

Artificial Intelligence as a Reconstruction Engineer: Leveraging Computer Vision for Damage Assessment and Infrastructure Prioritization

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Abstract: This paper examines the transformative role of Artificial Intelligence (AI), particularly computer vision and machine learning, as a strategic tool for damage assessment and infrastructure prioritization in Syria's post-conflict reconstruction. Following the political transition of December 2024, Syria faces the unprecedented challenge of rebuilding physical infrastructure devastated by over a decade of civil war, with the World Bank estimating reconstruction costs between \$140 billion and \$345 billion. Traditional manual damage assessment methods are inherently slow, incomplete, and potentially biased, creating critical bottlenecks in resource allocation and reconstruction planning. This paper synthesizes insights from AI literature, post-conflict reconstruction frameworks, and Syria-specific applications—including drone-based remote sensing in Kafr Nabl, deep learning damage detection from satellite imagery, the SKAI tool developed by WFP and Google Research, and the AI-driven multi-criteria decision framework for prioritizing structural interventions—to propose an integrated AI-enabled reconstruction framework. The framework addresses three interconnected pillars: rapid damage assessment using computer vision and remote sensing, evidence-based infrastructure prioritization using AI-driven multi-criteria decision-making, and capacity building for sustainable AI adoption. The paper argues that AI is not merely a technical tool but a strategic enabler that can accelerate recovery, optimize scarce resources, and build a more transparent and accountable reconstruction process. Key recommendations include establishing a national AI-enabled damage assessment system, adopting AI-driven prioritization frameworks, investing in local AI capacity building, and ensuring that AI systems are designed with principles of transparency, accountability, and inclusion.

Keywords: Artificial Intelligence; Computer Vision; Damage Assessment; Infrastructure Prioritization; Post-Conflict Reconstruction; Machine Learning; Remote Sensing; Deep Learning; Decision Support Systems.

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1. Introduction

After more than thirteen years of conflict, the Syrian Arab Republic faces one of the most complex reconstruction challenges of the twenty-first century [1]. The conflict, now in its tenth year, has massively destroyed housing, schools, hospitals, water systems, electricity networks, roads, telecommunications and other vital infrastructure. The World Bank estimates total reconstruction costs at about \$216 billion, of which about \$82 billion would go to housing. These Figures 1 and 2 underscore the scale of the challenge and the need for reconstruction strategies that can direct scarce financial and technical resources to the sectors of greatest social and economic importance [2]. The scale of the destruction is particularly clear in the big cities. Official reports state that in Aleppo alone 24,262 homes were destroyed, 24,606 partially damaged, and 105,408 lightly damaged. In addition, 227 schools were destroyed and 215 partially damaged. Critical infrastructure in Syria's health, water, electricity, transportation and telecommunications sectors has been damaged to varying degrees [3]. Reconstruction cannot be limited to the rebuilding of individual structures. This includes systematically identifying damaged assets, assessing their physical condition, estimating reconstruction needs, assessing their importance to communities, and prioritizing investments using transparent, measurable criteria [4]. The magnitude and complexity of this work make traditional evaluation methods insufficient on their own. Traditional damage assessment relies on eyewitness reports, visual inspections, engineering surveys, photographs, and administrative records [5].

These methods provide useful information, but can be slow, expensive, inconsistent and difficult to implement over large or remote regions. Field teams may face security and transport constraints, and damaged areas may lack reliable records or communications infrastructure. As Mueller *et al.* [8] note, information on post-conflict damage is often scarce, incomplete, and potentially biased. In Syria, these restrictions are compounded by the scale of destruction and the need to make fast reconstruction decisions. Therefore, the main problem is not only access to reconstruction financing, but also the ability to use these resources efficiently [6]. If reconstruction needs far exceed available resources, governments must decide which buildings, roads, hospitals, schools, electricity facilities, water networks and telecommunication systems to repair first. A damaged hospital that serves a large population may take priority over a less critical public building and restoring an electricity substation may allow multiple hospitals, factories, schools and water facilities to operate [7]. These interdependencies mean reconstruction priority cannot be based solely on the apparent magnitude of physical damage. Artificial Intelligence (AI), specifically computer vision and machine learning, offers a key technological opportunity to address these issues. AI systems can evaluate large amounts of satellite, drone, overhead, and ground-level imagery to identify and categorize infrastructure damage [9]. Computer-vision algorithms can quickly flag areas that need closer inspection, rather than having engineers manually review every structure. Human experts can then verify the AI-generated assessments and focus their efforts on complex or high-priority cases. AI should be considered a decision-support technology that enhances engineering capacity, not a substitute for engineers [10].

The first basis for AI's strategic importance for Syrian reconstruction is accelerating damage assessment. Satellite imagery can cover entire cities and regions, allowing analysts to identify destroyed or damaged buildings at a scale that would be difficult to achieve through field surveys alone. High-resolution drone imagery can provide more detail on individual neighborhoods and infrastructure assets, and ground photographs can validate algorithmic classifications [11]. By combining these sources, a multi-level assessment system can be built in which satellite images provide broad patterns, aerial images provide detailed spatial information, and engineering inspections verify critical cases. Computer vision can also help with consistency in damage classification [12]. Machine-learning models can be trained to classify structures as intact, lightly damaged, moderately damaged or severely damaged. Change-detection methods can compare imagery collected before and after conflict or disasters to identify physical changes. Object-detection models can recognize buildings, roads, bridges, power facilities, and other infrastructure; image-segmentation techniques can identify the spatial extent of damaged areas. Deep-learning methods applied to high-resolution satellite imagery have shown value in reconstructing patterns of urban damage [13]. These techniques could be customized to Syria's specific architectural, geographical and infrastructural characteristics. International experience further demonstrates AI's potential. The SKAI tool, developed by the World Food Program in partnership with Google Research, uses advanced machine learning to speed up disaster damage assessments. Similar approaches were used in disaster contexts in Turkey and Syria, where AI-supported assessments helped humanitarian organizations gather information faster and improve emergency response efficiency.

The experiences show that conventional artificial intelligence can be useful not only in immediate humanitarian crises, but also in longer-term reconstruction [14]. But the models developed in other countries cannot be imported to Syria without adaptation [15]. Countries differ in building materials, architectural designs, urban density, environmental conditions, image quality and damage patterns. An algorithm trained primarily on earthquake-damaged buildings might act differently if presented with

structures damaged by protracted conflict. Hence, Syria needs locally representative training datasets. Universities, engineering schools, municipalities, government agencies and technology companies could collaborate to develop standardized datasets of images of Syrian buildings and infrastructure under different damage conditions [16]. Another important use of AI is developing a national infrastructure damage database. The system could include geographic coordinates, infrastructure type, physical condition, population served, estimated repair cost, economic importance, and access to essential services. This data can be translated into interactive maps of destruction concentrations and critical infrastructure gaps through Geographic Information Systems (GIS). This kind of platform would allow national authorities and reconstruction partners to identify where investment is most needed and coordinate projects across regions [17]. AI may also help prioritize infrastructure through multi-criteria decision-making. Physical damage should be one factor in prioritizing reconstruction. Other variables should encompass the number of people served, the facility's importance to essential services, economic significance, cost of repair, vulnerability, accessibility and the potential contribution to broader recovery.

The 2025 KFUPM study proposes a framework that combines an AI-based diagnostic layer with a multi-criteria decision-making layer to enable people-centric, resilient infrastructure prioritisation [18]. A viable Syrian framework could assign a normalized Structural Integrity Score (SIS) to each major infrastructure asset [20]. The score could be a physical condition rating of a building or facility derived from computer-vision analysis and engineering verification. Another set of indicators could be strategic importance. Hospitals, water-treatment plants, electricity substations, schools, major roads and telecommunications facilities may be given higher priority because their restoration has significant impacts on population welfare and economic recovery. The final priority score may include structural condition, social importance, economic impact, cost and feasibility [21]. It would also enable the government to identify infrastructure that, if rehabilitated, could have ripple effects. "Infrastructure systems are not independent systems; they are interdependent. For example, if a key electrical substation is restored, water pumping stations, hospitals, schools and industrial facilities can reopen. Likewise, rehabilitating a key transport corridor can help reconnect farming communities to markets and allow construction materials to move. AI can evaluate these relationships to identify critical network nodes that, when restored, would provide the greatest benefit from reconstruction spending. Predictive analysis is another important application. AI can study historical and spatial data to predict future infrastructure needs and identify locations likely to deteriorate further. Buildings that may appear only moderately damaged at first glance can become structurally unsound if left exposed to the weather and not maintained. Population movements can also affect the demand for housing, health care, electricity, water and transportation.

AI models can combine infrastructure condition with demographic and economic data to project future demand and enable long-term reconstruction planning. As Harrouk [1] notes, artificial intelligence can provide data-driven forecasts for infrastructure rehabilitation. Artificial intelligence can also help estimate reconstruction costs. Damage categories might be associated with past construction costs, building attributes, geographic data and material costs, enabling machine-learning systems to make initial estimates of required repairs and replacements [2]. Such estimates would not replace detailed engineering and procurement assessments, but could provide policymakers with rapid estimates at an early planning stage. This could help decision-makers compare alternative reconstruction strategies and identify where limited funding could generate the most benefits. Transparency and accountability are essential, too [3]. Mechanisms must enable governments, donors, investors and communities to understand how decisions about billions of dollars of reconstruction were made. An AI-supported system could register the status of each infrastructure asset, the indicators used to assess its priority, the estimated cost of intervention, and the results obtained after the investment. This provides an auditable reconstruction procedure that depends less on informal judgments. But AI should not be presumed to be objectively so [4]. Incorrect evaluations can arise from biases in training data, particularly for poorly documented communities or those in remote areas. Hence, human supervision, independent validation and periodic algorithmic audits are paramount. Developing AI capabilities could also help transform Syria's economy. AI-enabled reconstruction requires specialists in computer science, engineering, remote sensing, GIS, data science, photogrammetry, cybersecurity and infrastructure management. Training Syrian professionals in these fields could create jobs and build a domestic tech industry. The first Syrian AI Forum and the "Million Initiative" show growing efforts to build AI skills and awareness.

The Syria-UAE Hackathon exemplifies cooperation between programmers and institutions to produce technology-based solutions [5]. However, Syria faces considerable obstacles to deploying AI nationally. Data fragmentation is one of the most important obstacles. A variety of ministries, municipalities, humanitarian organizations, engineering firms and international agencies may hold information in incompatible formats [6]. A national reconstruction data standard is therefore vital. Federal agencies should use common definitions of damage types, geographic references, infrastructure classes, and data-sharing protocols. Interoperability would allow organizations to merge information into a single reconstruction platform. Organizations must also consider data privacy and digital sovereignty. Satellite and drone imagery can expose sensitive information about infrastructure and communities. Clear rules should govern how reconstruction data is collected, stored, accessed, shared and protected against cybersecurity threats. Sensitive information must be protected from unapproved access, and legitimate reconstruction partners must have enough information to coordinate effectively [7]. Developing national capacity to oversee critical infrastructure data will decrease dependence on foreign systems and strengthen Syria's digital sovereignty. A phased

implementation strategy would be appropriate. The first phase should focus on establishing a national reconstruction data platform, gathering available satellite and ground imagery, standardizing damage classifications, and developing pilot computer-vision models in heavily affected cities [8].

The second phase could widen the system to national infrastructure networks, combining AI-based prioritization with government investment planning. Phase three may include predictive analytics, automated cost estimating, infrastructure-network modeling, and ongoing tracking of reconstruction progress [9]. International partnerships can assist this process with technical expertise, satellite data, financing and capacity building [10]. Meanwhile, local universities and engineering institutions should help develop and validate models so technologies fit Syrian conditions. Government agencies should set regulatory standards, while private technology companies can offer software development, cloud infrastructure and specialized services. Such cooperation would reduce duplication and create a sustainable national ecosystem for AI-enabled reconstruction [11]. The ultimate goal should not be to build a system that automatically sets priorities for Syria's reconstruction. Rather, AI should be an intelligent analytical layer that helps engineers, policymakers, municipalities, donors, and communities make better-informed decisions. Reconstruction is a social activity that requires human judgment because algorithms do not fully capture social values, political considerations, ethical responsibilities, and community needs. In this way, Syria's reconstruction offers a chance to weave advanced technology into national recovery from the start, rather than tacking it on after traditional systems have been rebuilt. Computer vision can speed up damage assessments, GIS can organize and visualize data, machine learning can aid predictive planning, and multi-criteria decision models can enhance investment prioritization.

Together, these technologies could shift reconstruction from a disjointed, reactive process to a coordinated, evidence-based system [1]. The strategic value of AI ultimately lies in the efficiency and accountability gains it brings to reconstruction investments [2]. Given Syria's enormous needs and limited resources, every reconstruction decision must generate maximum social and economic value [4]. Artificial intelligence can help identify the most severely damaged assets, the facilities that matter most, the cost of delayed intervention, and how to rank projects on transparent criteria. These capabilities could greatly accelerate Syria's recovery when combined with skilled engineers, reliable data, effective institutions and community participation [5]. Artificial intelligence should therefore be considered as a powerful tool to assist reconstruction engineers, not as a replacement. An AI-driven rebuilding framework for Syria could combine satellite imagery, computer vision, engineering assessment, GIS, economic analysis and multi-criteria decision-making into a single evidence-based system. Such an approach would allow Syria not only to rebuild what was destroyed, but also to design infrastructure that is safer, more resilient, more efficient and better adapted to future needs. Thus, successful AI use in reconstruction can provide benefits beyond physical rebuilding, such as building local technological capacity, attracting investment, creating skilled jobs, increasing institutional transparency, and fostering a knowledge-based Syrian economy [3].

2. Review of Literature

2.1. Theoretical Foundations of AI for Disaster and Conflict Assessment

The application of artificial intelligence to disaster and conflict assessment has emerged as a significant field of study over the past decade. The literature draws on multiple disciplinary traditions, including computer vision, remote sensing, machine learning, and humanitarian studies, to understand how AI can support rapid, accurate, and scalable damage assessment. A foundational insight from this literature is that AI can overcome the limitations of traditional damage assessment methods. As Mueller et al. [8] observe, "existing data on building destruction in conflict zones rely on eyewitness reports or manual detection, which makes it generally scarce, incomplete, and potentially biased. AI systems, by contrast, can analyze vast quantities of imagery consistently and quickly, providing more comprehensive and reliable damage data. The literature identifies several key AI techniques for damage assessment. Deep learning, particularly convolutional neural networks (CNNs), has emerged as the dominant approach for image-based damage detection. These models can be trained on labeled datasets of damaged and undamaged structures, enabling accurate classification of new images. Transfer learning—adapting models trained on one dataset to another—has proven particularly valuable for damage assessment, where labeled data may be scarce. The literature also emphasizes the importance of multi-modal data fusion.

By combining satellite imagery, drone footage, ground-based photographs, and other data sources, AI systems can provide a more comprehensive picture of damage. As one study notes, "the integration of AI and IoT" can enable "more effective and faster assessment". Computer vision is a subfield of artificial intelligence that enables computers to analyze and understand visual information. Computer vision has been widely utilized for damage assessment in disaster and conflict-affected environments. Deep learning techniques applied to high-resolution satellite data can detect and classify building damage at scale and support fast, large-scale evaluation. Mueller et al. [8] demonstrated this in the Syrian context, using deep learning with label augmentation and spatial and temporal smoothing to reconstruct damage evolution in the country's major cities. Similarly, the SKAI tool, created by the World Food Program (WFP) and Google Research, applies powerful machine learning techniques to speed up catastrophe damage assessments and enable rapid decision-making. Uncrewed aerial vehicles (UAVs)

outfitted with high-resolution cameras and LiDAR, along with satellite imagery, can provide detailed aerial information and create detailed 3D models of damaged structures. For example, researchers conducted a building damage assessment in Kafr Nabl, Syria, using a DJI Mavic 2 Pro drone to collect aerial imagery over about 12 ha. Drones offer better spatial resolution than satellite imagery and can be deployed quickly in damaged areas to enable detailed assessment of individual structures and structural components.

Ground-based imagery is particularly valuable because it provides close-range visual information that aerial or satellite observations may not capture. Deep-learning-based image classifiers can classify buildings into different damage states, such as intact, damaged and collapsed. Additionally, integrated workflows like the Image-To-Insight approach merge automated 2D image segmentation with 3D photogrammetric point clouds to detect, quantify and visualize diverse types and scales of damage in historic masonry buildings, achieving an overall model test accuracy of around 88%. Sophisticated computer vision methods have also enabled 3D reconstruction of damaged structures, providing useful digital representations for examination, documentation and restoration. 3D scanning technology has been used in projects such as “Re-codifying Post-War Syria” to study structures damaged during conflicts, and virtual reconstruction methods have been developed for culturally significant heritage sites, such as the Great Mosque of Aleppo [21]. To summarise, combining satellite images, UAV images, ground-based images, deep learning, photogrammetry, LiDAR, and 3D reconstruction provides a complete framework for fast, accurate, and scalable damage assessment in areas affected by disaster and conflict.

3. Methodology and Scope

This paper employs a qualitative policy-analysis and conceptual-synthesis methodology, drawing on multiple sources of evidence.

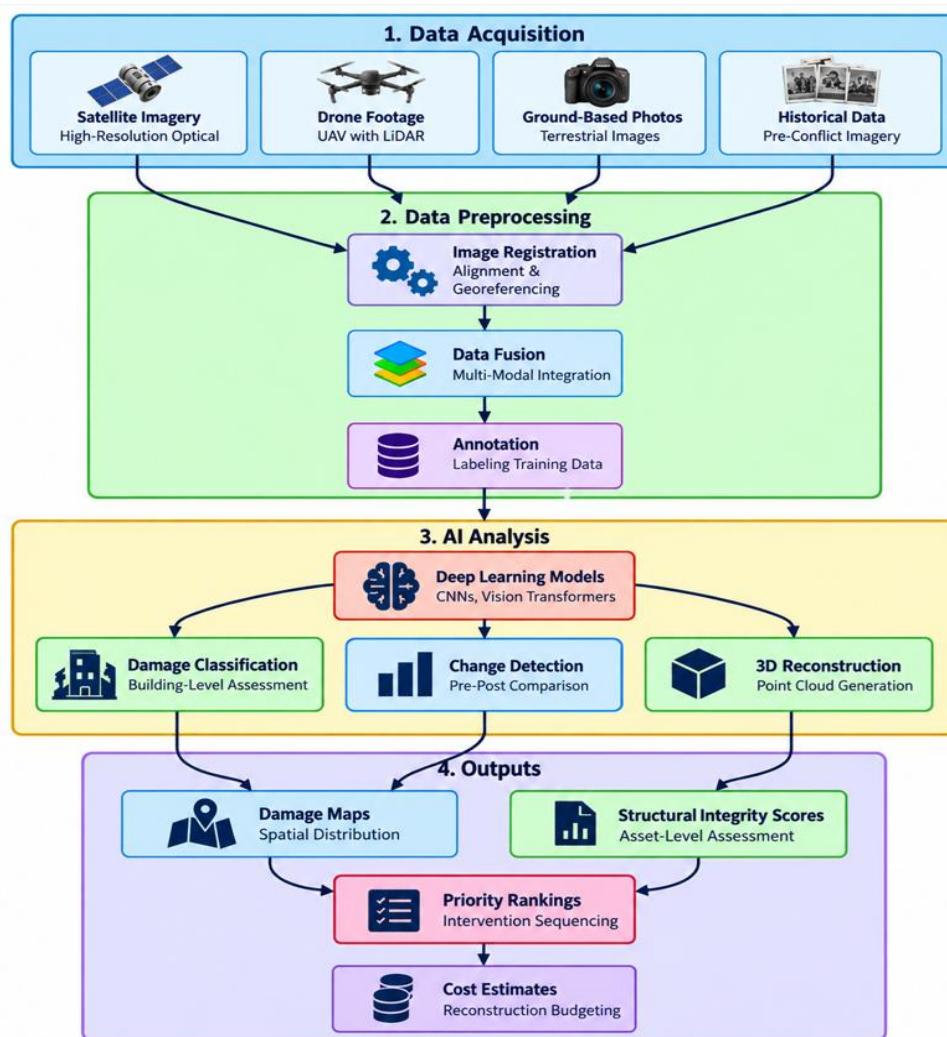


Figure 1: Computer vision pipeline for damage assessment

These include official Syrian government statements and policy documents; reports from international organizations including the United Nations and the World Bank; academic literature on AI, computer vision, post-conflict reconstruction, and decision support systems; industry publications and media reports; and analysis from think tanks and research institutions. The analysis is primarily documentary and interpretive, synthesizing disparate sources into a coherent framework for understanding and guiding AI-enabled reconstruction in Syria. This paper focuses on AI applications for damage assessment and infrastructure prioritization in Syria's reconstruction. While acknowledging the broader applications of AI in reconstruction—including education, healthcare, and governance—the paper focuses specifically on the technical and decision-support dimensions of AI for infrastructure recovery. The temporal scope extends from the political transition of December 2024 through the present, with forward-looking analysis extending to 2030. Figure 1 below illustrates the computer vision pipeline for damage assessment. Figure 1 demonstrates a complete computer vision pipeline for the automated damage assessment of buildings and infrastructure in disaster- and conflict-affected areas. The procedure starts with the data-gathering phase, where data are acquired from multiple sources, including high-quality satellite imagery, drone footage, ground-based photography, and historical pre-conflict images. These varied databases supply information from different perspectives and spatial resolutions.

The data are then processed through image registration and georeferencing to ensure all photos align correctly with their geographic locations. In data fusion, the data integrate information from different imaging sources to generate a more complete representation of affected structures. The datasets are then processed and labeled to produce labeled training data for artificial intelligence algorithms. In the AI analysis stage, deep learning models, including convolutional neural networks (CNNs) and vision transformers, detect and assess structural damage. Damage classification classifies buildings by their state and level of damage. Change detection examines pre- and post-disaster imagery to identify changes in building conditions. Point-cloud creation also generates 3D reconstructions that provide precise three-dimensional representations of damaged structures. These results inform decision-making and disaster-response outputs. Damage maps show the geographical distribution of damaged buildings within the impacted area. Structural integrity scores provide building-level assessments of the severity and condition of specific structures. The data are further integrated to produce priority rankings that help determine the sequence of structures to inspect, repair or reconstruct. Finally, it creates cost estimates to support reconstruction budgeting and resource allocation. To summarise, the pipeline provides an efficient and systematic solution for large-scale building damage assessment by integrating different data sources, preprocessing, artificial intelligence, change detection and 3D reconstruction:

- **AI-Driven Infrastructure Prioritization:** Beyond damage assessment, AI can support the critical task of infrastructure prioritization—determining which structures to repair or rebuild first when resources are scarce. The literature identifies several key approaches.
- **Multi-Criteria Decision Frameworks:** AI-driven multi-criteria decision frameworks integrate technical, economic, and organizational criteria to support prioritization. As one study notes, "post-war reconstruction requires effective decision-support tools capable of integrating technical, economic, and organizational criteria under conditions of high uncertainty". These frameworks enable "systematic prioritization of recovery strategies".
- **AI Diagnostic Layer:** The AI diagnostic layer processes aerial and ground imagery to "quantify each asset's physical condition as a normalized Structural Integrity Score (SIS)". This score provides an objective measure of damage severity that can inform prioritization decisions.
- **Strategic Revitalization Index:** The Strategic Revitalization Index (SRI) provides a composite measure of a building's recovery feasibility, integrating technical, economic, and social criteria. This index can support "the evaluation and prioritization of damaged buildings for recovery interventions".
- **Scenario-Aware Frameworks:** Hybrid decision-support frameworks can integrate multiple models to support prioritization under different scenarios. As one study notes, these frameworks can support "humanitarian response coordinators, shelter cluster leads, local urban planners and other logistical officers" in making prioritization decisions. Table 1 below summarizes key AI techniques for damage assessment and prioritization.

Table 1: AI techniques for damage assessment and infrastructure prioritization

Technique	Application	Data Sources	Key Advantages	Syria Application
Deep Learning (CNNs)	Building damage classification	Satellite, drone, ground imagery	High accuracy, scalable	Mueller et al. [8] - Syrian cities
Vision Transformers	Structural element damage detection	BIM, ground imagery	Instance segmentation	ASCE
SKAI Tool	Rapid disaster damage assessment	Satellite imagery	WFP/Google collaboration	Türkiye-Syria earthquakes
LiDAR + UAV	3D damage reconstruction	Drone point clouds	Precise 3D models	SciEngine - Kafr Nabl

AI-MCDM Framework	Infrastructure prioritization	Aerial/ground imagery + criteria	Transparent, defensible	KFUPM
Strategic Revitalization Index	Building recovery feasibility	Technical, economic, social data	Composite scoring	MDPI
Change Detection	Pre-post event comparison	Multi-temporal imagery	Damage evolution tracking	Mueller et al. [8]

A large body of literature now applies artificial intelligence (AI) to post-conflict rebuilding, producing key case studies with helpful lessons for Syria. Mueller et al. [8] show how deep learning can use satellite data to automate damage assessment in large Syrian cities. They combined label augmentation with spatial and temporal smoothing to reconstruct damage evolution over time. More recently, a drone-based study in Kafr Nabl showed how UAVs, modern imaging systems, and LiDAR technologies may be used for detailed three-dimensional damage reconstruction. The 2023 Türkiye-Syria earthquakes also served as an important test case for AI-based damage assessment. The SKAI tool, developed by the World Food Program (WFP) in partnership with Google Research, was critical to enabling rapid damage assessments, thereby speeding up and simplifying humanitarian assistance. Furthermore, vision foundation models have shown promising performance in building damage mapping across various geographical regions. In Ukraine, the Urban Recovery Planning System (URPS) – a collaborative project between the United Nations Innovation Technology Accelerator for Cities (UNITAC) and others – is an open-source spatial decision-support platform capable of visualizing and analyzing datasets across several sectors. This shows the potential of open-source spatial systems to enable post-conflict recovery planning. Similarly, the Smart Sustainable City Baghdad effort in Iraq presents a multi-sectorial framework for urban transformation in fragile and conflict-affected areas by integrating real-time analytics and decision-support technologies across critical urban sectors.

But AI in post-conflict reconstruction confronts several key hurdles. One major limitation is limited data. AI models typically need large, well-labeled datasets for training, but conflict-affected areas often lack reliable, comprehensive data. Mueller et al. [8] addressed this problem through label augmentation, which helped expand the number of accessible training examples. Another key challenge is data quality, as differences in image resolution, cloud cover, lighting conditions and acquisition methods can greatly affect damage-detection accuracy. Bias and fairness are further issues that must be addressed, since AI models might replicate or amplify biases in their training data. Hence, representative datasets and well-founded model development techniques are critical to achieving equitable and inclusive outcomes. Another problem is interpretability, particularly when powerful AI models function as black boxes, making it impossible for planners, engineers and affected people to understand or validate their conclusions. Therefore, transparent and explainable artificial intelligence systems are vital to build confidence in AI-assisted reconstruction. Capacity restrictions are also a big challenge, as countries emerging from conflict may lack the technical competence and institutional capacity to build, deploy and manage advanced artificial intelligence (AI) systems. Ethical issues, including privacy, surveillance, data ownership, and digital sovereignty, also require appropriate governance structures to enable the responsible deployment of artificial intelligence (AI) technologies.

However, the literature still has shortcomings, despite significant growth in research on AI-based damage assessment and reconstruction. Although war environments can involve varied damage patterns, prolonged instability, and limited data availability, much of the research still focuses on natural disasters. Furthermore, relatively little research examines how standard artificial intelligence can be integrated into broader governance frameworks for restoration. The implications of AI for post-conflict state-building, institutional legitimacy, public involvement and trust are similarly underexplored. Most current research focuses on technical performance. Social, political, ethical and institutional aspects of AI adoption are comparably rarely explored. Addressing these gaps is essential to developing standard artificial intelligence systems that are not only technically competent but also socially responsible and appropriate for complex post-conflict contexts such as Syria. Several AI-enabled damage-assessment efforts have either been deployed or are under development in Syria. One of the most essential uses is damage detection using satellite-based systems. Mueller et al. [8] used high-resolution satellite data to reconstruct the evolution of destruction in major Syrian cities using deep-learning methods combined with label augmentation and spatial and temporal smoothing. This technique could enable ongoing surveillance during reconstruction by detecting newly damaged locations, monitoring recovery, and delivering updated information to decision-makers. Another key application is UAV assessment. A DJI Mavic 2 Pro drone was deployed in Kafr Nabl to capture aerial imagery over approximately 12 hectares.

Advanced imaging technologies and LiDAR technology were used to create detailed three-dimensional representations for damage assessment. Drones can provide much higher-resolution local information than satellite photography and are therefore valuable for analyzing specific structures and infrastructure. Another major development in Syria is the CoordiMap project, which uses artificial intelligence, machine learning, and satellite imagery to extract structures, roads, and infrastructure automatically; classify damage levels; produce confidence scores; and detect changes between pre-event and post-event images. These skills show how artificial intelligence can move from a system that merely identifies damage to a full system for rebuilding information. Similarly, WFP and Google Research used SKAI during the Türkiye-Syria earthquakes to provide rapid damage assessments and support humanitarian relief, showcasing AI's promise in complex disaster settings. Syria has also

begun work on projects to improve its AI capabilities, technological innovation and damage assessment. Both the Syrian AI Forum and the Million Initiative focus on building AI literacy through training coaches and reaching a large number of AI users. The program was launched during the second Syrian AI Olympiad and is part of efforts to build a wider base of AI expertise in Syrian society, the statement added. Syria has also launched Tech Town in Damascus as an innovation hub designed to support startups, foster the digital economy and speed up digital transformation. Artificial intelligence, cybersecurity and virtual reality laboratories are specialized spaces within the complex that will provide a home for technological development and experimentation.

Programmers also met at the Syria-UAE Hackathon, sponsored by the Syrian Programmer Empowerment Program in conjunction with the SyrDevUae community, to explore AI-based technical solutions for reconstruction challenges. The Regional Conference on AI and Entrepreneurship in Damascus also highlighted growing interest in applying AI to sustainable development. Negotiations are also underway to transfer and localize advanced artificial intelligence (AI) technologies, indicating Syria's expanding engagement with international technological partners. International partnerships are also underway. Less established than damage assessment, AI-based infrastructure prioritization in Syria is supported by several efforts that pave the way for future uses. For example, the Greater Aleppo Vision Program aims at developing a participatory vision for urban growth. It uses spatial information and participatory planning methods that might be combined with AI-based prioritization algorithms. The Damascus 2040 Smart City Project also presents an integrated framework for sustainable urban recovery in a post-conflict setting, while using AI and Internet of Things (IoT) technology. KFUPM's AI-based multi-criteria decision-making system could set a new standard for Syria. This architecture integrates an AI diagnostic layer with a multi-criteria decision-making layer for robust and people-centered prioritization. Such an approach would allow Syrian authorities and reconstruction organizations to assess damaged infrastructure against numerous criteria, including structural condition, population needs, economic relevance, accessibility and possible social impact.

However, major structural hurdles limit Syria's capacity to scale up deployment of these technologies. "Damaged electricity networks and poor internet connection make it difficult to deploy computationally intensive artificial intelligence (AI) systems, especially in rural and severely impacted regions." There is also a dearth of specialized human resources such as data scientists, machine-learning engineers, and computer-vision professionals. The conflict's disruption of the education system has further reduced technical capacity. Another major challenge is the lack of data. Comprehensive, uniformly tagged datasets are scarce, and damaged data is scattered across several institutions and platforms. International organizations, domestic institutions, technology businesses, and research groups also need to coordinate, because fragmented efforts can lead to redundancy, inefficiency, and missed collaboration opportunities. Moreover, Syria needs stronger governance structures for data protection, algorithmic transparency, accountability and responsible AI use. Law No. 12 of 2024 on electronic personal data protection lays a basis for data governance. Still, more AI-specific rules and institutional procedures are needed to address the unique hazards of automated decision-making. From a technological perspective, AI-based damage assessment starts with collecting and fusing credible data from different sources. High-resolution satellite imagery also offers wide geographical coverage and can often be acquired retroactively, which is especially helpful when comparing pre- and post-damage conditions. Commercial satellite providers such as Maxar and Planet can provide imagery at resolutions ranging approximately from 0.3 to 3 meters.

Historical satellite imagery can reveal baseline conditions before conflict-related destruction. UAV imagery can be captured quickly over targeted damaged areas and provides much higher spatial resolution. Drones can also be equipped with LiDAR sensors to produce detailed 3D models of buildings and infrastructure. Ground-based images also provide additional street-level information and may reveal damage not obvious from aerial or satellite imagery. Historical architectural data, municipal data and pre-conflict images can further support the evaluation process and provide reference data for the original state of buildings and infrastructure. These datasets can subsequently be processed through several AI modeling methodologies. Convolutional Neural Networks (CNNs) remain among the most popular techniques for image-based damage classification because they can learn hierarchical visual features and distinguish damaged from undamaged structures. Another promising technique is Vision Transformers (ViTs), especially for tasks that require stronger spatial and contextual links. Recent studies have merged vision transformers for image classification with instance-segmentation frameworks such as Detectron2 to identify structural damage more accurately. Change-detection algorithms offer another key capability by comparing pre-event and post-event photos to identify newly damaged buildings and changes over time. These models can support emergency evaluation and long-term rebuilding monitoring.

3D reconstruction techniques that combine automated 2D image segmentation with 3D photogrammetric point clouds can further improve damage assessment. Different types and amounts of damage can be recognized, measured and visualized. Finally, AI-based damage assessment may classify structures by severity level. The most straightforward method is binary classification identifying damaged and undamaged structures. A more detailed multi-class technique can classify buildings as no damage, minor damage, moderate damage, severe damage or full collapse and is therefore more relevant for rebuilding priority. Alternatively, a Structural Integrity Score (SIS) can provide a continuous numerical representation of an asset's physical condition. The KFUPM framework shows how aerial and ground-level images are processed to estimate a normalized

SIS for individual assets. Incorporating these categorization approaches with spatial data, demographic data, infrastructure relevance, accessibility and socio-economic factors may give a comprehensive AI-based decision framework for post-conflict reconstruction in Syria. Such an integrated strategy would enable decision-makers to move from identifying damaged structures to methodically assessing their condition, selecting reconstruction priorities, tracking rehabilitation progress and allocating scarce resources more effectively (Table 2).

Table 2: Damage classification schemes for AI assessment

Scheme	Categories	Application	Advantages	Limitations
Binary	Damaged / Undamaged	Rapid screening	Simple, fast	Limited information
Multi-Class	None / Minor / Moderate / Severe / Collapsed	Detailed assessment	More information	Subjectivity in categories
Structural Integrity Score	Continuous (0-100)	Prioritization	Objective, granular	Requires calibration
Strategic Revitalization Index	Composite score	Recovery feasibility	Integrates multiple criteria	Complex to compute

Validation and accuracy are essential components of AI-based damage assessment because they determine whether an AI model's results are reliable enough to support reconstruction planning and decision-making. AI damage assessment models should be validated against ground truth data, meaning damage information collected and verified by human experts through field inspections. Ground truth data provides a reference for comparing AI predictions. However, obtaining such data can be difficult in conflict-affected areas because of security risks, limited accessibility, damaged infrastructure, and a lack of trained personnel.

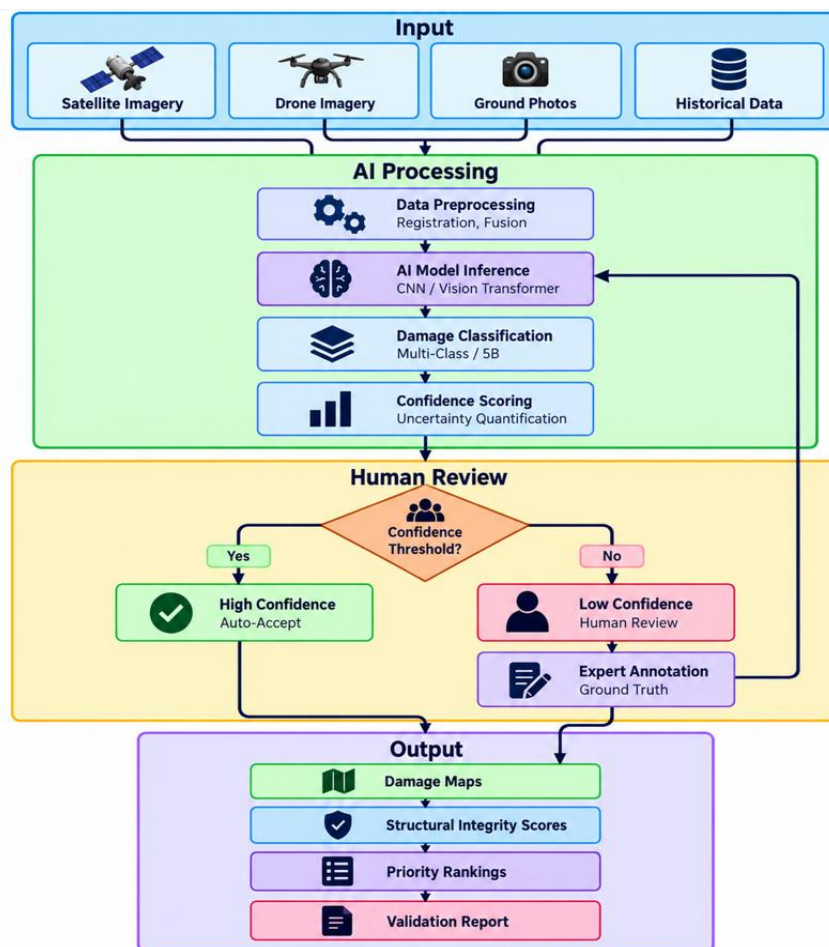


Figure 2: Damage assessment workflow with AI and human review

Cross-validation across multiple datasets is also important to determine whether a model performs reliably across locations and environmental conditions. For example, the vision foundation model study based on the 2023 Türkiye-Syria earthquake dataset evaluated model performance using Leave-One-Domain-Out (LODO) and Specific Source Domain Combination (SSDC) settings, helping to examine the model's ability to generalize across different geographic and data domains. Model performance can be evaluated using several accuracy metrics, including precision, recall, F1-score, and overall accuracy. Precision indicates how accurately the model identifies actual damaged structures among its damage predictions, while recall measures its ability to detect present damaged structures. The F1-score provides a balanced measure of precision and recall, particularly when the dataset contains unequal numbers of damaged and undamaged structures. Overall accuracy provides the proportion of correctly classified cases across the complete dataset. The Image-To-Insight workflow, for example, reported an overall model test accuracy of 88%, demonstrating the potential of AI-based image analysis for automated damage identification. However, high numerical accuracy alone does not guarantee reliable results in real-world reconstruction environments, and models should also be tested for robustness, uncertainty, and performance across different building types and damage conditions (Figure 3).

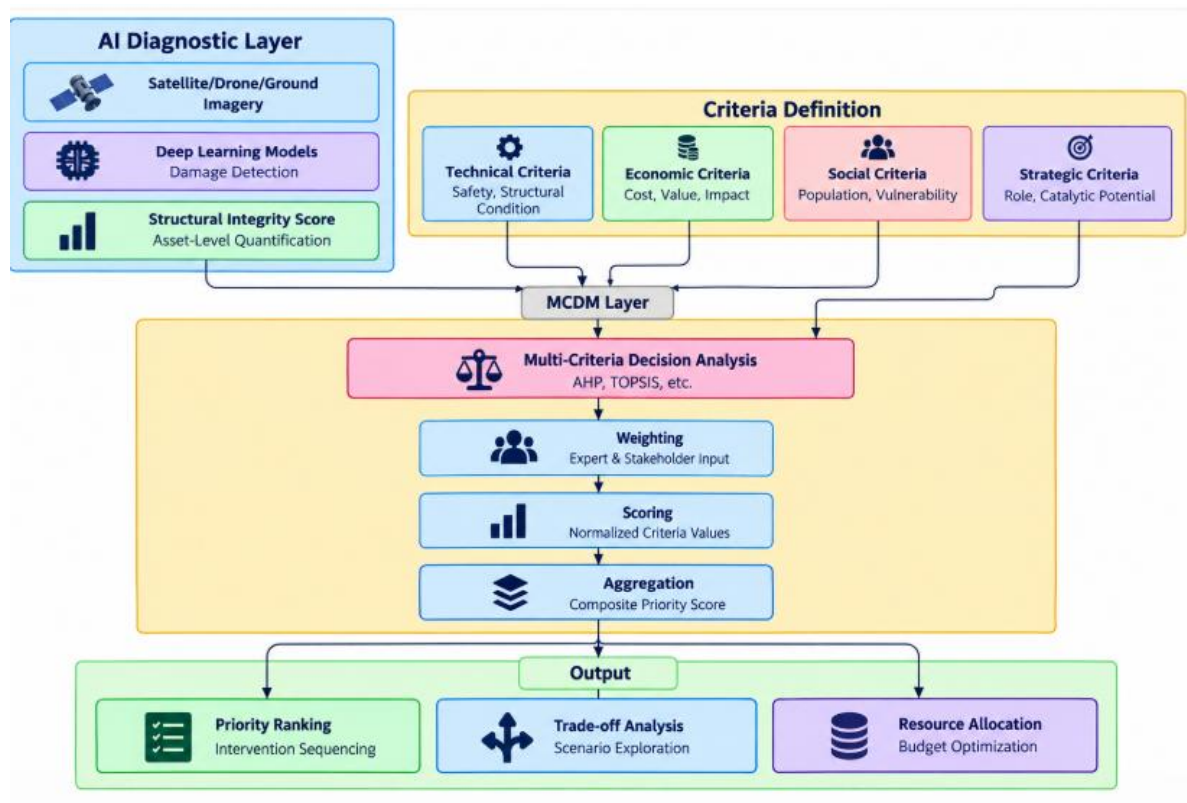


Figure 3: AI-MCDM infrastructure prioritization framework

Human-in-the-loop validation can further improve reliability by combining automated AI predictions with expert review. In this approach, AI systems can rapidly analyze large volumes of imagery and identify potentially damaged areas, while human experts verify uncertain or high-risk predictions. The system can also assign confidence scores and direct expert attention toward locations where the model is less certain. This combination of automated analysis and human judgment can reduce errors, make better use of limited expert resources, and increase confidence in AI-assisted reconstruction decisions. Figure 2 below illustrates the damage assessment workflow with AI and human review. After a conflict, the reconstruction process demands open, systematic and defensible judgments about which damaged structures to repair or rebuild first. This is especially true when the number of destroyed buildings is vast, and the available financial, technical and human resources are limited.

The prioritization procedure should consider several dimensions, not only the physical severity of the damage. Technical criteria include each structure's structural condition, the extent of damage and its integrity and safety. Economic factors include repair and reconstruction costs, the structure's economic value, and potential economic benefits from restoration. Social factors include the number of individuals affected, the vulnerability of local populations, and the building's social relevance. Strategic criteria include a structure's value in broader reconstruction plans, its importance to key services, and its ability to support or accelerate further recovery. The KFUPM 2025 study could serve as a model for applying this method in Syria through an AI-based multi-criteria decision-making (AI-MCDM) approach.

The framework has an AI diagnostic layer and an MCDM layer that work together to generate evidence-based infrastructure priorities. The AI diagnostic layer processes aerial and ground-based data to determine the physical status of specific assets using a normalized Structural Integrity Score (SIS). This enables an objective, data-driven appraisal of structural deterioration and reduces reliance on subjective visual judgment. The MCDM layer then integrates the SIS with other economic, social, and strategic parameters to produce priority rankings. The framework combines these dimensions to help decision-makers quantify damage objectively, merge multiple criteria into a single prioritization system, consider trade-offs among competing needs, and develop transparent, defensible rankings of reconstruction interventions. This is especially true for Syria, where rehabilitation resources are likely to be scarce, and decisions will need to balance structural safety with social demands, economic recovery and strategic development goals. Another way to assess the feasibility and priority of recovery of damaged structures is the Strategic Revitalization Index (SRI). The SRI is a composite indicator that includes technical, economic, social, and strategic factors, not only the severity of the harm. Technical feasibility reflects the structure's current condition and the technical difficulty of repair or rebuilding. Economic feasibility assesses the estimated cost of repairs against the building's value and the economic benefits expected from its restoration. Social feasibility evaluates the building's relevance to the surrounding community, the number of people affected by its condition, and those communities' vulnerability. Strategic feasibility considers the building's contribution to broader rebuilding objectives and its ability to trigger further recovery in the surrounding areas. Thus, the SRI enables systematic comparison of damaged buildings and can help assess and prioritize recovery actions.

AI-enabled infrastructure decision-making can also be improved through scenario-based prioritization, which lets planners review multiple rebuilding scenarios, assumptions and resource constraints. Scenario-aware systems can, rather than providing a single fixed priority rating, incorporate numerous information and analytical models to analyze alternate situations. For example, one situation may focus more on structural safety, while another may focus more on essential public services, economic recovery or severely vulnerable people. Such frameworks can help to assess competing rebuilding needs for humanitarian response coordinators, shelter-sector heads, local urban planners and logistics officers. Sensitivity analysis can identify which criteria most influence the final ranking and how changes in assumptions alter the results. Visualization tools can then show trade-offs, alternative priorities and possible repercussions in an understandable way. Thus, combining AI-based damage assessment, MCDM, SRI-based assessment, and scenario analysis can provide a comprehensive decision-support framework for post-conflict infrastructure prioritization in Syria, allowing authorities and reconstruction organizations to direct limited resources to interventions with the greatest technical, economic, social and strategic benefits—an Integrated AI-Enabled Reconstruction Framework for Syria. Building on the analysis above, an integrated AI-enabled reconstruction framework for Syria is organized around three interconnected pillars: rapid damage assessment, evidence-based infrastructure prioritization, and capacity building for sustainable AI adoption. Figure 4 illustrates this integrated framework.

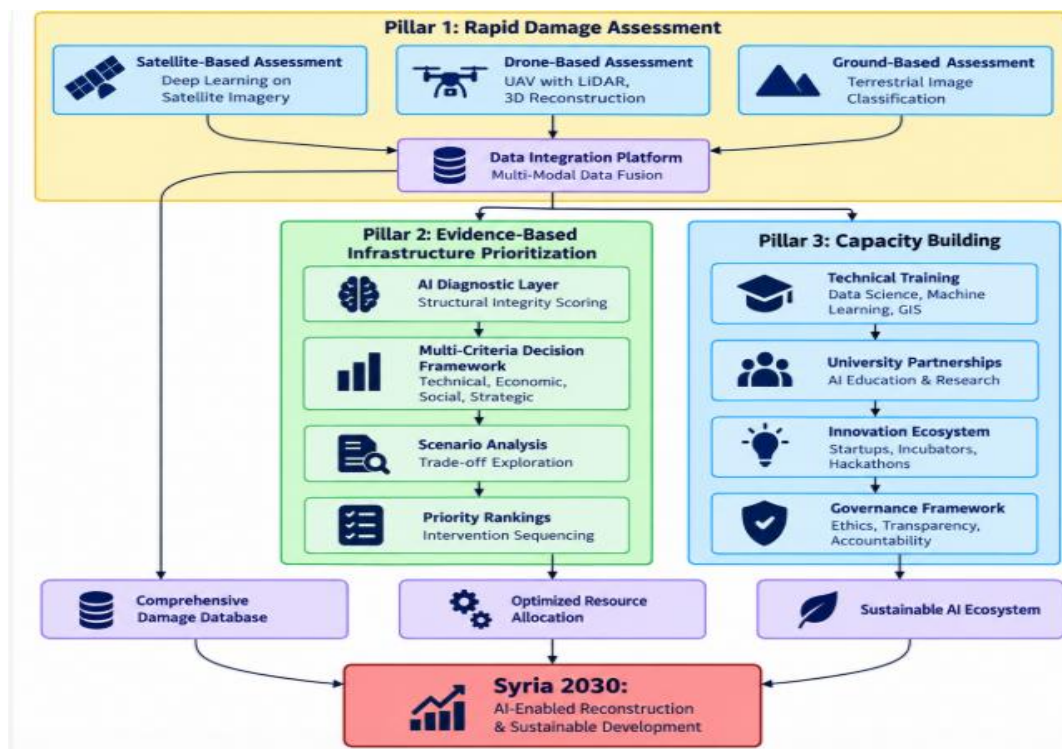


Figure 4: Integrated AI-enabled reconstruction framework for Syria

The proposed AI-driven restoration strategy for Syria can be structured around three interrelated pillars: rapid damage assessment, evidence-based infrastructure prioritization, and capacity building for sustained AI implementation. The first pillar is establishing a comprehensive, continuously updated knowledge base on conflict-related damage. Between 2025 and 2027, satellite-based evaluation can be accomplished using deep-learning models applied to high-resolution satellite images, building on the approach presented by Mueller et al. [8] and the SKAI tool. The main purpose would be to create a baseline damage record of the impacted locations in Syria. From 2026 to 2028, drone-based evaluation can supplement satellite analysis by deploying UAVs equipped with modern imaging systems and LiDAR to conduct detailed, localized assessments. The Kafr Nabl case shows that teams can prioritize dense urban areas and critical infrastructure. During 2027-2028, ground-based imagery and field surveys can validate and improve aerial assessments. Deep-learning classifiers can classify damage visible at ground level. At the same time, a universal data integration platform can integrate satellite, drone and ground-based information. Through multi-modal data fusion, this platform would offer a more holistic view of the damage and improve the trustworthiness of information available to reconstruction planners.

The second pillar is evidence-based infrastructure prioritization, ensuring limited rebuilding resources are allocated to the assets of greatest technical, economic, social and strategic relevance. An AI-based diagnostic layer will be developed between 2025 and 2027 to analyse aerial and ground imagery and assess the physical condition of individual assets through a Structural Integrity Score (SIS), adapting the 2025 KFUPM architecture to the Syrian context. This diagnostic information can be included in a multi-criteria decision-making framework that considers technical condition, reconstruction costs, economic value, population demands, social vulnerability and strategic importance for the period 2027-2028. Stakeholder input should be built into the process of formulating criteria and assigning weights so that resulting priorities match local needs and reconstruction aims. Scenario-analysis capabilities can be developed between 2028 and 2029, allowing planners to examine multiple reconstruction scenarios, resource constraints, and assumptions. This would help decision-makers understand trade-offs and uncertainties, rather than relying on a single, fixed prioritization model. By 2029–2030, the system can produce transparent, defensible infrastructure priority rankings that can inform resource allocation and reconstruction sequencing. Such a platform would translate AI-derived damage information into actionable decisions on where, when and how to deploy reconstruction resources.

The third pillar is to build the local competencies needed to sustain AI use beyond individual projects or foreign donor funding. Technical training programs in 2025-2027 can focus on data science, machine learning, computer vision, and geographic information systems (GIS). These programs can expand on projects like the Million Initiative and the Syrian AI Olympiad. Partnerships with overseas academic institutions, technology groups, and the private sector can provide additional technical expertise and training opportunities. From 2027 to 2028, university partnerships can boost AI teaching and research, develop specialist curricula in artificial intelligence and data science, and build on current cooperation, including with Syrian universities. Support for companies, incubators, research programs, innovation centers and hackathons can help establish an AI innovation ecosystem between 2028 and 2030. Syria can build this ecosystem through existing initiatives like Tech Town and the Syria-UAE Hackathon. Meanwhile, Syria should develop a complete AI governance framework addressing ethics, transparency, accountability, data protection, and responsible use from 2025 to 2028. This framework can build on Law No. 12 of 2024 on electronic personal data protection by adding relevant international best practices and AI-specific protections. Several cross-cutting concepts should guide the implementation process across all three pillars. Transparency and accountability are particularly crucial because AI-generated assessments and infrastructure priorities may shape major rebuilding decisions and the allocation of public resources.

Decision-makers, affected communities and other relevant stakeholders need to understand how standard AI systems produce outputs, using strategies such as explainable AI and clear disclosure of the methodologies employed, to build confidence in the system. Inclusion is equally vital, and AI systems should be built to benefit communities across disparate geographical regions and socio-economic conditions without systematically excluding disadvantaged or marginalized groups. This requires collecting representative data and actively involving local people and stakeholders in the prioritization process. Data sovereignty should also be preserved by retaining strategically critical data sets under appropriate Syrian control and through data-management arrangements that protect national interests, privacy and security. The system should integrate human-in-the-loop techniques to ensure the AI complements human judgment rather than replacing it. Trained specialists should check automated outputs, particularly in cases where judgments concern structural safety, key infrastructure, displacement or large public resources. Finally, consider sustainability early in system design. AI platforms must be continually maintained, models updated, data managed, technical support provided, and institutional ownership established. As such, building local capacity and ensuring sustainable finance and governance structures will be crucial to support Syria's ability to sustain and enhance its AI capacities over the long term, without becoming perpetually dependent on external technical support.

4. Results

4.1. Summary of Findings

Artificial Intelligence to Assess Damage and Prioritize Infrastructure in Syria. The findings suggest that Artificial Intelligence (AI), including computer vision, machine learning, satellite remote sensing, and multi-criteria decision-making (MCDM), can provide a feasible framework for post-conflict damage assessment and infrastructure prioritization in Syria. Mueller et al. [8] have previously shown that deep-learning approaches applied to repetitive high-resolution satellite data can detect war-related building destruction and reconstruct the evolution of damage in major Syrian cities. They combined spatial and temporal information to improve automated classification, showing that artificial intelligence can produce damage information at a much larger scale and more frequently than traditional manual assessment. The first key discovery is that standard artificial intelligence can dramatically increase the speed and spatial coverage of damage assessment. Broad screening of damaged urban areas can be done using satellite photography. At the same time, drone imagery can provide more detailed information on selected buildings, roads, bridges, utilities and public infrastructure. Therefore, the suggested workflow uses satellite data for initial assessment and UAV data for high-resolution verification. This combination is important in post-conflict circumstances where physical access may be challenging, hazardous, or time-consuming. AI-generated outputs can highlight locations that need urgent inspection and reduce the amount of territory that needs to be examined manually at first. The second observation is that damage classification alone is not enough for rebuilding planning. A badly damaged structure may not be the most important asset if it serves a tiny population. In contrast, a somewhat damaged hospital, water facility, school or transport connection may have far higher social importance. Hence, the proposed framework considers damage severity, population vulnerability, infrastructure criticality, accessibility and reconstruction cost. This leads to a more open, people-centered ranking of reconstruction needs. The following proposed equation can be used to determine a priority score:

$$P_i = w_D D_i + w_V V_i + w_C C_i + w_A A_i - w_K K_i \quad (1)$$

where P_i = priority score for infrastructure asset i ; D_i = damage severity; V_i = population vulnerability; C_i = infrastructure criticality; A_i = accessibility or connectivity benefit K_i = anticipated rebuilding cost $w_1 - w_5$ = normalized weights. This equation is a suggested decision-support formulation and must be calibrated with Syria-specific data before operational use. A second metric might characterize the percentage of badly damaged assets within a specific evaluation area:

$$DR = \left(\frac{N_r}{N_t} \right) \times 100\% \quad (2)$$

DR is the ratio of severe damage; N_s is the number of severely damaged or destroyed assets, and N_t is the total number of assets assessed. The indicator can be updated with new satellite or UAV imagery as it becomes available (Table 3).

Table 3. Results of the proposed AI-based assessment framework

Component	Result	Reconstruction Use	Limitation
Satellite AI assessment	Rapid large-area damage classification	Identify affected zones and initial priorities	Image resolution, clouds and model uncertainty
UAV/drone assessment	Detailed local condition information	Verify priority structures and infrastructure	Coverage and access constraints
Damage database	Georeferenced, updatable inventory	Common evidence base for agencies	Requires standardized data
AI-MCDM prioritization	Ranked intervention priorities	Support transparent resource allocation	Sensitive to criteria and weights
Field validation	Correction and confirmation of AI outputs	Improve reliability of decisions	Time, cost and security requirements

5. Discussions

The results reveal that the main advantage of AI is not the automatic recognition of images per se, but the capacity to connect different forms of information in a single reconstruction judgment process. Damage maps can be coupled with population, road connections, health and education facilities, water and electricity networks and socio-economic vulnerabilities (Table 4).

Table 4: Challenges and recommended responses

Challenge	Effect on Results	Recommended Response
Incomplete datasets	Reduced model reliability	Standardized georeferenced database and quality control
Limited computing/connectivity	Slower processing and reduced availability	Resilient cloud/edge processing infrastructure

Skills shortage	Dependence on external specialists	Training in AI, GIS, remote sensing and engineering
Model uncertainty	Incorrect classification or ranking	Confidence scores, field validation and human review
Changing conditions	Outdated priority rankings	Periodic imagery and dynamic model updates
Data governance risks	Potential misuse of sensitive information	Access control, ethical review and clear governance

This avoids prioritizing projects based only on observable physical destruction and instead supports judgments based on both damage and human need. The framework also identifies major shortcomings. AI forecasts can also produce false positives and false negatives, especially when footage is poor or destruction is hard to distinguish from typical urban change. High-priority judgments should therefore include confidence scores and human validation. Despite this, field engineers and humanitarian specialists are still needed to classify observed structures as technically unsafe, socially critical or repairable.



Figure 5: AI-based damage assessment workflow

Other limitations are data availability and infrastructure. Inconsistent datasets, missing historical imagery, insufficient computing resources, inconsistent connectivity, and a lack of experienced AI and GIS specialists can degrade system performance. A sustainable Syrian AI reconstruction system should therefore comprise standardized geographic databases, local technical training, shared data standards and continual model evaluation. The result is a three-tier decision system: quick satellite screening, in-depth UAV/field validation, and AI-MCDM prioritization. Figure 5 demonstrates the path from imaging to confirmed damage information, and Figure 2 shows how various criteria can be combined to produce prioritized reconstruction priorities. The framework supports decision-making and does not replace engineering judgment or community input. Figure 5. Proposed procedure to turn satellite and UAV data into validated AI-based damage information.

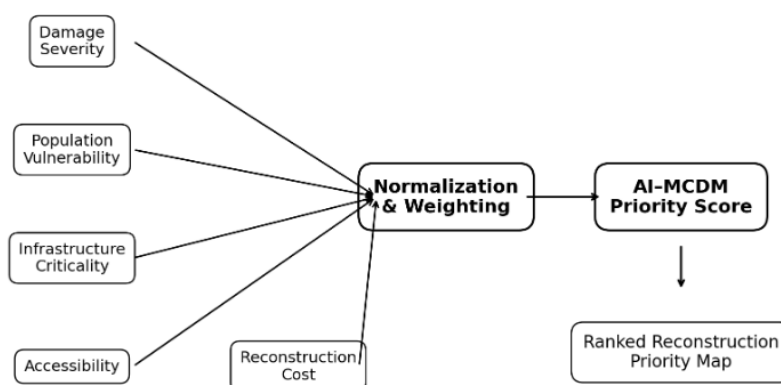


Figure 6: AI-MCDM infrastructure prioritization framework

Figure 6. Proposed framework for transforming damage, vulnerability, criticality, accessibility and cost indicators into reconstruction priorities. Note: These two drawings are original schematic designs drawn for this paper to explain the suggested framework.

6. Conclusion

Syria's AI-enabled reconstruction represents both an immense challenge and an unprecedented opportunity. The challenge lies in the scale of destruction, the depth of institutional weakness, the severity of financial constraints, and the complexity of the coordination environment. The opportunity lies in the potential to leapfrog traditional development pathways, to build a more efficient, transparent, and inclusive reconstruction process, and to position Syria as a leader in AI adoption in the region. The foundation for this transformation is being laid. Syria has demonstrated AI-enabled damage assessment tools. The SKAI tool has been applied to the Türkiye-Syria earthquakes. The Coordi Map project is operationalizing AI for damage assessment in

Syria. The Syrian AI Forum, Million Initiative, and Tech Town are building AI capacity. The UNDP's \$1.3 billion package includes support for AI adoption. However, technology alone is insufficient. As one observer notes, "reconstruction in the 21st century is no longer merely a battle of cement and iron—at its core, it has become a battle of data." AI is a powerful tool in this battle, but its success depends on governance quality, the depth of human capital, and the inclusiveness of the transformation process. The path forward requires strategic sequencing, careful attention to governance and ethics, and a commitment to learning from both successes and failures in other contexts. The integrated framework proposed in this paper—addressing rapid damage assessment, evidence-based infrastructure prioritization, and capacity building—offers a roadmap for this transformation. Syria's AI-enabled reconstruction is not merely about technology; it is about rebuilding the social contract between state and citizen, about creating opportunities for a generation that has known only conflict, and about re-establishing Syria's place in the regional and global economy. The stakes could not be higher. The opportunity, however, is real.

6.1. Recommendations

Based on the analysis, the following recommendations are offered for Syria's AI-enabled reconstruction:

- **Establish a National AI-Enabled Damage Assessment System:** Syria should establish a national AI-enabled damage assessment system that integrates satellite, drone, and ground-based data. The system should build on existing initiatives, including the CoordiMap project, the SKAI tool, and the Mueller et al. [8] approach. The system should provide comprehensive, up-to-date damage data for all affected areas.
- **Adopt AI-Driven Infrastructure Prioritization Frameworks:** Syria should adopt AI-driven multi-criteria decision frameworks for infrastructure prioritization. Syria can take lessons from the 2025 KFUPM framework. The framework should be developed through inclusive stakeholder engagement and include technical, economic, social and strategic criteria.
- **Invest in Drone-Based Assessment Capabilities:** Syria should invest in drone-based assessment capabilities, including UAVs with advanced imaging systems and LiDAR. The 2026 Kafr Nabl study published in SciEngine is a strong example of how this approach can support detailed, localised damage mapping.
- **Build Local AI Capacity:** Syria should invest in local AI capacity through technical training, university partnerships, and innovation ecosystems. The Million Initiative, Syrian AI Olympiad, and Tech Town provide foundations that should be expanded. Syria should strengthen partnerships with international institutions and the private sector.
- **Develop a Comprehensive AI Governance Framework:** Syria should develop a comprehensive AI governance framework that addresses ethics, transparency, accountability, and data protection. The framework should build on Law No. 12 of 2024 and international best practices. It should ensure that AI systems are transparent, accountable, and inclusive.
- **Ensure Data Sovereignty and Protection:** AI systems must respect Syria's digital sovereignty. Data should remain under Syrian control, and AI systems should be developed or adapted to serve Syrian interests. Ensure data protection and privacy.
- **Adopt a Phased Approach:** AI-enabled reconstruction should be phased strategically, balancing immediate needs with long-term vision. The phased framework proposed in this paper provides a roadmap.
- **Foster International Partnerships:** International partnerships can provide access to technology, expertise, and financing. Syria should foster partnerships with international organizations, technology companies, and research institutions. The UNDP's \$1.3 billion package and the Saudi-Syrian smart city agreement provide models.
- **Ensure Inclusion:** AI systems must be designed to include all Syrians, with particular attention to marginalized populations. Inclusive stakeholder engagement in prioritization is essential to ensure reconstruction serves all segments of the population.
- **Monitor and Evaluate Progress:** AI-enabled reconstruction requires ongoing monitoring and evaluation. Syria should develop indicators to track progress across the three pillars—damage assessment, prioritization, and capacity building—and use these indicators to inform policy decisions.

6.2. Limitations and Future Research

This paper has several limitations. The analysis is based on publicly available sources and may not capture all relevant developments, particularly those not reported in international media. Syria's rapidly changing political and economic situation means some findings may quickly become dated. The paper focuses primarily on technical and decision-support dimensions and does not fully explore the social, political, and ethical dimensions of AI adoption in post-conflict reconstruction. Future research should address these gaps. Specific areas for future investigation include: the social and political implications of AI-enabled reconstruction; the ethical dimensions of AI in post-conflict settings; the role of AI in supporting transitional justice and reconciliation; the gender dimensions of AI adoption; and comparative analysis of AI-enabled reconstruction across post-conflict settings.

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