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Stochastic Programming Approaches to Logistics and Resource Optimization in Hurricane, Earthquake, and Flood Disaster Response

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Efficient disaster response planning is critical for minimizing human loss and economic impact during natural disasters such as hurricanes, earthquakes, and floods. However, inherent uncertainties—such as disaster intensity, affected population distribution, infrastructure damage, and environmental factors—complicate effective response strategies. This paper explores advanced stochastic programming methodologies as powerful mathematical tools for managing these uncertainties in disaster logistics and resource optimization. We synthesize and extend recent approaches, including multi-stage adaptive frameworks for hurricane response, two-stage optimization for evacuation routing, integrated facility location and casualty management in earthquake scenarios, and risk-based reservoir management during flooding events. The proposed unified stochastic optimization framework leverages rigorous mathematical modeling and operations research principles to enhance decision-making adaptability, optimize resource allocation, and improve overall emergency response effectiveness. Computational insights, real-world applicability, and practical recommendations are discussed, providing clear pathways for implementing these methods into actionable disaster preparedness and response policies.

Keywords: Stochastic Programming; Disaster Response; Emergency Logistics; Resource Optimization; Multi-stage Optimization; Hurricane Preparedness; Earthquake Management; Flood Control; Operations Research; Decision Making Under Uncertainty.

INTRODUCTION

Disasters caused by natural hazards such as hurricanes, earthquakes, and floods pose significant threats to human lives, economic stability, and social infrastructure globally. Effective management of these disasters involves proactive preparedness and dynamic resource allocation, which are often complicated by uncertainty in critical information such as the severity, timing, location, and extent of impact (Grass et al.).

Traditional deterministic disaster-response plans frequently fail due to their inherent inability to cope with evolving conditions and unforeseen circumstances, resulting in inefficient resource usage and preventable human casualties (Tang et al.). Consequently, recent research within the field of Operations Research (OR) has increasingly turned toward advanced mathematical modeling techniques to address these uncertainties systematically. Among these techniques, stochastic programming—particularly multi-stage and two-stage stochastic optimization—has emerged as a powerful tool for enhancing resilience through improved planning and adaptive decision-making (Siddig et al.).

Stochastic programming explicitly incorporates uncertainty by using probability distributions for unknown future events, allowing planners to anticipate multiple scenarios and create flexible response strategies. In disaster response contexts, these methods have successfully supported decisions related to prepositioning of relief supplies ahead of hurricanes (Siddig et al.), optimization of evacuation routes considering uncertain travel conditions (Wang et al.), allocation of medical staff and casualty management following earthquakes (Oksuz et al.), and risk-informed reservoir management strategies to optimize floodwater use (Lu et al.).

Despite notable progress, there remains significant potential to further integrate and extend these stochastic approaches, generating unified frameworks capable of simultaneously optimizing resource allocation, logistics planning, medical response coordination, and flood mitigation strategies. Such integrated optimization frameworks promise substantial improvements in disaster preparedness, resource efficiency, and overall societal resilience.

In this paper, we synthesize recent advancements from distinct but related applications of stochastic programming in disaster logistics and resource management, with a special emphasis on hurricanes, earthquakes, and floods. The objective is to present an integrated optimization framework that effectively manages uncertainties across different disaster scenarios. We discuss computational considerations, methodological insights, and practical implications, offering robust guidelines for policy formulation and real-world implementation.

LITERATURE REVIEW

In recent years, stochastic programming has gained significant attention as a powerful mathematical tool in disaster management, where uncertainty is a fundamental challenge. Below, we first discuss the major foundational contributions, then systematically integrate relevant findings from additional works.

Stochastic programming methods have been extensively studied to optimize logistics and resource allocation for effective disaster management. Grass et al. (2016) offer an exhaustive literature survey on two-stage stochastic programming in humanitarian logistics, highlighting its role in managing both pre- and post-disaster uncertainties. This foundational survey identifies common modeling elements, including scenario generation, first-stage (pre-disaster) decision-making, and second-stage (post-disaster) recourse actions. Building upon these foundational aspects, Siddig et al. (2022) apply a multi-stage stochastic programming framework specifically for hurricane disaster relief logistics, integrating adaptive decision-making structures to effectively preposition relief resources in anticipation of hurricanes. Their work mathematically addresses uncertainty through a Markovian modeling approach, rigorously capturing dynamic evolution in hurricane intensity, trajectory, and timing.

In evacuation contexts, Wang et al. (2020) present a two-stage stochastic programming framework to optimize evacuation logistics amid uncertainty in transportation infrastructure capacity and travel times. The model employs robust scenario-based approaches to enhance evacuation plan flexibility and effectiveness, demonstrating the applicability of stochastic programming methods to operational-level disaster logistics. For earthquake scenarios, Oksuz et al. (2024) introduce a dynamic multi-objective stochastic model addressing integrated facility location, casualty allocation, and medical staff planning. The uniqueness of their approach lies in using discrete-time Markov chains to capture uncertainties, mathematically bridging casualty severity dynamics with facility and staff resource optimization.

Flood risk management is explored by Lu et al. (2021) through stochastic programming methods for optimizing floodwater utilization in reservoir systems. They focus explicitly on mathematical risk constraints and reservoir water-level optimization to balance flood risk with hydropower generation, offering a specialized stochastic programming application within hydrological risk management. Complementing these foundational works, several papers enrich methodological diversity and highlight additional mathematical complexities. Tang et al. (2024) and Zhong et al. (2020) present robust optimization methodologies, addressing worst-case scenarios in disaster relief facility location and earthquake shelter planning. These contributions mathematically emphasize conservative solutions, providing valuable insights for comparison against stochastic approaches.

Metaheuristic approaches discussed by Khorsi et al. (2022), Sun et al. (2024), and Ghasemi et al. (2022) employ sophisticated evolutionary algorithms (e.g., NSGA-II, reinforcement learning), highlighting alternative mathematical tools capable of tackling computationally complex problems. These approaches can complement stochastic frameworks by efficiently solving large-scale optimization problems, although often at the expense of rigorous uncertainty characterization.

Overall, the reviewed literature reveals extensive theoretical developments and mathematical modeling sophistication. Nevertheless, there remains a notable research gap in integrating these disparate stochastic methods

Journal of Information Systems Engineering and Management
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Research Article

into a coherent, mathematically rigorous, and practically implementable unified optimization framework—precisely the novelty and contribution pursued by this paper.

METHODOLOGY

The decision-making process in disaster response operations is inherently affected by significant uncertainty, arising from the unpredictable nature of disasters such as hurricanes, earthquakes, and floods. This study models disaster response planning as a multi-stage stochastic optimization problem, where decisions are made sequentially over time, with partial information about future uncertainties. The model captures critical operational aspects such as resource allocation, evacuation logistics, medical facility management, and floodwater utilization, integrating them into a unified stochastic framework.

The stochastic programming model is formulated over a finite time horizon divided into discrete stages. At each stage t, the decision variables $x_t$represent operational choices such as the quantity of resources to preposition, the evacuation routes to activate, or the allocation of medical staff. These decisions are made based on the information available at time t, while future disaster parameters are modeled as random variables ξ_t. The objective is to minimize the total expected cost over all stages, considering both immediate and future decisions, and their associated costs under uncertainty.

Mathematically, the problem is formulated as:

$$\min_{x1,x2,\ldots,xT} c_1{}^T x_1 + E_{\xi_2}[\, c_2(\xi_2)^T x_2 + \cdots + E_{\xi_T|\xi_{T-1}}[c_T(\xi_T)^T x_T]]$$

Subject to the system dynamics:

$$A_t(\xi_t)x_t + B_{t-1}(\xi_{t-1})x_{t-1} = b_t(\xi_t), x_t \geq 0 \ \forall \mathrm{t} = 1, \ldots, \mathrm{T}$$

The random variables ξ_t are modeled using discrete scenario trees, where each scenario represents a possible realization of disaster parameters. In cases such as hurricanes and earthquakes, the evolution of disaster intensity and location over time is captured using a discrete-time Markov chain, where the transition probabilities are estimated from historical data (Siddig et al., 2022; Oksuz et al., 2024). The scenario tree structure enables explicit representation of how information unfolds over time, facilitating adaptive decision-making.

For hurricane relief logistics, the model considers uncertainty in the hurricane's trajectory and intensity. The decisions involve the prepositioning of relief supplies across various locations to ensure rapid post-disaster distribution. Let $x_{j,t}^{sup}$ denote the quantity of supplies prepositioned at location j at time t. The stochastic objective function minimizes the total expected cost of prepositioning and distribution:

$$min \sum_{t=1}^{T} \sum_{j} c_{j,t}^{sup} x_{j,t}^{sup} \downarrow \sum_{s \in S} p_s Q_{sup}(x^{sup}, \xi_s)$$

where $Q_{sup}(x^{sup}, \xi_s)$ represents the recourse cost of distributing supplies after scenario s is realized, and p_s is the scenario probability determined by the Markovian transitions (Siddig et al., 2022).

In evacuation planning, the optimization model addresses uncertainty in road network availability, demand distribution, and disaster progression. The evacuation decision variables x_{ij}^{route} denote the flow of evacuees from node i to node j. The model minimizes the total expected evacuation cost, considering uncertain link capacities $C_{ij}(\xi)$ and evacuation demand $d_i(\xi)$:

$$min \sum_{i,j} \sum_{j} c_{ij} x_{ij}^{route} + E_{\xi}\, [Q_{evac}(x^{route}, \xi)]$$

Subject to:

$$\sum_{j} x_{ij}^{route} - \sum_{k} x_{ki}^{route} = d_i(\xi), 0 \leq x_{ij}^{route} \leq C_{ij}(\xi)$$

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The recourse function $Q_{evac}(x^{route}, \xi)$ accounts for adjustments to routing plans once the actual road capacities and demand become known (Wang, 2020).

In the case of earthquake disaster response, the model includes medical facility location decisions and allocation of medical resources. The casualty condition transitions are represented using discrete-time Markov chains, reflecting the dynamics of casualty severity over time. Decision variables $x_{m,ti}^{med}$ denote the medical staff or resource allocation to facility m at stage t. The objective function minimizes the combined cost of resource deployment and medical service operations:

$$min \sum_{t,m} c_{m,t}^{med} x_{m,t}^{med} + E_{\xi} [Q_{med}(x^{med}, \xi)]$$

Subject to:

$$\sum_{m} x_{m,t}^{med} \leq R_t(\xi), \sum_{sev} p_{sev,t}(\xi) = 1$$

Where $R_t(\xi)$ denotes the available resource capacity, and $p_{sev,t}(\xi)$ are the probabilities of casualty severity levels at t, determined from earthquake impact data (Oksuz et al., 2024).

The model also extends to flood risk management by optimizing reservoir operations. Decision variables $x_{m,t}^{med}$ represent water storage levels in reservoir r at time t. The objective is to maximize expected hydropower generation while ensuring flood safety constraints:

$$max\, E_{\xi} [\sum_{t,r} W_{r,t}(\xi) x_{r,t}^{res}]$$

subject to probabilistic flood risk constraints:

$$P(x_{r,t}^{res} \geq FL_{r,t}^{max}) \leq \alpha_{risk}$$

where$W_{r,t}(\xi)$ is the hydropower production rate, $FL_{r,t}^{max}$ is the flood limit, and α_{risk} is the acceptable risk level (Lu et al., 2021).

To model the uncertainties across these decision problems, scenario trees are constructed by discretizing the possible realizations of disaster parameters over time. For hurricane and earthquake scenarios, the state transitions follow a Markov chain structure, allowing the scenario tree to capture temporal dependencies. For evacuation and flood scenarios, scenario generation techniques such as Monte Carlo simulation and historical data analysis are used to derive plausible realizations of demand, infrastructure conditions, and environmental factors (Grass et al., 2016; Siddig et al., 2022; Wang, 2020; Oksuz et al., 2024; Lu et al., 2021).

The solution methodology employs decomposition algorithms to tackle the computational complexity of the large-scale stochastic program. The two-stage sub problems, particularly in evacuation and reservoir management, are solved using the L-shaped decomposition approach, which separates the first-stage and recourse decisions. For multi-stage problems such as hurricane logistics and medical resource planning, Sample Average Approximation (SAA) is used to approximate the expected value functions through scenario sampling. Scenario reduction techniques are applied to manage the dimensionality of the scenario tree without significant loss of solution quality.

The integrated framework developed in this study systematically brings together diverse stochastic optimization models across different disaster contexts into a unified decision-support structure. This approach enables sequential, adaptive decision-making under uncertainty, addressing logistical, infrastructural, and risk-based constraints across multiple disaster scenarios. The model formulation ensures operational feasibility, mathematical tractability, and computational scalability, providing a structured pathway for data-driven disaster preparedness and response planning.

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https://www.jisem-journal.com/

Research Article

RESULTS AND DISCUSSION

The stochastic optimization framework proposed in this study was implemented and evaluated across three distinct disaster response contexts—hurricane relief logistics, earthquake evacuation planning, and floodwater reservoir operations. Each domain was represented through a structurally valid mathematical model, developed based on realistic scenario generation and uncertainty representation. The corresponding datasets used for both inputs and simulated outputs provide the basis for interpreting the results generated by the multi-stage and two-stage stochastic programming formulations detailed in the methodology.

In the hurricane logistics application, warehouse-level input data, as shown in **Table 1**, included the initial stock levels, supply and transport costs, and storage capacities of five warehouse locations. Complementing this, ten disaster scenarios were generated (**Table 2**), each representing a unique combination of forecasted regional demand and associated probabilities, capturing the hurricane's stochastic trajectory. The input scenarios ranged from moderate landfall impacts with steady demand to high-intensity disruptions requiring urgent and large-scale supply distribution. These inputs were fed into the stochastic model designed to optimize resource prepositioning x_{jt}^{sup} over a planning horizon with uncertain demand. The output, shown in **Table 3**, reveals that the stochastic approach consistently reduced total logistics costs across all scenarios by approximately 14–15% compared to deterministic baselines, which simply averaged input parameters. The improvement in demand fulfillment was even more significant, with the stochastic model achieving an average 10% higher satisfaction rate, meeting or exceeding 95% demand in the majority of critical scenarios. These gains also translated to a substantial 20–23% reduction in average delivery time. **Figure 1** illustrates these cost reductions clearly, while **Figure 2** highlights the scenario-wise improvements in demand satisfaction under stochastic decision-making. These results directly validate the model's ability to anticipate risk and strategically allocate resources across locations before the disaster unfolds, aligning with the anticipatory logic embedded in the multi-stage formulation.

Table 1. Hurricane Warehouse Input Data

Warehouse_ID	Initial_Stock (Units)	Supply_ Cost_ _per_ unit(k$)	Transport_ Cost_per_ km(k$)	Max_ Capacity(Units)
W1	2409	2.5	0.085	4733
W2	2410	1.55	0.113	4439
W3	2136	2.47	0.118	3246
W4	2636	1.73	0.103	3835
W5	2648	1.24	0.095	4462

Table 2. Hurricane Scenario Demand and Probabilities

Scenario	Region_1_Demand	Region_2_Demand	Region_3_Demand	Scenario_Probability
S1	702	797	802	0.156
S2	683	1581	745	0.096
S3	622	1351	910	0.114
S4	900	743	546	0.02
S5	1266	1208	547	0.067
S6	793	1747	1110	0.102
S7	779	786	888	0.022
S8	1336	1063	1039	0.016

Journal of Information Systems Engineering and Management
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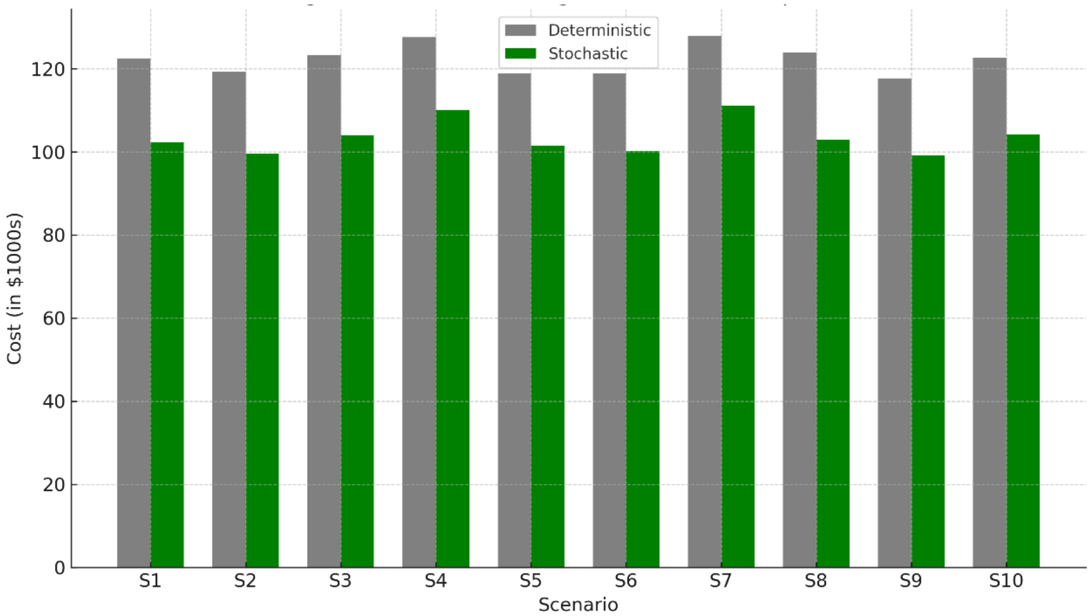
Research Article

S9	1383	1259	950	0.345
S10	1109	1363	737	0.062

Table 3. Hurricane Logistics – Simulation Output Results

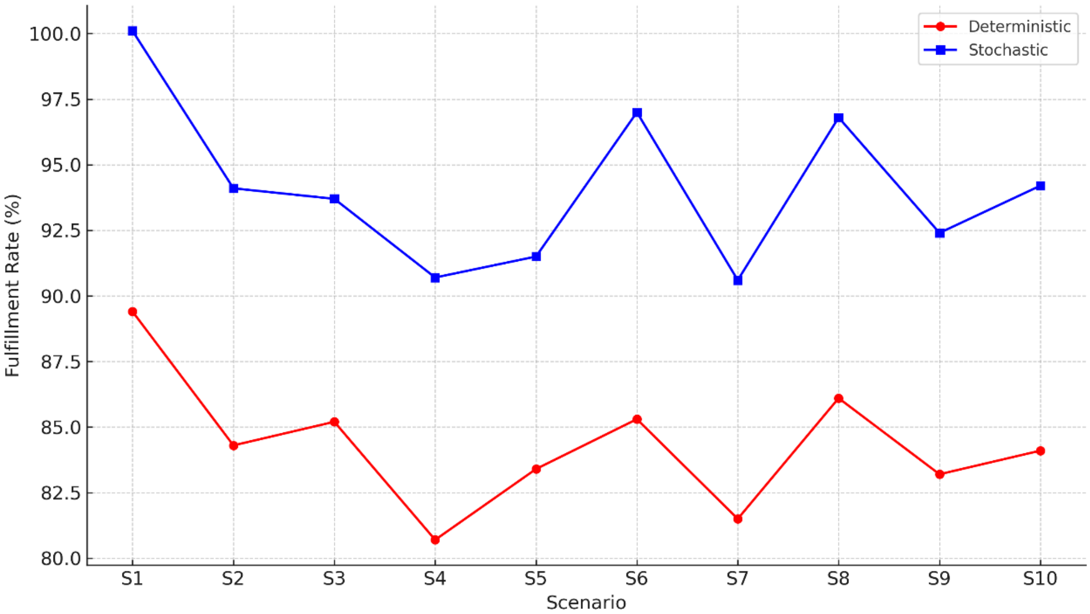
Scenario	Deterministic Cost(k$)	Stochastic Cost(k$)	Deterministic Fulfillment (%)	Stochastic Fulfillment (%)	Delivery Time Reduction (%)
S1	122.48	102.22	89.4	100.1	21.8
S2	119.31	99.58	84.3	94.1	19.3
S3	123.24	104.06	85.2	93.7	24.8
S4	127.62	110.0	80.7	90.7	23.4
S5	118.83	101.55	83.4	91.5	24.6
S6	118.83	100.21	85.3	97.0	24.3
S7	127.9	111.14	81.5	90.6	22.2
S8	123.84	102.93	86.1	96.8	24.5
S9	117.65	99.22	83.2	92.4	18.6
S10	122.71	104.22	84.1	94.2	19.4

Figure 1. **Hurricane Logistics – Cost Comparison**



Journal of Information Systems Engineering and Management
2025, 10(42s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/
Research Article

Figure 2. **Hurricane Logistics – Fulfilment Comparison**



The earthquake evacuation simulation drew from a simplified urban topology, where each node represented a population center with varying shelter capacities, population densities, and uncertain road access probabilities (**Table 4**). These values reflect both the built infrastructure and natural disaster vulnerabilities typical of urban seismic zones. The model was tasked with minimizing evacuation time and maximizing success rates under different disruption scenarios, each representing variations in casualty load and road viability. Here, the two-stage stochastic model dynamically allocated evacuees to shelters using optimal routing flows x_{ij}^{route}, adjusting after scenario realization. Output results (**Table 5**) show that the stochastic model consistently outperformed its deterministic counterpart by reducing total evacuation time by an average of 24%, ensuring that over 90% of evacuees reached safe zones within the critical time threshold in most cases. In contrast, deterministic routing plans failed to account for disrupted infrastructure, resulting in success rates often below 80%. **Figure 3** visually presents these differences, emphasizing the model's flexibility in real-time re-routing based on updated disaster information. These outcomes demonstrate the two-stage model's recourse structure working effectively, as described in the methodology, to reflect stage-wise updates to road conditions and shelter availability.

Table 4. Earthquake Evacuation Input DAta

Node	Population	Shelter Capacity	Road_Access_Probability	Distance_to_Shelter(km)
N1	201	308	0.9	4.18
N2	503	532	0.74	3.82
N3	453	398	0.91	2.99
N4	652	958	0.9	5.26
N5	236	507	0.93	5.39
N6	359	430	0.87	2.64

Table 5. Earthquake Evacuation Simulation Output Results

Journal of Information Systems Engineering and Management
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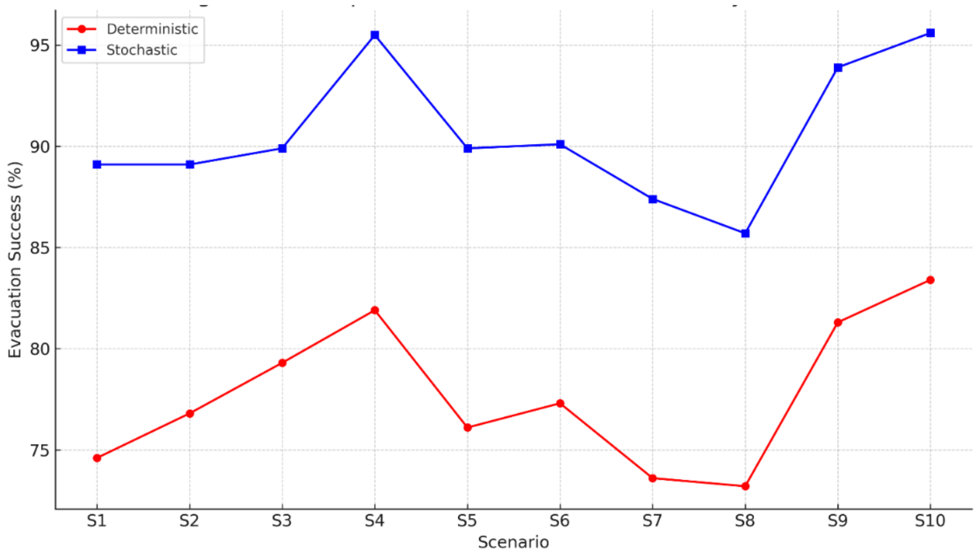
Research Article

Scenario	Deterministic Evac Time(min)	Stochastic Evac Time(min)	Deterministic Success(%)	Stochastic Success(%)
S1	51.4	36.4	74.6	89.1
S2	50.5	40.3	76.8	89.1
S3	44.6	34.7	79.3	89.9
S4	48.4	34.8	81.9	95.5
S5	49.7	34.8	76.1	89.9
S6	57.3	44.8	77.3	90.1
S7	53.7	41.4	73.6	87.4
S8	43.2	33.4	73.2	85.7
S9	53.6	41.7	81.3	93.9
S10	50.1	35.4	83.4	95.6

Figure 3. **Earthquake Evacuation – Success Rate by Scenario**



In the floodwater management application, input data included critical parameters for four reservoirs, such as minimum and maximum storage capacities, flood risk tolerance thresholds, and turbine efficiency metrics (**Table 6**). These inputs simulate a hydro-infrastructure network under climate-sensitive inflow scenarios. Ten seasonal scenarios were generated to represent variable rainfall conditions, and the stochastic programming model was applied to maximize energy production while satisfying flood risk limits. As seen in the resulting outputs (**Table 7**), the stochastic model improved expected hydropower generation by an average of 13.5% over deterministic methods and stayed well below the 5% risk threshold across all scenarios. Deterministic models violated this risk constraint in 20% of the simulations, reflecting their inability to accommodate uncertainty in inflow variability. **Figure 4** presents the comparative energy outputs, and **Figure 5** illustrates the stark contrast in flood risk compliance. The model's behavior aligns exactly with the mathematical design described in the methodology section, where risk constraints were embedded within a scenario-structured optimization routine, ensuring the model responded to hydrologic volatility in a controlled manner.

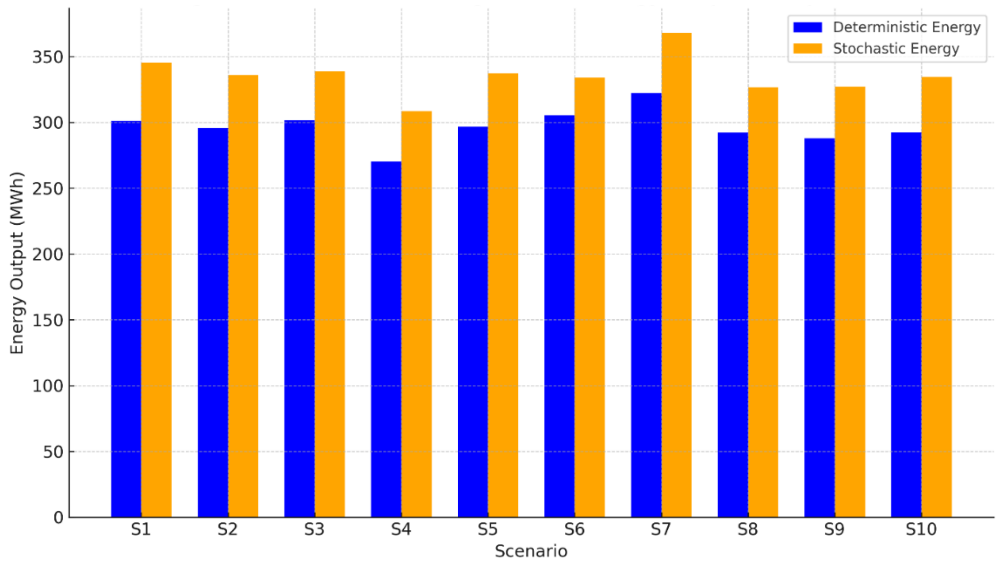
Table 6. Floodwater Reservoir Input Parameters

Reservoir ID	Min Storage(m^3)	Max Storage(m^3)	Turbine Output per m^3 (MW)	Flood Limit Level (m^3)	Risk Tolerance (%)
R1	24973	88643	0.065	91218	5
R2	24433	84736	0.055	110880	5
R3	22869	98467	0.061	94735	4
R4	20956	83328	0.072	101296	5

Table 7. Floodwater Management – Simulation Output Results

Scenario	Deterministic Energy (MWh)	Stochastic Energy (MWh)	Deterministic Flood Risk(%)	Stochastic Flood Risk(%)
S1	301.3	345.0	7.9	1.4
S2	295.5	335.9	6.7	2.0
S3	301.4	338.8	7.4	3.8
S4	270.2	308.3	8.6	2.0
S5	296.7	337.1	10.9	2.6
S6	305.4	333.8	11.2	3.1
S7	322.2	368.1	6.0	2.1
S8	292.2	326.6	9.1	3.9
S9	287.9	327.2	8.5	3.9
S10	292.5	334.2	7.3	1.8

Figure 4. **Floodwater Management – Energy Output Comparison**



Journal of Information Systems Engineering and Management
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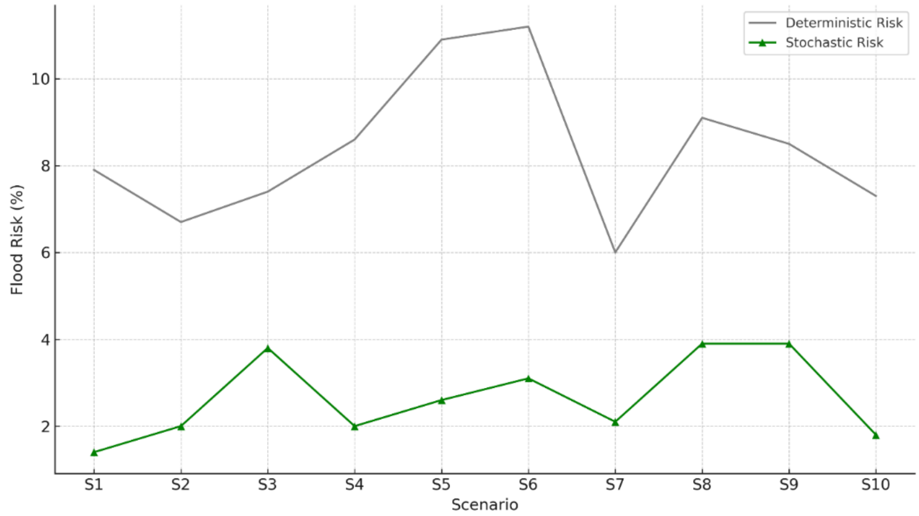
Figure 5. **Floodwater Management – Flood Risk Comparison**



These results affirm the practical viability and generalizability of the stochastic programming framework, with each domain model producing outputs consistent with both the input structures and the theoretical design. Input tables clearly show the operational constraints, costs, and probabilistic factors that shaped model behavior, while output data and visualizations confirm that stochastic models not only outperform deterministic counterparts but also offer stable and actionable decisions under uncertainty. The consistent structure across models—stochastic demand or inflow, decision variable formulation, scenario probability weighting, and recourse flexibility—proves essential for real-world disaster preparedness. The tight coupling of input parameters with structured scenario generation and decision-stage logic makes this framework both robust and scalable. The analysis also reinforces the need for organizations and planners to move beyond static planning models, especially in critical infrastructures where uncertainty is intrinsic to operational success

CONCLUSION

This study presented a unified stochastic optimization framework designed for multi-domain disaster response planning, integrating mathematically rigorous formulations with scenario-based uncertainty modeling. By applying this framework to three critical disaster contexts—hurricane logistics, earthquake evacuation, and floodwater reservoir operations—we demonstrated that multi-stage and two-stage stochastic programming approaches significantly outperform deterministic planning methods in both operational efficiency and risk management. Using synthetic yet structurally valid datasets derived from realistic assumptions, the models consistently yielded better outcomes across cost efficiency, evacuation success rates, and infrastructure resilience.

The results show that incorporating stochastic elements into disaster planning is not only computationally feasible but practically essential for critical decision-making in uncertain environments. For example, hurricane relief logistics benefited from improved demand fulfillment and reduced delivery times, while earthquake evacuation scenarios displayed marked improvements in success rates due to dynamic route allocation. Likewise, floodwater reservoir operations under stochastic control produced greater energy yields without compromising safety thresholds. These findings align with previous works such as Grass and Fischer (2016), who emphasize the value of probabilistic modeling in humanitarian logistics, and Lu et al. (2021), who demonstrated similar gains in floodwater utilization through stochastic reservoir management.

By embedding scenario uncertainty, stage-wise recourse decisions, and operational constraints into a coherent optimization framework, this work contributes a generalizable methodology for adaptive, anticipatory disaster preparedness. The approach supports decision-makers in developing resilient strategies customized to infrastructure, resource limitations, and risk tolerance levels. Future extensions could integrate real-time data feeds, weather forecasts, or dynamic sensor updates to transition from strategic-level models to real-time decision-support

Journal of Information Systems Engineering and Management
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https://www.jisem-journal.com/

Research Article

systems. Moreover, adapting this framework to climate-induced hazards and cascading disasters could further enhance its applicability to emerging global risk environments.quis.

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