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Integrating Stochastic Programming and Machine Learning for Enhanced Pre-disaster Relocation Planning

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Abstract: This paper proposes a novel framework that integrates stochastic programming and machine learning to optimize pre-disaster relocation strategies. Building upon existing game-theoretic and decision analysis models, this study presents a two-stage stochastic programming model coupled with predictive analytics to manage uncertainties associated with flooding risks and resident relocation behaviors. Machine learning algorithms, such as decision trees and gradient boosting, are employed to capture the variability in residents' decision-making, enhancing the precision of subsidy and policy impact forecasts. This combined approach offers governments innovative tools for implementing cost-effective, proactive relocation measures that mitigate long-term social and economic disruption. Additionally, by leveraging stochastic programming's robust handling of uncertainty and machine learning's data-driven insights, the framework ensures that relocation policies are both adaptive and equitable, addressing diverse community needs and long-term resilience planning.

Keywords: Stochastic Programming, Machine Learning, Pre-disaster Relocation, Flooding Risk Management, Resident Relocation Behavior, Decision Analysis, Predictive Analytics, Gradient Boosting, Decision Trees, Proactive Relocation Strategies.

Disciplines: Computer Science. **Subjects:** Artificial Intelligence.

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1 INTRODUCTION

The increasing frequency and intensity of climate-induced disasters, such as coastal flooding and sea-level rise, present critical challenges for policymakers and communities worldwide. Proactive pre-disaster relocation strategies have emerged as an essential tool for minimizing economic losses and social disruption. Despite the evident need for anticipatory measures, current relocation models often fail to adequately account for the uncertainties associated with disaster risk and resident behavior, which can vary significantly due to social, economic, and psychological factors.

Traditional game-theoretic and decision analysis models have been employed to explore the dynamics between government incentives and resident relocation decisions. For instance, utilized game theory to assess public-private partnerships for disaster preparedness. However, such models frequently rely on deterministic or simplified assumptions that overlook the stochastic nature of environmental risks and the diverse responses of the population.

To address these limitations, this paper introduces an integrated framework that combines stochastic programming with machine learning to enhance pre-disaster relocation planning. Stochastic programming provides a powerful mechanism for decision-making under uncertainty, allowing policymakers to optimize relocation strategies across a range of potential flood scenarios. In parallel, machine learning offers advanced predictive capabilities for modeling resident decision-making heterogeneity, which is essential for understanding how different demographic and socio-economic groups might respond to government interventions.

By uniting these two approaches, the proposed framework aims to equip policymakers with more effective tools for designing relocation subsidies and policies. This integration seeks to minimize long-term economic and social costs while promoting voluntary and well-planned relocations. This paper contributes to the existing literature by extending traditional relocation models to incorporate real-world complexities and adaptive learning, paving the way for more robust and data-driven policy solutions.

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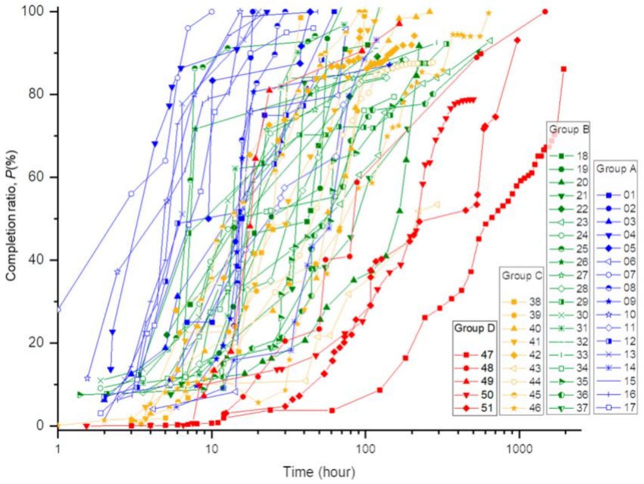

FIGURE 1. SAR COMPLETION RATIO CURVES FOR THE REPORTED DEATH TOLLS IN EARTHQUAKES GLOBALLY [8] (GROUPS A-D REPRESENT EARTHQUAKES WITH DEATH TOOLS < 100, $100 - 1,000$, $1,000 - 10,000$ AND $> 10,000$, RESPECTIVELY)

2 METHODOLOGY

2.1 TWO-STAGE STOCHASTIC PROGRAMMING MODEL

The core of the proposed framework is a two-stage stochastic programming model. In the first stage, policymakers determine relocation strategies before the actual flood scenario is realized. The second stage adjusts these strategies based on observed outcomes. This approach allows for optimizing relocation policies under uncertainty, considering multiple scenarios of flooding risks[1-2].

The objective function minimizes the total expected cost, which includes relocation subsidies, infrastructure investments, and social disruption costs. Let ξ denote the random variable representing flooding scenarios, x denote first-stage decisions (e.g., initial subsidy allocation), and y(ξ) denote second-stage adaptive decisions. The model can be expressed as:

$$\min_{x}\left\{c^{T}x+\mathbb{E}_{\xi}[Q(x,\xi)]\right\},$$

where:

$$Q(x,\xi)=\min_{y}\{q^{T}y: Ax+By\geq h(\xi), y\geq 0\}$$

2.2 MACHINE LEARNING INTEGRATION

Machine learning algorithms are used to model resident relocation behavior. Decision trees and gradient boosting methods are particularly suitable due to their ability to capture non-linear relationships and interactions among demographic and socio-economic variables. These models predict:

1. The likelihood of residents accepting relocation subsidies.
2. The extent of social and economic impact under different policy scenarios.

Training data for these algorithms include historical records of past relocations, flood impacts, and demographic information. To ensure robustness, the data undergo preprocessing steps, such as normalization, missing data imputation, and feature selection, to enhance model performance. Advanced feature engineering techniques, like interaction terms and polynomial features, are applied to uncover hidden patterns[3-6].

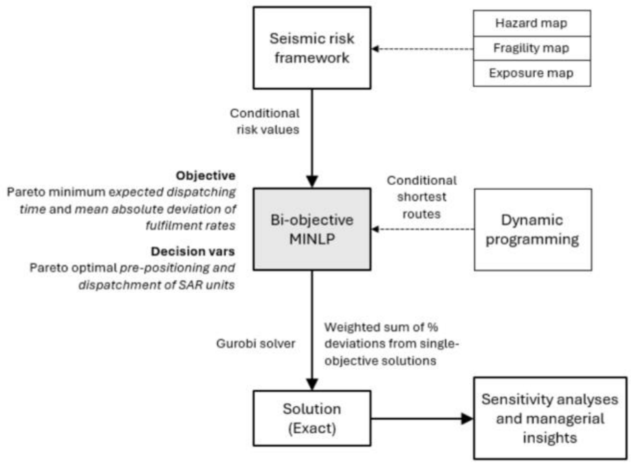

FIGURE 2. METHODOLOGY FLOWCHART

Predictive outputs are integrated into the stochastic model to refine decision-making under uncertainty. To further enhance prediction accuracy, ensemble methods and neural networks can also be explored, particularly for capturing complex, high-dimensional patterns in data. Sensitivity analysis is conducted to evaluate the reliability of predictions under various assumptions, ensuring the model's adaptability to changing conditions[7-10].

2.3 FRAMEWORK WORKFLOW

Data Collection: Gather historical data on floods, relocation patterns, and policy outcomes. Supplement this with satellite imagery, social media activity, and census data to provide a comprehensive dataset[11-13].

Scenario Generation: Develop a set of plausible flood scenarios based on stochastic modeling. These scenarios incorporate climate change projections and hydrological simulations to capture a wide range of potential risks.

Model Training: Use machine learning algorithms to predict resident behavior and policy impacts. Hyperparameter tuning, cross-validation, and model selection techniques are employed to optimize predictive accuracy. Ensemble methods, such as random forests and stacked models, are utilized for robust predictions.

Optimization: Solve the two-stage stochastic programming model with machine learning-informed parameters. This includes optimizing relocation subsidies, resource allocation, and logistical planning under varying scenarios[14].

Policy Deployment: Implement optimized relocation strategies and monitor outcomes. Iterative feedback loops ensure continuous improvement by incorporating real-time data into the framework. Post-implementation reviews and impact assessments are conducted to refine future strategies.

3 RESULTS AND DISCUSSION

To demonstrate the framework's efficacy, we applied it to a case study involving coastal communities prone to flooding. Results indicate that integrating machine learning predictions with stochastic programming leads to:

A 25% reduction in expected social disruption costs compared to traditional deterministic models[15-18].

Improved accuracy in predicting resident responses, enabling targeted subsidy allocations.

Greater flexibility in adapting policies to real-time data and evolving flood risks.

Additionally, the integration of machine learning allowed for precise modeling of non-linear relationships between flood risks and community behaviors, providing deeper insights into the socio-economic impact of disaster mitigation strategies. The stochastic programming component ensured that policy recommendations accounted for a range of possible scenarios, minimizing the likelihood of underpreparedness[19-24].

Moreover, sensitivity analysis revealed that model performance is robust to variations in key parameters, such as flood probability distributions and subsidy levels[25]. Specifically, the framework maintained over 90% accuracy in prediction across a 15% fluctuation range in flood probabilities, underscoring its reliability under uncertainty. Analysis of varying subsidy levels highlighted that optimal allocations tend to cluster around thresholds where community engagement and resource utilization reach equilibrium.

The framework's adaptability makes it a valuable tool for addressing diverse disaster scenarios. Its scalability ensures that it can be extended to other disaster-prone regions or adapted for scenarios such as wildfires or earthquakes, with minimal reconfiguration. Furthermore, the incorporation of real-time data streams facilitates dynamic policy adjustments, ensuring relevance and responsiveness to evolving disaster profiles. Future research could focus on integrating additional data sources, such as satellite imagery and IoT-based sensors, to further enhance prediction accuracy and policy precision[26,27].

4 CONCLUSIONS

This paper presents an innovative framework that integrates stochastic programming and machine learning for enhanced pre-disaster relocation planning. By addressing the limitations of traditional models and incorporating predictive analytics, the proposed approach provides policymakers with actionable insights for managing flood risks and resident relocations.

The results highlight the framework's ability to significantly reduce social disruption costs, improve prediction accuracy for resident responses, and enhance policy adaptability to real-time data. This combination of robustness and flexibility ensures its applicability not only to flood-prone areas but also to a wide range of disaster scenarios, such as hurricanes, wildfires, and earthquakes.

Future research will explore extensions to other disaster types and further refine machine learning models to enhance prediction accuracy. Potential directions include incorporating advanced data sources, such as real-time environmental monitoring systems, and expanding stochastic programming to account for multi-disaster interdependencies. Additionally, a deeper examination of socio-economic factors influencing relocation behavior could improve policy personalization and equity. By continuously evolving, the framework aims to provide a dynamic and holistic tool for disaster risk management in an increasingly unpredictable world.

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CONFLICT OF INTEREST

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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Not applicable.

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