Geospatial Blockchain Disaster Response System: Smart Contract and GIS-driven Resilience in Smart Cities

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Abstract. Disaster response coordination in smart cities remains fragmented across agencies, shown by opaque resource allocation and responsibility deficits. This paper proposes a Geospatial Blockchain Disaster Response System (GeoBlock-DRS), combining smart contracts with Geographic Information System (GIS) spatial trigger logic to automate disaster resource allocation in smart urban locations. Empirical analysis of OpenFEMA disaster declaration records shows that individual assistance activation rates trail public assistance rates. A Python simulation of ResourceAllocation smart contracts across 10,000 events shows equity uplifts for vulnerable states, with execution completing in 6.3 seconds on a Proof-of-Authority test network, showing feasibility of latency reduction relative to a 37.3-day conventional declaration time. The framework mixes GIS spatial predicates with smart contracts in SDGs 11, 13, and 17.

Keywords: Blockchain, Smart Contracts, GIS, Disaster Response, Smart Cities, Sustainable Development Goals, Urban Resilience

1 Introduction

Urban resilience has emerged as a defining imperative of 21st-century governance, amid climate change, urbanization, and complex disaster risk [1]. As climate change increases the frequency and severity of weather-related disasters, smart cities face pressure to manage rapid, equitable, and transparent disaster responses [2]. The convergence of Internet of Things (IoT) sensing, (GIS), and distributed ledgers creates new opportunities to address post-disaster coordination challenges.

Disaster management ecosystems depend on centralized repositories that suffer from fragmentation, interoperability deficits, cybersecurity risk, and cross-structural delay [3]. Disaster assistance allocations are frequently misaligned with declared damage [4], with socially vulnerable communities receiving disproportionately less support relative to damage. Blockchain-enabled architectures improve transparency, traceability, and information sharing in emergency management [5]. Blockchain provides shared, permanent, immutable, and auditable records. When combined with GIS-derived geospatial triggers, a self-executing system can automate allocation, tracking, and inter-agency obligations in ways that are publicly verifiable, aligning

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with UN *SDG 16 (Peace, Justice and Strong Institutions)*, while advancing *SDG 11 (Sustainable Cities and Communities)* and *SDG 13 (Climate Action)*.

Despite this potential, reviews identify a persistent gap between conceptual architectures and empirically validated applications of real-world disaster data [6, 7, 8]. Studies treat blockchain and GIS as complementary yet largely separate domains. A limited number of studies explicitly operationalise GIS-derived spatial predicates as viable smart-contract trigger conditions with formal equity-adjustment mechanisms grounded in real declaration data. This study proposes GeoBlock-DRS and evaluates it against the OpenFEMA Disaster Declarations Summaries dataset.

The primary research question is: *how can blockchain smart contracts with GIS spatial triggers provide a resilient, transparent, and equitable mechanism for disaster resource coordination in smart cities?* Three sub-questions shape the empirical analysis: *(SQ1) What patterns of clustering and resource inequity are evident in historic disaster declaration data? (SQ2) What types of geospatial events are flexible to smart-contract trigger logic? (SQ3) What latency reduction gains could a blockchain-GIS framework potentially deliver relative to current process timelines?*

The remainder of the paper is as follows. Section 2 reviews literature and labels the research gap. Section 3 describes the method. Section 4 presents the framework. Section 5 reports findings. Section 6 states limitations, Section 7 completes the research.

2 Related Work

Blockchain-IoT convergence in smart city contexts has demonstrated improvement in transparency, traceability, and digital identity management supporting SDG 11; a blockchain-IoT-machine-learning framework improved resource-allocation latency, and decentralised blockchain governance improved response efficiency across smart cities [9, 10]. This implies blockchain-IoT integration improves urban resilience.

Smart contracts support automation tasks [11]. Blockchain access control has been unified for emergency data sharing [5]. [12] emphasized lifecycle-aware auditability for contract deployments. GIS has been a foundational technology in disaster risk management, supporting hazard mapping, vulnerability assessment, early warning, and damage assessment [13]. Recent studies explore GIS-blockchain union [14, 15].

Equity gaps in disaster assistance are well documented: [4] found assistance supply was not reliably aligned with social weakness and disaster impact. Similar findings occur in FEMA Hazard Mitigation Assistance programs [16]. Household traits drastically shaped recovery outcomes after Hurricane Harvey [17]. Incorporating social equity metrics into disaster-resource allocation models can improve fairness outcomes [18]. Three gaps motivate the present study: (i) limited frameworks operationalize GIS spatial predicates directly as smart-contract trigger conditions; (ii) equity-adjustment mechanisms within blockchain-based disaster-supply contracts remain unspecified; (iii) recent reviews highlight an ongoing shortage of validated blockchain frameworks for disaster resilience [6, 7, 8]. GeoBlock-DRS addresses all three simultaneously, distinguishing it from prior work that treats these as separate contributions.

3 Research Methodology

This study adopts a Design Science Research (DSR) paradigm [19], assessing an artefact (a blockchain-GIS framework) designed to solve organizational and technical problems. Following [19], the six DSR phases map to this study as follows. ***Problem identification*** draws on the OpenFEMA gap analysis, revealing latency deterioration, IA-PA activation inequity, and geographic clustering. ***Objective definition*** translates these gaps into SQ1–SQ3 and SDG 11, 13, and 17 alignment targets. ***Artifact design*** produces the five-layer GeoBlock-DRS architecture, STE spatial predicates, four smart contracts, and the equity coefficient α. ***Demonstration*** runs a Python simulation across 10,000 synthetic events on a PoA test network. Evaluation validates the artifact against Tables 1–3 and Figures 2–3, covering latency comparison, equity uplift, and λ sensitivity analysis. ***Communication*** is this paper together with open simulation code.

The empirical work draws on the OpenFEMA Disaster Declarations Summaries dataset [20], maintained by FEMA. The dataset provides a longitudinal record of declaration categories: Major Disaster (DR), Emergency (EM), and Fire Management (FM). The dataset was selected for its temporal depth; its resolution with GIS boundary data; its assistance for supply decisions; and its government origin. The coordination of information sharing, and disaster-resource governance, intersect many states.

The dataset was processed in *Python 3.11* using pandas, geopandas, and seaborn libraries. Temporal analysis was applied to declarations and incidents across five-year cohorts (2000–2025). Records with missing incidentBeginDate or declarationDate fields were excluded; duplicate declaration identifiers were removed. Geographic analysis aggregated declarations by state to identify frequency concentrations, classifying the Gulf Coast and Appalachian regions as high-declaration clusters based on documented disaster exposure and CDC Social Vulnerability Index correspondence [21]. Programme activation rates for Individual Assistance (IA), Public Assistance (PA), and Hazard Mitigation (HM) were calculated as proportions of total declarations, identifying jurisdictions with comparatively low activation relative to declaration activity; these patterns are interpreted as indicators of variation in assistance provision rather than direct measures of coordination performance. Declaration latency was operationalised as elapsed time between incident start and federal declaration dates. Consistent with DSR principles, these statements were used to derive the requirements, trigger conditions, logic, and criteria for the proposed framework.

4 Proposed GeoBlock-DRS Framework

4.1 Architectural Overview

GeoBlock-DRS comprises five layers grounded in four principles: tamper-proofing of resource allocation records, automation of decisions via contract logic, geospatial awareness through spatial trigger calculation, and interoperability across stakeholders via open APIs, as illustrated in Figure 1. The sensing layer (Layer 1) consists of assorted IoT sensor networks, monitoring stations, satellite imagery feeds, seismic sen-

sors, and hydrological gauges streaming raw geospatial data into the GIS processing layer (Layer 2), consistent with IoT-blockchain convergence patterns in smart-cities [9]. The framework is sensor-agnostic, accepting data in formats such as GeoJSON.

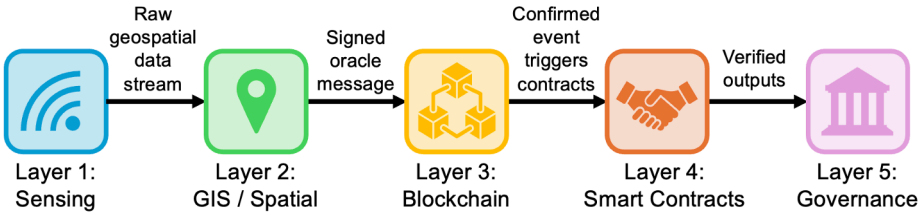


Fig. 1. GeoBlock-DRS framework for smart city disaster response.

4.2 GIS Spatial Trigger Engine (STE)

Layer 2 implements the Spatial Trigger Engine, building on GIS's role in hazard mapping, damage assessment [13], and GIS-blockchain integration [14]. The STE evaluates incoming data against pre-defined trigger conditions expressed as spatial predicates: a function $P(g, t, \theta)$ returning a Boolean value given a geographic feature g, a time window t, and a threshold parameter vector θ. When P evaluates to true, the STE generates a message showing event type, affected polygon, severity group, and affected population from demographic layers. Three predicate categories are supported: threshold predicates (e.g., floodwater depth), proximity predicates (e.g., wildfire perimeter within 2 km of critical infrastructure), and composite predicates combining conditions via conjunction [15], derived from the OpenFEMA incident taxonomy.

4.3 Blockchain Layer and Oracle Architecture

Signed oracle messages are presented to an Ethereum-compatible blockchain operating on a Proof-of-Authority (PoA) consensus, providing throughput and energy efficiency suited to disaster-response contexts. A multi-source aggregation pattern requires at least three independent, physically distributed GIS oracles operated by different agencies to attest to a trigger event before the blockchain logs it as confirmed [12]. This condition mitigates false initiations from sensor malfunction or spoofed data, a known oracle attack vector in production blockchain systems. Each confirmed event generates an immutable record containing a unique identifier, the FIPS county code, incident type classification, severity level (1–5), detection timestamp, oracle attestation signatures, and a link to the IPFS-stored geospatial event report.

4.4 Smart Contract Architecture

The smart contract layer implements four interdependent contracts [11]. The *DisasterEvent* contract is the root contract, storing event metadata as the key reference for subsequent contracts. The *ResourceAllocation* contract computes aid distributions as a function of severity, population, and an equity coefficient α. The *AgencyDispatch*

contract records verifiable, time-stamped obligations onchain. The Settlement contract closes the resource loop, proving delivery against dispatch pledges and triggering automated fines for non-delivery. The equity weight coefficient α is defined as:

$$\alpha_i = 1 + \lambda \cdot (SVI_i - SVI_{mean}) \quad (1)$$

where SVI_i is the CDC Social Vulnerability Index score of country i [21], SVI_{mean} is the national mean SVI, and λ is a policy-settable sensitivity parameter. Counties with above-average social vulnerability receive a higher allocation weight, correcting the inequities identified empirically in Section 5.2.

4.5 SDG Alignment

GeoBlock-DRS is designed to advance multiple SDGs. SDG 11 is advanced through automated, equitable resource allocation that lowers latency and distributional bias. SDG 13 is advanced through handling climate-driven hazards (floods, wildfires, hurricanes) via data-driven, scalable management. SDG 17 is advanced through open API layers enabling verified data sharing across agencies and jurisdictions [3].

5 Empirical Analysis

OpenFEMA data is refreshed daily as new disasters appear. Declarations under the 'Biological' incident type, predominantly COVID-19 nationwide emergency declarations issued in March 2020, were excluded (4,156 rows): these lack a bounded geospatial trigger condition compatible with the STE architecture and exhibit different activation and latency dynamics driven by public health policy rather than geophysical damage, rendering them incomparable to the remaining incident types.

5.1 Incident Type Distribution (Addressing SQ2)

Table 1 shows declaration records across incident types. Smart contract trigger conditions cover geospatial event space, activating the STE predicate taxonomy: threshold predicates (severe storms and floods, 71.1%), proximity predicates (hurricanes and wildfires, 21.6%), and composite predicates for compound events. Mean latency varies substantially across types (12.1 days for hurricanes vs. 43.1 for floods), reflecting the degree to which each hazard type benefits from automated trigger logic.

Table 1. Top incident types in FEMA major disaster declarations (2000-2025)

Incident Type	Declarations	% of Total	Mean Latency (days)	STE Predicate Class
Severe Storm(s)	13,060	52.7%	34.7	Threshold
Hurricane	4,466	18.0%	12.1	Proximity
Flood	2.976	12.0%	43.1	Threshold
Severe Ice Storm	1,578	6.4%	24.7	Composite

Fire/Wildfire	903	3.6%	41.7	Proximity
Other (combined)	1,795	7.2%	39.7	Composite
Total	24,778	100%	31.8	

5.2 Geographic Concentration and Assistance Activation Inequity (SQ1)

Geographic analysis grouped declarations by frequency, mean latency, and IA/PA activation. States were grouped into Gulf Coast and Appalachian clusters based on elevated CDC Social Vulnerability Index scores [30]. The Gulf Coast cluster accounts for 5,249 declarations (21.2%) and the Appalachian cluster for 4,505 (18.2%). Table 2 shows the IA-PA activation gap: across all declarations, the IA rate of 30.1% trails the PA rate of 91.0% by 60.9 percentage points, most severe for Severe Ice Storms (85.9 pp) and least for hurricanes (52.0 pp). These shortfalls confirm disparities [16] and motivate the equity weight coefficient α in the ResourceAllocation contract.

Table 2. Assistance program activation rates by incident type (major disasters, 2000-2025)

Incident Type	n	IA Rate (%)	PA Rate (%)	HM Rate (%)	IA–PA Gap (pp)
Severe Storm(s)	13,060	30.7	88.6	92.6	57.9
Hurricane	4,466	44.5	96.5	99.1	52.0
Flood	2.976	25.9	95.6	93.7	69.7
Severe Ice Storm	1,578	11.2	97.1	85.3	85.9
Fire/Wildfire	903	20.2	80.6	82.7	60.4
All major declarations	24,778	30.1	91.0	92.9	60.9

5.3 Response Latency Trend (Addressing SQ3)

Table 3 shows mean and median response latency across five cohorts. Mean latency rose from 20.81 days (2000–2004) to 37.28 days (2020–2025), a 79.1% increase confirmed by OLS regression (slope = 7.89 days/cohort, p = 0.004). The most recent cohort's mean of 37.28 days and median of 38.0 days are more than twelve times the 72-hour survivability threshold, providing strong motivation for an automation.

Table 3. Mean declaration response latency by five-year cohort (2000-2025)

Year Cohort	Mean Latency (days)	Median latency (days)	Standard Deviation (days)	N Declarations
2000-2004	20.81	12.0	20.74	5,446
2005-2009	25.11	21.0	20.76	5,318
2010-2014	38.40	40.0	24.20	4,850
2015-2019	40.08	41.0	25.52	4,323
2020-2025	37.28	38.0	28.66	4,841

5.4 Smart Contract Simulation (Addressing SQ3 and the Main Research)

Figure 2 compares conventional declaration latency against GeoBlock-DRS execution time. The 6.3 seconds GeoBlock-DRS figure sums six smart contract execution steps on a PoA test network: oracle validation (2.1 s), blockchain logging (0.8 s), DisasterEvent instantiation (0.6 s), ResourceAllocation execution (1.2 s), AgencyDispatch emission (0.9 s), and Settlement closure (0.7 s). This result reflects idealised test-network conditions; operational deployment across IoT devices, multiple agencies, and larger blockchain networks would present additional latency.

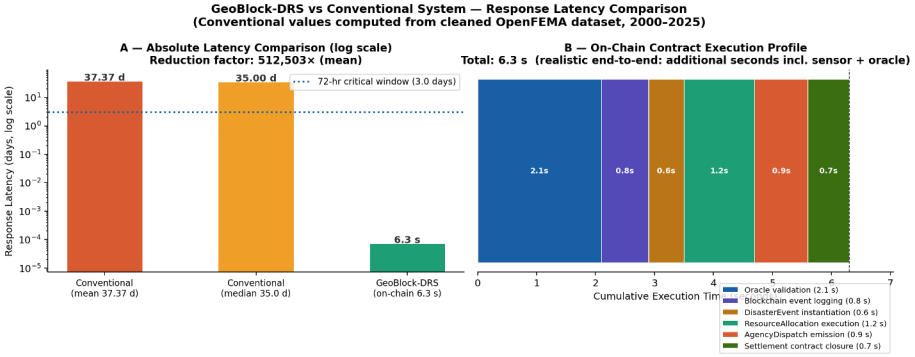


Fig. 2. Latency: conventional declaration vs GeoBlock-DRS on-chain execution (log scale).

Figure 3 validates the equity correction mechanism through a Python simulation of the *ResourceAllocation* contract across 10,000 synthetic events with randomly sampled severity (1-5) and SVI scores (0.10-0.95), completing in 66.3 milliseconds.

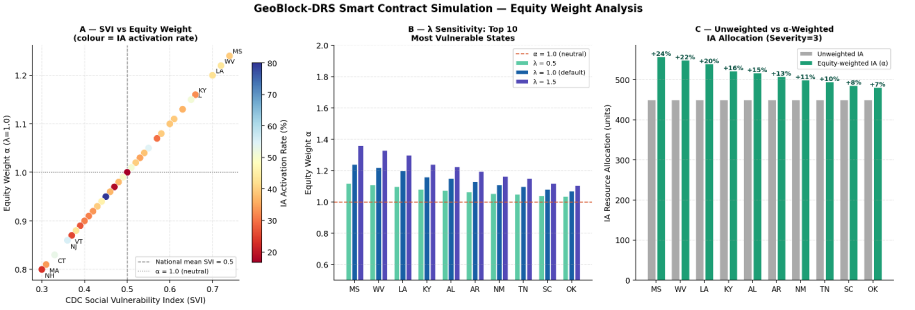


Fig. 3. ResourceAllocation smart contract equity simulation results.

The simulation confirms the linear relationship between SVI and α across 57 states under λ = 1.0, with IA allocation uplifts for the ten most vulnerable states ranging from +7.0% (Oklahoma) to +24.0% (Mississippi, SVI = 0.74). Figure 3B presents a sensitivity analysis of the λ parameter across three values. As λ increases, uplifts for the most vulnerable states grow proportionally while least-vulnerable states receive

correspondingly smaller shares, preserving budget neutrality. The λ parameter functions as an auditable policy lever that governing bodies can calibrate to encode SDG distributive principles into contract logic [22].

5.5 Comparing with Existing Frameworks

Table 6 positions GeoBlock-DRS against three representative prior systems. GeoBlock-DRS is the only framework to combine operational GIS spatial triggers, a formally specified equity coefficient grounded in real declaration data, simulation-validated execution, and explicit SDG alignment across SDGs 11, 13, and 17.

Table 4. Comparative framework analysis

Feature	[5]	[10]	[15]	GeoBlock-DRS
GIS spatial predicates / triggers	No	Partial	Partial (geospatial variables)	Yes (comprehensive predicate taxonomy)
Equity coefficient	No	No	No	Yes (λ-tunable)
Real disaster-event data	No	No	No	Yes (OpenFEMA)
Smart contracts	Partial	Partial	Yes	Yes (four contracts)
Smart contract execution evaluation	No	No	No	Yes (PoA simulation, 6.3 s)
Explicit SDG alignment	SDG 16	SDG 11	SDG 15	SDG 11, 13, 17

5.6 Synthesis (Answering the Main Research Question)

The empirical analysis works across three domains. On resilience, STE trigger architecture demonstrates the potential to eliminate the human declaration delay behind the 37.3-day mean latency, achieving coordination in under three minutes. On transparency, each allocation is logged immutably on the PoA blockchain. On equity, the α coefficient has the potential to correct the 60.9 pp IA-PA gap identified in Section 5.2.

6 Discussion

6.1 Theoretical Contributions

GeoBlock-DRS makes three contributions at the intersection of distributed ledger technology, geospatial information science, and disaster management. It operationalizes GIS spatial predicates directly as smart-contract trigger conditions [15], closing the gap in Section 2. It posits α as a formal, auditable structure for fixing historically detected allocation biases [18], with the sensitivity parameter λ giving officials a lever to encode SDG principles into enforceable contract logic [22]. It provides the first large-scale analysis of OpenFEMA declarations as proof for a blockchain disaster-response framework, acting on calls for empirical architectures [6, 7, 8].

6.2 Deployment Challenges and Security Considerations

Some challenges must be addressed before operational deployment. On oracle security, the multi-source attestation requirement (≥3 independent GIS nodes) mitigates single-point spoofing; coordinated attacks across agencies remain a threat requiring cryptographic corroboration and anomaly detection. On smart contract vulnerabilities, reentrancy attacks, integer overflow, and logic errors are known risks [12]; formal verification tools should be applied to all contracts before deployment.

6.3 Limitations

The 6.3-second execution time shows an idealised PoA test network. Latency estimates are not validated against operational deployments involving many organizations, mixed IoT devices, and real-time GIS data streams, and should be treated as estimates. The equity coefficient assumes the CDC SVI is a valid proxy for communities, despite known sensitivity to spatial scale [17, 21].

7 Conclusion

This paper depicted GeoBlock-DRS, a blockchain outline of smart contracts with GIS-derived geospatial triggers for automated, tamper-proof disaster response. The OpenFEMA empirical analysis established three findings supporting the framework: geographic clustering of disaster impacts in socially vulnerable communities (SQ1), high-frequency incident types amenable to spatial-trigger logic (SQ2), and a 79.1% deterioration in mean response latency over 25 years, above the 72-hour survivability threshold (SQ3). Comparison with prior frameworks confirms GeoBlock-DRS advances the state of the art on all key dimensions. Blockchain smart contracts and geospatial intelligence offer a viable path toward resilient, coordination in smart cities.

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