into a GIS environment with high-resolution imagery from Google Earth Pro further validates damage levels (Figure 5, b). This multi-source approach supports reliable damage assessment and restoration planning, minimizing downtime, optimizing traffic flow, and facilitating stakeholder coordination for rapid recovery.



(a)

(b)

Figure 5: Damage characterisation at asset scale for B1(LoK_H; DL_H): (a) assessment with CCD (CCD_{GL}=0.523; CCD_{LOC}=0.623); (b) high-resolution imagery from Google Earth Pro (on the right a temporary diversion route was constructed to bypass the bridge)

For bridge B1, classified with high reliability (LoK_H) and severe damage (DL_H), an automated component-scale damage assessment was performed using crowdsourced images from open-access platforms [28],[29]. Following the methodology outlined in Section 2.3, two computer vision tasks were conducted: instance segmentation for component detection and classification, and instance segmentation for identifying, locating, and classifying defects such as cracks. The results, shown in Figure 6, were obtained using the Segment Anything Model (SAM) and Grounded-SAM.

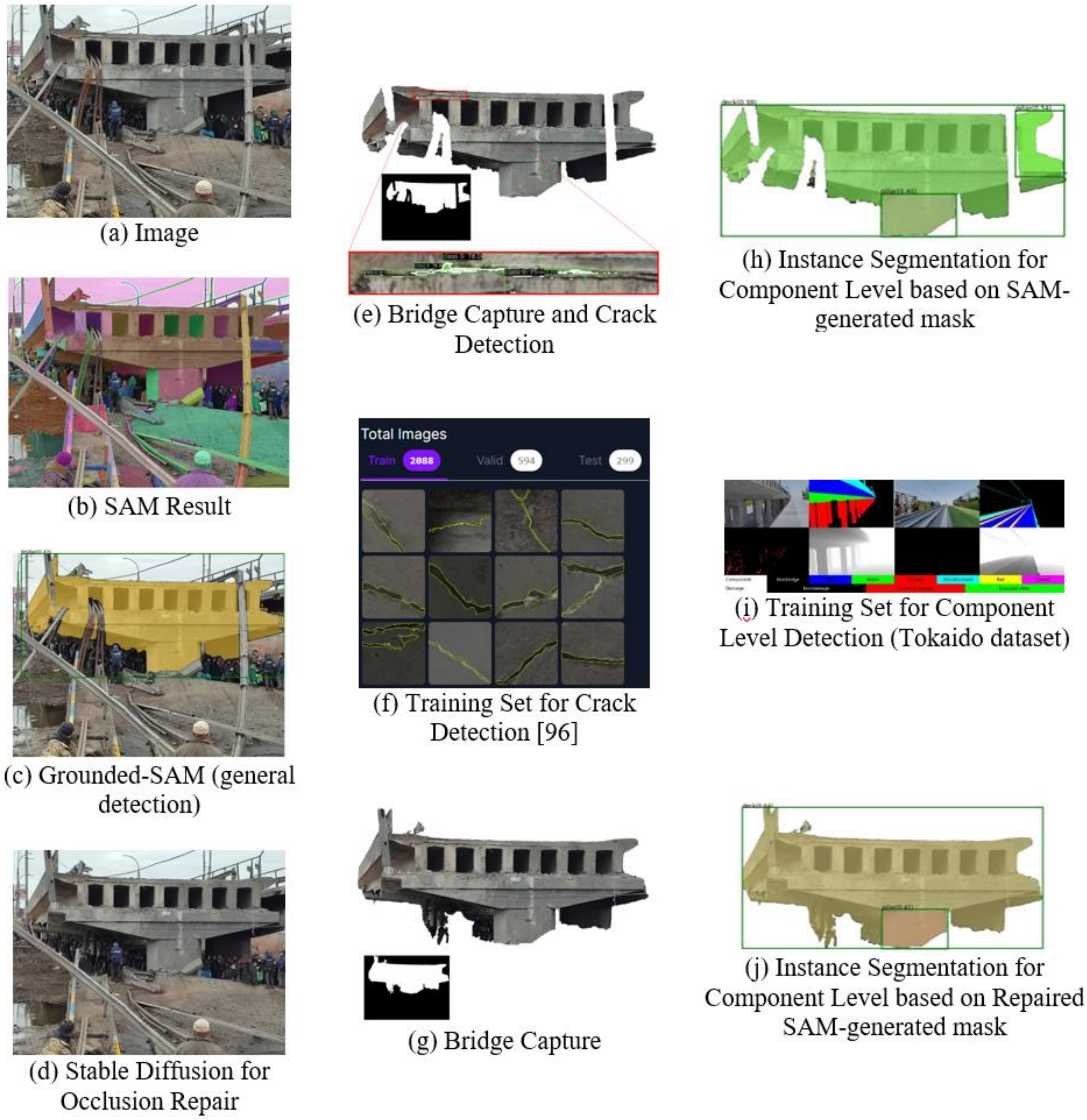


Figure 6: Combined component and damage detection for B1 bridge

SAM first extracted masks in “everything mode,” generating visual segmentations for the bridge components. Grounded-SAM then matched labels to the masks and filtered out low-recognition results, providing more refined segmentation. The process faced two primary challenges: the complexity of the background and occlusion that partially obscured the bridge. Grounded-SAM addressed these issues by conducting an initial general detection to isolate the bridge mask, followed by background removal and occlusion repair using Stable Diffusion. This process removed non-relevant details and restored the visibility of the bridge structure. Once the occlusions were repaired, a crack detection task was performed using a dedicated model trained on approximately 3,000 images, leveraging the query-based learnable prompt SAM algorithm. Bridge component detection was then carried out using a self-prompting SAM model trained on the Tokaido dataset, resulting in significantly improved detection accuracy [41],[42]. After completing crack detection and component recognition, a matching process was used to identify the precise location of cracks within specific bridge components. For instance, a critical crack was detected on a pier, a key structural element, providing clear evidence of severe deterioration. This component-scale approach, supported by advanced computer vision technologies, demonstrated exceptional capability in enhancing automatic damage detection. It aligns with the multi-scale framework presented in this study and offers a valuable tool for improving damage characterization and restoration planning.

4 CONCLUSIONS

This research presents a multi-scale framework for automated infrastructure damage assessment at regional, asset, and component scales using openly available data. The framework addresses the lack of automated multi-scale damage characterization methods and aims to improve potential for use of these cutting-edge digital technologies for post-disaster recovery for regions affected by conflicts or natural disasters. By applying this framework to damaged infrastructure, we demonstrate its ability to automatically and accurately assess damage at various scales. Damage at the regional and asset levels is assessed using a new proxy metric based on interferometric coherence change detection (CCD). Depending on the Level of Knowledge (LoK), which reflects data reliability, CCD values represent local (CCD_{LOC}) or global (CCD_{GL}) damage and are categorized into three distinct damage levels, validated with high-resolution imagery. At the component scale, advanced computer vision techniques are employed to detect and localize defects in individual bridge components by extracting and repairing occluded areas.

This approach supports rapid assessment and decision-making for critical infrastructure reconstruction by providing crucial information on the extent of damage. The framework is especially valuable for inaccessible areas, such as war zones or regions affected by floods and other climate hazards. Limitations of the methodology include spatial resolution constraints of Sentinel-1 images, challenges related to event timing, and line-of-sight issues. However, integrating multiple data sources significantly enhances the accuracy and feasibility of the approach. Future work will incorporate higher-resolution optical satellite data, such as Sentinel-2 and PlanetScope, for more detailed inspections of surface conditions. Integrating automated damage assessments with open-access data enables a more informed response to hazards, accelerating decision-making and optimizing recovery planning and restoration strategies.

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