

Communication Restoration at Disaster via LEO Satellites and Terrestrial Systems

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Abstract—Natural disasters often destroy terrestrial communication, limiting emergency response. This paper proposes an integrated recovery system combining LEO satellite backhaul with terrestrial Wi-Fi and Local 5G at evacuation shelters. We propose a risk-aware optimization framework. First, a dual-objective greedy algorithm selects low-risk shelter locations by considering population density and disaster hazard data. Second, a Genetic Algorithm (GA) optimizes the allocation of Wi-Fi vs. 5G to maximize a "restoration priority" score under a budget constraint. Simulations using real data from Osaka City show that the placement algorithm reduces site risk with minimal coverage loss. The GA also outperformed greedy heuristics under budget limits by effectively balancing cost and risk.

Index Terms—Post-disaster communication, LEO satellites, hybrid networks, risk-aware optimization, resource allocation, Genetic Algorithm (GA), ground station placement, Local 5G

I. INTRODUCTION

In recent years, the increasing frequency of large-scale natural disasters such as earthquakes, floods, and typhoons has highlighted the vulnerability of terrestrial communication infrastructures. When such infrastructures are damaged, information transmission for emergency response, rescue coordination, and disaster assessment becomes severely limited. Conventional terrestrial-based recovery systems, including portable base stations and vehicular communication units, often require significant deployment time and manpower, rendering them unsuitable for large-scale or rapidly evolving disasters.

To overcome these limitations, satellite communication systems—particularly low Earth orbit (LEO) constellations—have attracted growing attention. Compared with traditional geostationary satellites, LEO satellites provide lower latency and higher data throughput due to their proximity to the Earth's surface. Recent commercial deployments such as Starlink and OneWeb demonstrate the feasibility of wide-area, low-latency broadband services that can remain operational even when ground networks are disabled [1], [2].

Existing studies have explored various methods for emergency communication, including UAV-assisted wireless networks for flexible coverage restoration [3], and integration of cellular and satellite networks [4]. However, these approaches generally focus on limited coverage or single-technology optimization. Few works have comprehensively examined how to

jointly optimize ground station (BS) placement, wireless access technology selection, and population-risk-based prioritization to achieve rapid and efficient communication restoration in disaster scenarios.

This paper aims to design and evaluate an integrated post-disaster communication recovery system that leverages both LEO satellites and terrestrial wireless networks. The proposed framework optimizes the placement of satellite-compatible ground stations based on population density and disaster risk information, while comparing multiple access technologies such as Wi-Fi and local 5G. Through simulation-based evaluation, the effectiveness of the proposed method is assessed in terms of population coverage ratio and restoration speed. The results are expected to provide insights into the development of resilient hybrid communication infrastructures for future disaster response systems.

II. RELATED WORK

Recent advances in post-disaster communication research have explored multiple complementary directions, including satellite-based systems, aerial networks using unmanned aerial vehicles (UAVs), and hybrid architectures integrating satellite and terrestrial components [6]. LEO satellite constellations such as Starlink and OneWeb provide low-latency and high-throughput communication capabilities, enabling connectivity even when ground infrastructure is damaged. These systems are considered promising backhaul solutions for emergency communication restoration and remote sensing applications [5].

Meanwhile, UAV-based disaster communication and evacuation support systems have been actively studied as agile, deployable complements to terrestrial and satellite networks. UAVs can survey inaccessible or hazardous areas and serve as temporary aerial relays or guidance units. Ibuki and Kamiyama proposed an evacuation guidance system that employs large petrol-powered UAVs to search for evacuees and deploys small UAVs for local guidance, demonstrating a longer operation duration and independence from ground-based IoT devices [7]. Their work extended prior multi-UAV coordination frameworks [8], [9] by addressing battery endurance and infrastructure failure, confirming through simulation that the multi-

type UAV system can maintain continuous operation over wide disaster areas.

Complementary approaches have focused on hybrid satellite–terrestrial networks that integrate UAV or aerial segments for resilience enhancement. Tirmizi *et al.* surveyed key technologies for hybrid satellite–terrestrial systems toward 6G, identifying resource management and interference coordination as core challenges [4]. Similarly, Wang *et al.* proposed a hybrid satellite–aerial–terrestrial (HSAT) framework for public safety applications, demonstrating that such multi-layered integration can enhance throughput and coverage robustness [10].

Further studies have investigated UAV-assisted sensing and path planning. Liu *et al.* utilized multispectral imagery from UAVs to assess road conditions and generate optimized evacuation routes [11]. Sato *et al.* presented a UAV-based message-ferry communication scheme that maintained reliable data delivery between aerial and ground nodes in disrupted environments [12]. These contributions highlight the feasibility of aerial communication relays when ground infrastructure is inoperative.

However, most prior works have considered aerial or satellite systems independently. This separation limits their practical deployment in real disasters, where both satellite and terrestrial links must cooperate under constrained budgets. Few studies have attempted to integrate risk-aware ground station placement, population distribution analysis, and multi-technology access selection (e.g., Wi-Fi, local 5G, and LEO backhaul) within a unified optimization framework. The present study aims to bridge this gap by combining LEO satellite connectivity and terrestrial wireless networks to achieve robust, scalable, and risk-prioritized post-disaster communication recovery.

III. PROPOSED METHOD

A. Motivation and System Overview

Although recent LEO satellite constellations such as Starlink and OneWeb have demonstrated the capability to provide direct-to-user connectivity [13], only a limited number of commercially available terminals currently support this feature. Furthermore, because only a subset of satellites in a given orbital plane can maintain line-of-sight with ground users at any moment, connectivity in urban or mountainous regions remains intermittent and unstable [14]. These limitations motivate the use of terrestrial gateways deployed at reliable sites—such as evacuation shelters—to serve as access points bridging affected populations to the LEO satellite backbone.

In the proposed disaster recovery communication system, each evacuation shelter can host a low-power satellite gateway (BS) equipped with LEO-compatible terminals and local access interfaces (Wi-Fi or local 5G). The gateways communicate with visible LEO satellites to establish backhaul links, while users in the shelter vicinity connect through short-range wireless technologies. This configuration enables rapid and scalable restoration of essential connectivity, even under partial terrestrial infrastructure failure.

B. Risk-Aware Ground Station Placement

Let \mathcal{S} denote the set of candidate shelters obtained from GIS data, and \mathcal{G} the grid cells containing population estimates and disaster risk information. To balance between maximizing population coverage and minimizing exposure to hazard-prone zones, we define a disaster risk score R_{hazard} for each grid cell g_i :

$$R_{\text{hazard}}(g_i) = w_{\text{mud}} \times R_{\text{mud}}(g_i) + w_{\text{flood}} \times R_{\text{flood}}(g_i), \quad (1)$$

where R_{mud} and R_{flood} represent normalized landslide and flood risks, respectively, and w_{mud} , w_{flood} are weighting coefficients.

Population density $P(g_i)$ is normalized by the maximum population density P_{max} , and a composite priority score is calculated as:

$$Q(g_i) = R_{\text{hazard}}(g_i) \times \frac{P(g_i)}{P_{\text{max}}}. \quad (2)$$

Each candidate shelter $s_j \in \mathcal{S}$ covers a subset of grids $\mathcal{C}(s_j)$ determined by its coverage radius. The optimization goal is to select N shelters maximizing total weighted coverage:

$$\max_{\substack{\mathcal{S}^* \subseteq \mathcal{S} \\ |\mathcal{S}^*| = N}} \sum_{g_i \in \bigcup_{s_j \in \mathcal{S}^*} \mathcal{C}(s_j)} \frac{P_{\text{norm}}(g_i)}{1 + R_{\text{hazard}}(g_i)W} \quad (3)$$

where $W > 0$ is a penalty factor that controls the trade-off between risk and population. A larger W results in avoiding high-risk areas, while a smaller W prioritizes population coverage. The restoration priority index is designed to reflect the urgency of communication needs after a disaster.

The risk score represents the expected difficulty of evacuation and rescue operations, while the normalized population density indicates the concentration of people who would require communication services. By combining both factors, the index prioritizes areas where communication disruptions would have severe consequences.

C. Dual-Objective Greedy Algorithm

Algorithm 1 is the algorithm iteratively selects shelters that maximize the gain in the weighted objective function. When $W = 0$, the model prioritizes the maximum population coverage (“Coverage-first”), while larger values of W increase the avoidance of high-risk zones. The Dual-Opt model thus adapts to varying operational priorities depending on resource availability and disaster severity.

D. Priority-Based Restoration with Genetic Algorithm

Because available resources (budget, power, frequency licenses) are limited, local 5G installations incur higher deployment cost than Wi-Fi. To determine the optimal combination of technologies and sites under a fixed cost constraint, we employ a Genetic Algorithm (GA) that maximizes total restoration priority within a budget B .

Each chromosome encodes a deployment plan: gene $x_j \in 0, 1, 2$ indicates no deployment, Wi-Fi, or 5G at shelter s_j . The

Algorithm 1 Dual-Objective Greedy Station Placement

- 1: **Input:** Candidate shelters \mathcal{S} , grids \mathcal{G} , number of stations N , risk weight W
- 2: Initialize selected set $\mathcal{S}^* \leftarrow \emptyset$
- 3: **while** $|\mathcal{S}^*| < N$ **do**
- 4: **for** each $s \in \mathcal{S} \setminus \mathcal{S}^*$ **do**
- 5: Compute newly covered grids $\mathcal{C}_{\text{new}}(s)$
- 6: $U_s \leftarrow \sum_{g_i \in \mathcal{C}_{\text{new}}(s)} \frac{P_{\text{norm}}(g_i)}{1 + R_{\text{hazard}}(g_i)W}$
- 7: **end for**
- 8: $s^* \leftarrow \arg \max_s U_s$
- 9: $\mathcal{S}^* \leftarrow \mathcal{S}^* \cup \{s^*\}$
- 10: **end while**
- 11: **Output:** Selected shelter set \mathcal{S}^*

Algorithm 2 Priority-Aware Genetic Optimization

- 1: Initialize population \mathcal{P} with random chromosomes
- 2: **for** each generation $t = 1, \dots, T$ **do**
- 3: Evaluate fitness $F(\mathbf{x})$ for all $\mathbf{x} \in \mathcal{P}$
- 4: Select parents via tournament selection
- 5: Generate offspring via uniform crossover
- 6: Apply mutation with rate μ
- 7: Replace population with elites and offspring
- 8: **end for**
- 9: Return best feasible chromosome \mathbf{x}^* under budget B

fitness function evaluates the average priority score of covered grids:

$$F(\mathbf{x}) = \begin{cases} \text{AvgPriority}(\mathbf{x}), & \text{if } \text{Cost}(\mathbf{x}) \leq B, \\ -1 - \frac{\text{Cost}(\mathbf{x}) - B}{B}, & \text{otherwise.} \end{cases} \quad (4)$$

Algorithm 2 follows standard GA operations—tournament selection, uniform crossover, and mutation—while tracking the best budget-feasible solution throughout the generations. This GA-based optimization yields the deployment configuration that maximizes total covered priority score while satisfying cost constraints, effectively identifying where to deploy Wi-Fi and 5G gateways to achieve the fastest and most equitable communication restoration across the disaster region.

The GA parameters were selected based on preliminary convergence testing. We evaluated multiple combinations of population size, crossover rate, and mutation rate, and confirmed that 2000 generations with a mutation rate of 0.1 consistently converged to a stable solution while avoiding premature stagnation.

These settings achieve a balance between computation time and optimization performance, which is essential for rapid decision support during emergency response.

IV. PERFORMANCE EVALUATION

A. Data Sources and Simulation Settings

To evaluate the effectiveness of the proposed disaster recovery communication system, we conducted simulations based on real geographic and demographic data of Osaka City, Japan.

The geographic information, shelter locations, and disaster hazard data were obtained from the Geospatial Information Authority of Japan (GSI), including the landslide warning areas and flood inundation assumption zones. Population distribution data were derived from the 250 m mesh estimated population dataset provided by the Statistics Bureau. The simulation targeted two representative areas: **Central Osaka**, a high-density urban region, and **Suburban Osaka**, a lower-density residential area.

Each mesh cell contains population and disaster risk attributes. The disaster risk score R_{hazard} was calculated using normalized landslide (R_{mud}) and flood (R_{flood}) risk values as:

$$R_{\text{hazard}} = W_{\text{MUD}} \cdot R_{\text{mud}} + W_{\text{FLOOD}} \cdot R_{\text{flood}}, \quad (5)$$

where $W_{\text{MUD}} = W_{\text{FLOOD}} = 0.5$. The *restoration priority* was then computed by multiplying R_{hazard} by the normalized population density, representing the urgency of communication recovery for each mesh. Candidate ground stations (BSs) were assumed to be placed at evacuation shelters such as schools and public facilities. LEO satellite gateways were installed at selected BSs capable of power supply during disaster scenarios. Wireless access technologies including Wi-Fi and local 5G were compared under limited resource constraints.

B. Simulation Area and Input Data Visualization

Fig. 1 shows the simulation environment for Central Osaka: (a) the geographic map, (b) the disaster risk distribution, and (c) the computed communication restoration priority. Fig. 2 shows the same for Suburban Osaka. In both regions, the areas with high population density and high disaster risk received higher restoration priority scores.

C. Evaluation Metrics

To compare different site-selection algorithms, we used the following metrics:

- **Population coverage rate:** ratio of covered population to total population.
- **Average disaster score of selected BSs:** average R_{hazard} over chosen sites.
- **Average restoration priority score:** composite indicator of covered risk-weighted population.

For fair comparison, all algorithms share identical candidate sets and budgets.

D. Coverage Performance under Different Radii

Figure 3 shows the relationship between the number of BSs and population coverage for two radio ranges, $R = 0.1 \text{ km}$ and $R = 1.0 \text{ km}$. These radii are chosen to represent realistic effective ranges in urban disaster settings: short-range indoor/outdoor Wi-Fi coverage around shelters (100 m) and a plausible Local 5G cell radius ($\approx 1 \text{ km}$) for open area deployments with elevated antennas.

The Dual-Optimization method maintained almost the same coverage as the Coverage-First method, while effectively avoiding redundant overlap among stations. In dense central areas, coverage quickly reached saturation, while in suburban

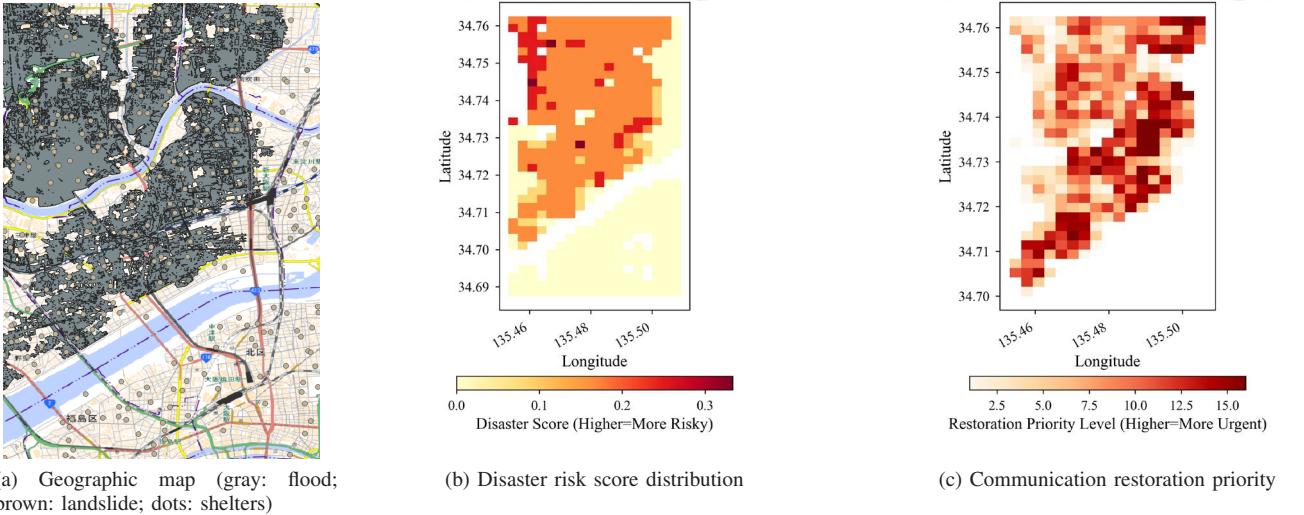


Fig. 1: Simulation area of Central Osaka

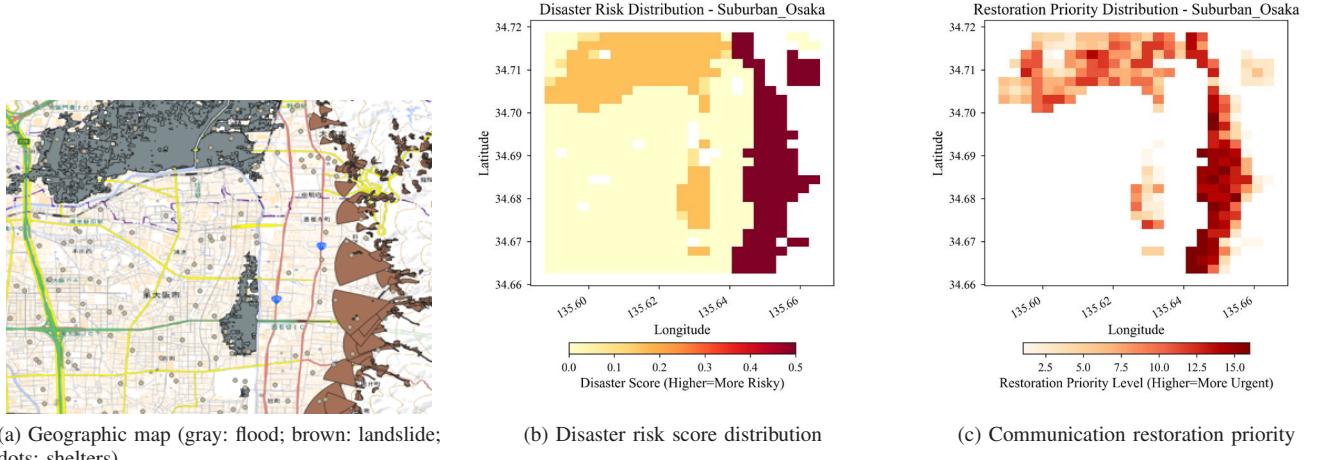


Fig. 2: Simulation area of Suburban Osaka

regions, additional BSs continued to contribute to new coverage due to spatial dispersion.

E. Average Disaster Score of Selected Sites

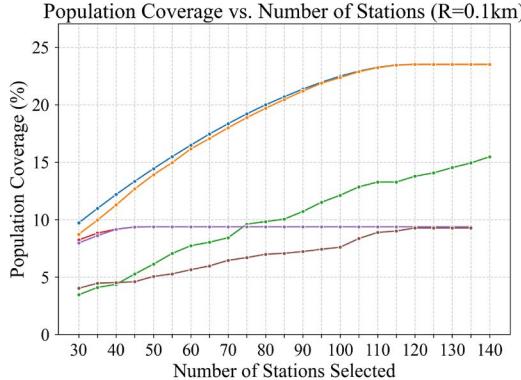
Figure 4 shows the average disaster score of selected stations for the two coverage radii. The Dual-Optimization method consistently selected lower-risk shelters compared with Coverage-First. The reduction effect was more visible at $R = 1.0\text{ km}$, since each BS covered a wider area including more hazard zones. This confirms that integrating hazard information into site selection contributes to safer deployment with only a minor loss of coverage.

For both Central and Suburban Osaka, the Dual-Optimization method achieved slightly lower population coverage (1–3% difference) compared to the Coverage-First method, but reduced the average disaster score by approx-

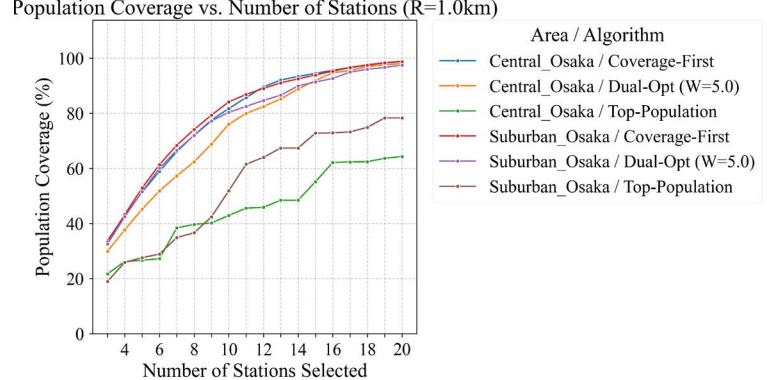
imately 20–25%. These results confirm that incorporating disaster risk into station selection can achieve safer and more resilient layouts without substantial loss of service area.

F. Optimization under Budget Constraints

In actual disaster recovery, the available budget and manpower are strictly limited. Deploying Local 5G requires higher cost and power consumption than Wi-Fi, and it is impossible to activate all shelters simultaneously. For this reason, the placement of BSs was optimized under cost constraints to maximize the overall restoration priority. A Genetic Algorithm (GA) was employed to optimize the joint selection of shelters and access technologies. Each shelter is represented by one gene indicating {no deployment, Wi-Fi, or Local 5G}. The fitness function is the total covered priority normalized by

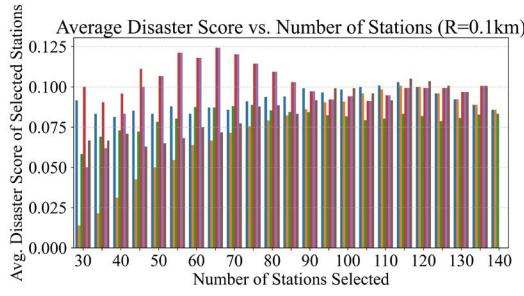


(a) $R = 0.1$ km

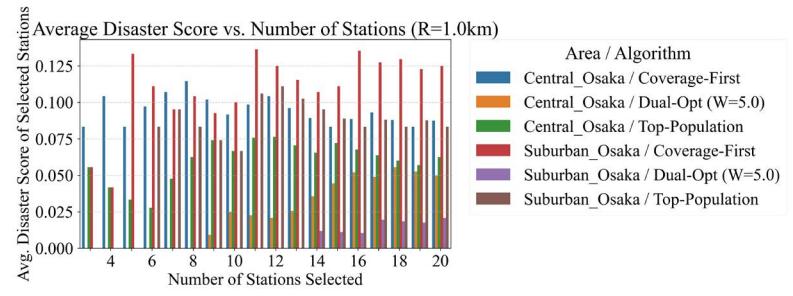


(b) $R = 1.0$ km

Fig. 3: Population coverage vs. number of deployed BSs. The Dual-Optimization method achieved similar coverage to the Coverage-First method, even with fewer stations.



(a) $R = 0.1$ km



(b) $R = 1.0$ km

Fig. 4: Average disaster score vs. number of BSs. The Dual-Optimization method selected safer sites while maintaining high coverage.

the deployment cost. Greedy methods were also tested for comparison.

Figure 5 shows the relationship between the total budget and the achieved average restoration priority. The GA obtained the highest priority across all budget ranges. When the budget was small, greedy methods tended to choose many low-cost Wi-Fi stations near dense populations, which caused overlapping coverage and poor efficiency. The GA effectively allocated resources to high-priority areas while avoiding hazardous shelters and unnecessary overlap.

For comparison, three baseline methods were implemented:

- **Greedy(C)** (Coverage-oriented): selects shelters sequentially based on the largest incremental *population coverage* without considering hazard levels.
- **Greedy(P)** (Priority-oriented): selects shelters according to the highest incremental *restoration priority* defined in Eq. (2), incorporating both population and risk information but without budget optimization.
- **Top-Top (Wi-Fi)**: a naive reference strategy that deploys Wi-Fi access points at the top- N shelters ranked purely by population density, ignoring hazard or cost differences.

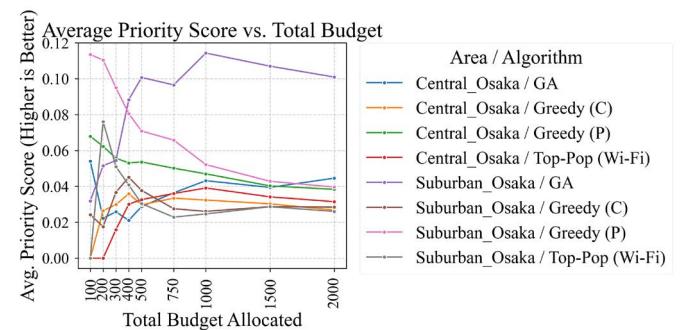


Fig. 5: Average restoration priority vs. deployment budget. The GA achieved higher scores under all cost conditions.

These baselines allow evaluation of the proposed Genetic Algorithm (GA) under different heuristic assumptions, highlighting the benefits of global optimization in balancing coverage, risk, and cost.

G. Discussion and Summary

The evaluation confirmed that the proposed risk-aware optimization framework improves the balance between safety and coverage. When disaster risk was included in the placement model, the average hazard score of selected stations decreased by approximately 20–25% with only a small reduction in coverage. The Dual-Optimization method maintained stable coverage performance in both urban and suburban environments. Under cost limitations, the GA efficiently identified the most effective deployment plan by prioritizing high-risk and high-population areas. This approach can support rapid and reliable communication restoration in large-scale disaster scenarios using a limited number of deployable shelters.

V. CONCLUSION

This paper presented a disaster recovery communication system that combines LEO satellite backhaul with terrestrial wireless access using Wi-Fi and Local 5G. A risk-aware optimization framework was developed to determine shelter-based ground station deployment considering both population distribution and disaster hazards. The model introduced a disaster risk score and a restoration priority index to evaluate each region, enabling the system to balance service coverage and safety.

Simulation results using actual Osaka data demonstrated that the proposed method can restore communication efficiently even when terrestrial infrastructure is severely damaged. The Dual-Optimization approach achieved almost the same population coverage as conventional placement methods while significantly reducing exposure to high-risk areas. Under limited budgets, the Genetic Algorithm provided the highest restoration priority by allocating resources to high-population and high-risk zones while avoiding redundant and hazardous shelters. These findings suggest that the proposed framework can serve as a practical decision-support tool for post-disaster network planning and resource allocation.

Future work will focus on implementing the proposed method in real emergency environments. Practical considerations include securing power supply at shelters, transportability of satellite terminals, and temporary spectrum licensing for Local 5G operation. We also plan to incorporate real-time LEO satellite visibility, mobility of affected users, and integration with UAV-based temporary relays, making the system deployable in diverse disaster scenarios. These improvements will bring our approach closer to practical deployment in collaboration with local governments and satellite service providers, contributing to more resilient communication infrastructure.

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REFERENCES

- [1] M. Handley, "Delay is not an option: Low latency routing in space," in *Proc. ACM HotNets*, 2018, pp. 85–91.
- [2] G. Giambene, S. Kota and P. Pillai, "Satellite-5G Integration: A Network Perspective," in *IEEE Network*, vol. 32, no. 5, pp. 25–31, September/October 2018.
- [3] X. Zhou, Q. Wu, S. Yan, F. Shu and J. Li, "UAV-Enabled Secure Communications: Joint Trajectory and Transmit Power Optimization," in *IEEE Transactions on Vehicular Technology*, vol. 68, no. 4, pp. 4069–4073, April 2019.
- [4] A. Tirmizi, A. Yahya, M. Bennis, *et al.*, "Hybrid Satellite–Terrestrial Networks for 6G: Architecture, Key Technologies, and Open Challenges," *IEEE Network*, vol. 36, no. 2, pp. 56–63, 2022.
- [5] M. Matracia, A. Alkhateeb, and J. M. F. Moura, "Post-Disaster Communication Networks: A Review of Emerging Technologies and Future Directions," *IEEE Access*, vol. 10, pp. 78412–78435, 2022.
- [6] H. Gupta, N. R. Kuraku, R. Tripathi and T. S, "Design and Implementation of a Resilient Communication Network for Disaster Recovery Using Satellite Links," 2025 International Conference on Wireless Communications Signal Processing and Networking (WiSPNET), Chennai, India, 2025.
- [7] K. Ibuki and N. Kamiyama, "Evacuation Guidance System Using UAVs of Multiple Types at Disaster," 2024 IEEE Cyber Science and Technology Congress (CyberSciTech), Boracay Island, Philippines, 2024.
- [8] K. Katayama, H. Takahashi, N. Yokota, K. Sugiyasu, G. Kitagata, and T. Kinoshita, "An Effective Multi-UAVs-Based Evacuation Guidance Support for Disaster Risk Reduction," IEEE International Conference on Big Data and Smart Computing 2019.
- [9] K. Katayama, H. Takahashi, N. Yokota, and K. Sugiyasu, "Evacuation Guide Supporting System using UAV for Coastal Area," IEEE Global Conference on Life Sciences and Technologies 2021.
- [10] P. Wang, Y. Li, Z. Han, *et al.*, "A Hybrid Satellite–Aerial–Terrestrial Communication System for Public Safety," *IEEE Wireless Communications*, vol. 23, no. 6, pp. 122–128, 2016.
- [11] Y. Liu, X. Zhang, and Q. Wang, "UAV-based multispectral road condition assessment and evacuation route planning," *Remote Sensing*, vol. 14, no. 8, pp. 1234–1248, 2022.
- [12] R. Sato, O. Oyakhire, and K. Gyoda, "Performance evaluation of Disaster Information Communication System using Message Ferry," ITCCSCC 2019.
- [13] S. Kassing, D. Bhattacharjee, L. Chiang, *et al.*, "Exploring the 'Internet from Space': Analyzing Starlink's Broadband Performance," in *Proc. ACM Internet Measurement Conf. (IMC)*, 2020, pp. 214–230.
- [14] A. K. Dwivedi, S. Chaudhari, N. Varshney and P. K. Varshney, "Performance Analysis of LEO Satellite-Based IoT Networks in the Presence of Interference," in *IEEE Internet of Things Journal*, vol. 11, no. 5, pp. 8783–8799, 1 March1, 2024.