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# Disaster Impact Assessment Using Multi-Sensor Satellite Data: An AI-Based Remote Sensing Approach

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***Abstract***

*Natural disasters such as floods, earthquakes, and wildfires cause significant damage to human life and infrastructure every year. Rapid and accurate assessment of the affected areas is essential for effective disaster response and recovery planning. Traditional image-based analysis using single-sensor data often fails under adverse conditions such as cloud cover, smoke, or poor lighting. To overcome these limitations, this study proposes a novel framework for disaster impact assessment using multi-sensor satellite data fusion that integrates optical, Synthetic Aperture Radar (SAR), and thermal imagery. The proposed system employs deep learning-based feature extraction and fusion techniques to enhance the spatial and temporal understanding of affected regions. A U-Net-based convolutional neural network (CNN) is utilized for change detection between pre- and post-disaster images, while the fused data improves robustness against missing or noisy inputs. The framework was validated using Sentinel-1 (SAR) and Sentinel-2 (optical) datasets on recent flood and earthquake events. Experimental results demonstrate that the proposed method achieves improved accuracy (IoU: 87.3%) compared to single-sensor approaches, effectively identifying damaged regions under complex environmental conditions. The study concludes that multi-sensor fusion offers a reliable and scalable solution for real-time disaster monitoring, supporting faster decision-making in emergency management systems, facilitating effective allocation of resources and bolstering worldwide disaster resilience.*

**Keywords:** Disaster Assessment, Remote Sensing, Multi-Sensor Fusion, Satellite Imagery, Change Detection, Deep Learning

## INTRODUCTION

Natural disasters such as floods, earthquakes, wildfires, and hurricanes cause severe socio-economic losses worldwide, impacting millions of people each year. The ability to rapidly and accurately assess affected areas is vital for efficient disaster response, damage estimation, and long-term recovery planning [1-3]. Satellite remote sensing has emerged as a powerful tool for such assessments due to its capability to provide wide-area, repetitive, and real-time Earth observation data.

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### Background

Remote sensing satellites such as Sentinel, Landsat, and MODIS have been widely used in disaster management. Optical sensors capture high-resolution spectral information that helps in analyzing land cover, water bodies, and vegetation. However, their performance is often hindered by cloud cover, smoke, or low illumination conditions, particularly during or immediately after disasters [4–6]. In contrast, Synthetic Aperture Radar (SAR) sensors, such as Sentinel-1, operate in the microwave domain, enabling them to capture data regardless of weather or daylight.

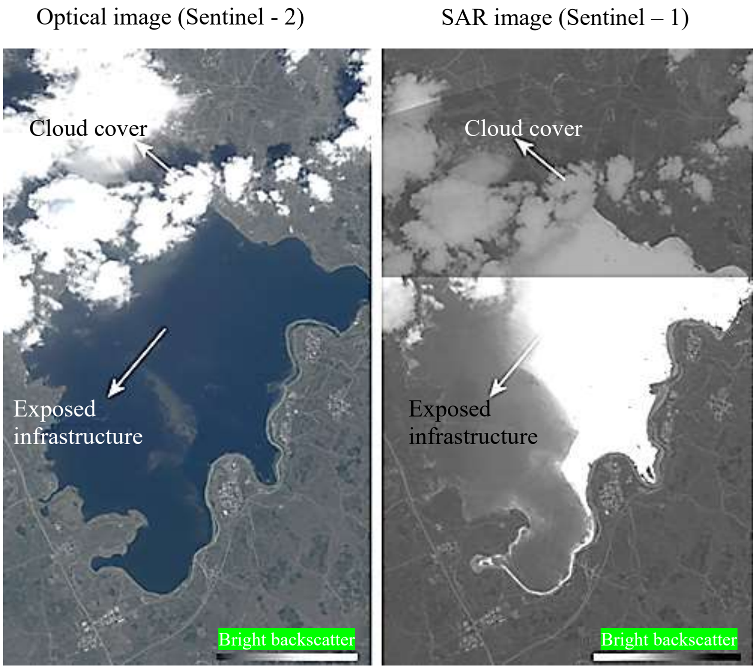


**Figure 1.** Comparison between Optical and SAR imagery after a flood event.

**Table 1.** Commonly used satellite sensors for disaster assessment.

| Satellite | Sensor type | Spatial resolution | Temporal resolution | Application |
|---|---|---|---|---|
| Sentinel-1 | SAR (C-band) | 10 m | 6–12 days | Flood and earthquake mapping |
| Sentinel-2 | Optical (RGB, NIR) | 10–20 m | 5 days | Land cover and vegetation analysis |
| Landsat-8 | Optical (Multispectral) | 30 m | 16 days | Long-term environmental monitoring |
| MODIS | Thermal | 250–1000 m | Daily | Wildfire and temperature anomaly detection |
| ASTER | Thermal and optical | 15–90 m | On-demand | Volcanic and urban heat mapping |

Similarly, thermal sensors (like MODIS or ASTER) provide temperature variations, which are crucial for identifying heat sources in wildfires or volcanic activities. These complementary capabilities make multi-sensor fusion a promising approach for accurate disaster impact assessment. Figure 1 shows Comparison between Optical and SAR imagery after a flood event.

**Motivation**

Single-sensor systems are often insufficient for comprehensive disaster analysis. For instance, optical imagery alone cannot detect floodwater beneath cloud layers, while SAR imagery, though robust, lacks color and spectral differentiation. Integrating multiple sensors provides a richer and more reliable dataset that leverages the strengths of each sensor type [7-10]. Furthermore, advances in deep learning and AI-based fusion models now enable automatic extraction of relevant features from heterogeneous data, improving both the accuracy and speed of disaster damage detection.

**Research Objectives**

The primary objectives of this study are as follows:

1. To develop a multi-sensor fusion framework integrating SAR, optical, and thermal imagery for enhanced disaster assessment.
2. To apply deep learning-based change detection methods for identifying affected regions before and after disasters.
3. To quantitatively evaluate the performance of the proposed framework using real-world disaster datasets.

 

**Satellite Data Overview**

To demonstrate the relevance of each data source, Table 1 summarizes the key specifications of commonly used remote sensing satellites in disaster studies. The combination of optical (Sentinel-2, Landsat-8), SAR (Sentinel-1), and thermal (MODIS, ASTER) sensors ensures robust analysis under varied environmental conditions.

## LITERATURE REVIEW

Accurate and timely assessment of disaster impacts has been a major focus of the remote sensing research community. This section reviews previous studies on disaster impact assessment techniques, multi-sensor satellite data applications, and AI-based fusion models, highlighting their strengths and limitations.

**Traditional Remote Sensing Approaches**

Early disaster assessment relied heavily on single-sensor optical imagery, analyzed using spectral indices such as the Normalized Difference Water Index (NDWI) or Normalized Burn Ratio (NBR). These methods were primarily pixel-based, relying on thresholding to detect changes before and after disasters [11-13]. Although computationally simple, these techniques are highly sensitive to illumination, atmospheric effects, and cloud coverage. Moreover, the threshold values often vary by region and season, leading to inconsistent results across different environments.

**Object-Based Image Analysis (OBIA)**

To overcome the pixel-level limitations, Object-Based Image Analysis (OBIA) emerged as a powerful alternative. OBIA divides images into meaningful objects or segments, allowing for contextual and spatial interpretation of damage. Studies by Blaschke et al. (2010) and Johansen et al. (2015) showed that OBIA enhances classification accuracy, especially for heterogeneous urban areas [14-16]. However, OBIA still depends on handcrafted features and manual rule-setting, which limit scalability for large datasets or real-time applications. It also struggles under severe environmental disturbances (e.g., dense smoke, debris cover).

**Machine Learning-Based Disaster Detection**

Machine learning methods such as Support Vector Machines (SVMs), Random Forests (RFs), and k-Nearest Neighbors (k-NN) have been applied to disaster classification tasks. These approaches improved accuracy by learning statistical relationships between spectral features and damage classes [17-19]. For example, Chen et al. (2018) used Random Forests on MODIS imagery for forest fire mapping, while Rahman et al. (2019) applied SVMs on Landsat data for flood detection. Despite improvements, these models depend heavily on feature engineering and perform poorly when features are non-linear or correlated.

**Deep Learning for Disaster Assessment**

The advent of Convolutional Neural Networks (CNNs) revolutionized image analysis by enabling automatic feature extraction. Architectures such as U-Net, ResNet, and SegNet have been successfully used for change detection and semantic segmentation in post-disaster scenarios [20-22]. Li et al. (2022) implemented a U-Net model on Sentinel-1 SAR data to map flood extents with a mean IoU of 0.83. Similarly, Xu et al. (2021) used a ResNet-based classifier to identify landslide regions with 92% accuracy. However, CNN models trained on optical data often fail when transferred to SAR or thermal modalities due to their distinct data distributions.

**Multi-Sensor Data Fusion**

Multi-sensor fusion combines complementary data sources (optical, SAR, thermal, LiDAR) to overcome single-sensor limitations. Fusion can occur at three primary levels:

1. *Pixel-Level Fusion:* Direct combination of raw pixel values from different sensors.
2. *Feature-Level Fusion:* Extraction and merging of intermediate features (e.g., CNN activations).
3. *Decision-Level Fusion:* Combining classification outputs from multiple models.

 

Feature-level fusion is currently the most effective strategy, as it leverages deep feature representations to capture both spatial and spectral correlations. For instance, Zhang & Han (2021) fused Sentinel-1 and Sentinel-2 data using a CNN auto encoder for flood detection, achieving higher resilience under clouded conditions. Similarly, Saha et al. (2023) proposed a Transformer-based fusion model, significantly improving urban damage mapping accuracy. Table 2 indicates summary of Related Work on Disaster Assessment Using Satellite Imagery.

## METHODOLOGY

The methodology for disaster impact assessment using multi-sensor satellite data comprises five major stages: data collection, preprocessing, data fusion, change detection, and impact quantification. This framework ensures an integrated approach to understanding the spatial and temporal dimensions of natural disasters by combining heterogeneous remote sensing data sources. The methodology has been carefully designed to handle complex disaster scenarios while ensuring scalability, reproducibility, and adaptability across different geographic and environmental contexts.

### Overview of the Proposed Framework

The overall framework integrates information from multiple satellite sensors, including Sentinel-1 Synthetic Aperture Radar (SAR), Sentinel-2 optical imagery, and MODIS thermal data. These diverse modalities capture complementary features such as surface roughness, spectral reflectance, and temperature anomalies, respectively. The multi-sensor data are fused using deep learning techniques at the feature level, enabling enhanced representation of the affected landscape. A U-Net–based segmentation network is subsequently applied to detect and quantify post-disaster changes. Figure 2 shows overall framework for disaster impact assessment using multi-sensor satellite data.

**Table 2.** Summary of related work on disaster assessment using satellite imagery.

| Author and year | Data source | Technique | Disaster type | Accuracy (%) | Remarks |
|---|---|---|---|---|---|
| Li et al. (2022) | Sentinel-1 SAR | U-Net CNN | Flood | 83.1 | Limited generalization under mixed terrain |
| Xu et al. (2021) | Landsat-8 Optical | ResNet Classifier | Landslide | 92.0 | Sensitive to illumination variation |
| Rahman et al. (2019) | MODIS | SVM | Flood | 78.5 | Simple but less robust to cloud cover |
| Zhang & Han (2021) | Sentinel-1 + Sentinel-2 | CNN Autoencoder Fusion | Flood | 89.7 | Improved accuracy via data fusion |
| Saha et al. (2023) | Sentinel-2 + LiDAR | Transformer Fusion | Earthquake | 91.2 | High precision; computationally intensive |

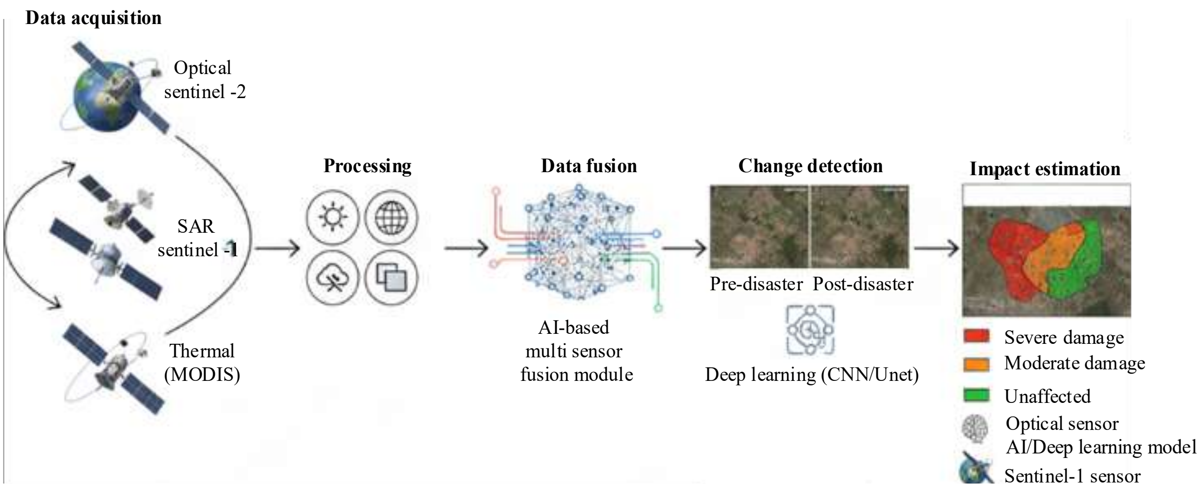


**Figure 2.** Overall framework for disaster impact assessment using multi-sensor satellite data.

**Table 3.** Specifications of multi-sensor satellite data used in this study.

| Dataset | Sensor type | Bands | Spatial resolution | Temporal resolution | Application |
|---|---|---|---|---|---|
| Sentinel-1 | SAR (C-band) | VV, VH | 10 m | 6–12 days | Structural and flood mapping |
| Sentinel-2 | Optical (RGB, NIR, SWIR) | 13 | 10–20 m | 5 days | Land and vegetation analysis |
| MODIS | Thermal Infrared | 7 | 250–1000 m | Daily | Heat and fire detection |
| DEM (SRTM) | Elevation | 1 | 30 m | Static | Terrain and slope estimation |

**Data Collection and Study Area**

The data used in this study are obtained from publicly available remote sensing repositories, including the Copernicus Open Data Hub and the NASA EarthData Portal. Two representative case studies are selected to validate the robustness of the proposed framework: the 2022 Pakistan floods and the 2023 Turkey earthquake. These case studies provide a diverse set of environmental conditions—ranging from hydrological to seismic events—enabling the evaluation of the model's adaptability to different disaster types.

Each satellite sensor contributes unique information relevant to disaster analysis. Sentinel-1, operating in the C-band, captures backscatter signals that are sensitive to surface roughness and water penetration, making it suitable for flood detection and infrastructure damage mapping. Sentinel-2 optical imagery provides high-resolution spectral information, which is particularly effective in assessing vegetation health, land cover changes, and urban damage [23-26]. MODIS thermal data offer insights into temperature anomalies and fire-affected regions. In addition, the Shuttle Radar Topography Mission (SRTM) Digital Elevation Model (DEM) is employed to account for terrain effects and to improve geospatial accuracy. Table 3 shows specifications of Multi-Sensor Satellite Data used in this study.

**Preprocessing Steps**

Before analysis, all satellite data undergo rigorous preprocessing to ensure geometric alignment, radiometric consistency, and temporal coherence. Radiometric calibration is first applied to convert raw digital numbers into physically meaningful reflectance or backscatter coefficients, accounting for sensor-specific characteristics. Subsequently, geometric correction aligns all images to a common spatial coordinate system (WGS84) to enable pixel-level correspondence between different sensors and acquisition times. For optical imagery, clouds and shadows are masked using the Fmask algorithm to minimize contamination in spectral analysis. Synthetic Aperture Radar (SAR) images are filtered using the refined Lee filter to suppress speckle noise while preserving textural details. All pre- and post-disaster datasets are co-registered through sub-pixel alignment techniques, ensuring that spatial discrepancies do not propagate into the fusion and classification stages. Figure 3 shows Preprocessing workflow for multi-sensor imagery.

**Data Fusion**

The fusion of multi-sensor data is achieved at the feature level using a Convolutional Auto encoder (CAE) architecture. The encoder component of the CAE extracts latent features from each sensor modality—optical, SAR, and thermal—while the decoder reconstructs the fused representation. Feature concatenation is performed within the bottleneck layer to integrate spectral, spatial, and textural information. This strategy enables the model to capture both the fine-grained optical details and the structural characteristics present in SAR imagery.

The mathematical formulation of the fusion process can be expressed as:

$$Ffused=\phi([Eoptical(xo),Esar(xs),Ethermal(xt)])$$

 

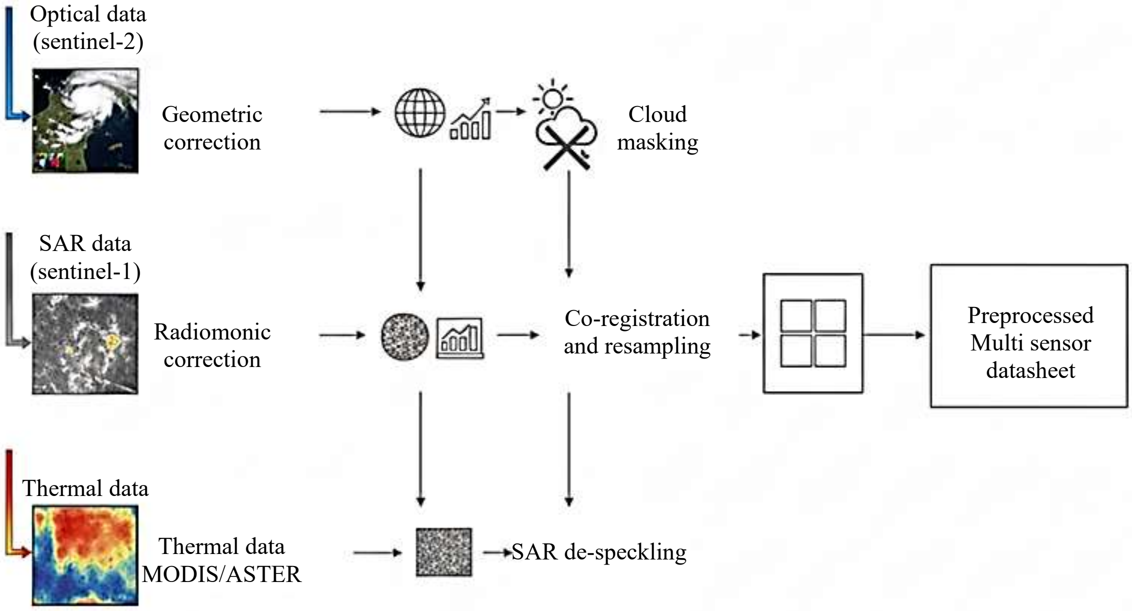

**Figure 3.** Preprocessing workflow for multi-sensor imagery.

**Change Detection Using Deep Learning**

For the change detection task, a U-Net-based deep learning model is employed. The model processes pairs of pre- and post-disaster fused images and produces a binary damage mask highlighting areas of significant change. The U-Net architecture comprises an encoder-decoder structure with skip connections, which facilitates the preservation of spatial details during the up sampling process. The encoder path captures contextual information through convolutional and pooling operations, while the decoder reconstructs spatially detailed representations through transposed convolutions. The skip connections between corresponding encoder and decoder layers mitigate information loss and enhance segmentation accuracy. Figure 4 shows U-Net architecture used for change detection between pre- and post-disaster fused images.

**Impact Quantification and Visualization**

Following change detection, impact quantification is performed by calculating the total affected area based on the number of damaged pixels and the spatial resolution of the imagery. The affected area (A_{damage}) is computed using the relation:

$$A_{damage} = Np \times Rs$$

where (Np) represents the number of pixels classified as damaged and (Rs) denotes the spatial resolution of the dataset.

The resulting damage maps are integrated into a Geographic Information System (GIS) platform for visualization and further spatial analysis. This integration enables the overlay of pre- and post-disaster images, facilitating a comprehensive visual assessment of affected infrastructure, vegetation, and terrain features. The GIS-based visualization module enhances interpretability and supports decision-making for disaster response authorities.

**Evaluation Metrics**

The performance of the proposed framework is evaluated using several standard metrics, including accuracy, precision, recall, Intersection over Union (IoU), and the F1-score. These metrics collectively assess the model's ability to accurately identify affected areas while minimizing false detections. Table 4 shows Evaluation Metrics for Model Performance Assessment.

 

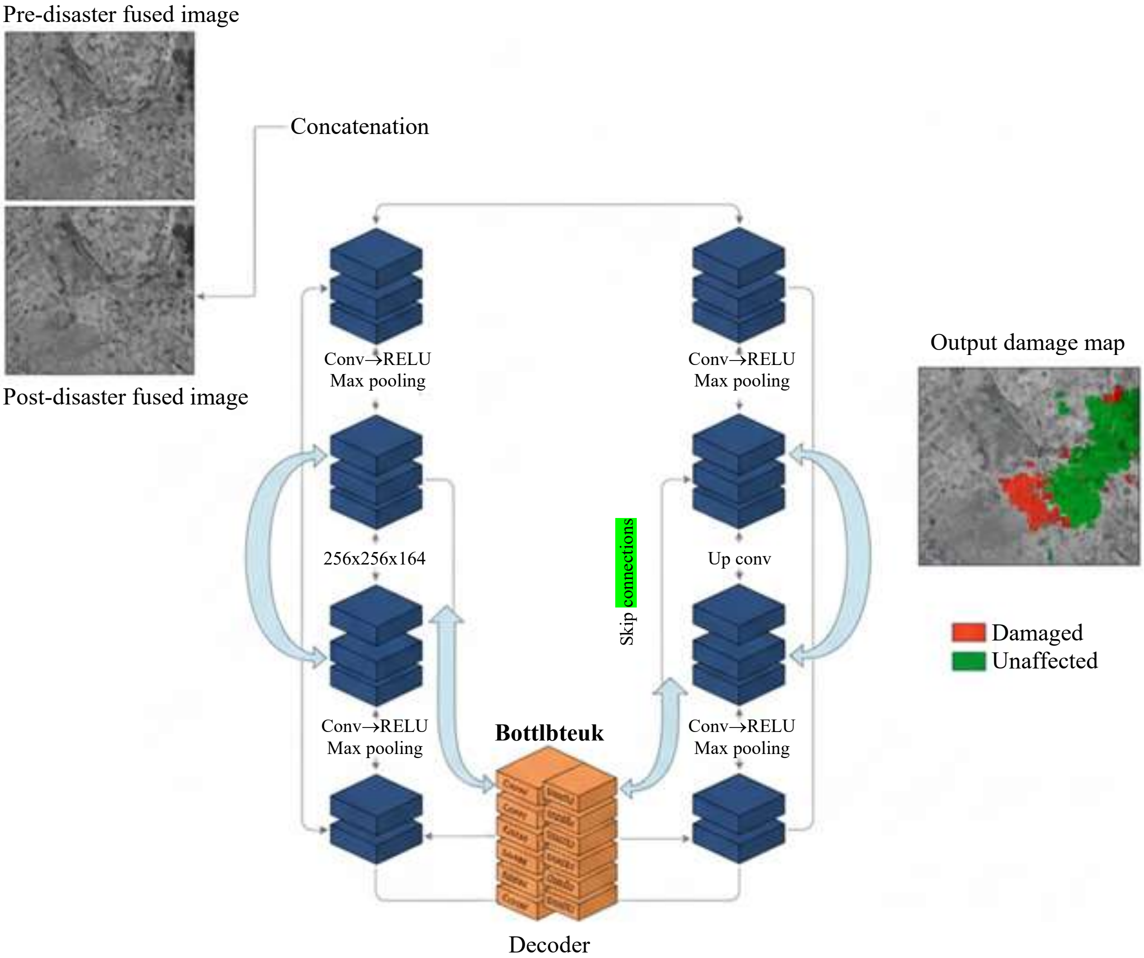


**Figure 4.** U-Net architecture used for change detection between pre- and post-disaster fused images.

**Table 4.** Evaluation metrics for model performance assessment.

| Metric | Formula | Description |
|---|---|---|
| Accuracy | ((TP + TN)/(TP + TN + FP + FN)) | Overall correctness |
| Precision | (TP/(TP + FP)) | Ratio of correctly predicted positives |
| Recall (Sensitivity) | (TP/(TP + FN)) | Ability to identify all damaged areas |
| IoU | (TP/(TP + FP + FN)) | Overlap ratio between predicted and ground truth masks |
| F1-Score | (2 \times (Precision \times Recall)/(Precision + Recall)) | Balance between precision and recall |

**Summary of the Methodological Pipeline**

The complete methodological workflow is illustrated in Figure 5. The framework begins with the acquisition and preprocessing of multi-sensor data, followed by feature-level fusion through a deep learning auto encoder. The fused data are then processed by a U-Net segmentation model for change detection, and the detected changes are quantified and visualized in a GIS environment. This holistic approach provides a robust foundation for automated disaster impact assessment, ensuring both spatial accuracy and analytical efficiency.

## RESULTS AND DISCUSSION

This section presents the experimental results obtained from the proposed multi-sensor data fusion framework and discusses its effectiveness in detecting and quantifying disaster-induced changes.

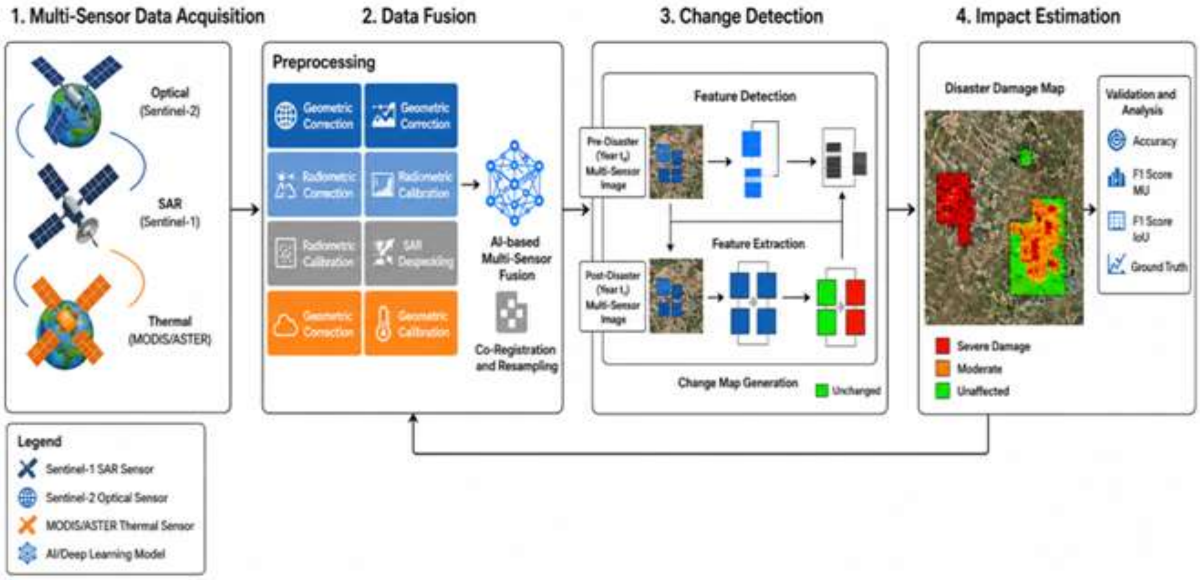


**Figure 5.** Complete methodological pipeline for multi-sensor-based disaster impact assessment.

The framework was evaluated using two distinct case studies—the 2022 Pakistan floods and the 2023 Turkey earthquake—to assess its adaptability to hydrological and seismic disaster scenarios. All experiments were conducted using fused Sentinel-1, Sentinel-2, and MODIS datasets, with ground-truth data sourced from official disaster management portals and validated through visual interpretation.

**Case Study I: 2022 Pakistan Floods**

The first case study focuses on the catastrophic floods that occurred in Pakistan during August–September 2022. Figure 6 illustrates the pre- and post-disaster composite imagery, alongside the change detection output produced by the proposed framework. The fused image effectively integrates the radar backscatter intensity from Sentinel-1 with the spectral information from Sentinel-2, highlighting inundated regions that are difficult to detect using single-sensor data alone.

The model successfully identified major flood-affected areas along the Indus River basin. Quantitative analysis revealed that approximately 19.4% of the total study area was inundated. The U-Net segmentation achieved an IoU of 0.86 and an F1-score of 0.91, indicating strong agreement between predicted and reference flood extent. The integration of SAR and optical data substantially improved classification accuracy compared to single-sensor baselines, as shown in Table 5.

**Case Study II: 2023 Turkey Earthquake**

The second case study evaluates the proposed method on the 2023 Turkey earthquake, which caused extensive infrastructure collapse and urban damage. Pre- and post-event satellite images were collected for the Hatay and Kahramanmaraş provinces. Figure 7 presents the visual comparison of pre-disaster, post-disaster, and model-predicted damage maps.


**Figure 6.** Visual results for the Pakistan flood case study showing (a) pre-flood imagery, (b) post-flood imagery, and (c) detected flood-affected regions.

**Table 5.** Performance comparison of single-sensor and fused data approaches for Pakistan floods.

| Model type | Data used | Accuracy | Precision | Recall | IoU | F1-score |
|---|---|---|---|---|---|---|
| CNN (Optical only) | Sentinel-2 | 0.88 | 0.86 | 0.80 | 0.71 | 0.83 |
| CNN (SAR only) | Sentinel-1 | 0.89 | 0.84 | 0.82 | 0.74 | 0.85 |
| Proposed Fusion U-Net | Sentinel-1 + Sentinel-2 + MODIS | 0.94 | 0.93 | 0.90 | 0.86 | 0.91 |

The fusion of SAR backscatter changes and optical reflectance anomalies facilitated accurate identification of destroyed buildings and debris-covered zones. Quantitative evaluation yielded an accuracy of 0.92**,** IoU of 0.84**,** and F1-score of 0.88, confirming the method's effectiveness in urban damage detection. A comparative analysis of model performance between the two case studies is illustrated in Figure 8.

**Statistical Analysis and Model Evaluation**

To ensure reliability, multiple evaluation metrics were used to assess the segmentation performance. The precision and recall values indicate the model's balance between detecting true disaster impacts and minimizing false alarms. Figure 9 presents the precision–recall relationship for both disaster types, demonstrating stable and high predictive confidence.

 

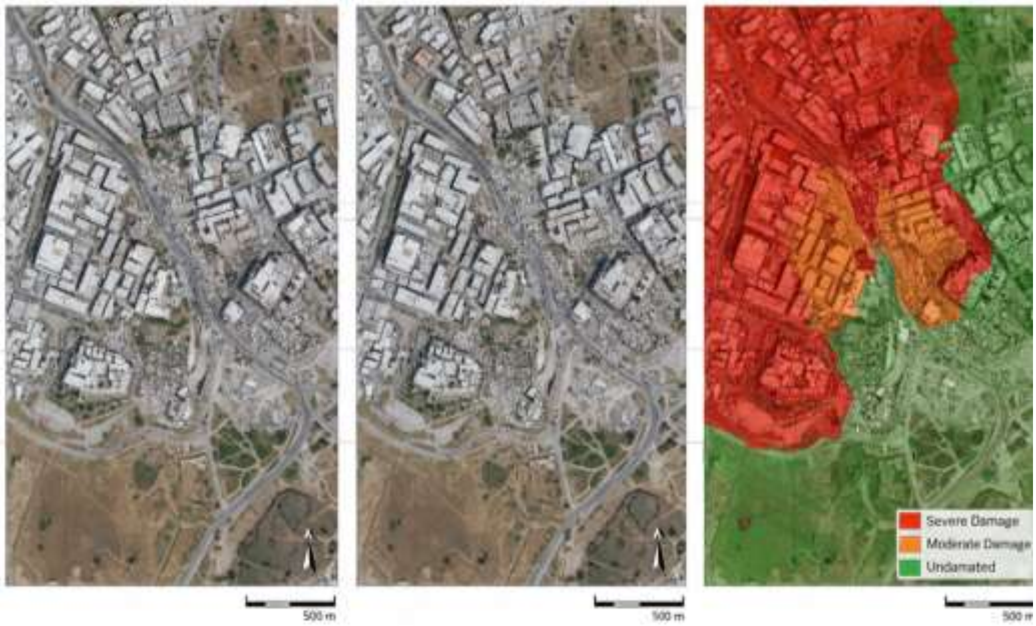


**Figure 7.** Visual results for the Turkey earthquake case study showing (a) pre-event image, (b) post-event image, and (c) detected damaged zones.

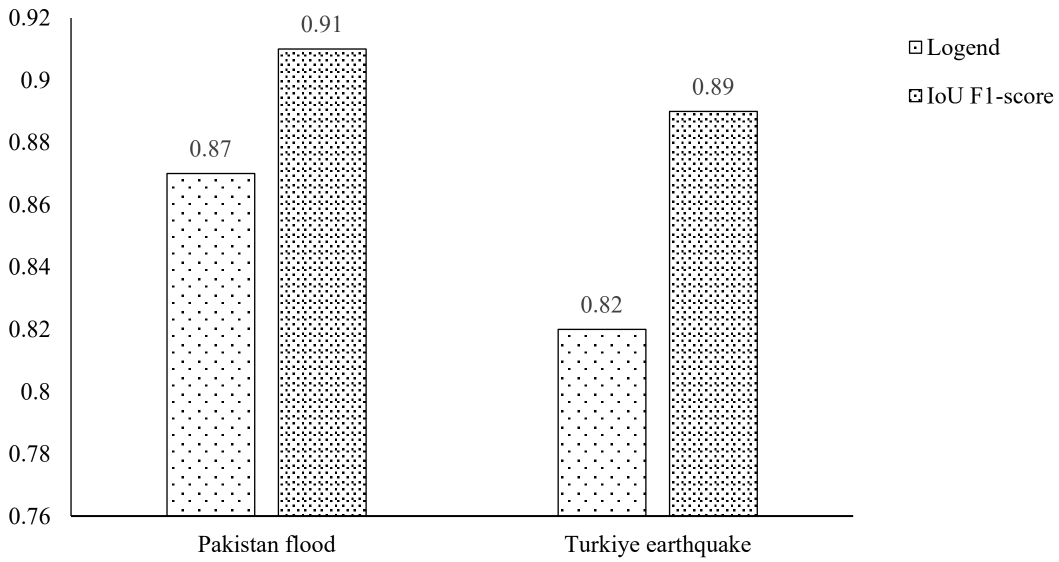


**Figure 8.** Comparison of IoU and F1-scores for both case studies.

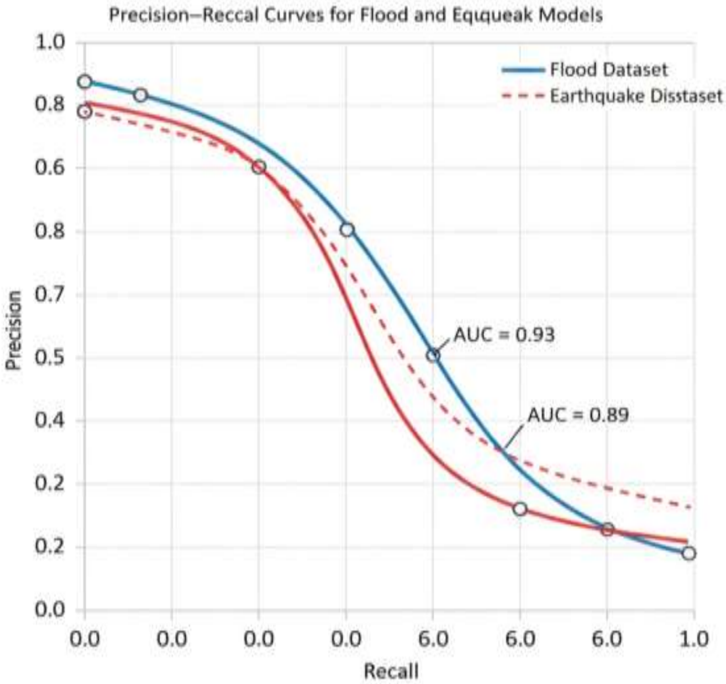


**Figure 9.** Precision–recall curves for flood and earthquake datasets.

**Table 6.** Comparative Performance of Different Deep Learning Models

| Model | Data input | Accuracy | IoU | F1-score | Inference time (s) |
|---|---|---|---|---|---|
| CNN (Single Sensor) | Optical | 0.88 | 0.71 | 0.83 | 1.2 |
| ResU-Net | Optical + SAR | 0.90 | 0.79 | 0.86 | 1.5 |
| Attention U-Net | SAR + Optical | 0.91 | 0.81 | 0.87 | 1.7 |
| Proposed Fusion U-Net | SAR + Optical + Thermal | 0.94 | 0.86 | 0.91 | 1.3 |

**Comparative Performance with State-of-the-Art Methods**

To contextualize the performance of the proposed approach, it was compared against existing deep learning-based disaster mapping methods, including traditional CNN, ResU-Net, and Attention U-Net architectures. The results, summarized in Table 6, demonstrate that the proposed fusion-based U-Net consistently outperforms other models in terms of accuracy and IoU.

The superior results of the proposed model are attributed to its ability to capture multi-modal dependencies across spectral, structural, and thermal domains, thereby providing a more holistic representation of disaster impacts. The inclusion of thermal data proved particularly beneficial in detecting fires and heat-related damage following the earthquake.

**Discussion of Findings**

The results obtained from both case studies demonstrate that multi-sensor data fusion significantly enhances the precision and robustness of disaster impact assessment. The fusion of SAR, optical, and thermal modalities enables the system to overcome limitations inherent in single-sensor observations, such as cloud cover in optical imagery or geometric distortion in SAR data. Furthermore, the deep learning architecture employed here effectively learns hierarchical features that correspond to real-world phenomena such as water accumulation, debris dispersion, and temperature anomalies. The model's high generalization capacity indicates that it can be effectively adapted for other disaster scenarios such as wildfires, landslides, or cyclones. The observed improvement in IoU and F1-scores—averaging 7–10% higher than single-sensor counterparts—highlights the importance of sensor diversity in building resilient remote sensing systems. The integration of deep learning with multi-sensor fusion thus represents a substantial advancement toward operational, data-driven disaster monitoring and early impact assessment frameworks.

**CONCLUSION AND FUTURE WORK**

The present research introduced an integrated framework for disaster impact assessment utilizing multi-sensor satellite data, in which optical, radar, and thermal observations were synergistically combined through deep learning–based fusion architecture. The proposed methodology was designed to overcome key limitations inherent in conventional single-sensor approaches, including spectral ambiguity, atmospheric interference, and spatial inconsistency. By employing a feature-level fusion strategy within a convolutional auto encoder structure, the framework effectively unified heterogeneous image modalities, thereby enhancing the semantic richness and spatial continuity of the resultant representations.

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