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Multi Sensor Vision Fusion for Real Time Disaster Damage Assessment

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ABSTRACT

Rapid and accurate assessment of damage following natural or man made disasters is critical for effective emergency response and recovery planning. Traditional ground-based inspection methods are often time-consuming, hazardous, and resource-intensive. In contrast, multi sensor vision fusion — combining data from optical satellite imagery, Synthetic Aperture Radar (SAR), LiDAR, and UAV-based sensors — offers a powerful alternative. By applying advanced computer vision and deep learning techniques on fused sensor data, it is possible to perform near real-time structural damage detection, inundation mapping, and debris estimation. This paper reviews recent literature in multi-sensor fusion for disaster assessment, proposes a unified real-time vision fusion pipeline, discusses practical and technical challenges, and outlines future research directions. The proposed methodology aims to improve accuracy, robustness, and speed of damage assessment, supporting first responders and decision makers with timely, reliable information.

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1. Introduction

Disasters — whether natural (earthquakes, floods, hurricanes, wildfires) or man-made (industrial accidents, large scale structural failures) — can result in widespread destruction of infrastructure, housing, and critical services. In the immediate aftermath, one of the pressing needs is to assess the extent and severity of damages quickly and safely, to prioritize rescue, relief, and resource allocation. Traditional damage assessment methods rely heavily on ground surveys and manual inspection, which are often slow, hazardous for responders, and limited in coverage, especially in geographically large or inaccessible areas.

Recent advances in remote sensing, unmanned aerial vehicles (UAVs), and computer vision have opened the door to more efficient, large scale damage assessment. Instead of relying on a single data source (e.g., optical satellite imagery), a multi-sensor approach — integrating optical, radar (SAR), LiDAR, multispectral, and UAV-based data — provides complementary information that can overcome limitations inherent in individual modalities. For example, SAR imagery penetrates cloud cover and captures surface displacement even at night; LiDAR provides accurate elevation/3D structure data; UAVs deliver high-resolution, up-to-date imagery; and optical sensors provide rich spectral and spatial detail. By fusing these data streams, assessment systems can deliver faster, more accurate, and more robust damage estimates, even under challenging environmental conditions.

However, combining data from multiple sensors poses significant technical and practical challenges: data registration across modalities, resolution differences, temporal mismatches, noise reduction, proper feature fusion, and computational demands. Moreover, while research has accelerated, a unified, operational, real-time framework for multi-sensor vision fusion tailored to disaster damage assessment remains limited. This paper aims to fill that gap by reviewing the state-of-the-art, proposing a comprehensive fusion pipeline, and discussing the challenges and future directions toward real-world deployment.

This paper makes several key contributions to the field of disaster damage assessment using computer vision and remote sensing. First, it provides a structured and up-to-date review of multi-sensor vision fusion techniques applied to post-disaster scenarios, highlighting the complementary strengths of optical, SAR, LiDAR, and UAV-based data. Second, it proposes a unified, end-to-end real-time fusion framework that integrates multi-level feature fusion, uncertainty estimation, and explain ability to support operational disaster response. Third, the paper discusses practical deployment challenges and design considerations, bridging the gap between academic research and real-world emergency management applications. These contributions aim to advance the development of accurate, robust, and interpretable damage assessment systems for time-critical disaster response.

The remainder of this paper is structured as follows: Section 2 reviews relevant literature and existing approaches. Section 3 proposes a multi-sensor vision fusion framework for real-time damage assessment. Section 4 outlines major challenges and considerations. Section 5 offers conclusions and future research directions.

2. Literature Review / Background

2.1 The Rationale for Multi-Sensor Fusion

In remote sensing, image fusion refers to combining information from two or more images — often from different sensors — to produce a single image or dataset that is more informative than any of the inputs alone. This approach helps overcome limitations present in individual sensors, such as limited spectral vs. spatial resolution trade offs, or interference from weather conditions (e.g., clouds blocking optical imagery) For disaster damage assessment, multi-sensor fusion significantly enhances robustness and coverage. For instance, fusing optical satellite imagery with SAR data helps overcome the weather and illumination limitations of optical imagery; integrating LiDAR or UAV derived 3D data provides structural and elevation details critical for assessing building collapse or terrain changes

2.2 Previous Work: LiDAR + Aerial Imagery Fusion for Change Detection

One of the early effective approaches combined airborne LiDAR data with aerial images to detect structural changes in post disaster scenarios. In a study by Trinder and Salah (2012), the authors fused LiDAR-derived Digital Elevation Models (DEMs) with multi-temporal aerial imagery to detect changes in building elevation and structure after destructive events. Their method involved data pre-processing (registration), change detection using techniques such as image differencing, PCA, MNF, and classification, and validation against manually generated reference data. The fusion approach improved detection accuracy significantly, reaching up to 92.2% accuracy compared with much lower rates when using aerial imagery alone.

This work demonstrated that combining elevation (3D) and spectral/visual data yields a more reliable damage assessment than either modality alone. It laid a foundation for later multi-modal fusion approaches.

2.3 Deep Learning & Multi Step Feature Fusion for Satellite Images

As deep learning advanced, new studies proposed multi-step feature fusion networks that process pre and post-disaster satellite image pairs through convolutional neural networks (CNNs), performing fusion at multiple levels (both “horizontal” and “vertical” in the network’s layers). A recent work by Żarski & Miszczak (2024) introduced such a network and validated it on large-scale disaster datasets (IDA-BD and xView2). Their approach outperformed baseline architectures by

ENGINEERING SCIENCE
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Vol. 1, No. 7, 2025, pp. 1-10
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more than 3 percentage points in classification accuracy for building damage states (e.g., no damage, moderate damage, severe damage).

Multi-step feature fusion helps the model learn both fine-grained local changes (e.g., difference in texture, rubble) and high-level structural changes (e.g., collapsed buildings), enhancing detection robustness across diverse disaster scenarios.

2.4 Multimodal Fusion: Optical + SAR for All Weather & All Time Assessment

One of the critical limitations of optical-only disaster assessment is dependency on weather (clouds) and lighting (daylight). To overcome that, recent studies fuse SAR (radar) with optical imagery, enabling reliable damage assessment regardless of clouds or night. For example, a 2023 study developed an explainable deep learning architecture for flood inundation mapping by combining multispectral optical data with SAR inputs. Their model significantly outperformed single-modality baselines, achieving higher Intersection-over-Union (IoU) scores for inundation maps. They also applied explainability techniques (e.g., activation mapping) to shed light on how their model makes decisions — increasing transparency and trust in results.

This multimodal fusion is particularly valuable for rapid disaster response since it reduces dependence on weather or daylight conditions and provides more consistent coverage.

2.5 UAV-Based Multi-Sensor Fusion for High-Resolution Local Assessment

While satellite-based fusion offers wide-area coverage, UAV-based fusion enables high-resolution, localized damage assessment. For example, in urban land cover mapping, a study fused UAV-mounted LiDAR data with RGB and multispectral imagery, using a deep convolutional neural network (DCNN) to classify land cover into building, road, vegetation, etc. This fusion significantly improved classification accuracy (by up to 20–30% compared to image-only data), showing the value of combining different sensor data in urban or built-up environments.

Such UAV fusion approaches are particularly useful for post-disaster scenarios in urban zones, where rapid, detailed assessment of building damage, debris, and accessibility is required.

2.6 Recent Advances: Multimodal Vision Language Systems for Disaster Assessment

Newer research is exploring vision-language models (VLMs) that combine remote sensing imagery with natural-language descriptions to support disaster response. A 2025 paper introduced a dataset called DisasterM3, comprising ~27,000 bi-temporal satellite images across 36 historical disasters globally, along with instruction image pairs for tasks including structural damage assessment, object recognition, and disaster reporting. This multi-sensor, multi-task dataset supports VLMs tuned for real-world disaster assessment and response, highlighting an important future direction for integrating human readable reporting with automated vision-based detection.

This blending of vision and language enables not just detection but also automated summarization and reporting, facilitating quicker understanding for humanitarian teams and decision makers.

3 Proposed Multi Sensor Vision Fusion Framework for Real-Time Damage Assessment

Based on the reviewed literature and technological developments, I propose a unified real-time vision-fusion pipeline for post-disaster damage assessment. The framework comprises the following components:

3.1 Pre Disaster Data Preparation

Database construction: Before disasters strike, collect and archive multi-modal data for regions at risk. This includes high-resolution optical satellite imagery, SAR baseline data, LiDAR scans (if available), and UAV based 3D / RGB / multispectral maps for urban or high-risk zones.

Data standardization: Normalize all datasets to common geographic projections, georeference them, and store metadata such as acquisition date, sensor type, resolution, and quality.

3.2 Post Disaster Rapid Data Acquisition

Satellite imagery: Immediately task optical satellites and SAR satellites to collect post-event images. SAR imagery is prioritized if cloud cover or adverse weather prevents optical imaging.

UAV deployment: Dispatch UAVs equipped with RGB, multispectral, and/or LiDAR sensors to capture high-resolution local data, especially in urban or heavily damaged areas.

Ground based sensors (optional): Use ground-based LiDAR or mobile mapping if available to enhance local structure data.

3.3 Data Pre processing and Registration

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Co registration: Align all datasets spatially — for example, aligning SAR and optical images, or aligning UAV and satellite data. This may involve orthorectification, ground control points, and correction for sensor distortions.

Temporal matching: Match pre- and post-disaster datasets to ensure accurate change detection.

Normalization & noise reduction: Apply noise filtering (especially for SAR speckle), atmospheric correction (for optical), and smoothing or interpolation for LiDAR data as needed.

3.4 Multi-Level Feature Extraction & Fusion

Feature-level fusion: Use a deep neural network (e.g., convolutional neural network, or transformer-based model) that takes multi-modal inputs (e.g., optical + SAR + LiDAR point cloud / raster + multispectral + UAV imagery). The network should include specialized fusion modules that merge features at different stages: early (low-level), mid-level, and high-level, to capture textural, structural, and semantic information.

Architecture suggestion: Inspired by multi-step feature fusion networks (e.g., Żarski & Miszczak, 2024), implement horizontal and vertical fusion layers, plus a "Fuse Module" that adapts standard CNN backbones to multi-modal input.

3.5 Damage Classification & Severity Mapping

The fused network outputs classification of damage state per building / per area: e.g., "no damage," "minor damage," "moderate damage," "severe damage / collapse."

Generate geospatial damage maps (e.g., GIS layers) with severity gradations, suitable for first responders and decision-makers.

3.6 Uncertainty Estimation & Explainability

Incorporate uncertainty estimation (e.g., Bayesian deep learning, Monte Carlo dropout) to provide confidence scores on each prediction.

Implement explainability tools (e.g., activation mapping, saliency maps, attention visualizations, or other XAI methods) to highlight which features (sensor, modality, region) led to the damage classification — improving trust and interpretability.

3.7 Real-Time Pipeline & Deployment

Deploy the pipeline on a cloud-based or edge-computing architecture to minimize latency — ideally enabling initial damage assessment within hours of data acquisition.

Provide a decision support dashboard for emergency management agencies, with interactive maps, damage statistics, and uncertainty indicators.

This pipeline aims to combine the strengths of multiple sensing modalities while addressing their individual weaknesses, delivering rapid, accurate, and explainable disaster damage assessments at scale.

3.8 Evaluation Methodology

To assess the effectiveness of the proposed multi-sensor vision fusion framework, this study outlines an evaluation strategy grounded in commonly used disaster damage assessment benchmarks. The framework is intended to be evaluated using publicly available datasets such as xView2 and IDA-BD, which provide annotated pre- and post-disaster satellite imagery with building-level damage labels.

Performance evaluation would rely on standard metrics, including overall accuracy, F1-score, Intersection-over-Union (IoU), and class-wise damage classification accuracy. Comparative experiments would be conducted between single-sensor baselines (e.g., optical-only or SAR-only models) and the proposed multi-sensor fusion approach to quantify the contribution of each modality.

In addition, uncertainty estimation outputs would be analyzed to assess prediction confidence in highly damaged or ambiguous regions. Explainability results, such as saliency maps or attention visualizations, would be qualitatively evaluated to verify whether the model focuses on physically meaningful damage indicators (e.g., collapsed structures, debris patterns, or flooded areas). This evaluation strategy provides a foundation for future empirical validation and operational benchmarking.

4. Challenges and Considerations

Despite its promise, multi-sensor fusion for real-time damage assessment faces a set of significant challenges and limitations:

4.1 Data Availability and Timeliness

Sensor access delay: Immediately after a disaster, acquiring fresh satellite imagery (optical or SAR) may be delayed due to satellite revisit times, sensor tasking constraints, or coordination delays.

UAV deployment limitations: Deploying UAVs rapidly may encounter regulatory, logistic, or safety issues — especially in large-scale disasters or unsafe environments.

Baseline data scarcity: For many regions, pre-disaster LiDAR or high-resolution data may not be available, hampering change detection or accurate damage estimation.

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4.2 Data Registration and Fusion Complexity

Aligning data from heterogeneous sensors (optical, SAR, LiDAR, UAV) involves complex co-registration and georeferencing, especially when resolutions, viewpoints, and acquisition times differ. Misalignment may cause false positives/negatives in damage detection.

Fusion of modalities with very different data geometry (e.g., LiDAR point clouds, SAR radar rasters, optical images) requires careful interpolation or rasterization, and may introduce artifacts or loss of detail.

4.3 Computational and Infrastructure Requirements

Multi-modal deep learning models that fuse several data streams tend to be large and computationally intensive, requiring high-performance GPUs or distributed computing — which may be impractical for some agencies, especially in resource-limited contexts.

Real-time deployment adds further constraints on latency, data transfer, storage, and processing capacity.

4.4 Ground Truth & Validation Difficulties

Obtaining accurate ground-truth data for damage (especially in disaster zones) is challenging due to safety risks, missing access, or chaotic conditions. Without reliable ground truth, evaluating model performance, calibration, and uncertainty becomes difficult.

Damage types and severity are often subjective and context-dependent (e.g., what counts as “moderate” vs “severe”), making consistent labeling non-trivial.

4.5 Generalizability Across Regions and Disaster Types

Models trained on data from certain regions, building types, or disaster scenarios may not generalize well to others — due to differences in architecture, terrain, climate, sensor settings, or disaster mechanisms.

A fusion framework needs to be adaptable, requiring extensive diverse training data across geographies and disaster types to ensure robustness.

In addition to technical challenges, ethical and operational considerations must be addressed when deploying automated damage assessment systems. Overreliance on automated predictions may introduce risks if uncertainty estimates are ignored or misinterpreted by decision-makers. Therefore, human-in-the-loop designs are essential to ensure that automated assessments support, rather than replace, expert judgment. Transparency and explainability are particularly critical in high-stakes disaster response, where incorrect assessments may lead to misallocation of limited resources or delayed rescue efforts.

4 Limitations

This study has several limitations that should be acknowledged. First, the proposed framework is conceptual and has not yet been validated through large-scale empirical experiments. While the design is informed by prior studies and best practices, real-world implementation may reveal additional constraints related to data availability, sensor coordination, and computational scalability. Second, the performance of multi-sensor fusion models is highly dependent on the quality and alignment of input data, which may vary significantly across disaster scenarios. These limitations highlight the need for future experimental validation and real-world pilot deployments.

5 Conclusion

Multi-sensor vision fusion holds substantial promise for improving speed, accuracy, and safety of disaster damage assessment. By combining complementary data sources — optical imagery, SAR, LiDAR, UAV-based sensors — and leveraging advanced deep-learning fusion architectures, it is possible to deliver near real-time damage maps that support emergency response and recovery efforts. The proposed fusion pipeline outlines a practical route toward operationalizing such systems, balancing technical sophistication with real-world constraints.

Nevertheless, significant challenges remain: data availability, fusion complexity, computational costs, validation difficulties, and generalizability. Overcoming these will require coordinated efforts: building large, diverse multi-modal disaster datasets; developing efficient, lightweight fusion architectures; establishing protocols for rapid data acquisition and sharing; and creating standard evaluation benchmarks.

Future research should focus on expanding multi-modal disaster datasets globally, optimizing fusion models for edge computing, integrating temporal change detection and uncertainty quantification, and enhancing explainability and interpretability so that decision-makers can trust and act on automated assessments. In sum, Multi-Sensor Vision Fusion represents a transformative approach with potential to revolutionize.

Overall, this work emphasizes that multi-sensor vision fusion is not merely a technical enhancement, but a critical enabler for timely, reliable, and actionable disaster intelligence. By integrating complementary sensing modalities with deep learning, uncertainty estimation, and explain ability, the proposed framework supports more informed decision-making in time-critical emergency contexts. Future advancements in data sharing, sensor availability, and computational efficiency will further strengthen the role of multi-sensor fusion as a core component of next-generation disaster response systems.

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