Dependency-Aware Logistic Modeling of Lifeline Recovery and Hospital Functionality

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Abstract

Hospitals rely on lifelines like transportation, power, and water, which must recover together after disasters. This paper compares two recovery strategies: Uniform Recovery (UR), which spreads resources evenly, and Targeted Recovery (TR), which prioritizes hospital lifelines first. Using logistic recovery models with dependency factors (transportation → power; transportation + power → water), we simulate outcomes for three hospitals with different resilience levels. Results show that TR accelerates recovery across systems, with transportation reaching higher functionality sooner, which then speeds up power restoration and shortens delays in water recovery. Quantitatively, in a 200-day simulation, TR reached ~80% functionality for transportation by day 50 vs. day 75 under UR (full by ~120 vs. ~150); power reached ~80% by ~100 vs. ~125 (near full by ~150 vs. ~175); and water reached ~80% by day 200 under TR vs. ~70% under UR. Recovery dynamics highlight cascading effects: hospitals with stronger infrastructure stabilize faster, while less resilient ones suffer compounding delays under UR. TR not only increases recovery speed but also reduces disparities across hospitals and ensures critical routes regain functionality sooner, improving access for patients, staff, and supplies. Overall, dependency-aware, hospital-first planning supports quicker stabilization and more equitable recovery across communities.

Keywords

Logistic Modeling, Recovery, Interdependencies, Transportation Systems, Healthcare Functionality

1. Introduction

Hospitals, fire stations, and emergency services depend on complex infrastructure systems (Milanovic & Zhu, 2018). Their performance relies on the condition of the infrastructure. Disruptions can lead to cascade failures and network collapse (Dueñas-Osorio et al., 2007). These facilities provide essential services during post-disaster recovery, aiding affected communities and rescuers (Guth et al., 2019). However, natural hazards like earthquakes and hurricanes can hinder recovery (He & Cha, 2018). Historical cases, such as Hurricane Katrina, highlight the risks of neglecting utility needs (Arboleda et al., 2007). Infrastructure interdependencies complicate managing natural hazards, as different entities with conflicting priorities slow recovery and create vulnerabilities (Eidsvig et al., 2017). Prioritizing the recovery of critical healthcare facilities is vital for effective post-disaster planning.

Recent studies have explored infrastructure restoration planning to reduce recovery time and costs while addressing interdependencies (Shahverdi et al., 2024; Moore et al., 2022; Der Sarkissian et al., 2022). Ouyang (2014) offers frameworks for modeling infrastructure failures. However, a practical approach prioritizing healthcare facilities is necessary. This study proposes a directed recovery framework for interdependent systems, emphasizing healthcare functionality. By unifying decision-making, the framework optimizes recovery outcomes and enhances resilience against future events.

Hospitals are vital during disasters, but their ability to operate depends on the quick restoration of key services like power, water, and transportation. Delays in these systems lead to longer patient wait times, strained resources, and challenges in delivering care, hindering community recovery. Therefore, disaster recovery plans must prioritize restoring hospital-reliant infrastructure first.

This study compares Uniform Recovery (UR), which spreads resources evenly, and Targeted Recovery (TR), which prioritizes crucial utilities and services for hospitals. Targeted Recovery allocates resources based on urgency, supported by prior studies (Baghersad et al., 2024; Soden et al., 2023). This method enhances hospital recovery speed, care during crises, and overall system resilience. The study models strategies using a logistic recovery function to simulate the recovery of systems like roads, power, and water over time, considering their interdependence. For instance, road repairs can accelerate power and water restoration. Hospitals are classified into three categories- high, moderate, and low performers- to assess their response to recovery efforts.

2. Methodology

2.1 Framework for Recovery Planning

This study investigates post-disaster recovery planning for critical healthcare infrastructure, focusing on hospitals. It examines two strategies: Uniform Recovery (UR) and Targeted Recovery (TR), assessing their impact on hospital functionality and resilience. The UR strategy distributes resources evenly across demand nodes, including hospitals. Although it ensures equal allocation, it often leads to slower restoration times for critical facilities, prolonging essential service disruptions. In contrast, the TR strategy prioritizes resources for critical facilities based on need or importance, aligning with equity principles. This approach accelerates recovery by restoring utility supply lines and transportation networks, reducing patient delays, and enhancing resilience.

2.2 Hospital-Specific Characteristics and Recovery Dynamics

The recovery dynamics of hospitals are influenced by their structural and operational characteristics, represented in this study by levels for three hospitals: H1 (Level 1), H2 (Level 3), and H3 (Level 2). These levels summarize differences in capacity, infrastructure resilience, and resource availability. H1, the high-performing hospital, has a larger capacity, more emergency department (ED) rooms or beds, and a greater number of medical staff, enabling it to manage patient flow efficiently. H2, the lowest-performing hospital, faces significant challenges due to limited capacity and fewer resources, resulting in longer delays and reduced treatment efficiency. H3 occupies a middle ground with moderate capacity and resources, demonstrating balanced recovery behavior.

Each hospital's recovery process is modeled using its assumed specific initial utility supply levels and the logistic recovery function. For example, H1 begins with approximately 20% of its utility supply restored, reflecting its strong infrastructure resilience, while H2 starts with less than 40% due to its operational limitations. The TR approach accelerates recovery for all hospitals by prioritizing critical resources, ensuring that the disparities in functionality are minimized as recovery progresses.

2.3 Comparative Analysis of Recovery Strategies

The UR and TR strategies are compared using performance metrics such as waiting time, TIS, and recovery rates. For each hospital, the simulation evaluates the differences in recovery efficiency and operational performance under the two strategies. Key insights are derived from the trajectories of utility restoration, patient flow, and overall system resilience.

2.4 Mathematical Foundations of the Generalized Logistic Function and Recovery Modeling

The Generalized Logistic Function, or Richards' Curve, is a mathematical model for growth and recovery processes that exhibit saturation over time. It extends the logistic function by adding flexibility through its parameters, enabling varied growth rates, saturation levels, and asymmetric recovery. The equation is as follows:

$$Y(t) = A + \frac{K-A}{\left(C+Qe^{-B(t-M)}\right)^{1/v}} \qquad \text{(Eq. 1)}$$

$Y(t)$ represents the function value at time t, modeling system recovery or growth. A is the lower asymptote, often zero in resilience studies. K is the upper asymptote, indicating full recovery or capacity. B is the growth rate, determining how quickly the system approaches its upper limit. ν modifies the maximum growth location on the time axis, allowing asymmetry in the recovery process. Q relates to the function value at t=0. C is usually set to 1, but can be changed to alter the function's behavior. M represents the inflection point, where the recovery rate is fastest. This function offers a robust framework for resilience modeling, widely applicable in epidemiology, environmental science, and engineering. A key reference is Richards (1959), who introduced the Richards' Curve, generalizing the logistic model for empirical growth processes.

2.5 General Recovery Model with Cascading Dependencies

The recovery of critical infrastructure, especially in disasters, is affected by cascading dependencies among components. A hospital's recovery relies on supporting infrastructure like transportation, water supply, and electricity. To address these dependencies, the recovery process can be modeled with an extended logistic function that incorporates cascading effects and external disruptions. The logistic recovery function for an infrastructure component $C(t)$ is:

$$C(t) = \frac{C_{init}}{1+e^{-s(t-m)}} \qquad \text{(Eq. 2)}$$

$C(t)$ is the capacity at time t, C_{init} is the initial capacity after a disaster, s controls the recovery speed, and m indicates when the system hits half of its maximum capacity. This function is used in resilience modeling, particularly in disaster recovery (Cimellaro et al., 2010). Cimellaro et al. (2010) discuss various resilience formulations and show how logistic functions model system restoration over time. Hospital recovery relies on restoring interdependent infrastructure systems, particularly transportation, water, and electricity. Transportation is essential for access to hospitals and repairs of critical utilities, ensuring that patients, medical staff, and supplies reach healthcare facilities. It enables mobilization of repair crews and delivery of essential equipment, which are crucial for restoring water and electric power.

3. Results and Discussions

3.1 Restoration of Critical Infrastructure Systems

Recovering critical infrastructure- transportation, electric power, and portable water- is essential for restoring community functionality after a disaster. Figure 1 shows the restoration trajectories under UR and TR strategies. Functionality is measured on a normalized scale from 0.2 (minimal functionality) to 1.0 (fully restored) over 200 days. The simulations utilize logistic growth models that consider system-specific recovery rates and interdependencies, notably the dependence of electric power on transportation and the reliance of portable water on both power and transportation.

Transportation recovery is vital for infrastructure restoration. Repairing other systems is delayed without functional roads and transit networks. With UR, transportation achieves 80% functionality by day 75 and full restoration by day 150. In targeted recovery, repairs are prioritized, reaching 80% functionality by day 50 and full recovery by day 120. This accelerated timeline shows that prioritizing transportation helps recover other dependent systems.

Electric power restoration relies on transportation recovery for access to lines, substations, and plants, delaying post-disaster electricity restoration. It begins once transportation reaches a sufficient level, around day 20. With a 0.8 dependency factor, power functionality reaches approximately 80% by day 125 and is fully restored by day 175. Alternatively, TR prioritizes system repairs, achieving 80% functionality by day 100 and near-full recovery by day 150.

Portable water infrastructure recovers slowly due to its reliance on electricity and transportation. Without access to transportation, water distribution networks remain unrepaired, and treatment plants cannot operate without power. Under UR, water restoration reaches about 70% functionality by day 200, with no complete restoration in that timeframe. TR improves this, achieving 80% functionality by day 200, yet full restoration remains elusive.

The TR strategy outperforms UR in all infrastructure sectors by prioritizing the recovery of transportation. This approach shortens recovery times for power and water, highlighting the importance of interdependent systems. Transportation recovery aids in restoring other infrastructure; delays impact power and water. Electric power restoration depends on transportation, making it essential to focus on road and transit systems. Water recovery is the slowest due to reliance on power and transport. Addressing these dependencies hastens water restoration, ensuring timely public health services. TR optimizes resources, reducing downtime and enhancing community resilience for a quicker return to normal after disasters.

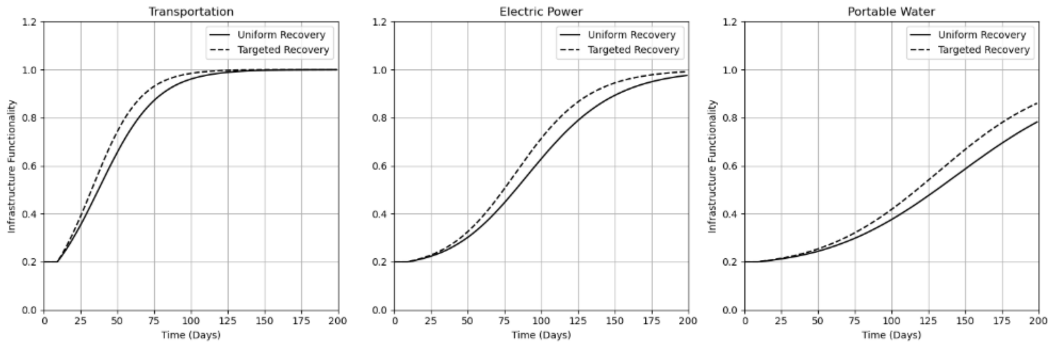

Figure 1. Restorations of critical infrastructure systems under UR and TR.

3.2 Analysis of Recovery Speeds

The recovery speed plots for water and power utilities in Figure 2 illustrate the rate at which infrastructure functionality is restored under various recovery strategies. The analysis compares UR and TR strategies for hospitals H1, H2, and H3. These plots show the derivative of functionality curves, showing recovery rates over time and peak recovery speeds.

The water recovery speed plots indicate that the TR strategy achieves higher peak speeds and earlier peak times than the UR strategy. In H1, the TR peaks around day 20, while UR peaks around day 30. This earlier peak highlights the advantage of prioritizing restoration efforts for resilient hospitals. Moreover, TR achieves a higher maximum value, indicating faster restoration of water capacity. For H2 (Level 3), lower baseline resilience leads to significant differences in recovery speed trends. With UR, the peak speed occurs at a lower level and is reached around day 40, compared to day 30 in TR. This delay highlights the challenges faced by less resilient hospitals when resources are distributed unevenly, leading to prolonged service interruptions. H3 exhibits intermediate behavior, with a TR peak around day 25 and a UR peak around day 35. The faster rise in water recovery speed under TR for H3 highlights the effectiveness of prioritization in reducing delays.

The power recovery speed plots show similar trends. In H1, TR peaks around day 15, while UR peaks around day 25. The earlier peak in TR stabilizes power infrastructure faster, preventing cascading failures in systems like water supply. For H2, UR peaks around day 40, while TR peaks at about day 30. The slower speeds under UR show that less resilient hospitals struggle more with prolonged disruptions without prioritization. H3 displays a pattern between H1 and H2, with TR peaking at day 20 and UR at day 30. These results confirm that prioritizing hospitals with targeted interventions significantly speeds up power restoration.

The recovery speed analysis shows the efficiency of the TR strategy in restoring infrastructure. All hospitals benefit from higher speeds and earlier peak times, reducing recovery periods. Results indicate higher-grade hospitals (H1) stabilize faster due to resilience, while lower-grade hospitals (H2) experience longer disruptions under UR, highlighting the need for prioritization. Recovery speeds are the first derivative of the logistic growth function for recovery trajectories, illustrating the dynamics of two strategies and the importance of targeted interventions. TR ensures faster peak speeds and earlier stabilization, minimizing disruptions and enhancing resilience for effective disaster responses. Recovery speed is the rate of change of *C(t)*:

$$C'(t) = \frac{s\,.(1-C_{init})\,.e^{-s(t-m)}}{\left(1+e^{-s(t-m)}\right)^2} \qquad \text{(Eq. 3)}$$

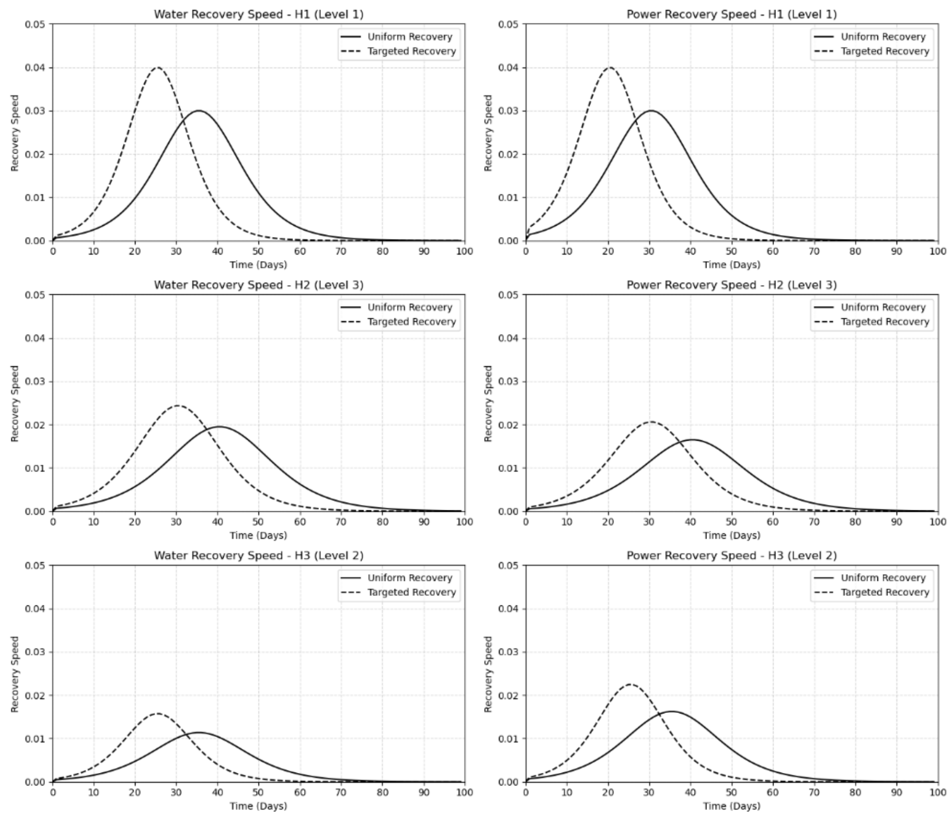

Figure 2. Recovery speed plots for utilities at three hospitals under two recovery strategies.

3.3 Recovery Dynamics

Figure 3 illustrates the recovery dynamics of transportation, water, and power systems for hospitals H1, H2, and H3. Each curve represents cumulative recovery, highlighting the impact of transportation disruptions on water and power recovery. Findings reveal distinct patterns, emphasizing the need for prioritization and resilience in recovery efforts. In H1, transportation recovery achieves high functionality (0.6) by day 20, with a steep rate of improvement (0.18). Transportation recovers swiftly, followed by water, while power recovery is slower and reliant on water, eventually reaching full recovery, reflecting H1's resilient infrastructure. In contrast, H2's recovery is slow due to weak infrastructure; transportation begins at 0.4, peaks by day 50 with a slope of 0.08, resulting in delayed water recovery. Power recovery, the slowest due to dependence on water, reveals H2's vulnerabilities, complicating operations. H3 exhibits an intermediate recovery profile; transportation starts at 0.5, follows a moderate trajectory, and reaches its midpoint by day 35 with a slope of 0.12, indicating less severe delays than H2. Water recovery initiates earlier in H3 due to a stable network, while power recovery progresses steadily despite minor delays, suggesting that balanced priorities enable efficient recovery without the rapid pace of H1.

Transportation, water, and power systems are interdependent. The transportation system recovers first, supporting others, while water recovery closely follows, depending on it. Power recovery experiences the most extended delays due to its reliance on both transportation and water. This cascading effect is more pronounced in H2, where delays compound compared to H1's quicker recovery. Results indicate a need to prioritize post-disaster recovery. Hospitals with efficient transportation recovery, like H1, face fewer delays in restoring water and power, while slower hospitals, like H2, experience longer disruptions. Findings underscore the necessity of integrated recovery strategies. Prioritizing transportation recovery accelerates the restoration of healthcare services. Insights highlight the importance of proactive resilience planning for effective recovery of essential services.

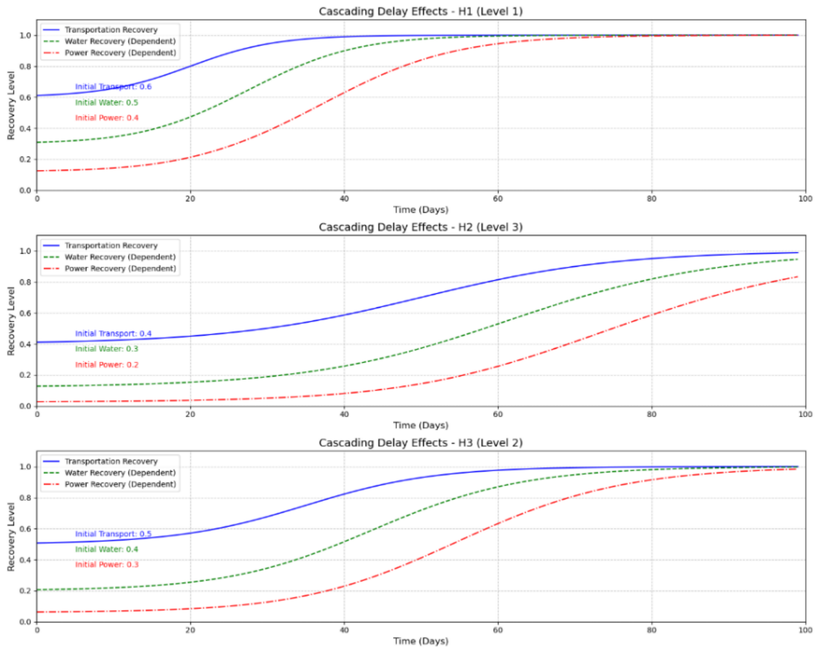

Figure 3. Interdependencies and recovery of hospital transportation, water, and power systems.

3.4 Recovery of Critical and Alternative Routes.

The recovery trajectories of critical and alternative routes offer insights into the resilience and prioritization of the transportation network among hospitals H1, H2, and H3. Figure 4 illustrates how recovery prioritization affects accessibility restoration, with critical routes designated as high-priority infrastructure for immediate disaster response and alternative routes serving as secondary paths for network redundancy.

For H1, critical routes start at 0.6 functionality, compared to 0.7 for alternatives, prioritizing access for the latter and reserving routes for emergencies. They recover faster, reaching Day 20 at a 0.2 recovery rate, whereas other options reach Day 30 at a 0.15 recovery rate. This rapid recovery supports essential services and emergency operations, facilitating patient transport and ensuring adequate supplies. By Day 40, critical routes near completion, while alternatives improve more slowly, highlighting the need for coordinated restoration planning. In H2, both route types are at low initial conditions of 0.4 and 0.5. Recovery takes 40 days for critical routes and 50 days for alternatives, both with low steepness (0.1), indicating poor resource allocation and access challenges during peak demand. This highlights inadequate transportation planning that isolates patients and staff, underscoring the need for proactive interventions that prioritize key routes for equitable healthcare access. H3 shows recovery rates of 0.5 for critical routes and 0.6 for alternatives, with recovery midpoints of 30 days for critical routes and 40 days for alternatives, and steepness values of 0.15 and 0.12, respectively. While alternative routes appear more dependent initially, critical ones recover faster and reach higher functional levels. By Day 50, both categories recover similarly, suggesting balanced but slightly delayed recovery. H3's transportation strategy aligns with prioritization principles; however, further optimization could enhance its resilience.

These underscore the vital role of transportation planning in post-disaster recovery. Prioritizing critical routes, as shown in H1, allows faster access to essential services and emergency response. The delayed recovery in H2 highlights the risks of poor prioritization, which can lead to prolonged hospital disruptions. H3 differentiates route types, suggesting a balanced recovery approach; however, better prioritization could boost efficiency. Comparing critical and alternative route recovery highlights the need for strategic prioritization to ensure timely access to healthcare. While alternative routes add redundancy, recovering critical routes must be a priority to minimize disruptions and strengthen healthcare infrastructure resilience during disasters.

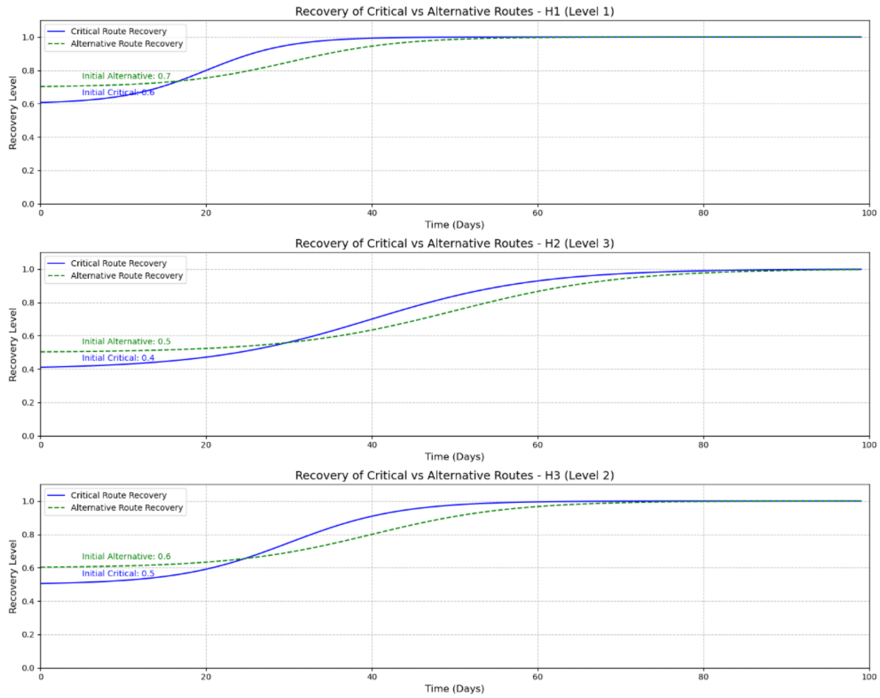

Figure 4. Recovery trajectories of critical and alternative routes for the resilience and prioritization strategies of the transportation network across different hospital facilities.

4. Conclusions

This study shows that recovery strategy choices directly shape how hospitals regain function after disasters. Prioritizing transportation first under TR pulls power and water forward, cutting delays compared with UR. The simulations reveal clear cascades: roads enable power repairs, and roads plus power enable water. High-resilience hospitals recover quickly in any case, but lower-resilience hospitals face long disruptions unless TR is applied; TR narrows these gaps and leads to fairer outcomes. Recovery of critical routes is especially important for hospital access, speeding emergency response and supply delivery more than restoring alternatives first. The core takeaway is to plan by dependencies, not silos, focus first on lifelines that unlock others to stabilize hospitals sooner, reduce unequal access, and strengthen resilience. Future work should calibrate with real event data, include crew and resource limits, and add equity-based prioritization to guide which hospitals and neighborhoods come first.

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