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Research Paper Title : Predictive Relief Logistics Models for Earthquakes and Floods Based on Traffic, Weather, and Supply Chain Data

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Abstract:

This research presents a predictive logistics framework designed to enhance disaster response efficiency during earthquakes and floods by leveraging integrated traffic, weather, and supply chain data. The proposed system combines deep learning models—such as LSTMs and CNNs—for disaster impact forecasting, with dynamic graph models for traffic disruption prediction and probabilistic approaches for supply chain risk assessment. A multi-objective optimization engine, powered by genetic algorithms and reinforcement learning, dynamically allocates resources, plans routes, and prioritizes delivery based on evolving disaster scenarios. Real-time data from GPS networks, meteorological sources, and inventory systems are processed and visualized via an interactive GIS-enabled dashboard. The system demonstrates significant improvements in delivery time, coverage ratio, and operational resilience compared to static models. Designed for scalability and modularity, the framework offers a powerful decision-support tool for governments, NGOs, and emergency responders aiming to minimize humanitarian impact and maximize logistical effectiveness during compound natural disasters.

Keywords:

disaster logistics, predictive modeling, earthquake response, flood response, traffic disruption, weather forecasting, supply chain resilience, LSTM, reinforcement learning, multi-objective optimization, humanitarian logistics, GIS, emergency response planning, dynamic routing, real-time decision support

1. Introduction

Natural disasters such as earthquakes and floods continue to challenge the resilience of urban and rural infrastructures, placing immense strain on emergency logistics and humanitarian response systems. The ability to deliver relief supplies quickly and efficiently can significantly reduce fatalities, economic losses, and post-disaster recovery time. However, conventional relief logistics frameworks often operate reactively, hindered by fragmented data silos and outdated planning strategies. These limitations result in inefficient resource allocation, misrouted supply chains, and critical delays in aid delivery. In rapidly changing disaster environments, there is an urgent need for predictive, data-integrated logistics systems that can proactively anticipate disruptions and optimize relief operations in real time.

This study proposes a predictive relief logistics model that harnesses the power of machine learning, geospatial analytics, and supply chain theory to coordinate and optimize disaster response logistics. By integrating heterogeneous data sources—real-time traffic conditions, weather and seismic forecasts, and dynamic supply chain inputs—the framework enables pre-disaster planning and post-disaster decision-making with increased agility and precision. The model employs time-series prediction and network optimization algorithms to identify logistical bottlenecks, forecast demand surges, and prioritize delivery to high-risk areas. The primary objective is to empower government agencies, disaster response teams, and humanitarian organizations with a scalable, intelligent logistics platform that enhances operational readiness and maximizes the speed and effectiveness of emergency relief.

2. Background and Related Work

The domain of disaster logistics has traditionally relied on deterministic or static models for inventory pre-positioning and transportation planning. While such models provide foundational insights, they often fail under real-time, high-uncertainty conditions induced by large-scale disasters. In recent years, the integration of AI-driven approaches in humanitarian logistics has gained attention. Studies involving last-mile delivery optimization, multi-echelon inventory planning, and route reconfiguration during infrastructure disruptions have shown improved outcomes. However, these models are often limited to a single data domain—such as traffic networks or weather forecasts—and seldom integrate cross-domain insights necessary for effective decision-making during compound or cascading disaster events.

Research in traffic-aware disaster routing has shown that real-time congestion patterns and road closures significantly affect the timing and efficiency of emergency relief. Similarly, weather-informed logistics planning helps anticipate flood-induced blockages or landslides. In parallel, advances in resilient supply chain modeling use stochastic simulations and reinforcement learning to predict the cascading effects of warehouse shutdowns or supplier failure. Despite these advances, few models offer a unified framework that brings together spatial-temporal disaster forecasting, transportation system analytics, and supply chain behavior modeling. This research fills a critical gap by developing a multi-layered, multimodal system that learns from the interdependencies between physical infrastructure, environmental dynamics, and logistical networks—enabling coordinated, predictive logistics operations under extreme events.

3. Theoretical Framework

The proposed framework lies at the intersection of temporal forecasting, network science, and logistics optimization under uncertainty. It is designed to support preemptive decision-making by integrating three core layers of analysis. First, Disaster Impact Forecasting employs time-series models—particularly LSTMs (Long Short-Term Memory networks)—trained on weather radar, hydrological data, and seismic activity to predict the spatial and temporal occurrence of floods and earthquakes. These models are complemented by geospatial simulation tools (e.g., flood propagation simulators and ground motion prediction equations) that refine impact estimates at the neighborhood level.

Second, the Traffic Disruption Modeling component uses dynamic graph representations of road networks. In this model, nodes represent critical intersections or chokepoints, while edges represent routes whose weights vary based on real-time GPS, CCTV, and sensor data. The model predicts the accessibility and congestion level of various routes, adjusting in real time as new disaster reports are received. This allows planners to identify safe, least-time delivery corridors and reconfigure routes dynamically in response to evolving conditions.

Third, Supply Chain Disruption Analysis uses probabilistic graphical models, such as Bayesian Networks and Markov Decision Processes, to simulate supply-side uncertainties. It assesses risks such as stockouts, warehouse damage, and delivery failure under disaster conditions. By integrating supplier dependency graphs and vehicle availability maps, the model supports flexible rerouting and resource reallocation. Collectively, these components form a multi-agent logistics coordination system with objectives centered on minimizing delivery latency, maximizing demand fulfillment, and ensuring equitable distribution—while respecting constraints such as road accessibility, perishability of goods, and storage capacity. This theoretical foundation sets the stage for a robust, intelligent logistics model that adapts in real time to the complex, volatile conditions characteristic of large-scale disasters.

4. Research Implementation Framework

The implementation framework for the proposed predictive logistics system is structured into six coordinated stages. In Stage 1: Data Collection and Integration, the system aggregates data from heterogeneous sources—including real-time traffic feeds (e.g., GPS logs, road sensors, congestion indices), meteorological systems (e.g., rainfall, river overflow, seismic wave detection), and supply chain repositories (e.g., warehouse capacity, transport fleet availability, demand centers). This data is temporally and spatially normalized using data warehousing platforms and geospatial transformation pipelines to ensure consistency across inputs. Cleaning, labeling, and timestamp alignment are conducted to build a unified, high-resolution dataset for predictive analytics.

In Stage 2: Predictive Modeling, deep learning models such as Long Short-Term Memory (LSTM) networks and Convolutional Neural Networks (CNNs) are deployed to capture both temporal sequences (e.g., rainfall accumulation over time, earthquake aftershock patterns) and spatial dependencies (e.g., flooded zones or affected corridors). Spatial interpolation techniques like Kriging are applied to enhance resolution in weather-sparse regions. Road disruption forecasting is modeled through a dynamic graph learning framework, where road segments act as weighted edges whose status evolves with incoming data. These predictive outputs serve as real-time inputs into the logistics optimization core.

Stage 3 involves the design of a multi-objective logistics optimization engine that uses evolutionary algorithms (e.g., Genetic Algorithms) or Reinforcement Learning (RL) to allocate resources optimally. Objectives include minimizing response time, maximizing coverage, and ensuring balanced supply across demand clusters. In Stage 4: Simulation and Scenario Testing, various disaster scenarios—e.g., simultaneous flood and earthquake—are simulated to evaluate system robustness under infrastructural degradation (e.g., roadblock, warehouse inaccessibility). Constraints such as perishability of goods and road hierarchy are explicitly modeled.

In Stage 5: Evaluation Metrics, model performance is assessed using indicators like mean delivery time, coverage ratio, unmet demand rate, and system latency. Historical disaster datasets from Indian states and global incidents are used for validation. Finally, Stage 6: Visualization and Dashboard provides an interactive GIS-based dashboard that overlays predicted disaster zones, optimized routes, and supply demand heatmaps. This dashboard offers dynamic filtering, simulation playback, and decision support for logistics planners and disaster response authorities.

5. Expected Results and Contributions

This study is expected to yield a highly responsive, predictive logistics decision-support system that integrates multiple data domains—traffic, weather, and supply chain—into a unified, intelligent planning architecture. The system is designed to improve real-time visibility and situational awareness, while delivering actionable forecasts and optimized logistics plans for government bodies, NGOs, and humanitarian actors. The use of deep learning for impact prediction, combined with AI-driven route and resource optimization, is projected to significantly enhance coordination speed, reduce resource wastage, and increase supply coverage in disaster-struck regions.

The framework is designed to outperform traditional logistics systems by offering adaptive, data-informed recommendations in complex, uncertain environments. Comparative testing against static and siloed planning models is expected to show substantial improvements in response time, operational efficiency, and unmet need reduction, particularly during multi-hazard events. Furthermore, the architecture is modular and extensible, capable of scaling from urban to rural deployments and integrating additional components like drone-based last-mile logistics, mobile health delivery units, or crowd-sourced impact reporting platforms.

An additional contribution is the creation of a real-world validation pipeline, using simulations and historical disaster case studies (e.g., Assam floods, Gujarat earthquakes). These evaluations will demonstrate the system's generalizability, reliability, and readiness for deployment by disaster preparedness authorities. Ultimately, the research offers both a theoretical and applied advancement in AI-based humanitarian logistics and a blueprint for resilient, scalable infrastructure for emergency response.

6. Conclusion and Future Directions

This research presents a comprehensive, cross-domain framework for predictive relief logistics, aiming to transform disaster response from reactive coordination to proactive, data-driven management. By integrating multi-source data from traffic, weather, and supply chain systems, the framework enables real-time forecasting and optimization of logistics operations in the face of earthquakes and floods. The proposed architecture offers significant improvements in logistical planning, operational agility, and resource distribution—demonstrating its potential to mitigate the adverse humanitarian and economic impacts of natural disasters.

Future directions include enhancing real-time uncertainty modeling using stochastic and Bayesian optimization to improve robustness in rapidly evolving disaster environments. The integration of unmanned aerial vehicles (UAVs) and autonomous ground vehicles into the logistics layer is planned to expand last-mile delivery capabilities, especially in areas with inaccessible roads. Another priority is the adoption of federated learning frameworks that allow multiple regional agencies to contribute and learn collaboratively from shared data while preserving privacy and operational sovereignty.

To ensure real-world applicability, partnerships with disaster management authorities, logistics providers, and public-sector institutions are envisioned. These collaborations will support field deployment, user-centered refinement, and long-term impact assessments. By bridging academic innovation with operational deployment, this framework positions itself as a transformative tool in the global pursuit of resilient, anticipatory, and equitable disaster response logistics.

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