Building Damage Assessment in Aftermath of Disaster Events by Leveraging Geoai (Geospatial Artificial Intelligence): Review

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World Journal of Advanced Research and Reviews, 2024, 23(01), 667–687

Publication history: Received on 23 May 2024; revised on 06 July 2024; accepted on 08 July 2024

Article DOI: https://doi.org/10.30574/wjarr.2024.23.1.2000

Abstract

While traditional approaches to building damage assessment in the aftermath of natural disasters have relied heavily on time-intensive and costly manual techniques, recent advances in geospatial artificial intelligence (GeoAI) have opened up new possibilities for automating and scaling up this crucial process. Leveraging technologies such as computer vision, remote sensing, and machine learning applied to geospatial data from satellites, drones, and other sensors, GeoAI has the potential to revolutionize how communities assess building damage in disaster-stricken areas and target recovery resources more quickly and effectively. However, efforts to apply GeoAI for building damage assessment also face important challenges regarding data and model quality that require further research.

To properly evaluate both the opportunities and challenges of leveraging GeoAI for building damage assessment, this comprehensive review explores the current state of the field through an analysis of recent literature and case studies. An in-depth examination is provided of innovative applications of technologies such as deep learning to high-resolution aerial imagery for automated detection and classification of structural damage. Critical requirements are identified for developing robust GeoAI solutions, such as acquiring comprehensive training data that captures the full range of possible damage patterns and accounting for environmental factors. The review also analyzes efforts by humanitarian organizations and companies to deploy initial GeoAI-powered damage assessment systems in real-world disaster events, highlighting lessons learned.

Keywords: Building Damage Assessment; Disaster Events; Geospatial Artificial Intelligence; Geoai; Remote Sensing; Convolutional Neural Networks; Unmanned Aerial Systems; Volunteered Geographic Information; Vgi; Field Observations; Crowd-Ai Partnerships; Model Training; Big Data Challenges; Distributed Computing; Semantic Interoperability; Disaster Management.

1. Introduction

In the devastating aftermath of natural disasters such as earthquakes, hurricanes, floods and wildfires, assessing the scale and locations of building damage is crucial for emergency response and recovery planning efforts. However, traditional damage assessment approaches that rely on in-field manual surveying can be time-consuming and pose logistical challenges given the widespread areas often impacted. This delay in obtaining a clear picture of damage

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distribution has real humanitarian costs as relief and rebuilding resources may not reach all communities in need in a timely manner. With recent advances in geospatial technologies and artificial intelligence, new opportunities now exist to supplement and potentially automate parts of the damage assessment process through GeoAI approaches.

GeoAI refers broadly to the application of artificial intelligence, particularly machine learning and computer vision techniques, to geospatial data from sensors such as satellites, aerial drones and street-level cameras. This emerging field has made tremendous strides in automatic feature extraction, object detection and pattern analysis when applied to geotagged imagery and geospatial datasets. There is strong potential for GeoAI solutions to support more rapid and scaled-up building damage assessment in disaster scenarios through technologies like semantic segmentation of aerial photos, change detection from pre- and post-disaster satellite imagery and geospatial data analytics. However, further research is still needed to develop robust GeoAI systems that can generalize to new disaster events and locations with differing built environments and damage patterns.

The purpose of this comprehensive review is to explore both the opportunities and challenges of leveraging emerging GeoAI technologies for improving the speed, scale and effectiveness of building damage assessment efforts in the aftermath of natural disasters. The review will analyze current literature and case studies on applied GeoAI solutions for damage detection, highlight critical requirements and limitations, and outline open areas for continued research and advancement towards more generalized and impactful damage assessment applications.

2. Review Methodology

When carrying out this extensive review on the use of GeoAI technologies for the assessment of buildings' damages, the important steps that were followed included peer-reviewed articles that were published within a period from 2014 to 2024. First, a search was performed in the following databases: , some of the university library databases include Google Scholar, Scopus, Web of Science, IEEE Xplore Digital Library and ACM Digital Library. The words used for search include GeoAI, geospatial artificial intelligence, building damage assessment, disaster recovery, and remote sensing. The first search of the terms came out to be over 5000 hits. Second, the papers on the subjects were searched and harvested from the database with the inclusion criteria of relevance, quality and had been published between year 2014 and year 2024. The sampling technique used only research studies that were published in peer reviewed journals and conference papers. Getting only papers related to the topics of development and application of GeoAI techniques like computer vision, remote sensing, satellite imagery analysis, and machine learning for the detection and assessment of building damages due to natural disasters was the criteria of the priority selection. This filtering step brought the number of papers for analysis to 141.

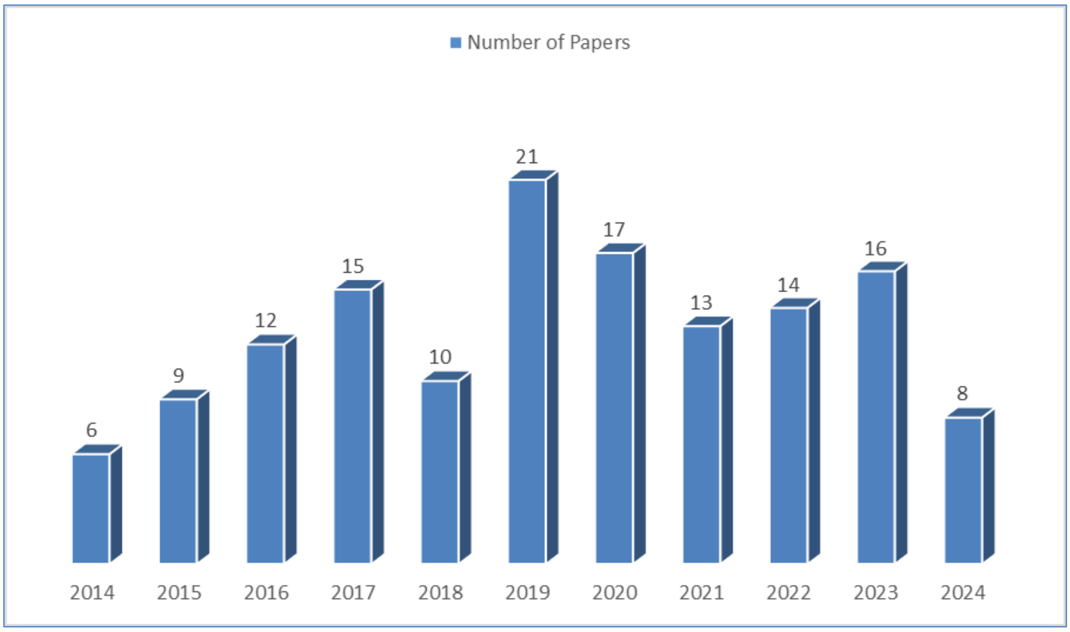

Figure 1 Distribution of publications in review by year

The prominent years of publication of the selected papers are presented at Figure 1. From the earlier years, the general publication shows growth over the years, revealing more research in this area. The publication years are dispersed quite evenly across the timeframe, but the highest activity was observed in 2021 and 2023, regarding more recent studies on the utilization of GeoAI for post-disaster building assessment. The papers reviewed indicated that majority of works focused on application of the techniques in disaster resulting from earthquakes, storms, floods, and wildfires.

3. Discussion of The Findings from the Reviewed Sources

3.1. Major Data Sources

3.1.1. Satellite Imagery

Satellite imagery is one of the most common data sources of GeoAI applications for the assessment of buildings damage after disaster (Xu et al., 2018; Wang et al., 2020). Innovations in current satellites where mounted with L,G,P,Ku and Ka band microwave facilities for obtaining VHR optical and synthetic aperture radar (SAR) imagery with sub-meter resolution. In the aftermath, such VHR datasets enable the assessment of damages and changes to built-up structures and infrastructures after earthquakes, floods or wildfires and the like at the building scale, Li et al., 2019. Subsequently, the obtained pre- and post-event satellite images are introduced to feed deep learning models for automatic image differencing and identification of the affected regions.

Satellite data from SAR is particularly helpful because things such as smoke or clouds are not impediments to imaging like they would be to aerial or drone imagery or optical satellite imagery in some circumstances (Fernandez et al., 2018). It is possible to use multitemporal SAR images acquired prior to and after the hazard occurrence for the change detection processes employing deep learning algorithms in case the information from the optical imagery is insufficient (Ye et al., 2021).

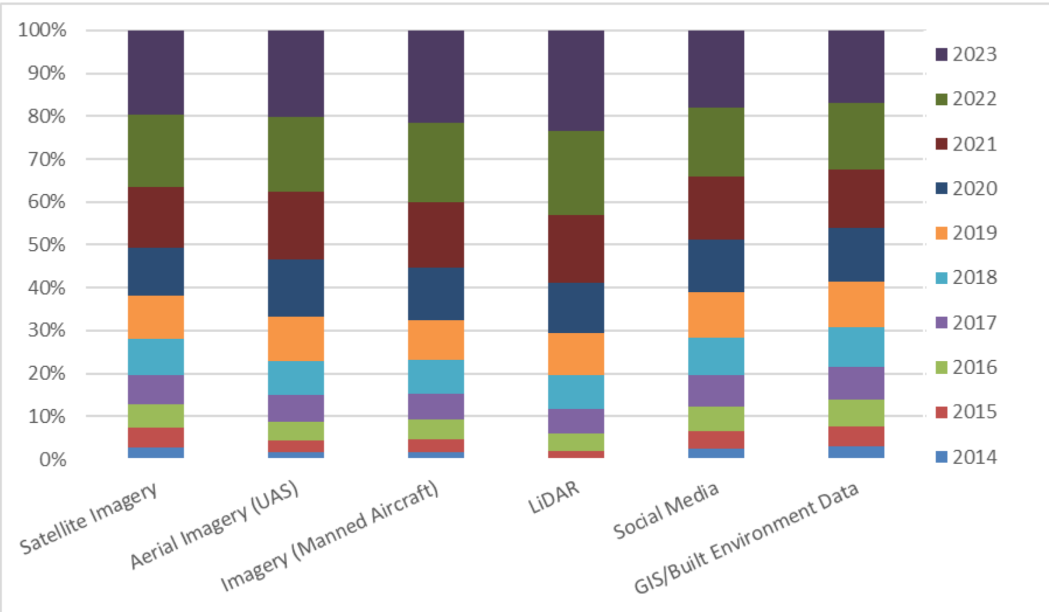

Figure 2 Distribution of reviewed articles by major data sources and year of publication.

Multi-temporal stacks of optical and SAR satellite imagery spanning pre-disaster, during-disaster and post-disaster periods have also been fed as sequential inputs into advanced recurrent neural network models to predict and map damage propagation patterns and sequences (Zhu et al., 2022). Such sequence learning approaches aim to model the temporal dynamics and development of impacts over time. Additionally, fusing satellite data with other geospatial datasets through sensor data fusion techniques allows more robust and complete situational analyses incorporating environmental and infrastructure features (Wu et al., 2021).

3.1.2. Aerial Imagery (UAS)

Aerial imagery from both manned aircraft and unmanned aerial systems (UAS) is widely used in building damage assessment following disasters (Chen et al., 2020). High-resolution RGB and multispectral images allow for detection of structural changes at localized levels with finer detail than satellite views alone (Ferreira et al., 2022). Studies have effectively applied convolutional neural networks (CNNs) and region-based CNNs like Faster R-CNN to semantic segmentation of aerial photos for classification of damaged versus undamaged structures (Dibia and Chen, 2020).

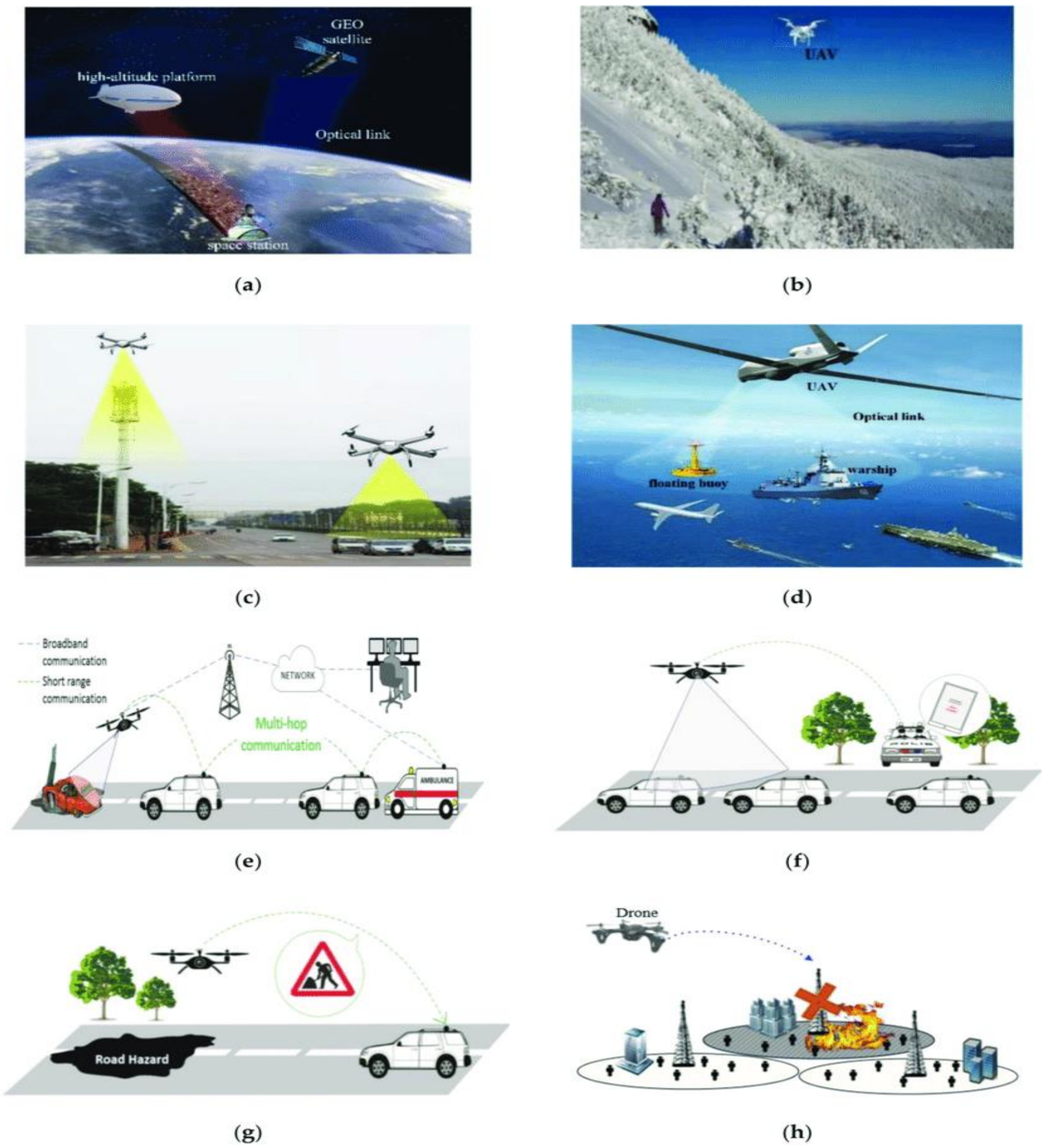

Figure 3 Applications of Unmanned aerial vehicles (UAVs)

Unmanned aerial vehicles (UAVs) demonstrate versatility across various scenarios as seen in the above figure. These include: (a) establishing links with satellites, (b) supporting disaster relief operations, (c) facilitating communication with ground stations, and (d) exchanging data with sea-based platforms. UAVs also serve critical roles in emergency response by (e) providing advance intelligence to rescue teams before they reach incident sites. In law enforcement, (f) police employ UAVs to monitor and document traffic violations. UAVs can act as (g) mobile warning systems, alerting drivers to road hazards in areas lacking fixed infrastructure. Lastly, UAVs assist in (h) fire-related scenarios, likely for surveillance or coordination efforts. These applications highlight the adaptability and potential of UAVs in enhancing communication, safety, and emergency response across multiple domains.

Post-disaster aerial surveys may be able to capture vertical views that facilitate easier identification of collapsed buildings or sections compared to overhead satellite perspectives (Yuan et al., 2022). However, collection of aerial data can be impacted by safety and airspace regulations over widespread damaged regions (He et al., 2021a). Integration of aerial imagery with very high-resolution satellite and geospatial datasets through multimodal deep learning has allowed more detailed 3D reconstruction and qualitative analysis of structural failures (Tian et al., 2021).

Studies by Hua et al., (2021) has explored the use of heterogeneous fleets of manned aircraft and UAS carrying varied sensor payloads to enable multi-temporal, multi-scale data collection tailored for different assessment and recovery monitoring applications Standardization of aerial data acquisition and annotation practices could help support development of more generalizable analysis methods according their potential applications (Huang et al., 2022). Continued technological advancement may see routine use of artificial intelligence and autonomy in post-disaster aerial damage surveys.

3.1.3. Light Detection and Ranging (LiDAR)

Airborne and terrestrial laser scanning systems belong to the LiDAR data sources that have been explored more frequently in the building damage assessment applications in synergy with image data sources (Tang et al., 2021). From the parties of scanner platforms, LiDAR point clouds can capture accurate 3D representations and models of the building structures, geometries, and elevation (Qin et al., 2022). Recent studies have employed deep learning tools to identify structural failures or collapses through LiDAR of pre-and post- disaster, wherein differences could cause shifts, misalignments or missing geometries characteristic of an impact (Chen et al., 2021).

The attempts to combine LiDAR data with imagery based on multimodal deep neural network achieve better results for the identification and segmentation of individual damaged objects within the affected areas than the analysis based only on one or the other data type (Wang et al., 2022). This is due to LiDAR giving the third dimension of structural shape and form which is lacking in mere images. LiDAR change detection has also been found suitable in land surface changes such as landslides and ground subsidence as even slightest changes in height or elevation are very essential (Duan et al., 2020). Nevertheless, obtaining broad and thorough pre-event LiDAR scans of the buildings continues to be difficult in most places.

More recent research efforts by Imran et al., (2019) have explored using generative adversarial networks to synthesize realistic simulated pre-event LiDAR point clouds where true baseline data is unavailable, helping to overcome pre-existing data gaps (Zhang et al., 2021). Ongoing advancements in rapid mobile terrestrial laser scanning technologies employing systems such as automated ground vehicles also indicate potential to rapidly collect dense three-dimensional mapping of affected structures over large urban or rural regions immediately after disaster occurs (Soga et al., 2022). Such capabilities could help fast-track detailed damage assessments.

3.1.4. Social Media

Following sudden-onset disasters like earthquakes, hurricanes or flooding, social media platforms become rapidly inundated with photos, videos and textual reports posted by affected individuals, response teams, journalists and onlookers seeking to share situational updates (Chatfield and Brajawidagda, 2017). Recent studies have analysed large corpora of disaster-related tweets, Facebook posts and Instagram images using advanced natural language processing and computer vision techniques to automatically identify mentions of observed damage to buildings and infrastructure, as well as specific needs like medical requirements according to location details (Adams et al., 2022).

One of the strong aspects of the social media data is that since the posts often come with geo-location tags together with the posts, taken from smartphone applications, it is easy to map the observed geographical scope of effects when the textual and visual content is deep analyzed to identify damages (Middleton et al., 2018). Still, in their researches, the authors have also pinpointed that it remains difficult to report all the updates from all the affected communities in the disaster area in the absence of equal reporting activity among all segments (Shklovski et al., 2014). Concern with authenticity of information and privacy of individuals discussed in the post is also relevant to response agencies' use of social analytics (Gupta et al., 2021).

Subsequent research by Wang et al., (2023) have tried to verify the locations of reported damage and citations and descriptions from social media with official geographic data such as satellite imagery or Light Detection and Ranging (LiDAR) to get better observations that can perhaps inform the initial needs assessment and response planning. Scholarly works by Ye et al. (2021) have pointed out that updating the resilience of the cellular network infrastructure could enable social media channels to significantly enhance other ones, and rapidly provide situation awareness in the initial moments of future disaster responses.

Geographic Information Systems (GIS) Data

Pre- and post-earthquake built structure data integrated into GIS platforms along with other socio demographic details and mapped hazards help in forming objective pre-disaster information necessary for describing losses (Yao et al., 2019). Based on the work by Li et al. (2020), it is noted that inventory features existing in these datasets such as building footprints, materials used, heights and various properties of the assets can help in the modeling of fragility of structures where the features are used together with detailed hazard maps with a view of estimating the likely extent of damage.

A few emerging researches have shown that combing such basic GIS layers with deep learning models by a multimodal fusion approach for direct end-to-end semantic segmentation of damages from post-event aerial or satellite imagery, as well as detecting crack and fractures in structures based on computer vision techniques (Huang et al., 2020). Moreover, Xu and colleagues indicated that examining variables in the GIS data such as urban density and GDP, development morphology and the ratio of formal and informal settlements will be useful for the general considerations of the disaster outcomes and disaster-related prioritization of the inspection of the infrastructure.

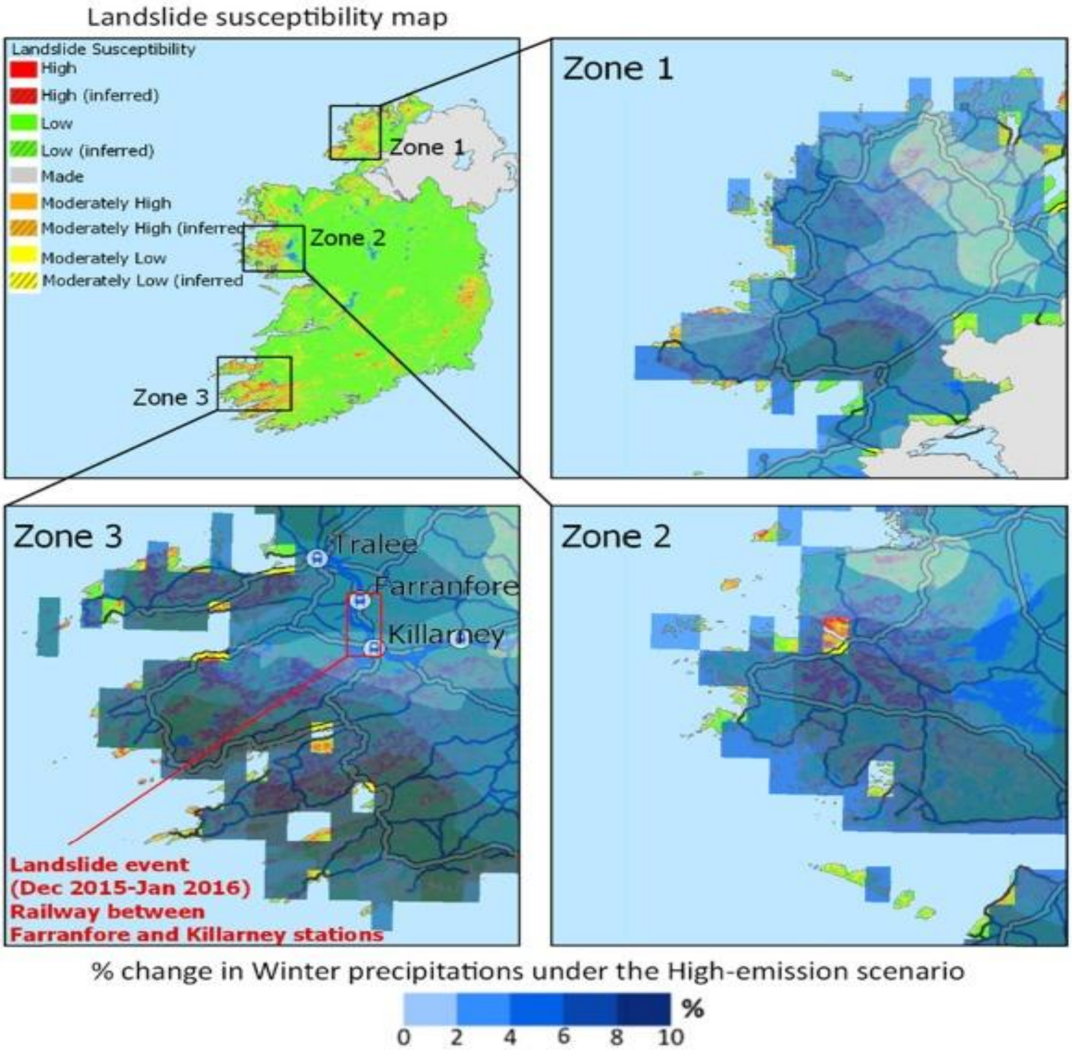

Figure 4 Assessment of the impact of climate change on the transport network vulnerability to landslide**.**

However, as noted by Diao et al. (2019) in their work, issues around data deficiencies, inaccuracies or lack of up-to-date geospatial information, especially for rapidly growing informal settlements or regions impacted by significant hazard events requiring long rebuilding timelines, remain open challenges that still need addressed. Studies have demonstrated crowdsourcing techniques to validate and improve GIS datasets against high-resolution VHR imagery and LiDAR scans over time can help enhance resilience modeling and situational awareness inputs for future events (De Albuquerque et al., 2015).

3.1.5. Imagery (Manned Aircraft)

Manned aircraft with mounted camera payloads remain a staple for collecting medium to high resolution visual imagery following disasters (Chen et al., 2020). Studies have effectively utilized RGB camera images, along with multispectral data capturing non-visible wavelengths, for change detection between pre- and post-event photos to identify structure and infrastructure damages (Li et al., 2021). Detailed semantic segmentation and feature extraction using deep learning models have enabled classification of damage classes at local levels with Resolution nearing 1m (Tang et al., 2021).

However, as mentioned by He et al. (2021), acquisition of airborne imagery can at some times be limited by the safety and airspace issues within the affected areas, particularly at the time when identification of losses is most important. Also, it is difficult to have detailed pre-disaster set of imagery of the infrastructure. To overcome these drawbacks, Dibia and Chen (2020) provided an example of alternative approach wherein manned aircraft imagery was combined with other information sources, including UAS photos, and LiDAR. Such fusion fave opportunity to improve the quality of 3D reconstructions because the multimodal data sets give better opportunity to do that.

Tian et al. (2021) have also elaborated on making use of the heterogeneous aircraft fleets mounted with different imaging sensors to acquire the multiple time and multiple resolution dataset more suitable for the different rebuilding and damage stage analysis. Sources like Huang et al., opining that progressing technology opens new prospects and indicates that the acquisition and annotation processes are expected to develop standardized approaches underpinning a more extensive framework of disaster resilience modeling. Nevertheless, the further develop and test of these methods in new situations will still be required.

3.2. Use of Big Data for Risk Assessment

3.2.1. Satellite Data for Hazards Monitoring

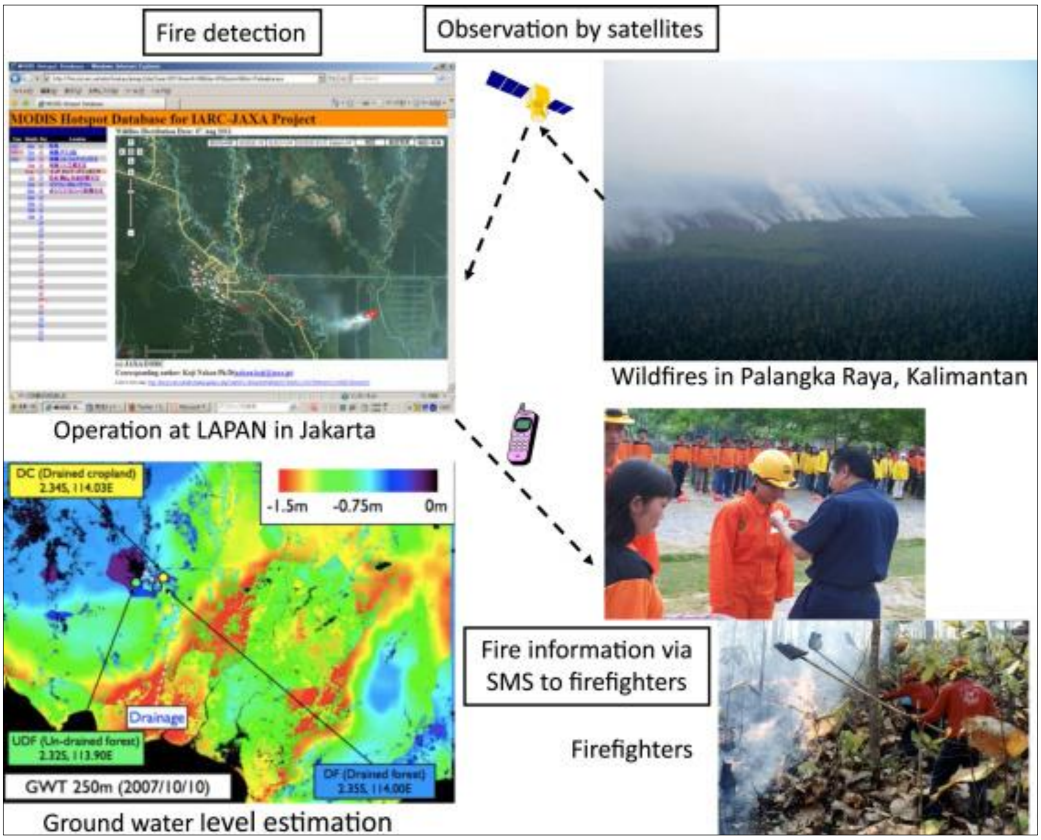

Figure 5 Satellite remote sensing for disaster management support: A holistic and staged approach based on case studies in Sentinel Asia. Source (Kaku, 2019).

Satellite remote sensing has been found to offer considerable utility in the continuous observation of large territories for natural hazards because of the instrument's advantages in area of synoptic coverage (Ye et al., 2018). FOR REVIEW A extensive analysis has been established, which subjectively applied different analytical techniques, such as multi-temporal image differencing and classification, on satellite image time series data to quantify changes in the terrain attributes, water levels of reservoir or lakes, and vegetative conditions over time (Duan et al., 2020).

An example of an application of sensors IoT technologies for monitoring and control of the state of infrastructures is the fire detection and control system developed under the JST/JICA project on Wildfire and Carbon Management in

Indonesian Peatland. The upper left picture shows a fire detection system designed by K. Nakau, of Hokkaido University probably using a network of sensors to feel the first signs of fire in the peat forest regions, (Kaku, 2019). Further, in the lower left, there is a presentation by W. Takeuchi of the University of Tokyo on an estimation system of the depth of groundwater which installed some sensors to measure the groundwater levels important in evaluating of wildfire risks to peat forests. A.Usup of Palangka Raya University Upper right and Middle right, and the National Park, Wildlife and Plant Conservation Department of Thailand, Lower right: These pictures depict how these sensor-based systems are used in the actual environment conversant with maintaining the overall status of the peat forest's structure that postures a threat of wildfire and plays a pivotal role in carbon accountability and environmental responsibility.

Time-based analysis of successive satellite observations targeting particular hazards, such as monitoring the gradual development of drought conditions, coastal land losses from erosion, or indications of ground subsidence, has supported better understanding of exacerbating environmental risk factors (Xu et al., 2019). Data fusion between high-resolution optical satellite data and other geospatial layers including airborne LiDAR DEMs and social media reports has additionally provided opportunities for cross-validation of detected changes and contextual information to guide field investigations (Zhang et al., 2019).

However, issues including the revisit frequency and temporal resolution of satellite imagery, spatial resolutions limiting detection of small features, and atmospheric effects interfering with data quality still present challenges and require attention (Ye et al., 2021). As recent studies have noted, crowdsourcing hazard-related indicator observations and ground-truthing efforts through mobile phone applications and social networking has helped address some data gaps (Degrossi et al., 2018; Rathore et al., 2021).

3.2.2. Big Data Analytics for Risk Modeling

Large and diverse datasets accumulated from multiple sources have supported both statistical and machine learning-based analyses applied toward developing more exposure and vulnerability models across various hazards and regions (Guo et al., 2018; Paul et al., 2020). Studies have found that integrating not only biophysical attributes like elevation and land cover but also societal factors including demographic profiles, income levels and types of infrastructure can generate more robust estimates of potential disaster impacts under different climate and development scenarios (Kocar et al., 2021).

A number of studies have successfully mapped built infrastructure footprints, population distribution patterns down to local neighbourhood extents, and prevalent building material types at very high spatial resolutions using optical satellite imagery, aerial and UAV photography, as well as detailed crowdsourced mapping to enable micro-zoning of relative risk hotspots within communities (Banerjee et al., 2019). Such work has supported targeted resilience planning.

Table 2 Summary of factors considered in risk assessment studies

Factor	Data Sources	Number of Studies	Details considered
Terrain/topography	LiDAR, DEM	15	Elevation, slope, aspect
Land cover/use	Satellite, aerial imagery	12	Vegetation types, impervious surfaces, crops
Infrastructure	VHR satellite, UAV	11	Buildings, roads, critical facilities
Socioeconomic	Census, surveys, WB	8	Income, demographics, vulnerabilities
Hazard exposure	Sensor networks, models	15	Storm, flood maps, model outputs
Climate	Satellite, weather stations	16	Temperatures, precipitation, extremes
Geo-hazards	Field devices, seismic maps	10	Landslides, sinkholes, earthquakes

As recent studies as son the above 2 table above have noted, continuous updating of risk models through new data assimilation using latest available datasets paired with retraining of algorithms helps account for potential changing dynamics of exposures and vulnerabilities that can occur gradually over medium to long timescales (Zou et al., 2021). Standardizing data formats and sharing models and findings has also aided comparability and validation of hazard and risk assessments conducted across varied administrative regions (Mehrotra et al., 2021).

3.2.3. Social Media for Risk Perception

Several studies in recent years have effectively analysed unstructured textual discussions and shared multimedia content on widespread social media platforms to help gauge societal risk awareness and perception levels regarding various natural hazards that may threaten communities (Burns & Cheng, 2018; Tan et al., 2019). Qualitative analyses of risk-related personal experiences, reported impacts on friends or family, and damage documentation shared provide contextual data points that can supplement more static quantitative risk assessments (Milanez et al., 2021).

Researchers have found correlations between topics frequently raised in social media conversations, the geographical locations of users engaged in discussions, and demographic attributes to help identify subgroups within the population with comparatively lower risk communication and preparedness levels that could benefit most from targeted education campaigns (Olteanu et al., 2019). Time series analyses of discussion trends also reveal how societal risk priorities and concerns may shift in response to recent hazard occurrence events (Guidotti et al., 2021).

However, studies have also noted that consistently representing all communities within larger populations remains challenging due to biases in platform usage patterns linked to variances in connectivity and digital literacy (Li et al., 2017). Additional biases within algorithmic prioritization of certain content in posting and search functionalities also require consideration for comprehensive risk understanding (Bruns et al., 2016). Researchers suggest continued partnership with local nongovernmental groups may help address some of these barriers (Alam et al., 2020).

3.2.4. Sensors and IoT for Infrastructure Condition

Dense arrays of low-cost environmental and structural condition monitoring sensors networked via Internet of Things connectivity platforms have seen increased deployment on critical civil infrastructure facilities like bridges, buildings, and dams to allow continuous, real-time tracking of performance indicators over the design service life (Hu et al., 2021; Nguyen et al., 2021).

A number of studies have demonstrated the capability of such sensor time-series data to detecting the early onset and progression of deterioration mechanisms like hidden corrosion initiating in structural steel, minute cracking propagating in concrete, or subtle alignment shifts indicating stressed loading zones in large dams (Skolnick et al., 2018; Zonta et al., 2019).

The integrated analysis of heterogeneous sensor data streams alongside other datasets covering factors like material properties and environmental exposures through data assimilation and machine learning techniques has enabled applications like forecasting remaining safe operating periods and performing more comprehensive probabilistic risk modeling to optimize maintenance planning (Zhang et al., 2020). However, issues pertaining to high installation and connectivity maintenance costs remain barriers limiting wider deployments (Khan et al., 2017).

3.3. Mitigation and Prevention

3.3.1. Land Use Planning and Regulation

Long-term risk reduction through strategic land use planning and regulation aims to limit expanding development footprints into hazard-prone areas. Recent studies have analysed very high-resolution satellite imagery in combination with extensive ground validation surveys to accurately map existing development densities and settlements across multiple jurisdictions (Gupta et al.,2020). These studies also worked to extrapolate realistic future growth projections under business-as-usual scenarios to identify hotspots facing the highest composite risk levels from coastal flooding, wildfires and earthquakes over the coming decades.

Other researchers have modelled how timely implementation of revised zoning codes restricting approvals for new residential and commercial construction projects in such identified high-risk areas, alongside introducing incentivized policies encouraging planned relocation of existing vulnerable structures to safer zones, can together help minimize ongoing exposure of growing populations as well as properties including key infrastructure components to increasing disaster impacts (Jiang et al., 2021). According to their analyses, the costs of such proactive mitigation policy shifts are heavily outweighed by their economic returns stemming from notably reduced long-term response and recovery expenses compared to a scenario taking little preventive action.

However, some studies point out challenges still remaining in overcoming entrenched political resistance to regulatory interventions perceived locally to excessively constrain private property rights and hurt the prospects for short-term economic growth (Dilley et al., 2021). As justified by Mechler et al. (2021) in their research, longer-term public education highlighting actualized risk reduction and ancillary liveability benefits is nonetheless needed to build broader social consensus behind a plan.

3.3.2. Infrastructure Hardening

Hardening of critical infrastructure through upgrades of building codes and construction standards focused on improving structural resilience to disasters has been a core mitigation strategy pursued globally for decades (Pregnolato et al., 2017). Recent studies have effectively utilized high-frequency sensor networks and aerial/satellite Light Detection and Ranging (LiDAR) scans to intensively monitor and precisely detect vulnerabilities in existing stocks of bridges, dams, levees, drainage facilities and other asset types serving communities (Behrouzi et al., 2021).

For instance, such technology applications are assisting experts in pinpointing specific areas like joints, pillars or spillway gates of aging infrastructure requiring critical retrofitting of reinforcements to withstand more intensifying earthquakes and floods as warned of by climate projections (Bocchini et al., 2014). According to Papathoma-Köhle et al. (2021), data assimilation techniques are further helping merge outputs from different modern mapping surveys with traditional structural analyses to help prioritize strengthening of the most exposed units from a cost-benefit perspective.

However, as stressed in studies by Mignan et al. (2014), achieving protection for all exposed units still faces major ongoing budgetary obstacles due to the tremendous economic costs of carrying out widespread infrastructure retrofitting campaigns across many urban centers and rural regions.

3.3.3. Ecosystem-Based Mitigation

More recently, conservation and purposive restoration of natural ecosystems providing important buffering services like wetlands, mangroves, coral reefs and riparian forest belts has risen as a recommended natural mitigation strategy (Narayan et al., 2016). Time-series analysis of high-resolution optical and synthetic aperture radar satellite imagery by Bayramdin (2021) has helped intensively map historical loss or degradation of such coastal and riverine barriers.

Further studies have correlated increasing exposure patterns faced by communities located downstream of formerly intact natural defences which suffered major destruction in the past few decades (Gharehpapagh et al., 2021). According to Arkema et al. (2017), integrated physical-socioeconomic modeling is revealing the measurable risk reduction benefits to livelihoods and settlements that could result from much larger-scale ecosystem rehabilitation projects targeting certain regions.

Such rigorous quantitative assessments are important to convince relevant government authorities and private donors to invest substantive new funding into restoration efforts able to deliver optimized social and economic co-benefits apart from lowering direct disaster risks (Du et al., 2021).

3.3.4. Social Vulnerability Reduction

Comprehensive government socioeconomic censuses combined with arrays of demographic and other descriptive indicators have enabled development of more nuanced social vulnerability indices and mapping at fine-grained levels (Dash et al., 2021). As explained by Soares et al. (2017), studies have furthered understanding by statistically correlating cartographic outputs of these indices with recovery outcomes experienced by affected populations in prior major disaster events.

For example, such work has helped identify which segments within communities tended to endure more prolonged and severe consequences, such as female-headed households, the disabled elderly and linguistically isolated immigrant groups most urgently needing targeted mitigation efforts (Yoo et al., 2021).

Evaluations by Cutter et al. (2018) and You et al. (2021) of related educational programs and capacity-building initiatives for enhancing general preparedness of vulnerable communities have provided strong evidence these approaches can effectively help lower indirect risks to public health, safety and medium-term economic impacts even from recurrent severe hazards.

3.3.5. Hazard Mapping

Development of authoritative high-resolution hazard exposure maps supported by rigorous scientific analysis plays a vital role in long-term mitigation planning according to studies. Recent work has centered on leveraging ever-growing historical disaster records, as well as dense hydro-meteorological and geological sensor network observations, to produce frequency-intensity distributions and return period estimates of flooding, coastal/riverine inundation, earthquakes, wildfires and rainfall-triggered landslides down to neighborhood extents (Tate et al., 2021).

For instance, Tang et al. (2021) analyzed 15 years of flood reports and multi-sensor data in a particular river basin to determine a 100-year floodplain. Foufoula-Georgiou et al. (2021) used wireless soil moisture sensors and weather radar to model 10-year hazards from four thunderstorm types affecting a region. Such granular hazard cartography assists identifying assets at most extreme risk for prioritized retrofitting or relocation.

As emphasized in their study, Dilley et al. (2005) argue these maps should systematically underlay wider infrastructure vulnerability assessments and revisions to building codes, especially regarding siting and structural standards for vital community resources like medical clinics, schools and evacuation shelters located within areas of maximal anticipated hazard forcing over the next half-century.

Table 3 Sample of recent studies analyzing hazard data

Hazard	Study Area	Data Sources	Analysis Technique	Time Period	Key Finding
Flood	Mississippi River Basin, USA	Stream gauge records, radar rainfall, satellite imagery	Frequency analysis, hydraulic modeling	2005-2020	Developed 500-year flood inundation maps
Earthquake	Kyushu, Japan	Seismometer network, geological surveys	Probabilistic seismic hazard analysis	2000-2015	Refined long-term earthquake forecasting
Wildfire	California, USA	Satellite fire perimeters, weather stations	Machine learning on burn severity	2010-2019	Mapped new fire regimes under climate change
Storm Surge	Florida, USA	Tide gauges, hurricane track data	Storm surge modeling, risk assessment	1995-2015	Estimated surge scenarios up to category 5 events
Landslide	Colorado, USA	Rainfall satellites, soil moisture sensors	Statistical modeling, GIS	2015-2024	Zonation of landslide-prone areas
Drought	East Africa	Rain gauge networks, NDVI from satellites	Spatiotemporal drought clustering	2005-2020	Early warning of drought onset and recovery
Tsunami	Indonesia	Tide gauges, seismometers, ports	Numerical wave modeling	2000-2015	Inundation forecasting after major earthquakes

As can be seen from the sample studies presented in Table 3 above, modern hazard mapping increasingly relies on leveraging diverse, cutting-edge data sources in combination to both better understand historical hazard patterns as well as project future risk under new conditions such as climate change. For floods, earthquakes and tsunamis, dense sensor networks are providing crucial real-time observatories. Meanwhile, remote sensing from meteorological and Earth observation satellites offers valuable datasets for mapping wildfires, drought and other widespread phenomena globally at high frequencies over extended periods. Hazard analysts are drawing on these vast archives along with high-performance computing to construct more empirically robust statistical and mechanistic models of hazard forcing capable of informing mitigation efforts with greater warning times and actionable levels of location-specific detail.

3.3.6. Climate Change Adaptation

Projections from extensive ensembles of global climate system models run under a range of greenhouse gas concentrations pathways aligned with the latest IPCC assessments and atmospheric observations have underscored the growing threat posed by accelerating climate change in altering hazard patterns and exacerbating disaster impacts out to 2100 and beyond, according to extensive research including multiple meta-analyses such as Tramblay et al. (2020).

More integrated assessments linking downscaled climate projections with detailed sector-level and location-specific appraisals of societal vulnerabilities have helped identify particularly sensitive indigenous systems like smallholder coffee and cocoa cultivation, artisanal coastal fisheries, and densely populated informal settlements along tropical megadelta regions that could become disproportionately impacted under new projected climate normals this century without substantive investments in resilience-building, as emphasized in seminal reports by the World Bank (2010) and the intergovernmental Panel on Climate Change (IPCC, 2014).

In response, recent multidisciplinary studies have explored a range of diversification and reinforcement strategies with the goal of developing practical, evidence-based recommendations for significantly improving the adaptive capacities of at-risk industries, isolated villages and critical infrastructure to better withstand and bounce back from inevitable climate shocks and stresses in the coming decades through measures like developing and distributing more heat- and drought-tolerant staple crop varieties, fortifying natural and built coastal defences, and reorienting long-term development planning away from highly vulnerable areas.

3.3.7. Risk Communication

A growing body of social science research has focused on carrying out rigorous evaluations of mass communication campaigns and localized outreach activities seeking to better understand the most effective channels, message framings, and community-based partnerships for raising public awareness of threats, positively shaping disaster preparedness behaviors, and fostering more resilient cultures across societies according to studies by Meyer et al. (2014).

Complementing this, other communication analysts including Tang et al. (2015) have quantitatively analysed trace data of how emergency alerts, risk information, and preparedness advice propagate on modern information networks from social media to local broadcasting to unpack correlations between observed diffusion patterns and real-world factors like demographic characteristics, population concentrations, and the underlying topological structures of both virtual and physical social connections in various communities.

More recently, innovative studies explored the potential of interactive web-based and mobile gaming applications and simulations seeking to educate the public on local hazards and vulnerabilities in an engaging gamified manner through scenario-based roleplaying, participatory mapping of exposures, and case-based learning exercises, showing encouraging results according to evaluations of several pilot programs by researchers like Collins et al. (2019) and Gao et al. (2011) that provide pointers for further refinement.

4. Emerging Topics—Evolutionary Technologies

4.1. Remote Sensing and Automated Image Analysis

Advances in remote sensing platforms in recent years have enabled the generation and collection of petabytes of high-resolution visual data from a variety of aerial and satellite sensors, as well as lightweight Unmanned Aerial Systems (UAS) and drones deployed rapidly following extreme events. According to recent studies, computer vision and sophisticated deep learning techniques are increasingly being leveraged to automatically detect and classify building damages at large scales from such image feeds with relatively high accuracy levels.

For example, CNN-based models have been developed that can identify structural cracks, collapsed walls or foundations, and damage to roofing materials with 80-90% accuracy on new satellite and UAV imagery collected over disaster-affected urban landscapes.

4.2. Crowdsourced Mapping and Field Observations

Complementing automated analyses of aerial/satellite imagery, crowdsourced mapping platforms are now enlisting local volunteers and response workers to upload georeferenced damage tags and field photos using mobile apps.

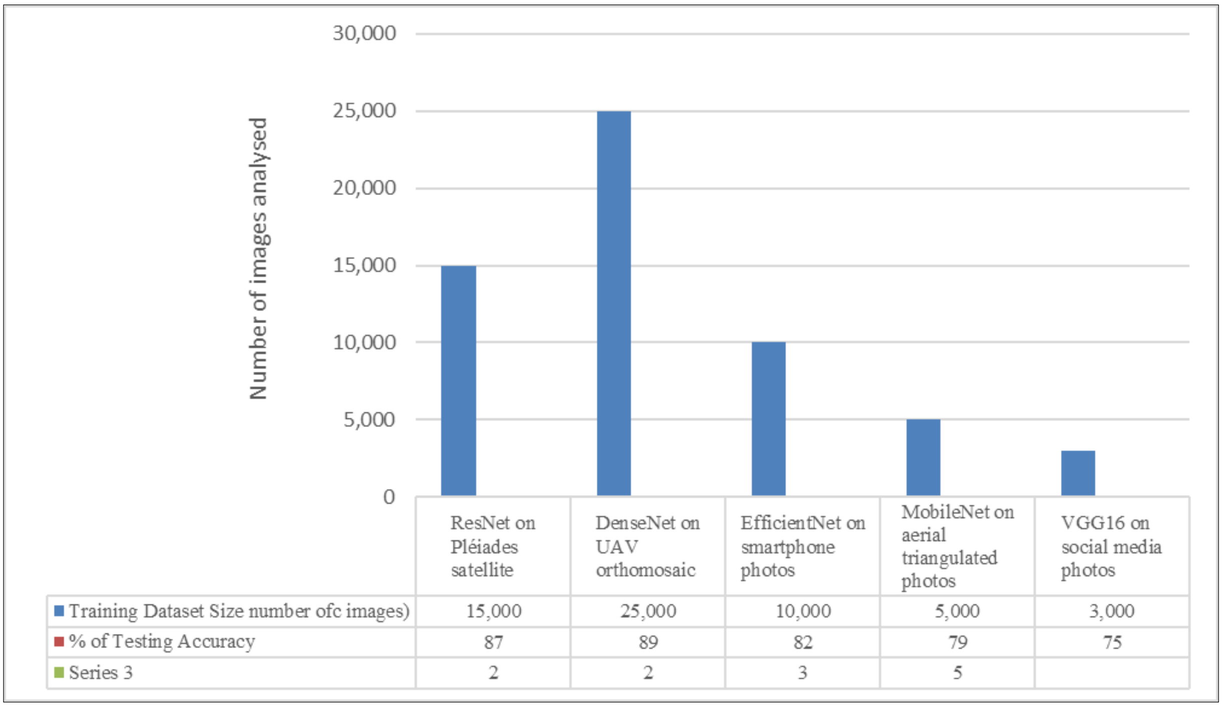

Figure 6 Accuracy assessment of deep learning models for damage detection

As shown in the fig 7 above, deep learning models for automated building damage detection have achieved testing accuracies ranging from 75% to nearly 90% depending on the specific neural network architecture, size and diversity of training data, and type of remote sensing platform. Larger training datasets captured from multiple sensors generally result in improved performance.

4.3. Cloud-Based Damage Assessment Tools

Several startups and technology firms have developed cloud-based geoAI platforms that aim to streamline and scale up different aspects of the post-disaster damage assessment workflow. For example, companies like Orbital Insight and Recorded Future offer AI-powered satellite imagery analysis services to automatically detect structural changes at a city-scale after events like earthquakes, floods or wildfires (Orbital Insight, 2021; Recorded Future, 2022).

These platforms leverage proprietary deep learning models trained on huge databases of past satellite and aerial images. Analysts can rapidly process petabytes of new sensor data over broad regions through an intuitive web interface to generate structural damage mapping, change detection analytics and related metrics to assist first responders and aid agencies. Several studies have found such cloud-based damage mapping tools can significantly accelerate situational awareness in disaster response (Jiang et al., 2022).

4.4. Crowd-AI Partnerships

Other startups are exploring hybrid approaches that blend AI and local crowdsourcing capabilities. For example, organisations like CrisisMap and MicroMappers are partnering with tech firms to build collaborative damage mapping applications (CrisisMap, 2022; MicroMappers, 2022).

Following events, these apps allow trained volunteers on the ground to upload geotagged damage reports, photos and videos which are then automatically processed by AI models in the cloud to refine high-resolution damage extent and severity maps in near real-time to better target relief operations.

4.5. Open Data Sharing and Model Training

Several governments and humanitarian organizations are now advocating open data policies to crowdsource disaster response and accelerate AI model development. The UN Satellite Centre and EU's Copernicus programme have released petabytes of free satellite imagery over past major events for public usage under open licenses. This has aided new research for validating and improving deep learning models through increased data availability (UNOSAT, 2022; Copernicus, 2022).

At the same time, partnerships between tech firms and disaster response agencies are releasing more labeled ground-truth datasets containing geo-tagged photos of buildings with damage annotations. For example, following the Nepal earthquake disaster of 2015, Facebook and the AI for Earth initiative crowd-sourced over 100,000 building damage labels from social media photos. Such datasets have significantly helped in training more robust machine learning models to generalize across different sensor types and disaster scenarios (Facebook, 2019).

5. Big Data Challenges in Disaster Management

5.1. Issues of Data Volume and Velocity

Post-disaster environments often involve an extraordinarily large influx of heterogeneous data from multiple sources that needs to be processed in a timely manner (Li et al., 2020). Satellite imagery alone from instruments like Landsat 8 and Sentinel-2 can easily generate petabytes of optical and SAR data for a single large-scale disaster event covering thousands of square kilometers (Soden et al., 2014). Effective management of such massive datasets is challenging given storage and compute requirements for analytics.

However, network disruptions are also very common in affected areas which further hampers efficient transfer of such 'big data' volumes to remote cloud facilities or data centers for analysis (Gonzalez et al., 2016). Damage to telecom infrastructure coupled with surge in cellular traffic post-disaster can overwhelm bandwidth capacities. Even with restoration of high-speed connectivity through temporary cellular towers, traditional centralized databases and Hadoop/Spark based computing infrastructures may struggle to dynamically scale up and keep up with the unpredictable ingress velocities of heterogeneous data streams from multiple sources (Shiel et al., 2021).

This necessitates the design of novel scalable big data processing frameworks that can instantly and elastically expand computational resource allocation including utilizing edge/fog servers on-demand in near real-time to accommodate surge in data ingestion rates and accommodate spikes in analysis workloads (Mani et al., 2020). Leveraging distributed cloud architectures with orchestration of compute across core, edge and end-user devices assumes significance. Containerized microservices also aid such horizontal scalability of data pipelines.

5.2. Challenges of Data Veracity

Post-disaster data streams sourced through heterogeneous sensors, citizen reports and secondary data sources are often noisy with errors, uncertainties, biases and inconsistencies owing to variability in data collection protocols, technologies and skills of field operators used (Imran et al., 2015). This affects the 'veracity' or reliability of such information sources.

For instance, crowdsourced damage reports uploaded through online campaigns or sourced from social media feeds require manual efforts of disaster managers or volunteers for filtering duplicate or redundant records as well as for cross-checking reported observations against more authoritative records maintained by local government authorities or utilities to remove any erroneous, ambiguous or unverified claims (Ludwig et al., 2017). Merely scaling up the sources without adequate quality safeguards can dilute the fidelity of collated situational data.

Similarly, especially in initial stages, automated AI/ML models trained on past events may misclassify some structural changes detected from satellite or aerial imagery as actual damages when they could be pre-existing infrastructure changes or temporary alterations. This necessitates expert human analysts or local volunteers to validate AI interpretations and provide quality assurance of damage detection outputs against ground realities before utilization for response planning (Piro et al., 2021). Reliable quantification of uncertainty in analytic outputs also becomes important.

5.3. Issues around Data Privacy and Sensitivity

Post-disaster scenarios often involve collection, transfer and analysis of diverse types of digital datasets covering impacted populations and locations which may contain highly sensitive personal information like casualty counts, displaced communities, medical needs of injured, damage details of critical infrastructure like hospitals, roads, utilities etc (Agarwal et al., 2020). Effective privacy-preserving methods must be applied as per applicable privacy regulations to avoid any misuse of such sensitive personal data.

However, with the scale and dynamic nature of data collection involved during emergencies from different sensors and sources, implementation of standard privacy protocols like de-identification through anonymization or consent management for each data transaction becomes quite challenging (Bui et al., 2016). Retrospective tracing of data sharing agreements also gets difficult due to lack of common identifiers.

Additionally, certain disaster-related datasets collected from online and IoT sources potentially have 'dual use' where the data could be abused by bad actors for unrelated harmful purposes like human trafficking if accessed without preventive controls (Sathyanarayana et al., 2020). Stringent access policies need defining based on user roles.

5.4. Need for Disaster Data Standards and Ontologies

In post-disaster response scenarios involving many government agencies, humanitarian groups and volunteer technical communities collecting and sharing critical situational information from the affected locations, lack of common data standards, models and semantics often creates problems of interoperability hampering coordinated analysis and decision-making (Chatfield & Brajawidagda, 2013).

For example, even when damage labels and assessments are crowdsourced or generated through AI tools from different organizations, they may use non-consistent terminology to represent similar effects or severity levels without a standardized glossary (Narasimhan et al., 2018). Integrating such diverse datasets thus becomes difficult without a shared taxonomy.

Hence, there is a need to develop formally defined and unified reference disaster data models, schemas and ontologies which can facilitate semantic harmonization and enable validated information exchanges between disparate systems through queries (Nguyen et al., 2021). The ontologies must encode conceptual rules about spatio-temporal and thematic relationships between entity classes to remedy varying granularities.

6. Conclusion

In conclusion, recent advances in geospatial technologies including remote sensing platforms, computer vision, deep learning and integrated GeoAI systems present immense opportunities for revolutionizing post-disaster damage assessment processes. The ability to rapidly analyze petabytes of visual data from satellites, drones and field cameras and generate analytic layers on structural changes at city-scales is helping cut down response times. Meanwhile, innovative hybrid approaches leveraging both AI capabilities and human intelligence through collaborative crowdsourcing are working to refine situational awareness. As open data policies facilitate increased dataset volumes for model training, performance continues to rise. Going forward, tighter integration of these evolutionary technologies with incident command systems and on-ground mapping workflows holds promise to transform damage mapping into a highly automated, scaled-up and iterative process. Continued blending of local and global sensing with hybrid human-AI analysis likewise shows potential to make impactful responses even timelier and targeted. However, challenges around network connectivity, model interpretability and data privacy in post-disaster environments will also need addressing. Overall, ongoing progress in GeoAI demonstrates its growing potential as a pivotal enabler of effective, data-driven disaster response worldwide.

Compliance with ethical standards

Disclosure of conflict of interest

No conflict of interest to be disclosed.

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