

Online ISSN

3007-3197

Print ISSN

3007-3189

<http://amresearchreview.com/index.php/Journal/about>

Next Generation Disaster Resilience: Integrating Cloud-Native GIS, Deep Learning, and Geospatial Digital Twins

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ABSTRACT

Natural disasters are the fastest-growing global threat: floods alone cost 23% of all disaster-related economic losses, impacting 250 million people annually. While traditional emergency response relied on flat, desktop GIS on static two-dimensional spatial grids limited by compute power and siloed data. In this survey paper we review a radical paradigm shift that merges three distinct fundamental domain areas – cloud-native GIS architectures, deep learning algorithms (GeoAI), and high fidelity geospatial digital twins (GDTs). Together, this combination allows us to move beyond passive disaster recovery towards a proactive, predictive framework for disaster management. We review the dynamically fusing of the building information modeling (BIM) and GIS spatial, with the Internet of Things (IoT) telemetry at a locality with a cloud environment within hybrid local-cloud computing environments. We look at a spectrum of optimized spatial data standards that allow for a break from traditional scalability limits, such as cloud-optimized georeferenced tag-based files (COGs), spatio-temporal asset catalogs (STAC), geo-parquet and Zarr, to allow for streamlined data ingestion, with Zero-Trust based access controls. Cognitively we overview of GeoAI state-of-the-art techniques, from the application of the U-Net for Synthetic Aperture Radar (SAR) and its processing, convolutional damage mapping, Graph Neural Networks (GNNs) to model highly irregular infrastructure, to Hierarchical Reinforcement Learning to facilitate autonomic communications recovery. Finally we critically compare state of the art in neural rendering such as 3D Gaussian Splatting (3DGS) against limitations of traditional photogrammetry, to address the operational challenges posed by a mixed reality within edge environments. In conclusion, we establish a novel, integrated platform to realize active and predictive, closed-loop disaster recovery systems, at community scale.

Keywords: Cloud-Native GIS; Deep Learning; Geospatial Digital Twins; Disaster Resilience; GeoAI; 3D Gaussian Splatting; BIM-GIS-IoT Fusion.

1. Introduction

As natural disaster threats escalate globally due to climate change, rapid urbanization, and aging infrastructure, we must transform how we model and mitigate spatial risk. Flooding alone, the most widespread, frequent, and economically crippling natural disaster in the world, already causes roughly 23 percent of global economic losses due to disasters and affects nearly 250 million people every year (CRED & UNDRR, 2023). By 2100, we face more than doubling exposure to coastal floods-at high-emission levels, a staggering 1.6 billion people could be exposed.

Wildfires, earthquakes, and severe storms, too, continue to pose a risk to exposed assets and infrastructure (UNDRR, 2021).

These modern challenges are outpacing conventional disaster management, which has long been stuck in the realm of two-dimensional, static geographic information systems (GIS) residing on desktop computers and hampered by localized computing power, long delays in obtaining, ingesting imagery, and siloed datasets unable to grasp changing hazardous environments in their temporal and spatial dimensions (Voigt et al., 2016). That's why, on the bleeding edge of the geospatial field, an imminent paradigm shift in spatial risk analysis and management is driven by three foundational technologies coming into confluence: cloud-native GIS architectures, deep learning algorithms, and high-fidelity geospatial digital twins (GDTs) (Janowicz et al., 2020). We review the synergistic convergence of these three domains. First, cloud-native GIS offers elastic infrastructure and the open, optimized data standards required to quickly access, ingest and query petabyte-scale EO datasets.

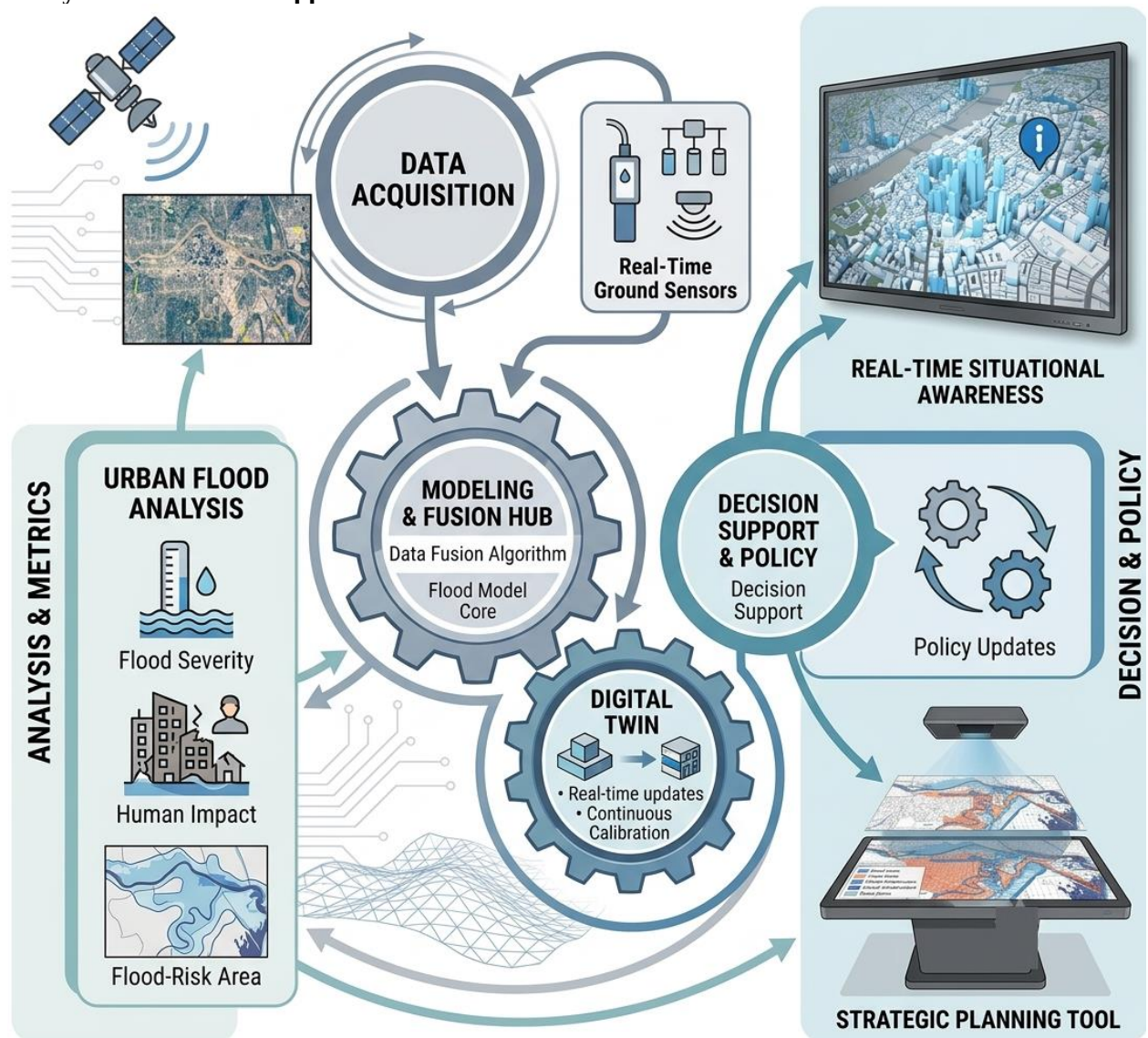
Second, GeoAI, the cognitive engine in this ecosystem, processes multi-source data to extract features automatically, predict the propagation of hazards, and identify infrastructure damages at an unparalleled level of accuracy (Zhu et al., 2017).

Finally, geospatial digital twins provide the dynamic, multi-dimensional simulation and rendering capabilities, integrating the real and digital world with real-time data streams and intuitive visualizations. Taken together, these three elements transform disaster response from historical recovery to active and predictive community resilience (Ford & Wolf, 2020).

2. Architectural Foundations of Integrated Geospatial Digital Twins

This new era in cloud-native GIS with geospatial digital twins, powered by deep learning, necessitates an architecturally balanced, multi-tier structure capable of handling diverse and numerous inputs, intensive computations, and the physical display of high-fidelity spatial simulations. Whereas existing spatial approaches are segmented with separate data gathering, simulation, and representation stages, the innovative disaster resilience architecture will form an integrated, open-feedback, loop-in-time framework encompassing the cycles of perceive, model, and plan action (Pettit et al. 2021).

Figure 1: Operational Framework for a Cloud-Native, Digital Twin-Driven Urban Flood Analysis and Decision Support Hub



Deep Learning Paradigms in GeoAI and Multi- 2.1. The BIM-GIS-IoT Data Fusion Paradigm

The process of constructing a mature digital twin on geospatial technology is rooted in a profound and fluid union of three distinct data realms. This entails the dynamic integration of Building Information Modeling (BIM), Geographic Information Systems (GIS), and the Internet of Things (IoT). Each data realm addresses a significant dimension of the real physical world but historically remained physically disparate because of differing data models, proprietary formats and scales of geometries (Ketzler et al., 2020).

BIM tools deliver an ultra-precise, object-centric, geo-referenced and information-rich model. They model a facility right down to its fundamental structural and mechanical systems, including component, material, property and operation characteristics. Although BIM can offer precise 3D modeling, they can be understood as objects floating “in space”, without awareness of geography, environmental variables and regional hazards (Sacks et al., 2018). GIS adds the

crucial geography layer. This places individual facilities within a global coordinate system and overlay their geographical location with data regarding the environment – topography, hydrology, demography, transportation infrastructure, and previous historical hazard boundaries (Batty, 2018).

To make this model move beyond the static 3D realm and transition it into a digital twin – a living replica – you need to feed it real-time data through a layer of Internet of Things (IoT) broker. Live sensor readings from sensors, Supervisory Control and Data Acquisition (SCADA) systems, and live smart meters send forth to this dynamic data layer the “heartbeat” of the environment-water levels, ground and structural vibrations, earthquakes, local precipitation events, and the local power grid demand. Through the linking of these dynamic streams with real spatial data from GIS, as well as linking to the corresponding 3D object from BIM, you have the capability to monitor the actual real-time state of a particular building structure within its environment (Jones et al., 2020).

2.2. Distributed Infrastructure and Asset Inventory

The complex integration workload necessitated by extreme natural events can be achieved through a hybrid computing model, where raw telemetry from the physical environment is preprocessed in a local workstation using high performance compute such as graphic processing units with high resolution to perform model renderings or local deep learning training (Zhu et al. 2018). Telemetry is synchronized with a real-time scalable cloud database deployed on virtual infrastructure.

The geospatial database such as PostGIS provides spatial storage and relational query capabilities, while distributed brokers can ingest massive volume of real-time telemetry and distribute it into operative dashboards. To organize large-scale utility networks and assets, digital twins benefit from using consolidated inventory systems like FNT Command, that provides pre-created device classes and templates that normalize multi-vendor resources in physical, logical and virtual layers (Goodchild, 2010).

Table 1: Hybrid Compute and Storage Specifications for Geospatial Digital Twins

Architectural Tier	Component Spec Type	Specific Hardware/Software Configuration	Operational Role & Integration
Local Processing & Modeling	CPU	AMD Ryzen 9 7950X	Execution of local 3D modeling pipelines and spatial preprocessing tasks
	GPU	NVIDIA RTX 4070 Ti	Local neural model development, image annotation, and Unreal Engine visualization rendering
	RAM	64 GB DDR5	Multi-threaded memory buffering for complex spatial joins and data extraction
	Storage	2 TB NVMe SSD	Low-latency caching of raw point clouds, imagery, and structural assets
Cloud Storage & Querying	Platform Host	AWS / DigitalOcean Virtual Instances	Scalable remote runtime environment hosting services and databases

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3007-3197

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	Compute vCPUs	8 vCPUs	Processing remote API requests, geoprocessing algorithms, and user commands
	Memory & Disk	32 GB RAM / 1 TB SSD	Scaling concurrent database sessions and dynamic spatial querying operations
	Database Engine	PostgreSQL / PostGIS	Georeferenced indexing, spatial overlays, and relational database management
Telemetry & Protocols	Protocols	LoRaWAN, Wi-Fi/5G, MQTT	Transmitting high-frequency sensor streams (e.g., seismic, water level) to cloud brokers
	VPN Security	WireGuard / OpenVPN	Encrypted tunneling between edge gateways and the cloud database

3. Cloud-Native GIS Infrastructure and Modern Open Spatial Standards

The scale problems with traditional geospatial data management, primarily rooted in locally managed, file-based desktop GIS platforms. Traditional workflow require geoprocessing tools and remote sensing imagery to move huge datasets with dozens to hundreds of Gigabytes from a shared file server to local desktops, load into memory and run through single-threaded geoprocesses (Batty, 2018). This bottleneck, critical in urgent events like sudden environmental catastrophes, often prohibits effective collaboration across users and slows down the speed of responses. Cloud-native GIS architecture breaks through those limitations with raw data residing in the object store (AWS S3, GCS, Azure Blob Storage) and exposed via elastic, API-based data services (Ertz et al., 2021).

3.1. Optimized Formats and Dynamic Querying

At the center of the cloud-native GIS story is the migration of spatial data formats to optimized, chunked versions suitable for HTTP range-request querying. No longer is it necessary to download a whole imagery file to a client application or cloud model; the application will simply read the byte-range of the image file it requires, based on the precise spatial area of interest (AOI). Cloud Optimized GeoTIFFs (COGs) organizes raster layers into an internal tiling system and downsampling overviews, enabling on-demand pixel access for cloud-based dynamic tiling servers such as TiTiler (Appelbaum & Mertic, 2021).

The SpatioTemporal Asset Catalogs (STAC) standards complement these data structures with a machine-readable specification for metadata-rich JSON objects representing catalogs of EO datasets in space and time (STAC Community, 2023).

Large, columnar vector analytics datasets in GeoParquet exploit data-warehouse-style column-store optimizations to reduce large tabular geometries and accelerate repeated queries on the geometry data. Cloud-native datasets represented as chunked Zarr files optimize the storage and multi-threaded access to large, multi-dimensional arrays, such as meteorological, climate, or satellite data time series or spatio-temporal gridded arrays of temperature, pressure, precipitation, and solar radiation (Miles et al., 2022).

Table 2: Comparison of Spatial Data Formats for Cloud-Native GIS Architectures

Format Name	Spatial	Data	Key	Technical	Operational
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3007-3197

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	Type	Innovation	Advantage in Disasters
Cloud Optimized GeoTIFF (COG)	Raster Imagery & Elevation	Internal tiling, downsampled overviews, and HTTP range-request compatibility	Streaming high-resolution satellite/UAV rasters directly to web maps without local storage
SpatioTemporal Asset Catalog (STAC)	Spatial/Temporal Metadata	Standardized JSON indexing of geographic coordinates and acquisition times	Automated querying of pre- and post-event imagery over specific hazard perimeters
GeoParquet	Tabular Vector Geometries	Column-oriented structure, compressed binary storage, and parallel SQL execution	Rapid spatial joins and querying of millions of property assets against active hazard zones
Zarr	Multidimensional Array	Chunked multidimensional storage for gridded data structures	Low-latency querying of time-series climate, wind, and precipitation models

3.2. Open Geospatial Software Stack Advancements

To capitalize on this, the open source spatial software ecosystem has abandoned its locally run desktop-centric workflow, moving towards a more containerized, serverless, and API enabled architecture, with the modern GIS software stack embracing a suite of applications tailored to run at high speed on cloud-based infrastructure (Goodchild, 2010):

- **QGIS (Version 3.40)**: Functions as a flexible spatial modeler, incorporating native support for temporal visualizations, 3D scene rendering, and tight integrations with PostGIS and GeoServer databases. Field-level updates are synchronized using the QField mobile application, which enables offline caching and data collection in disconnected hazard zones (Kulp & Strauss, 2019).
- **eoAPI**: Built as a cloud-native STAC metadata framework, eoAPI uses Infrastructure as Code (IaC) templates (AWS CDK and Kubernetes Helm charts) to deploy spatial search and visualization endpoints in minutes, providing disaster management systems with an interoperable baseline for dynamic Earth observation (IPCC, 2022).
- **Actinia & Rasdaman**: Actinia provides REST API endpoints for scalable geoprocessing tasks using GRASS GIS as a background engine, while Rasdaman operates as an array database specifically optimized for large-scale, time-series climate analytics (Arora & Tiwari, 2024).

3.3. Security Workflows and Private Data Management

Cloud-Native GIS solutions are proving themselves very beneficial in a multitude of different use cases; however, their actual implementation within active crises highlights many data privacy and security exposures that could result in devastating impacts (Yang et al., 2020). Default cloud-optimized architectures typically rely on publishing raster datasets in public buckets for the underlying dynamic tiling engines (such as TiTiler) to request over HTTP. In highly active situations such as complex emergency operations, combat zones, or industrial emergencies, having exposed spatial datasets containing information such as vulnerable utility

Online ISSN

3007-3197

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3007-3189

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corridors, building stability reports, or responder tracking on a public server may expose significant personal risk and intellectual property challenges (Scassa, 2020).

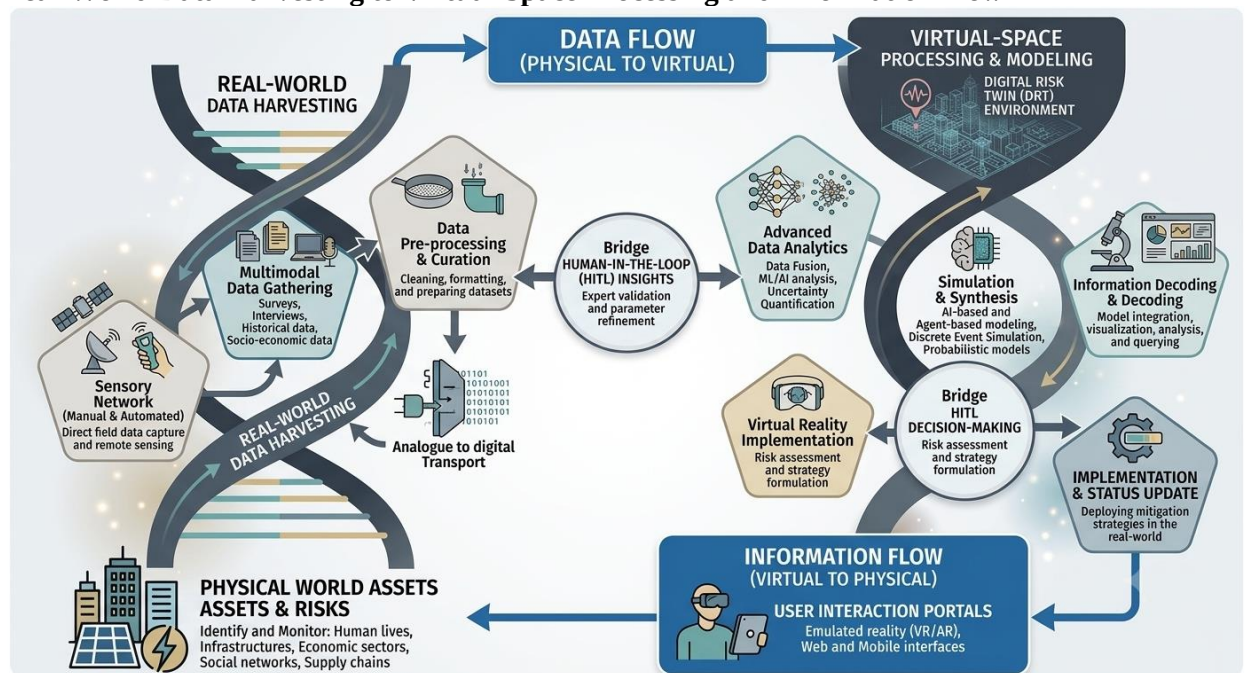
Modern GIS platforms have incorporated a secure private spatial data workflow by utilising extension-specific software, such as the Kartoza CloudNativeGIS module, and implementing Zero-Trust security in conjunction with Fine-Grained Identity and Access management (IAM) and Object-Level Access Controls (Ferraiolo et al., 2021).

Securely authenticate dynamic tiling services, and validate user permissions with Secure Headers before accessing private COG data (Mas et al., 2021), with Automated Patching and encrypted data transit, in certified cloud spaces (such as AWS GovCloud) (NIST, 2020).

4. Deep Learning Paradigms in GeoAI and Multi-Hazard Analysis

Geospatial Artificial Intelligence (GeoAI) is the brain of new, cutting edge systems for disaster resilience, automating tedious human analysis of images through deep learning techniques with predictive power. Historical risk assessment maps were created through time-intensive manual selection and extraction of map features, weighted overlays, and other static techniques, often influenced by human bias (Li & Ning, 2019).

Figure 2: Closed-Loop Architecture of Digital Risk Twin (DRT) Environments: From Real-World Data Harvesting to Virtual-Space Processing and Information Flow



4.1. Remote Sensing Platforms and Optical versus SAR Processing

Multi-platform Earth observation systems (EOS) feeding GeoAI pipelines Spatial data used by the pipelines are derived from multi-platform EOS systems. High-resolution optical imaging such as from the Sentinel-2, Landsat-9 or from commercial constellations such as the Maxar and Planet constellations provide high-resolution visual information of the situation but are severely hindered by cloud coverage that is often prevalent during such extreme weather phenomena (Drusch et al., 2012). The use of microwave-based Synthetic Aperture Radar (SAR) systems (e.g., Sentinel-1C, the Capella Space, and ICEYE constellation) offer cloud and smoke penetrating observation capabilities, monitoring soil moisture, land deformation and surface water inundation accurately. SAR acquisition modes range from localized imaging (StripMap) to Interferometric Wide (IW) modes that, based on the TOPSAR processing mode, offer

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3007-3197

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3007-3189

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coverage of 250" km" with a 520" m" resolution that is applicable for regional flood mapping (De Zan et al., 2006).

However, SAR data processing has specific challenges that distinguish them from optical data. Simply applying a thresholding on the post-event SAR scene can result in significant classification errors. Permanent water, urban smooth surfaces (asphalt road, flat roof) and radar shadows behind the steep terrains appear as black pixels because they reflect the SAR signal at a steep angle (specular reflection). Conversely, the surface roughness of the water (e.g., due to wind action) increases the backscatter and can cause missed flood events (Horritt et al., 2001). To overcome these issues, deep learning architectures are trained using multiple channels as inputs such as pre-event and post-event intensity of SAR acquisitions, ratio differences, digital elevation model to allow the neural network (e.g. U-Net architecture) learning spatial context based features across multiple scales and to output the per-pixel flood probability map. Final classification is then exported as post-processing Parquet files together with binary flood maps (with optional 80" m" and 240" m" spatial buffering) and historical inundation recurrence layers to detect persistent flood-prone areas (Bauer-Marschallinger et al., 2022).

4.2. Deep Learning for Structural Damage Mapping

Assessing the stability of a structure is often the most important task after a natural disaster in order to prioritize the delivery of search and rescue resources. However, after a disaster, collecting this structural data via manual means (claims adjusters or structural engineers) is far too slow to deliver timely aid to those affected. Thus, organizations have developed and are implementing deep learning models to quickly analyze post disaster imagery.

For instance, when wildfire perimeters have been established, insurance carrier USAA deployed a ResNet34 CNN in hosted Jupyter notebooks (ArcGIS Notebooks) that could identify potentially damaged buildings within active perimeters. This workflow handled greater than 40 GBs of high-resolution imagery with a spatial pipeline managed by a mosaic dataset, and the ResNet34 CNN was trained on manually annotated building footprints, yielding greater than 99% accuracy (Roy et al., 2014; Torres et al., 2012). The workflow used ArcGIS API for Python to apply this model to 9,000 plus individual buildings with greater than 99% confidence. This immediately informed claims adjusters and emergency planners of damaged buildings (red) versus undamaged buildings (green), and this was further enhanced with demographic data using ArcGIS Business Analyst to highlight areas containing vulnerable populations, such as children and the elderly (Moreira et al., 2013).

When a 3D analysis of structural damage is required, the models must perform dual channel vision analysis. In the Galveston digital twin project, Image2Damage uses a pre-trained dual channel system that consists of a Swin Transformer and ConvNeXt models to perform an F₁ score of 77.11 on classifying local structural damage (i.e., roof failure or debris on roads) through dual image analysis of pre-and post-disaster satellite imagery along with street-level view and UAV imagery (Matgen et al., 2011).

4.3. Relational Infrastructure Modeling with Graph Neural Networks

However, critical infrastructure systems - like roadway networks, electricity grids, and water pipes - are naturally relational and not necessarily organized on regular grids like raster images of natural phenomena. For such irregular structures like road intersections or power stations that have nodes and arcs representing road segments and transmission lines, Graph Neural Networks (GNNs) were designed to process them (Rose et al., 2020).

Using the topology and relationship information between them, GNNs are ideally equipped for predicting cascade failure in infrastructure systems when exposed to extremes. Specifically in road networks analysis, the predictive GNN for roadway serviceability assessment can simulate

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3007-3197

Print ISSN

3007-3189

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potential infrastructure failure in extreme floods by leveraging data including road structural condition, disruption caused by operations traffic and roadway damage history, as well as current inundation depth, and simulate real-time optimal route path changes based on flooding and traffic telemetry - as opposed to fixed simulations (Stafford, 2020). In hydraulics models, the computational gains offered by GNNs also significantly speed up the simulation.

A number of GNN based hydraulics modeling frameworks, such as MSWE-GNN, the Multi-Source Water Elevation GNN model simulate flooding spreading through networks at fractions of a second time scales without numerical solving calculations of typical hydraulics models, and produce comparable spatial accuracies to them (Gewirtz, 2020).

Combined GNN with LSTM models further allow incorporation of time trends, whereas LSTM-GNN architecture filters spatial dependencies by graph convolutions while filtering temporal telemetry trends through recurrent units, resulting in better performances compared to traditional statistical approaches when dealing with noisy and partial data ($p < 0.05$) (Kounad et al., 2018).

4.4. Video Georeferencing and Target Detection

Urban smart city digital twins benefit from the integration of live video from traffic cameras or unmanned aerial vehicle surveillance to trace evacuations for emergencies or local hazards. Raw videos do not include the latitude and longitude information to be directly superimposed on GIS data for real-time navigation. In this paper, to address this problem, our GeoAI approach establishes a complex space-time target detection and video georeferencing pipeline (Kindervag, 2010) using an efficient small object detection model YOLOv5 Pyramid and two Siamese network video tracking models, MPSiam and FSSiamese (Kartoza, 2023). Integrating 3D city digital twins with real-time videos, our model automatically identifies, tracks and georeferences moving objects (e.g. Vehicles and pedestrians) in the digital twin coordinates system, achieving 3.3 times faster processing speeds and real-time performance (up to 83 FPS), while reducing average expected overlap by only 3% (Bertino, 2021).

4.5. Autonomous Communication Recovery and Resource Management

During severe natural disasters, ground-based telecommunication networks are frequently disrupted, hindering search and rescue operations. Unmanned Aerial Vehicle Base Stations (UAV-BSs) represent a promising solution to restore communication coverage, but optimizing their deployment in dynamic, uncertain hazard environments is highly difficult. To resolve this, digital twins deploy an Artificial General Intelligence (AGI)-inspired framework that aligns with a closed-loop perception, modeling, and action planning cycle (Cloud Security Alliance, 2019).

This framework utilizes a predictor and an optimizer to coordinate UAV deployments in real time:

- **Predictor:** Combines a Graph Neural Network (GNN) and a Multilayer Perceptron (MLP) to model the real-world state of the UAV-base station network, predicting communication service satisfaction with an average accuracy of 98.49% (AWS, 2021).
- **Optimizer:** Leverages Hierarchical Reinforcement Learning (HRL) to plan optimal trajectories and coordinate the movement of multiple UAV base stations. The HRL-based optimizer reduces training and computing times by 63.73% compared to standard multi-level deep Q-learning methods (Bhattacharjee, 2020).

For resource management of MEC networks, The Resource-Allocation and Digital Twin (RADiT) algorithm is deployed to control rsus and uavs and optimize task offloading, while meeting latency and energy constraints to enhance completion rates and system delay than greedy and normal rl algorithms (Yan et al., 2022).

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3007-3197

Print ISSN

3007-3189

<http://amresearchreview.com/index.php/Journal/about>**Table 3: Core Deep Learning Architectures and Performance Benchmarks in GeoAI**

Neural Model Class	Specific Architecture Name	Primary GIS Integration	Evaluated Performance Metric
Image Segmentation	U-Net / ResNet34	Managed imagery mosaic datasets; executed via ArcGIS API for Python	Accuracy > 99% in automated building damage classification
Dual-Channel Vision	Swin Transformer + ConvNeXt	Integrates satellite and street-view photography inside 3D digital twins	F ₁ Score of 77.11% (<i>Image2Damage</i> platform)
Relational GNN	GNN + MLP Predictor	Models spatial topologies and telemetry states of UAV networks	98.49% average accuracy on service satisfaction forecasting
Reinforcement Learning	Hierarchical Reinforcement Learning	Coordinates dynamic UAV path planning and resource allocation	63.73% reduction in algorithmic compute training time
Small Object Tracking	YOLOv5-Pyramid Siamese +	Integrates live video streams with virtual 3D city models	Real-time inference of 83 FPS (3.3times speedup)
NLP Text Parsing	BERT-CNN Model	Extracts geo-coordinates from unstructured social media feeds	F ₁ score of 91.9% (<i>VictimFinder</i> platform)

5. High-Fidelity Neural Rendering and Immersive Interfaces

To be capable of inspect damage to structure and conduct simulations with high detail to decision makers, a geospatial digital twin needs to provide accuracy to the physical reality as well as good visual quality. Meshes and point clouds generated with traditional photogrammetry capture the main structure of the environment, but they are often limited in details of complex objects (powerlines of fine size, guard rails, foliage etc.) and have limitations with visuals like texture stretching and baked in shadows (Clement et al., 2018).

5.1. NeRF versus 3D Gaussian Splatting

Modern neural rendering techniques for high fidelity 3D reconstruction Modern rendering methods for creating 3D reconstruction of objects and environments require advanced deep neural networks such as Neural Radiance Field (NeRF) [15] and 3D Gaussian Splatting (3DGS) [14] have led to realistic render and fast training performance. NeRF models scene implicit using deep neural network for both density and view-dependent color prediction. Structural Health Monitoring (SHM) systems can perform fine-grained analysis for damages of structures by mapping damage models onto the 3D geometry. For SHM applications, the "Nerfacto" architecture from Nerfstudio and a deep learning based crack detection model (STRNet) was trained on datasets consisting of a bridge model annotated with structural edge markers [3] where the detected cracks are mapped to the 3D model. NeRF renders 3D scenes very slowly and require significant computation power, which limit the possibilities of real-time interactive 3D applications (Nemni et al., 2020). [15] Neural Radiance Field (NeRF) (a survey and survey analysis). 3D Gaussian Splatting (3DGS) [14] represents a new rendering paradigm, different from NeRF in terms of how a scene is represented. Instead of learning a continuous function

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3007-3197

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for density and color estimation via deep neural network, 3DGS represent a scene with millions of semi-transparent anisotropic 3D Gaussian (ellipsoids) (Ronneberger et al., 2015). The parameters for each Gaussian element are: x,y,z position, orientation (rotation), scale, color (in terms of Spherical Harmonics coefficients), and opacity. These ellipsoids blend interactively during the rendering to achieve smooth, photo-realistic 3D view. Colors and Specularities can be tuned in accordance with viewpoint changes for realistic representation of the surfaces and geometric complexity including sharp edges and fine structures such as tree branches, power lines and structural cracks (Zollmann et al., 2021).

5.2. Operational Mixed Reality and Performance Constraints

These neural rendering tools are being added to live Operational VR/AR (AR/VR) solutions in order to enable immersive technologies to move beyond their initial training-only use cases to support live, tactical operations. This approach is a key element of the European Union's Horizon Europe TRIFFID (auTonomous Robotic aId for increasing First responders Efficiency) project (TRIFFID Consortium, 2023). In the TRIFFID framework, streams of drone-captured video are transformed into high fidelity 3D reconstructibles with very low latency using real time RTMP streaming, fused sensors synchronized to that data, and rapid 3DGS optimization (Kerbl et al., 2023).

The 3D model is exported as a spatial .ply file and pushed to front end clients over WebSockets. To avoid cognitive overload, a combination World-in-Miniature (WIM) intuitive 3D map combined with semantic POIs for which the user can then on-demand filter to select only for critical hazards, like electric wires or damage (Dong et al., 2022). These early versions of TRIFFID architecture have demonstrated the very important practical limitation of local hardware rendering where standalone mobile AR headsets fail to deliver anything greater than ~10 FPS" when processing many millions of splats in high resolution, large area 3DGS landscapes, likely due to thermal/compute limits (Schubert et al., 2023). While an AR-tethered to a powerful workstation configuration, however, can maintain a smooth 72 FPS" by offloading all the computation (including all 3D rendering) to a local graphics workstation, and then streaming only the results back to the head-mounted device (Li et al., 2024). Therefore, any practical deployments of neural rendering software must be supported by a hybrid base-station/headset architecture whereby the powerful field edge servers perform all the real time model generation and rendering, and the light weight clients simply consume the resultant visualization streams (Rokhsaritalemi et al., 2024).

The subsequent output gaussian splat layers can then be used as a service layer that enterprises can utilize - for example the Esri® ArcGIS Drone2Map™ (Advanced) has an option for producing the gaussian splat output in the 3D Tiles format to combine neural reconstructed images and any existing GIS vector and imagery services (Esri, 2025).

Conclusion

This convergence of cloud-native GIS, deep learning and geospatial digital twins represents a paradigm shift for disaster resilience and emergency response. It breaks down the old barriers separating isolated desktop applications to usher in a new active, predictive and collaborative system that provides community scale resilience beyond simple after-the-fact recovery. The analysis herein demonstrated how this architectural union of BIM, GIS and IoT network data directly mirrored physical systems in real-time, creating a living replica.

Cloud-optimized range request data formats that are highly efficient at the petabyte scale enabled fast analysis by public safety without data silos or data privacy challenges.

Simultaneously, GeoAI, acting as a highly sophisticated AI engine, could autonomously model hazard propagation, analyze infrastructure relationships, and classify data from multiple sensing platforms to deliver results at unparalleled precision. Although advanced visualization through new techniques such as 3D Gaussian Splatting offered stunning new possibilities for

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3007-3197

Print ISSN

3007-3189

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visually assessing damaged areas, it revealed that localized processing within a hybrid base station structure will likely be needed to resolve limitations regarding graphics hardware capabilities for deployment. Further innovation on this front and establishing open interoperable pipelines is critically needed. It's through such deep embedding of intelligent, multi-dimensional digital twins in emergency operations that we will effectively protect our communities and their resources in an increasingly unpredictable environment.

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