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Robotics and AI in Disaster Recovery: Autonomous Assessment, Infrastructure Inspection and Emergency Logistics

Natt Leelawat

Assistant Professor, Chulalongkorn University, Thailand

Abstract

Disaster recovery depends on timely situational assessment, safe infrastructure inspection, reliable communication, and equitable delivery of emergency supplies. Conventional recovery operations are often constrained by damaged roads, unstable structures, hazardous materials, disrupted communication, incomplete information, and continuing environmental threats. Robotics and artificial intelligence can strengthen these operations through aerial mapping, ground-based inspection, automated damage recognition, structural monitoring, route optimization, and last-mile logistics. This paper develops an integrated framework for applying robotics and AI across post-disaster assessment, infrastructure inspection, and emergency distribution.

A conceptual and simulation-based methodology compares initial damage-assessment completion times under conventional and robotics–AI-integrated configurations. Forty-eight illustrative incident observations are modeled, with twenty-four observations in each configuration. Conventional assessment records a simulated mean completion time of 13.7 hours, compared with 5.4 hours for the integrated configuration, representing an illustrative reduction of 60.5%. These values are not operational evidence and do not support causal inference.

The analysis indicates that autonomous systems may accelerate data collection, but their effectiveness depends on validated sensing, interoperable information, human command authority, communication resilience, cybersecurity, community knowledge, and transparent prioritization. The study proposes a staged deployment model combining mission definition, technology verification, supervised field operation, multi-source data fusion, accountable decision-making, and post-mission evaluation. It concludes that robotics and AI should extend the reach and safety of emergency personnel rather than operate as unaccountable substitutes for human judgment.

Keywords: disaster robotics, artificial intelligence, damage assessment, infrastructure inspection, emergency logistics, unmanned aerial systems, humanitarian response, resilient recovery.

1. Introduction

Disasters disrupt the physical, institutional, social, and economic systems on which communities depend. Earthquakes can damage buildings, bridges, roads, water networks, and energy infrastructure within seconds. Floods can isolate settlements and alter transport routes. Wildfires can create hazardous air conditions and destroy communication infrastructure. Industrial accidents may release toxic, radioactive, or combustible materials. Recovery personnel must make urgent decisions despite incomplete information and continuing danger.

The earliest recovery decisions depend on situational awareness. Authorities need to determine where damage has occurred, which infrastructure remains usable, which communities are isolated, and where medical supplies, food, water, shelter, energy, and rescue support are required. Delayed or inaccurate assessment can misdirect scarce resources and expose responders to avoidable hazards.

Conventional assessment relies on field teams, piloted aircraft, ground vehicles, engineering inspection, public reports, and administrative records. These methods remain indispensable, but damaged environments can restrict access. Entering an unstable building, tunnel, industrial plant, or contaminated area may place responders at serious risk. Wide-area assessment may also take considerable time when roads and communication networks are disrupted.

Robotics can extend observational reach without requiring immediate human entry. Unmanned aerial vehicles can produce high-resolution images and three-dimensional maps. Ground robots can enter collapsed or contaminated structures. Aquatic robots can inspect submerged infrastructure. Sensor-carrying platforms can measure temperature, gas, radiation, water conditions, vibration, and structural movement.

Artificial intelligence can process these data to detect damaged structures, identify blocked roads, estimate debris, classify accessibility, recognize people, prioritize inspection, and propose logistics routes. AI can also combine imagery, sensor data, weather information, infrastructure records, emergency calls, and field reports into a common operational picture.

Technology nevertheless introduces new failure modes. Communication may be unavailable, positioning signals may be unreliable, sensors may be obstructed, batteries may be difficult to recharge, and models may misclassify unfamiliar damage. Automated prioritization may overlook communities poorly represented in available data. Cyberattacks or unauthorized access may compromise sensitive maps and operational decisions.

Murphy explains that disaster robotics requires close alignment between technological capability, responder needs, mission conditions, and human–robot interaction. A robot that performs well in a controlled environment may not remain reliable amid debris, smoke, rain, unstable terrain, or damaged communication.

This paper examines how robotics and AI can support three recovery functions: autonomous assessment, infrastructure inspection, and emergency logistics. Its central argument is that disaster autonomy should be designed as a human-supervised resilience system rather than an isolated collection of robots and algorithms.

2. Literature Review

2.1 Disaster Robotics and Autonomous Assessment

Disaster robots are designed or adapted to operate in conditions that are unsafe, inaccessible, or inefficient for direct human work. They may include aerial, ground, aquatic, and hybrid platforms. Their value is determined by mobility, sensing, endurance, communication, manipulability, reliability, and compatibility with emergency procedures.

Ground robots can enter partially collapsed buildings, tunnels, mines, and industrial areas. Cameras, thermal sensors, microphones, gas detectors, and mapping instruments may help responders identify survivors, hazards, pathways, or structural conditions. Aerial platforms can survey broader areas and access locations separated by floodwater, debris, damaged bridges, or unstable slopes.

Kruijff and colleagues emphasize that disaster-response systems must support human–robot teams rather than treat autonomous machines as independent responders. Operators need usable interfaces, reliable communications, understandable system states, and procedures for managing uncertainty.

NIST's emergency-response robotics work has highlighted the importance of standardized performance testing. Mission-specific capabilities should be measured before field deployment, including mobility, sensing, radio communication, endurance, manipulation, operator proficiency, and safety.

AI-supported assessment typically includes image classification, object detection, semantic segmentation, change detection, and geospatial analysis. Post-event imagery can be compared with earlier maps or images to identify collapsed roofs, damaged roads, debris, inundation, fire boundaries, or displaced populations.

Automated assessment should be treated as preliminary evidence. A model-generated damage label may help prioritize inspection, but consequential decisions require validation through additional sensing, engineering review, field reports, or direct observation.

2.2 Intelligent Infrastructure Inspection

Infrastructure recovery requires inspection of buildings, bridges, roads, railways, power networks, communication towers, dams, ports, water systems, hospitals, and emergency facilities. Damage may be visible, hidden, progressive, or indirectly caused by loss of connected services.

Robotic inspection can reduce exposure to falling debris, electrical hazards, hazardous substances, unstable ground, confined spaces, and aftershocks. A drone may inspect an elevated bridge component, while a tracked robot may enter a damaged industrial structure. Underwater robots can inspect foundations, pipelines, and submerged components after floods.

Computer vision can assist crack detection, deformation analysis, corrosion identification, component displacement, and surface-change mapping. Three-dimensional reconstruction can provide geometric records for engineering analysis. Thermal imaging may detect overheating, water intrusion, or electrical abnormalities.

AI outputs must be accompanied by confidence information and traceable source data. Infrastructure engineers need access to original imagery, sensor calibration, location, capture conditions, and model assumptions. A binary "safe" or "unsafe" classification is insufficient for high-consequence decisions.

Inspection systems should also support repeated monitoring. A structure that appears stable during an initial survey may deteriorate because of aftershocks, floodwater, fire, wind, or load redistribution. Time-series comparison can help identify progressive change.

2.3 Emergency Logistics and Humanitarian Distribution

Emergency logistics involves transporting medical supplies, water, food, shelter materials, communication equipment, fuel, and repair components under severe uncertainty. Demand changes rapidly, inventories may be incomplete, routes may be blocked, and transport capacity may be limited.

AI can assist demand estimation, inventory allocation, vehicle routing, warehouse selection, and last-mile distribution. Optimization models may combine population needs, road accessibility, vehicle capacity, delivery urgency, weather conditions, and facility status.

Aerial delivery may support isolated locations when roads are unavailable. Ground robots may transport supplies within dangerous industrial, medical, or contaminated environments. These platforms should complement rather than displace larger transport systems because payload, range, weather tolerance, and energy capacity remain constrained.

Humanitarian logistics also involves fairness. Optimizing delivery solely for speed or volume may disadvantage remote communities, people with disabilities, informal settlements, or groups absent from official records. Ethical routing requires transparent priority rules and local knowledge.

3. Research Objectives

The study aims to develop an integrated framework for applying robotics and artificial intelligence to disaster recovery while retaining human authority, safety assurance, and equitable resource allocation. It evaluates technology as part of a larger emergency-management system rather than as an independent operational solution.

The objectives are:

1. To identify robotic and AI capabilities relevant to damage assessment, infrastructure inspection, and emergency logistics.
2. To examine how autonomous technologies may reduce responder exposure and accelerate situational awareness.
3. To compare simulated damage-assessment completion times under conventional and robotics–AI-integrated configurations.
4. To identify operational, ethical, cybersecurity, and human-factor challenges affecting deployment.
5. To propose a staged implementation strategy for responsible disaster-recovery autonomy.

The principal research question is:

How can emergency-management organizations integrate robotics and AI to improve the speed, safety, and coordination of disaster recovery without weakening human command, technical verification, or equitable humanitarian decision-making?

4. Methodology

4.1 Research Design and Simulated Incident Context

The study uses a conceptual and simulation-based design. No observations were collected from an actual disaster, responder organization, infrastructure operator, affected community, or humanitarian agency. The numerical values are illustrative and were constructed to demonstrate a comparative assessment approach.

The modeled context represents a regional disaster affecting buildings, roads, utilities, communication networks, and community-access routes. Initial assessment requires aerial observation, ground verification, infrastructure-status reporting, hazard detection, mapping, and transmission of findings to the incident command structure.

Two assessment configurations were defined:

- The conventional configuration relies primarily on field inspection teams, ground vehicles, manual reporting, and centralized review.
- The integrated configuration combines aerial and ground robots, edge-based data processing, AI-assisted damage detection, geospatial information, and human verification.

4.2 Variables and Mission Metrics

Initial damage-assessment completion time was selected as the primary simulated variable. It represents the number of hours required to produce a preliminary, verified operational assessment of the designated area.

Completion requires:

- coverage of the assigned assessment area;
- identification of major access constraints;
- preliminary classification of visible infrastructure damage;
- confirmation of immediate hazards;
- geospatial organization of observations; and
- delivery of a usable report to authorized decision-makers.

The metric does not represent complete engineering certification, recovery completion, casualty reduction, or humanitarian impact. It measures only the initial assessment function.

Table 1: Comparison of Conventional and Robotics–AI-Integrated Approaches for Environmental Assessment and Restoration

Assessment component	Conventional approach	Robotics–AI-integrated approach
Area coverage	Field teams and ground vehicles	Aerial mapping coordinated with ground robots
Damage identification	Manual observation and reporting	AI-assisted detection with human verification
Hazard exposure	Direct entry may be required	Remote sensing used before personnel entry
Information integration	Sequential compilation	Multi-source geospatial fusion

Assessment component	Conventional approach	Robotics–AI-integrated approach
Report production	Manual consolidation	Automated structuring followed by command review

4.3 Descriptive Analysis

Twenty-four simulated incident times were generated for each configuration, producing forty-eight observations. Means, medians, standard deviations, ranges, and proportional mean difference were calculated.

The illustrative proportional reduction was calculated as:

PTR=(T¯CT¯C−T¯R)×100

where:

- PTR is the proportional time reduction;
- T¯C is the mean conventional-assessment time; and
- T¯R is the mean robotics–AI assessment time.

No inferential statistical test was performed because the values were not sampled from a real population. The analysis does not estimate actual disaster-response performance or establish causation.

5. Analysis and Results

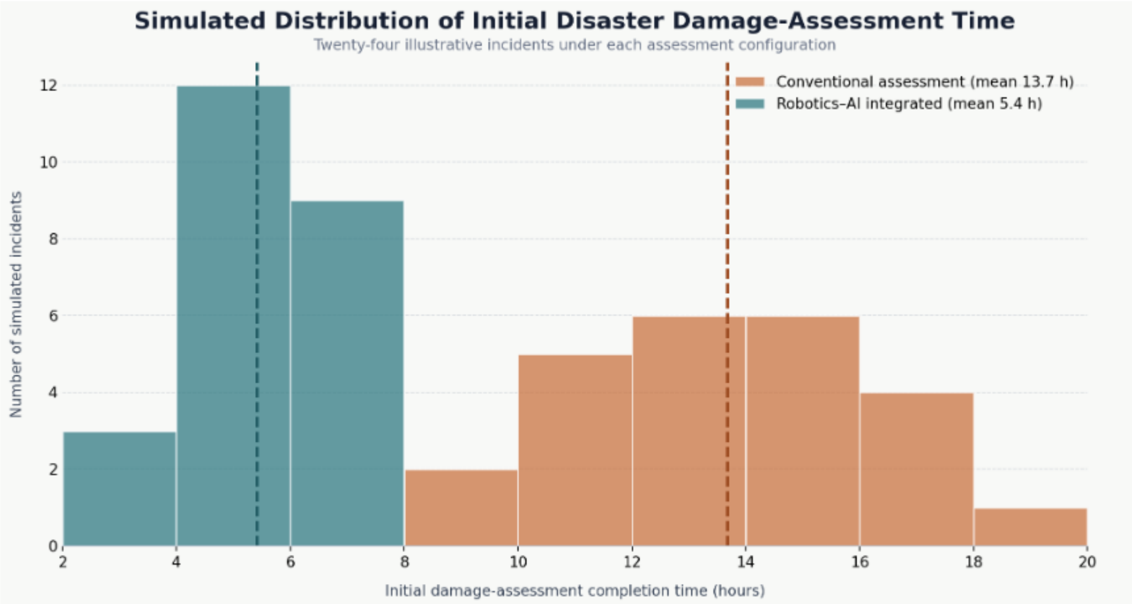
The conventional assessment configuration records simulated completion times between 9.5 and 18.1 hours. Its mean completion time is 13.68 hours. The integrated configuration records times between 3.2 and 7.4 hours, with a mean of 5.41 hours.

The difference between the two simulated means is 8.27 hours. Relative to the conventional mean, the integrated configuration produces an illustrative reduction of 60.5%. This difference reflects assumed improvements in aerial coverage, automated data organization, remote hazard observation, and parallel collection.

Table 2: Comparative Completion-Time Performance of Conventional and Robotics–AI-Integrated Assessment Approaches

Descriptive measure	Conventional assessment	Robotics–AI integrated
Simulated incidents	24	24
Mean completion time	13.68 hours	5.41 hours
Median completion time	13.55 hours	5.30 hours
Minimum time	9.50 hours	3.20 hours
Maximum time	18.10 hours	7.40 hours

Graph 1: Simulated Distribution of Initial Disaster Damage-Assessment Time



Interpretation: The histogram shows two separated simulated distributions. Integrated assessment observations are concentrated between approximately three and eight hours, while conventional assessment observations are concentrated between approximately ten and eighteen hours.

Key finding: Robotics and AI may accelerate preliminary assessment when aerial coverage, ground inspection, automated analysis, and human verification operate concurrently. The simulated difference should not be interpreted as a guaranteed field-performance improvement.

The operational implication is that faster assessment may support earlier infrastructure prioritization, route planning, and resource allocation. However, speed has value only when information is accurate, relevant, geolocated, and accessible to authorized decision-makers.

An integrated deployment sequence is presented below.

6. Challenges and Limitations

Communication failure is a major operational risk. Buildings, terrain, weather, distance, electromagnetic interference, and infrastructure damage can disrupt control and data transmission. Robots should therefore support degraded communication, safe return, local data storage, and predefined behavior when links are lost.

Energy availability also constrains deployment. Aerial vehicles may have limited endurance, while ground robots may consume significant power on irregular terrain. Charging infrastructure may be unavailable. Mission planning should include battery logistics, replacement cycles, transport, maintenance, and prioritization of high-value tasks.

Navigation can be difficult when satellite positioning is unavailable or inaccurate. Indoor environments, urban canyons, smoke, dust, water, debris, and changing landscapes may reduce perception quality. Multi-sensor localization, maps, operator oversight, and conservative movement policies are necessary.

AI models may fail when disaster conditions differ from training data. A model trained on earthquake damage may not classify flood-related failure correctly. Local building materials, informal construction, vegetation, lighting, and image angle may also affect performance. Automated outputs should include confidence estimates and access to underlying evidence.

Cybersecurity is critical because disaster systems may transmit sensitive information about infrastructure, vulnerable populations, access routes, and emergency facilities. Authentication, encryption, network segmentation, signed updates, access control, logging, and incident-response procedures should be established before deployment.

Airspace coordination is necessary when several agencies operate drones simultaneously. Conflicts may arise with rescue helicopters, medical aircraft, media platforms, and private operators. Unified mission coordination, identification, operating zones, and communication protocols are required. Autonomous logistics may create ethical concerns. Optimization based solely on delivery speed can neglect people outside recognized demand databases. Community representatives and humanitarian personnel should help define priority rules. Automated allocation must remain reviewable and contestable.

The simulated design limits the study. The distributions were constructed rather than observed. They do not incorporate weather severity, terrain, responder experience, infrastructure density, communication loss, regulatory delay, equipment failure, or data-validation workload. Empirical studies should use realistic exercises, pre-specified metrics, comparable mission areas, failure reporting, and independent evaluation.

7. Discussion

7.1 Autonomous Systems as Extensions of Emergency Teams

The simulated results illustrate how robotic sensing may shorten the time required to establish an initial operational picture. Aerial and ground platforms can work in parallel while human teams concentrate on verification, rescue, engineering judgment, and community coordination.

The objective should not be maximum autonomy under all conditions. Autonomy is useful when it reduces operator workload and enables safe execution of well-defined tasks. Human control becomes more important when conditions are uncertain, consequences are severe, or system confidence is low. Human–robot interfaces should communicate mission status, location, sensor condition, uncertainty, communication quality, and intervention options. Operators should know why a mission was paused, why an object was classified as damaged, and what the robot will do if communication fails.

7.2 Infrastructure Intelligence and Evidence Quality

Robotic inspection can improve access to damaged structures, but engineering decisions require more than visual classification. Structural safety depends on material properties, load paths, foundations, hidden damage, and continuing hazards. Robots can collect evidence; qualified professionals must interpret its significance.

Data provenance is therefore essential. Each image, point cloud, thermal record, or model output should retain its capture time, location, sensor configuration, calibration information, processing history, and reviewer decisions. Without provenance, rapid data collection may create confusion rather than situational awareness.

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Repeated inspection can be especially valuable. Comparing measurements over time may identify progressive movement, water intrusion, heat accumulation, or widening cracks. AI can support comparison, but thresholds for intervention should be determined through engineering and emergency-management standards.

7.3 Equitable Logistics and Accountable Prioritization

Emergency logistics is not simply a routing problem. It involves competing needs, incomplete demand information, uncertain access, and moral decisions about priority. AI can compare alternatives more quickly than manual planning, but optimization objectives must be visible and justified.

A route that delivers the greatest total quantity may not reach isolated households, medical facilities, or communities with limited political visibility. Algorithms should incorporate urgency, vulnerability, accessibility, medical dependency, and minimum service guarantees rather than only distance and volume.

Community knowledge can improve both assessment and logistics. Local responders and residents may identify informal roads, vulnerable people, cultural constraints, and hazards absent from official maps. Responsible systems should create mechanisms for incorporating this knowledge and correcting automated assessments.

8. Conclusion

Robotics and artificial intelligence can strengthen disaster recovery by extending observation into unsafe areas, accelerating damage mapping, supporting infrastructure inspection, and improving emergency-logistics planning. Their value is greatest when they provide responders with reliable and interpretable evidence rather than operating as isolated technical systems.

The simulated analysis produced a mean initial assessment time of 13.7 hours for the conventional configuration and 5.4 hours for the robotics–AI-integrated configuration. The resulting 60.5% illustrative reduction demonstrates a possible analytical scenario, not an empirical prediction. Actual performance will depend on disaster type, geography, equipment, communication, regulation, training, and mission coordination.

Responsible deployment requires validated equipment, resilient communication, cybersecurity, human oversight, data provenance, community input, and transparent prioritization. Robots should be assigned tasks appropriate to their tested capabilities, and AI-generated findings should be confirmed before they support high-consequence decisions.

Disaster autonomy should ultimately be evaluated according to whether it protects responders, improves situational understanding, restores essential services, and reaches affected communities fairly. The strongest recovery system is not one that removes humans from decision-making, but one that combines machine reach and computational speed with professional expertise, humanitarian values, and accountable public authority.

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