HEC MONTRÉAL
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Disaster Response Planning: Optimization Models for Evacuation, Sheltering, and Temporary Housing

par
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Résumé

La fréquence et la gravité croissantes des désastres naturels posent des défis majeurs aux systèmes de gestion des urgences dans le monde entier. Cette thèse développe des modèles d'optimisation complets et des outils d'aide à la décision pour la planification de la réponse aux désastres, couvrant l'ensemble du continuum des besoins en abris d'urgence et en logement temporaire, de l'évacuation immédiate à la récupération à long terme. La recherche intègre la programmation mathématique, les sciences comportementales et les méthodologies d'évaluation des risques afin d'améliorer les capacités de préparation (pré-désastre) et de réponse (post-désastre).

Le premier chapitre propose une approche basée sur les risques pour la conception de réseaux d'abris. Elle évalue systématiquement les risques inhérents au réseau (risques de population, d'abris et d'évacuation) en conditions d'inondation, à partir de résultats de recherche empiriques, de cartes d'aléa d'inondation à haute résolution et d'indices de vulnérabilité. À notre connaissance, il s'agit d'un effort pionnier intégrant l'évacuation piétonne dans un outil d'optimisation en contexte d'inondation; le modèle représente le risque d'une évacuation réelle à pied dans les eaux de crue. L'optimisation minimise le risque total du réseau, compte tenu des conditions d'inondation pendant la phase de réponse, tout en maximisant la couverture des populations les plus exposées et vulnérables, et identifie les emplacements d'abris optimaux qui servent efficacement les communautés pendant les désastres.

Le deuxième chapitre, s'appuyant sur ces fondements, incorpore la dynamique comportementale humaine dans la planification de l'évacuation via un nouveau cadre d'optimisation biniveau. En formulant la conception du réseau d'abris comme un jeu de Stackelberg, l'approche capture l'interaction décisionnelle entre les autorités et les évacués. Le modèle comportemental de Fogg est mobilisé pour construire des fonctions d'utilité intégrant la motivation, la capacité et les déclencheurs (facteurs critiques influençant les décisions d'évacuation). Cette structure d'optimisation biniveau établit un pont entre les réponses comportementales individuelles et la planification stratégique de niveau supérieur, reconnaissant qu'une évacuation efficace dépend non seulement de la disponibilité des infrastructures, mais aussi des processus décisionnels individuels. Le modèle s'ajuste dynamiquement aux conditions évolutives du désastre sur l'horizon de planification, fournissant aux autorités des aperçus sur la façon dont différentes politiques, incluant les systèmes d'alerte précoce, les stratégies d'atténuation des inondations et les normes de distance de déplacement, influencent les résultats d'évacuation.

Le troisième chapitre s'étend au-delà de la réponse immédiate pour traiter du logement temporaire post-désastre sur une période de récupération de 18 mois. Une approche de programmation stochastique à deux étapes optimise la planification des capacités et l'allocation des ressources à travers trois phases de récupération : la réponse immédiate, la récupération transitoire et la stabilisation. Le modèle considère cinq catégories de logement : les abris collectifs, l'hébergement tiers, les roulottes, les unités manufacturées et les unités temporaires transportables alternatives. Il intègre des fonctions d'utilité des ménages fondées sur la distance de déplacement, les attributs du logement et les considérations temporelles. Les décisions pré-désastre incluent les stratégies de stockage et la contractualisation avec les fournisseurs, tandis que les décisions post-désastre incluent l'activation de l'approvisionnement, le déploiement régional et la cartographie de l'hébergement des ménages. Cette approche équilibre les investissements de préparation et la flexibilité de réponse, sous incertitude quant à la localisation et à la gravité du désastre.

L'applicabilité pratique est démontrée au moyen de deux études de cas majeures. En collaboration avec la Banque mondiale et le gouvernement d'Haïti, les modèles de conception du réseau d'abris et d'évacuation comportementale ont été calibrés et testés pour le département des Nippes, en Haïti, confronté à des inondations dévastatrices récurrentes. Nos outils d'aide à la décision ont été adoptés par nos partenaires afin d'orienter 35 millions de dollars d'investissements dans les infrastructures d'abris en Haïti. Par ailleurs, le modèle de logement temporaire a été appliqué au système de réponse aux ouragans en Louisiane, en analysant les arbitrages d'allocation budgétaire, les impacts d'événements extrêmes, l'expansion de la capacité des fournisseurs et les politiques de financement fondées sur les besoins.

Mots-clés

Optimisation de la réponse aux catastrophes, Planification des évacuations, Conception de réseaux d'abris, Logement temporaire, Modélisation comportementale, Évaluation des risques, Programmation stochastique à deux étapes, Optimisation biniveau, Logistique humanitaire, Gestion des urgences

Méthodes de recherche

Programmation mathématique, Optimisation biniveau, Programmation stochastique à deux étapes, Modélisation comportementale

Abstract

The increasing frequency and severity of natural disasters pose significant challenges to emergency management systems worldwide. This dissertation develops comprehensive optimization models and decision-support tools for disaster response planning that address the complete continuum of emergency shelter and housing needs from immediate evacuation to long-term temporary housing recovery. The research integrates mathematical programming, behavioral science, and risk assessment methodologies to enhance both pre-disaster preparedness and post-disaster response capabilities.

The first chapter establishes a risk-based approach for shelter network design that systematically assesses the inherent risks of the shelter network (population, shelter, and evacuation risks) under flooding conditions based on empirical research outputs, high-resolution flood hazard maps, and vulnerability indices. As a pioneering effort in incorporating pedestrian-based evacuation into an optimization tool, it models the risk of real-life foot evacuation in floodwater. The optimization model minimizes the total risk of the network considering its flooding condition during the response phase while maximizing coverage for those most exposed and vulnerable to hazard, identifying optimal shelter locations that serve communities effectively during disasters.

Building upon this foundation, the second chapter incorporates human behavioral dynamics into evacuation planning through a novel framework utilizing bilevel optimization. By framing the shelter network design as a Stackelberg game, the approach captures the interactive decision-making between authorities and evacuees. The framework employs the Fogg Behavior Model to formulate evacuee utility functions that account for motivation, ability, and triggers (critical factors influencing evacuation decisions). This bilevel optimization structure bridges the gap between lower-level behavioral responses and upper-level planning, recognizing that effective evacuation depends not only on infrastructure availability but also on individual decision-making processes. The model dynamically adjusts to evolving disaster conditions over the planning horizon, providing authorities with insights into how different policies including early warning systems, flood mitigation strategies, and travel distance standards influence evacuation outcomes.

The third chapter extends beyond immediate response to address post-disaster temporary housing challenges throughout the 18-month recovery period. A two-stage stochastic programming approach optimizes capacity planning and housing resource allocation across three recovery phases: immediate response, transitional recovery, and stabilization. The model considers five housing categories: congregate shelters, third-party lodging, trailers, manufactured housing units, and alternative transportable temporary housing units. It incorporates household utility functions capturing preferences based on displacement distance, housing attributes, and temporal considerations. Pre-disaster decisions include stockpiling strategies and supplier contracting, while post-disaster decisions include procurement activation, regional deployment, and household accommodation mapping. This approach balances preparedness investments with response flexibility under uncertainty regarding disaster location and severity.

The practical applicability is demonstrated through two major case studies. In collaboration with the World Bank and Government of Haiti, the shelter network design and behavioral evacuation models were calibrated and tested for Haiti's Nippes Department, experiencing recurrent devastating floods. Our decision-support tools were adopted by our partners to inform \$35 million in shelter infrastructure investments in Haiti. Additionally, the temporary housing model was applied to Louisiana's hurricane response system, examining budget allocation trade-offs, extreme event impacts, supplier capacity expansion, and needs-based funding policies.

Keywords

Disaster response optimization, Evacuation planning, Shelter network design, Temporary housing, Behavioral modeling, Risk assessment, Two-stage stochastic programming, Bilevel optimization, Humanitarian logistics, Emergency management

Research Methods

Mathematical Programming, Bilevel Optimization, Two-Stage Stochastic Programming, Behavioral Modeling.

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Preface

This thesis consists of three articles listed as follows:

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2. Sharbaf, M., & Rancourt, M., & Bélanger, V. A behavior-driven framework for shelter network design and evacuation planning. *R&R*, *Production and Operations Management*, 2025.
3. Sharbaf, M., & Rancourt, M., & Goentzel, J., & Bélanger, V. Analysis and optimization of post-disaster temporary housing solutions: An application to hurricane response in Louisiana. To be submitted.

General Introduction

The frequency and intensity of natural disasters have increased dramatically over recent decades, presenting unprecedented challenges to communities worldwide. Before 1960, fewer than 50 disasters were typically reported annually; since 2000, this number has consistently exceeded 335 natural disasters per year. Between 2000 and 2019 alone, over 7,348 major disasters caused 1.23 million fatalities and affected more than 4 billion individuals globally. Floods have emerged as the most frequently recorded disaster type since 1995, averaging 156 occurrences annually with a peak of 226 events in 2021. Similarly, hurricane-prone regions such as the Gulf Coast of the United States face recurring threats, with states like Louisiana experiencing hurricane landfalls approximately every three years on average. This rising pattern of natural disasters underscores an urgent need for more effective disaster management strategies that can protect vulnerable populations and minimize human suffering.

Central to effective disaster management is the provision of safe accommodations for displaced populations throughout different phases of a disaster. The disaster management cycle consists of four interconnected phases: mitigation, preparedness, response, and recovery. When a disaster happens, we move from the planning stage to the immediate action stage and then to the long-term solution stage. Evacuation is an important initial decision in the aftermath of a disaster which involves relocation of people from a potentially hazardous area to a safe location. At the time of evacuation, emergency shelters as short-term solutions provide safety and protection for displaced people. Although shelters are physically used during the response stage, designing an effective shelter network happens in the preparedness phase, considering the dynamics of the response stage. This is the focus of our first chapter. Evacuation planning is the bridge between preparedness and response, and it accounts for how evacuees behave, what motivates them, how they travel, and how disasters evolve over time. Shelter network design and evacuation planning is the focus of our second chapter. After the initial crisis, people may not be able to return home right away. That's where temporary housing comes into play, and addressing temporary housing strategies is the focus of our third chapter. All three chapters are interconnected; by sequentially covering immediate sheltering and then long-term housing, this thesis contributes to a comprehensive view of how to optimize both short-term and long-term shelter solutions.

Planning effective shelter networks and housing strategies presents several complex challenges that must be addressed systematically. First, shelter network design must account for multiple sources of risk stemming from the interaction between hazards, exposure, and vulnerability. Shelters must be located in safe areas that minimize exposure to hazards while remaining accessible to vulnerable populations through evacuation routes that may be compromised by disaster conditions such as flooding. In the context of developing countries like Haiti, an additional critical challenge involves data collection. The lack of formal digital data gathering processes, scattered information across multiple stakeholders, and difficulties in understanding the contexts, constraints, and objectives of local stakeholders complicate the planning process considerably. Second, effective evacuation planning requires understanding and anticipating human behavior during disasters. The interplay between authorities who design shelter networks and individuals who make evacuation decisions creates inherent conflicts: authorities prioritize protecting vulnerable populations and minimizing system-wide risks, while evacuees face various barriers—motivational, logistical, and warning-related—that shape their evacuation choices. Failing to account for these behavioral dynamics can significantly undermine evacuation effectiveness. Moreover, understanding how disasters evolve over time is essential for accurately modeling human behavior during evacuation. This raises two fundamental questions: "How can we estimate disaster evolution over time?" and "How can we effectively model evacuees' behavior?" Third, temporary housing planning presents challenges on quantifying survivors' preferences (utility) for different housing types, characterizing how these preferences evolve throughout post-disaster recovery phases, and addressing stochasticity stemming from uncertainty in both the location and magnitude of disasters.

Despite the critical importance of sheltering and housing in disaster management, several significant gaps persist in the existing literature. First, while the shelter location problem has received considerable attention, most studies focus on vehicle-based evacuations in developed countries, with limited consideration of pedestrian-based evacuations prevalent in developing countries and resource-constrained settings. Second, human behavioral dimensions, including the barriers that shape evacuation decisions, remain substantially underaddressed in optimization frameworks, despite widespread recognition of their importance. Moreover, most models treat disaster conditions as static rather than incorporating the dynamic evolution of hazards over time. Third, the temporal housing literature has given limited attention to strategic capacity planning that integrates survivor preferences across multiple recovery phases. This thesis addresses these gaps by developing three optimization tools that advance both the theory and practice of disaster sheltering and housing management. Through collaborations with the World Bank, the Government of Haiti, and the Federal Emergency Management Agency (FEMA), this research is grounded in real-world contexts and informed by empirical evidence, ensuring practical applicability and relevance. The content of this thesis facilitates the transfer of knowledge and recommendations to practitioners and informs managerial insights and quantifies the impact of different policies in several key areas in the context of disaster sheltering and temporary housing.

The thesis comprises three chapters, each addressing distinct but complementary aspects of disaster sheltering and housing management across different disaster management phases, geographical contexts, and levels of analytical complexity. Chapter one introduces a risk-based mathematical programming model for shelter network design in the context of pedestrian-based evacuation in flood-prone areas of developing countries. Through collaboration with the World Bank as part of an initiative focused on strengthening disaster response capacity and improving infrastructure in Haiti, this chapter addresses a critical gap in shelter location literature by comprehensively assessing risks across all network components: population points (demand), shelter locations (supply), and evacuation paths (network edges). The model uniquely integrates the impact of flood waters on pedestrian walking speeds and considers multiple factors including flood hazards, population density, vulnerability indices, existing shelter capacities, and road accessibility. This chapter represents the first systematic attempt toward shelter network optimization that explicitly accounts for the challenges of pedestrian-based evacuation in flood contexts, establishing the foundation for risk-aware shelter planning in vulnerable communities. This risk-based approach serves as a deterministic alternative to scenario-based stochastic models when uncertainty is challenging to model due to a lack of disaster-related data.

Chapter two builds upon the first chapter by introducing behavioral dimensions into shelter network design through a bilevel optimization framework. Recognizing that effective evacuation planning involves two key decision-makers, authorities who establish shelter networks during preparedness and evacuees who make evacuation decisions during response, this chapter explicitly models the hierarchical interaction between these actors. The framework addresses four key conflict points: the evacuate-or-stay decision influenced by motivational barriers, route preferences shaped by logistical barriers, evacuation timing affected by warning barriers, and shelter assignment constrained by real-time accessibility. Through an interdisciplinary approach integrating operations research, behavioral science, and hydrology, the chapter develops a novel utility function grounded in the Fogg Behavioral Model that captures evacuee decision-making. The model also introduces the Flood Evolution Index to dynamically represent disaster progression over time at fine geographical scales. This chapter demonstrates that behavior-driven, decentralized approaches can outperform traditional centralized planning methods, offering more adaptable solutions that recognize the critical role of human behavior in evacuation effectiveness.

Chapter three shifts focus from immediate sheltering during evacuation to strategic planning for temporary housing throughout the extended recovery period following large-scale disasters. Applied to hurricane response in Louisiana, this chapter addresses the persistent challenge of temporary housing capacity planning facing U.S. emergency management agencies. Using two-stage stochastic programming, the tool incorporates uncertainty regarding disaster location and magnitude while optimizing pre-disaster and post-disaster procurement strategies across three recovery phases: immediate response, transitional recovery, and stabilization. The model integrates empirical insights from historical housing responses to quantify household preferences for different housing types, including congregate shelters, third-party lodging, and various mobile housing units, and captures how these preferences evolve across recovery phases. By optimizing stockpiling decisions, supplier contracting strategies, and resource allocation while maximizing survivor utility, this chapter provides a systematic approach that balances preparedness investments, response capabilities, and survivor-centered outcomes under uncertainty.

Collectively, these three chapters make several significant contributions to disaster operations management and humanitarian logistics. From a practical standpoint, the collaboration with international organizations and government agencies ensures that the developed tools address real-world needs and can inform policy and practice. This dissertation contributes to the advancement of United Nations Sustainable Development Goals 11, 13, and 17, which focus on sustainable cities and communities, climate action, and partnerships for the goals.

Chapter 1

Risk-based Shelter Network Design in Flood-Prone Areas: An Application to Haiti

Abstract

Evacuations occur when human safety is compromised by disasters, such as floods. Shelters play a crucial role in providing protection for individuals who have been displaced or have lost their housing, emphasizing the requirement for secure accessibility. This paper introduces a systematic optimization tool, utilizing mathematical programming, to assist decision-makers in designing an effective shelter network. It is effective preparedness decision as it minimizes the total risk of the network considering its flooding condition during the response phase while maximizing coverage for those most exposed and vulnerable to hazard. We propose a risk-based approach, wherein the inherent risks of the shelter network (i.e., population, shelter, and evacuation risks) have been thoroughly assessed and measured to consider the impacts of floods based on empirical research outputs. To formulate a well-parameterized and valid problem, extensive data collection and processing, incorporating the use of geographic information system (GIS) for data management, have been conducted. In collaboration with the World Bank and Government of Haiti, this project contributes to a development initiative focused on strengthening disaster response

capacity and infrastructure for Haiti, experiencing recurrent devastating floods and in need of enhancing its existing shelter network. Detailed computational results highlight the value of our risk-based methodology compared to more common approaches, emphasizing contributions to addressing real humanitarian problems.

1.1 Introduction

The frequency of disasters has seen a significant increase over the past decades. Before 1960, there were typically fewer than 50 reported disasters worldwide per year. Since 2000, the number has consistently exceeded 335 natural disasters annually, except in 2023, when there were 239 events [EM-DAT, 2021]. Floods have been the most frequently recorded disaster since 1995, with an average of 156 occurrences and a peak of 226 in 2021 [EM-DAT, 2021]. Since 1980, flooding has caused more than one trillion dollars in losses worldwide, and the number of victims is estimated to double globally by 2030 [WRI, 2020]. The risk of flooding is growing worldwide due to increased rainfall and storms caused by the effects of climate change, socioeconomic factors such as population growth, developments near rivers, and land subsidence caused by excessive extraction of groundwater [WRI, 2020]. These trends have considerable impacts on low-income populations, particularly those in vulnerable areas with low-density road networks, where populations tend to live in informal settlements highly exposed to the effects of flood disasters. In fact, floods pose a significant threat to people's livelihoods, with approximately 23% of the world's population (1.8 billion people) exposed to this hazard, negatively affecting global development [Rentschler et al., 2022].

When human safety is threatened by disasters such as floods, a critical decision must be made regarding whether to initiate an evacuation. The primary goal of this measure is to protect lives by relocating individuals to secure locations and providing them with essential support. Establishing potential shelter locations is crucial for ensuring effective evacuations, as these facilities are vital for accommodating people who cannot evacuate to other safe places [Amideo et al., 2019]. The shelter location problem refers to the problem of determining the most suitable sites to provide temporary or permanent accommodations for people displaced by disasters. This problem can be addressed through various approaches, such as opening temporary shelter sites using tents or mobile units, selecting from a set of predetermined locations like hotels or schools, or choosing sites to build new infrastructure specifically designed to serve as shelters. In our project, we focus on the last option, which involves locating and establishing permanent relief shelter infrastructures. The Sphere Handbook [Sphere Association, 2018], which sets post-disaster sheltering standards, emphasizes that shelter location and settlement planning should promote safe, acceptable, and accessible living spaces. These spaces should provide access to basic services and household items (e.g., items for sleeping, food preparation, eating and drinking, thermal comfort), livelihoods, and opportunities to connect to a broader network. These service facilities should be established where they are safe and most convenient for the beneficiaries, not solely based on logistic convenience for the providing agency. So, it is crucial to ensure that shelters remain accessible (with acceptable distance and safe travel) for evacuees during disasters, considering that roads may be compromised by disaster conditions, such as high water levels caused by floods [Sphere Association, 2018]. Moreover, these settlements should be located at a safe distance from actual or potential threats to minimize risks from existing hazards. Embedding response considerations (e.g., risk encountered in reaching a shelter in a flooded area) in preparedness decisions (e.g., shelter locations) leads to more effective disaster management [Van Wassenhove, 2006].

Recognizing the importance of ensuring the protection of people affected by disasters, it is acknowledged that shelter network design problems are fundamental facility location issues related to disaster operations management [Ozbay et al., 2019]. Shelter network design problems often represent decisions made in the preparedness phase of disaster management as part of evacuation planning, which in turn depend on the characteristics of the modeled systems. Anticipating the state of the network post-disaster and its contingent risks is challenging but must be considered to efficiently determine shelter locations. Understanding the context, evaluating the key considerations and particularities, and defining constraints and objectives of the stakeholders are crucial aspects of such problem formulation.

While ensuring that shelters are located in safe places to cover the most vulnerable population, it is also essential to understand how people evacuate from their households to shelters and the level of risk they face on their path when planning for and modeling effective evacuation [Lim et al., 2016]. Pedestrian-based evacuations, where people walk to secure zones or shelters, are common due to limited access to personal vehicles, a lack of public evacuation transport, road congestion, and damages [Lim et al., 2016, Wood et al., 2018]. This is especially prevalent in developing countries, although it also occurs in developed countries.

The aim of this paper is to introduce a systematic optimization tool, utilizing mathematical programming, to assist decision-makers in designing effective shelter networks. We propose a risk-based approach, thoroughly assessing and measuring the inherent risks of the shelter network (population, shelter, and evacuation risks). This assessment considers vulnerability and the impacts of floods, with risks measured based on previous empirical research outputs. To ensure relevance, validity, and practical applicability throughout the development of this decision support tool, we collaborated with the World Bank as part of an initiative focused on strengthening disaster response capacity and improving infrastructure in Haiti – specifically, the Haiti- Strengthening Disaster Risk Management and Climate Resilience Project (H-SDRMCRP) [World Bank, 2019a].

Our risk-based mathematical programming model offers several significant advantages over traditional approaches. Firstly, it allows for comprehensive analysis through simultaneous consideration of multiple factors, which is not feasible with manual methods. Additionally, our tool systematically optimizes the shelter selection problem in a significantly reduced time frame, unlike manual approaches. The model's ability to produce optimal solutions within several seconds greatly accelerates the process of evaluating multiple solutions and conducting what-if analyses. This rapid solution generation is particularly crucial given the recent devaluation of Haitian currency, as it enables quick adaptability to economic changes for governmental decision-making. Furthermore, by identifying potential shelter locations, the tool streamlines the in-depth field assessment process for our partners. We now describe in more detail the problem and challenges of this study.

1.1.1 Problem Description and Context of This Study

Several developing countries, like Haiti, struggle with insufficient capacities and inadequate local shelter networks. While communities often rely on public infrastructures like schools, churches, and municipal halls for sheltering needs, these facilities may lack essential amenities such as proper sanitation and cooking facilities, rendering them unsuitable for extended sheltering. As these facilities, intended for short-term shelter, are often used for longer periods, additional challenges arise. Moreover, they may not adequately cover the most vulnerable or at-risk population, and people may face significant risks when trying to reach these public infrastructures, especially when they have to walk long distances through water.

The Risk-Based Shelter Location Problem (RB-SLP) addressed in this paper involves deciding where to construct new shelters (i.e., shelter-location decisions) with the aim of maximizing the population enfold risk and minimizing the shelter and network risk under coverage, budget, and capacity constraints. It also involves determining to which shelter the covered population should evacuate to (i.e., population-shelter assignment decisions). More precisely, the three main components of the objective include: 1) maximizing the population risk covered by the shelter network, 2) minimizing the risk associated with new shelter locations, and 3) minimizing the evacuation risk encountered by the population when they reach their assigned shelter. Overall, population and shelter risk factors include exposure to flood hazards, the potential sheltering coverage provided by existing infrastructure, and vulnerability (measured by a series of indices accounting for wealth and the quality of infrastructure). Concurrently, evacuation risk considers the challenges associated with walking through water. Further details on the measurement of each risk are provided in Sections 1.4 and 2.4.

The RB-SLP is formulated on a graph with population points and potential locations for new shelters. Each population point is associated with an estimated number of people in need of sheltering services (i.e., the demand), determined by the population and a percentage of sheltering need. Potential new shelter locations must meet specific criteria, including low flood risk and road accessibility. Shelters, in accordance with humanitarian or national standards, should cover a population within a designated radius to limit walking distances and adhere to capacity limits based on the maximum required square footage per person. The construction of new shelters incurs costs, including building expenses and others dependent on factors like ownership, terrain type, and infrastructure availability (e.g., electricity, water, sanitation, landscaping). Decisions are made under budget constraints and predetermined financing limits for shelter network improvement.

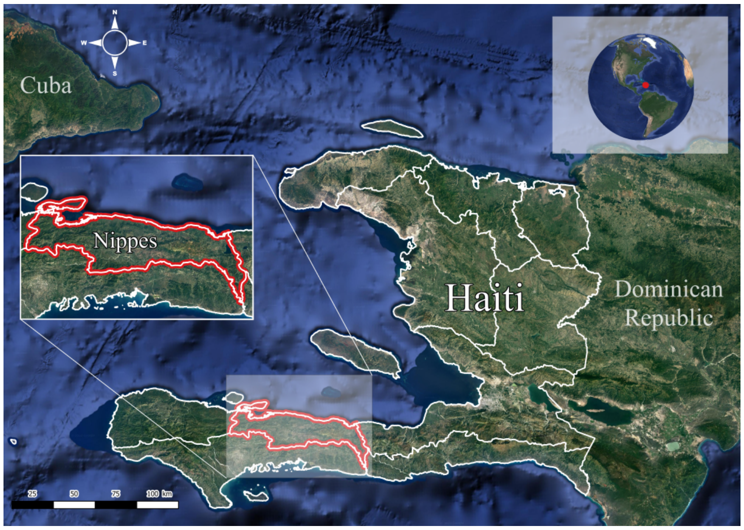

Fig. 1.1: Map of Haiti highlighting the Nippes department

In this paper, we assume the entire investment is allocated to new constructions, but in practice, planners might leverage parts of the existing infrastructure that remain functional and enhance them. Although our methodology is developed to solve the RB-SLP focusing on new constructions, it can easily adapt to cases involving partial network reconstruction and improvement. The proposed solution aims to support governmental entities and other decision makers involved in supporting local authorities to optimize the value provided by their investments and design efficient shelter network and evacuation plans.

For this study, we parameterized and tested RB-SLP to enhance the shelter network in the Nippes Department of Haiti (Figure 1.1). Haiti, ranking third among countries most affected by weather-related disasters [Eckstein et al., 2019], is one of the world's poorest nations [World Bank, 2022]. The country faces multiple hazards, with over 96% of the population exposed to two or more, including floods, hurricanes, earthquakes, and landslides [Llopis Abella et al., 2020]. The severe human and economic impact of disasters is exacerbated by Haiti's hazard exposure and infrastructure vulnerability [Llopis Abella et al., 2020]. Despite some progress, Haiti still lacks adequate preparedness and resilience-building mechanisms, especially considering the expected increase in the frequency, intensity, and impacts of extreme weather events due to climate change [World Bank, 2022]. After a flood, the affected population finds temporary housing in shelters. Existing buildings, such as schools, auditoriums, churches, and other public structures, can serve as shelters (referred to as existing shelters in this study). However, using these multi-functional centers as emergency evacuation shelters for an extended period poses challenges. Firstly, it disrupts their primary activities. Secondly, many of these buildings lack essential amenities required for long-term shelter use. Moreover, some may not comply with building codes and standards, and in some cases, might even be located within flood-prone areas.

Haiti faces insufficient shelter capacity, necessitating the expansion and enhancement of its network [World Bank, 2019a]. Given the high flood hazard in the Nippes Department of Haiti, it serves as a crucial case for testing and validating our methodological approach. Throughout the development of our risk-based approach, our aim has been to support the Government of Haiti and the World Bank, which is committed to addressing the sheltering issue through their financed project, H-SDRMCRP.

1.1.2 Challenges of the Study and Organization of This Paper

In this section, we synthesize the challenges of this study and present the general organization of this paper.

The first challenge of this study involved understanding the context, identifying the constraints and objectives of the stakeholders, and ultimately defining the problem. To address the lack of realistic assumptions in shelter location and evacuation planning studies [Amideo et al., 2019], we focused on making our approach more application-oriented rather than purely theoretical and model-driven. This required a deep understanding of the Haitian context, including its unique cultural, socioeconomic, geographical factors, and disaster risk profile. Our collaboration with the World Bank and the Government of Haiti was crucial in this process, allowing us to evaluate the key considerations, define the particularities of various stakeholders, and formulate a well-defined and realistic problem that balanced these diverse needs and perspectives. The second challenge was data collection and accessibility. The humanitarian sector often faces challenges due to the lack of standardized digital processes and the dispersion of critical data among various stakeholders [Van Wassenhove, 2006, Besiou et al., 2018, Pedraza-Martinez et al., 2013]. Risk assessment also poses challenges related to data availability, including climate data at sufficient resolution and socioeconomic data at the lowest levels of aggregation, as well as the capacities of the communities and their vulnerability. To address this issue, we integrated various geospatial data sources, as well as data obtained through extensive discussions and interviews with different experts from the World Bank and the Government of Haiti. This approach allowed us to adequately parameterize our problem despite the data-related obstacles. Again, our partnership with local authorities was instrumental in navigating this challenge and ensuring the reliability and relevance of the collected data for our study. Another challenge we encountered during the course of this project was the changing political situation in Haiti from the project's definition to its implementation phase. Several factors, including the high inflation rate, the COVID-19 pandemic, and the occurrence of natural disasters in Haiti during this period, contributed to considerable changes in construction costs. These fluctuations posed difficulties in accurately parametrizing the model, as the input data and assumptions were subject to change based on the volatile economic and political environment. Adapting the model to account for these shifting variables required continuous updates and adjustments, which added complexity to the project's execution and necessitated a flexible approach in order to ensure the model's relevance and reliability in the face of evolving conditions.

The remainder of this paper is organized as follows. Section 1.2 reviews the relevant literature. In Section 1.3, we introduce the proposed risk-based model along with the associated mathematical notation. Section 1.4 outlines our risk assessment methodology, providing an overview of how risk is defined in the literature and detailing the adaptation of each risk element to the three proposed risk measures. In Section 2.4, we present the specific case of Haiti, detailing the data collection, processing, and analysis procedures. Detailed computational results are reported in Section 2.5 to assess the performance of our risk-based approach compared with standard approaches, including a comparison with our partners' solution. We further conduct sensitivity analyses on key parameters. Conclusions are then provided in Section 1.7.

1.2 Literature Review

Responding to a disaster requires the management of complex supply chains, which is essential to meet the objectives of humanitarian aid. In particular, humanitarian logistics can play a crucial role in the mitigation, preparation, response, and recovery of sudden-onset disasters [Besiou and Van Wassenhove, 2020, De Vries and Van Wassenhove, 2020, Kovacs and Moshtari, 2019]. The literature on humanitarian logistics has attracted considerable attention from scholars, practitioners, and policymakers in recent years. Operations Research (OR) methodologies can make significant contributions by adapting supply chain practices to humanitarian logistics [Altay and Green III, 2006, Laporte, 2023], particularly in developing countries [White et al., 2011]. Indeed, the increasing trend of publications focusing on the application of OR techniques to solve complex decision-making and optimization problems in humanitarian logistics underscores the significance and potential of these methods [Farahani et al., 2020].

Evacuation is one the most important steps during the response phase, serving as the primary strategy to protect people from potential disaster impacts [Bayram, 2016]. Location problems are often solved during the mitigation and preparedness phases [Arslan et al., 2021, Paul and Wang, 2019], while evacuation operations happen during the response phase [Amideo et al., 2019]. Poorly located shelters can increase the risks faced by individuals and enhance exposure to hazards. Shelter site location and evacuation planning, i.e., the process of relocating individuals from their residences to predetermined safety zones, are therefore pivotal components of effective disaster response.

This section examines the literature pertinent to shelter site location. We first review two distinct categories of research: (i) studies under deterministic setting, where all data is assumed to be known in advance; (ii) studies under stochastic setting, where the data is subjected to different sources of uncertainty. Then, we discuss studies that specifically focused on flood disasters, including the ones related to evacuation planning. Finally, we position our contributions within the existing literature. We refer the reader to Farahani et al. [2020] and Sabbaghtorkan et al. [2020] for comprehensive reviews on location decisions in humanitarian supply chains.

1.2.1 Deterministic Shelter Location Studies

Deterministic studies assume that all parameters of the underlying problem, e.g., the number of individuals in need of shelter, are known with certainty. Following this assumption, Alçada-Almeida et al. [2009] developed a multi-objective model for locating shelters and identifying primary evacuation routes during wildfires, aiming to minimize both travel distance and fire risk for evacuees using predetermined risk indices. Coutinho-Rodrigues et al. [2012] extended the work of Alçada-Almeida et al. [2009] by adding objectives to minimize the number of open shelters and travel distance on a secondary evacuation path, which is used if the primary path is impassable. Chanta and Sangsawang [2012] developed a bi-objective model to find optimal shelter locations during flood disasters, aiming to maximize coverage and minimize weighted travel distance. Kılcı et al. [2015] proposed a model to optimize temporary shelter site locations for Turkish Red Crescent operations by scoring candidate sites based on multiple criteria and maximizing the minimum score of open shelters. Sheu and Pan [2014] proposed a centralized emergency supply network model to identify location of shelters, medical centers, and distribution centers, aiming to minimize operational costs, travel distance, and psychological costs for affected individuals. A multi-objective model was elaborated by Rodríguez-Espíndola et al. [2018] to identify facility locations (i.e., shelters and distribution centers), stock prepositioning, and relief distribution with the aim of minimizing the total cost. To account for evacuee's evolving needs over time, Pérez-Galarce et al. [2017] developed a hierarchical shelter location model with two shelter types providing basic service and medical/psychological service, aiming to minimize travel distance while considering shelter capacities and utilization rates.

Unlike previous studies that focused on either locating temporary shelter sites (such as tents or mobile units) at the tactical decision level [Alçada-Almeida et al., 2009, Coutinho-Rodrigues et al., 2012, Chanta and Sangsawang, 2012, Kılcı et al., 2015, Pérez-Galarce et al., 2017] or selecting existing buildings (such as schools, churches, or temples) for shelter use [Sheu and Pan, 2014, Rodríguez-Espíndola et al., 2018], our research aims to strategically locate permanent relief shelter infrastructures. Recognizing that post-disaster shelter needs can extend from days to months or even years, our approach involves constructing new buildings to provide long-term protection, safety, security, and privacy for individuals displaced by disasters. Moreover, our approach is an interaction between location science and GIS. While previous studies have primarily used GIS for visualizing solutions through color-coded maps [Coutinho-Rodrigues et al., 2012, Kılcı et al., 2015], identifying potential shelter locations [Chanta and Sangsawang, 2012, Rodríguez-Espíndola et al., 2018], or calculating road network distances [Coutinho-Rodrigues et al., 2012, Rodríguez-Espíndola et al., 2018], our research extends GIS application to manage potential disaster impacts and perform risk analysis. However, it is important to note that effective GIS utilization is context-dependent and requires tailored research and development, especially in developing countries like our region of interest [Der Sarkissian et al., 2019]. In these areas, where the majority of assets are at high risk and resources are limited, GIS can significantly contribute to building resilience when adapted to local contexts. In this regard, we contribute to the literature by contextualizing the efficient use of GIS in the specific context of a developing country like Haiti.

Evacuation is an important decision during emergencies which involves relocation of people from a potentially hazardous area to a safe location. Influenced by factors such as nature of the disaster (e.g., flood, hurricane, earthquake) and transportation mode (e.g., foot, car, bus, train, boat, and helicopter), three types of evacuation can occur: (i) self-evacuation, which includes evacuees who move towards shelters autonomously without any assistance from emergency services; (ii) assisted evacuation, which involves individuals who can arrange their own evacuation towards shelters but need some advice and guidance (e.g., directions) from authorities; and (iii) supported evacuation, which might be designed for special-needs populations (e.g., elderly, disabled) who require support from public authorities to reach designated shelter facilities [Amideo et al., 2019]. Few studies have considered the interdependencies between shelter location and evacuation planning, examining how each aspect influences the other. Integrated models in the literature examined three possible combinations of mentioned problems: (a) shelter location and self-evacuation [e.g., shelter location and car-based evacuation, see Kongsomsaksakul et al., 2005, Li et al., 2011, Bayram et al., 2015]; (b) shelter location and supported-evacuation [e.g., shelter location and bus-based evacuation, see Shahparvari et al., 2016]; and (c) shelter location, self- and supported-evacuation [e.g., shelter location, car- and bus-based evacuations, see Goerigk et al., 2014, Esposito Amideo et al., 2021]. While shelter location and car-based evacuation have been extensively investigated, pedestrian-based evacuation combined with shelter planning remains unexplored. Our research aims to address this gap in the literature by proposing a model that focuses on the intersection of shelter location and pedestrian-based evacuation strategies.

1.2.2 Stochastic Shelter Location Studies

Reviews highlight the importance of capturing uncertainty in disaster operations [Dönmez et al., 2021]. In shelter location problem, dealing with uncertainty is difficult due to the chaotic circumstances associated with the post-disaster phase as well as multiple stakeholder structure. While different paradigms (e.g., stochastic programming, chance-constrained programming) have been used in the literature to capture the uncertainty in shelter location problem, stochastic programming has emerged as the most popular modeling framework. Li et al. [2011] introduced a two-stage stochastic model for shelter location and allocation under uncertain demand and transportation cost, with the objective of minimizing the total cost. Li et al. [2012] rather proposed a scenario-based bi-level programming model considering uncertainties in demand, shelter disruptions, and road accessibility. In the upper-level, a two-stage stochastic process identifies shelter locations pre-disaster and shelter openings and evacuee allocations post-disaster. The lower-level models drivers' route choices using a user equilibrium approach. Bayram and Yaman [2018] proposed a two-stage stochastic model that accounts for uncertainty in evacuation demand, road network conditions, and disruption in shelters. The model aims to identify location of shelters and allocation of evacuees to shelters and routes while minimizing the expected total evacuation time. Ozbay et al. [2019] considered secondary disaster following the main disaster and proposed a three-stage stochastic programming model with uncertainty in demand. Temporary shelters for the main and secondary disasters are located in the first and second stages, and affected population are allocated to the nearest shelters, in the second and third stages. The objective is to minimize the expected number of open shelters while maximizing their weights. A chance-constrained model was introduced by Kınay et al. [2018] by considering uncertainty in demand with two types of probabilistic constraints: one concerning the utilization rate of shelters and the other concerning their capacity. The authors considered the deterministic model proposed by Kılcı et al. [2015] as starting point and proposed a probabilistic programming model to maximize the minimum score of open shelters. Kınay et al. [2019] extends the work of Kınay et al. [2018] following a multi-criteria framework. In addition to the original objective, two more objectives are added: maximizing the average score of selected shelters and minimizing the average distance traveled by evacuees. Dalal and Üster [2018] developed a combined stochastic-robust optimization model to optimize the location of shelters and distribution centers as well as assignments and flows. The model aims to minimize the weighted sum of average and worst-case transportation costs across all scenarios while considering demand uncertainty. Finally, Grass et al. [2023] addressed the inherent ambiguity and uncertainty in shelter location problems by combining cluster machine learning with stochastic optimization, effectively integrating divergent post-disaster information sources to improve humanitarian aid decision-making.

One approach to hedge against the uncertainty of disasters is to incorporate risk measures into the parametrization of optimization models, often quantified through estimation functions [Dönmez et al., 2021]. Based on our review of the existing literature, there is a gap in the literature regarding the use of risk measures to address uncertainty in shelter location problems. This aligns with the highlight made by Verma and Gaukler [2015] that risk management in facility location for disaster response is an area requiring further research. To address this gap, we have adopted a risk-based approach that utilizes descriptive data extracted via GIS. The integration of GIS in the analysis has also shown promise in managing the uncertainty of disaster impacts across different disaster management phases [Rodríguez-Espíndola et al., 2018]. Indeed, a review by Dönmez et al. [2021] identified GIS as one of the major paradigms for capturing and modeling uncertainty in humanitarian logistics. However, the number of studies leveraging GIS for this purpose remains limited. By combining risk measures with GIS-derived data, our study aims to contribute to this underdeveloped area of research, potentially offering new insights into effective shelter location planning in the face of disaster uncertainty.

1.2.3 Specific Applications to Flood Disaster

Different disasters necessitate different evacuation plans and may utilize diverse transportation modes, e.g., bus evacuation ahead of a natural hazard [Amideo et al., 2019]. Therefore, a hazard-specific approach to evacuation is necessary, as strategies effective for one type of hazard may not be safe or suitable for others. Given the increasing frequency and economic impact of flood disasters, it is crucial to plan appropriate emergency responses.

To the best of our knowledge, the number of studies that have developed an evacuation plan in the context of flood disasters is rather limited. Kongsomsaksakul et al. [2005] focused on pre-disaster, car-based evacuation planning for floods, without incorporating the effects of flooding on the evacuation process itself. Khalilpourazari and Pasandideh [2021] addressed flood evacuation planning for evacuees outside the coverage radius of shelters, using helicopters for rescue and transfer to shelters, without considering the impact of flooding on the evacuation process. Eom et al. [2022] investigated the consequences of large-scale floods in cross-border evacuation, assuming evacuees travel by foot toward destination shelters, and while they considered congestion at bridges as potential bottleneck points, they did not examine the effects of flood water level on the foot evacuation process. Unlike these studies, we incorporate effect of flood water depth into our evacuation planning.

In developed countries, where most research has been conducted, individuals typically evacuate using personal vehicles or public transportation. Consequently, a substantial portion of the literature concentrates on large-scale emergency evacuation planning [Bayram, 2016]. In developing countries, which warrant further research, limited access to personal vehicles and inadequate public transportation systems often leave walking as the only feasible evacuation mode for many residents [Lim et al., 2016]. Even in developed countries, pedestrian evacuation becomes increasingly important when roads are congested or rendered impassable by disasters [Wood et al., 2018]. Therefore, recognizing pedestrian evacuation as an essential response mechanism in flood scenarios is crucial, as it could yield solutions that are not only specific to flood conditions but also sensitive to the reality of vulnerable populations.

Few studies have developed evacuation plans and shelter location models specifically for flood-prone areas, as we have in our work. In fact, only Chanta and Sangsawang [2012], Rodríguez-Espíndola and Gaytán [2015], and Rodríguez-Espíndola et al. [2018] have proposed shelter location models in the specific context of floods (see Section 1.2.1 for details). However, these studies tend to overlook some important concerns related to flood evacuations, such as the mode of transportation, limited access to certain areas, and safety concerns.

1.2.4 Scientific and Practical Contributions of This Paper

With respect to the related literature, we made three main contributions: firstly, proposing a new optimization model; secondly, innovating data gathering and processing methods; and thirdly, conducting thorough analysis and facilitating the transfer of knowledge and recommendations to practitioners.

The most distinct part of our study is how we process data to conceptualize and address uncertainty in shelter location problem. Papers in this streams of literature mostly rely on scenario-based stochastic models. However, the scarcity of past disasters and limited historical data can lead to inaccurate predictions if too much reliance is placed on using this historical information [Arnette and Zobel, 2019]. Galindo and Batta [2013] stated two main drawbacks of scenario-based approach: (i) scenarios do not cover all the possible outcomes, and (ii) the set of scenarios is often considered as given input, without an efficient, systematic, and reliable method to define them. The authors argued that a more appropriate approach would involve conducting a thorough probabilistic analysis of the potential outcomes of a disaster. Risk-based approach is a deterministic alternative to scenario-based stochastic models when uncertainty is difficult to model due to lack of disaster-related data [Dönmez et al., 2021]. Only few studies proposed risk-based approaches in disaster preparedness and response. Akgün et al. [2015] examined the risk associated with a demand point and applied fault tree analysis to compute the vulnerability of a demand point (i.e., the probability that it is not supported by the facilities). The risk of a demand point is calculated by the multiplication of probability of threat, vulnerability of demand point, and consequences at the demand point (value or possible loss at the demand point due to threat). A risk-based approach was also proposed by Arnette and Zobel [2019] for prepositioning relief items in the pre-disaster phase. Their approach to addressing risk is similar to the work of Akgün et al. [2015]. It encompasses three different factors (i.e., product of hazard, exposure, and vulnerability) and focuses solely on the risk of the population. Although the risk-based method has been investigated, there are still research spaces for new attempts to extend this method in a facility location decision environment. Based on a review by Boonmee et al. [2017], risk is among the major criteria in emergency humanitarian logistics problems and new objectives focused on risk should be developed. There is no study that uses risk measures to cope with uncertainty in a shelter location problem as we do. Similar to the work of Akgün et al. [2015] and Arnette and Zobel [2019], in our approach, risk will be reflected through the product of hazard, exposure, and vulnerability. However, we develop risk measures not only for the demand, but also for the supply and edges of the network.

To the best of our knowledge, our proposed risk-based methodology is the first attempt toward shelter network optimization in the context of pedestrian-based evacuation in flood-prone areas, where risk is considered for all the network components: shelters (i.e., supply), populations (i.e., demand), and the evacuation paths (i.e., network edges). We developed a novel and practical optimization model that takes into account several significant factors driving needs and risks (e.g., flood hazards, population density, vulnerability, existing shelter capacities, road accessibility) to offer efficient holistic solutions for designing or strengthening shelter networks. Another distinctive aspect of our study lies in the unique integration of shelter location and evacuation operations, setting it apart from the existing body of literature. Combined shelter location and evacuation planning problems have typically focused on evacuation using private vehicles (i.e., car-based) or mass-transit systems (i.e., bus-based) [Amideo et al., 2019]. We contribute to this area of literature by proposing a model focusing on shelter location and pedestrian-based evacuation. We focus on flood-prone areas in developing countries and uniquely integrate the impact of bodies of water on walking speed, an important consideration often overlooked in existing models.

In order to measure risk in a disaggregated and small geographical scale – from almost household level to precise potential shelter locations like public schools – extensive data processing and analysis were required. We processed and integrated various geospatial data sources, including information extracted from high-resolution flood hazard maps, OpenStreetMap (OSM), vulnerability indices, demographic data, mostly using a GIS to construct and parameterize the underlying network in our region of interest, specifically the Nippes Department of Haiti. This approach enabled us to consider several pertinent factors related to hazard, exposure, and vulnerability, thus facilitating risk estimation for the network. These estimations were further refined by incorporating contextual knowledge from our partners and findings from empirical studies, such as those examining the influence of water depth on human walking speed [Bernardini et al., 2020]. As opposed to studies that propose optimization models for preparedness against general types of disasters [Sabbaghtorkan et al., 2020], our research specifically focuses on floods, which occur frequently and have significant impacts every year. This allowed us to fully grasp their characteristics and incorporate the driving factors of their impacts on shelter networks into our decision support tool. In this regard, we proposed innovative approaches to model flood-related risk for each network component by integrating the outputs of data science methods from various disciplines, including hydrology, socio-demographic analysis, Geographic Information Science (GIScience), and mathematical programming.

While our methodological contribution is generally applicable and replicable for countries addressing flood-related challenges and aiming to enhance their sheltering capacity, we consider our collaboration as an essential component of this research project, grounded in a real-life application. Extensive computational analyses were conducted to ensure robustness and correctness, while demonstrating the efficacy of our risk-based methodology compared to more conventional approaches. Sensitivity analyses were also performed to assess the impact of costs and budget constraints on network effectiveness. This collaboration proved advantageous for our partners as they recognized the approach as an innovative tool that can be applied to different departments and different fields of investment. The solution approach was validated by the H-SDRMCRP technical team, and our method have been extended to make recommendations on possible shelter locations in another department of Haiti, namely Nord-Ouest Department, which have been used for further field investigation by the Government. This highlights our scientific and practical contributions in addressing a crucial decision-making and design problem within the humanitarian and public safety sectors, leveraging data-science methodologies. We bridge the gap between practice and academia for shelter network design and evacuation planning in developing countries, offering implementable solutions within a real-life setting.

1.3 Mathematical Formulation

The RB-SLP is defined on an undirected graph $G = (V, E)$, where V is the set of vertices and E the set of edges. The set $V = I \cup J \cup J'$ comprises the set of population points I, the set of potential shelter locations J, and the set of existing shelters J'. Each population point $i \in I$ is associated with a population in need of shelter p_i and a normalized population risk $\tilde{r}_i^p$. Each shelter $j \in J \cup J'$ is associated with a capacity q_j representing the maximal number of people that can be assigned to that shelter, and with its normalized shelter risk $\tilde{r}_j^s$. In addition, each potential shelter $j \in J$ has a cost $c_j \geq 0$, representing the cost of locating (building) a shelter in location j. Each edge $(i, j) \in E, i \in I, j \in J \cup J'$ is associated with its travel distance d_{ij} and its normalized evacuation risk $\tilde{r}_{ij}^e$. Each shelter can cover population points within a maximal coverage radius r. Therefore, we define $W_j(r) \subseteq I$ as the set of population points located within a coverage radius of r from shelter location j, i.e., $W_j(r) = \{i \in I | d_{ij} \leq r\}, j \in J \cup J'$. We also define $V_i(r) \subseteq J \cup J'$ as the set of shelters located within a coverage radius of r from population point i, i.e., $V_i(r) = \{j \in J \cup J' | d_{ij} \leq r\}$. The maximal budget to locate (build) new shelters is B.

In the RB-SLP, the decisions consist of opening new shelters and determining which population points to assign to each of these new shelters. Therefore, we define two sets of decision variables. First, y_j is a binary variable equal to one if and only if a new shelter is located (built) at vertex $j \in J$, and zero otherwise. Second, x_{ij} is a continuous variable representing the proportion of population from $i \in I$ assigned to shelter $j \in J$. The RB-SLP can be formulated as follows:

Model 1

$$\text{Minimize} \quad \theta_1 \sum_{j \in J} \sum_{i \in W_j(r)} -\tilde{r}_i^p p_i x_{ij} + \theta_2 \sum_{j \in J} \tilde{r}_j^s q_j y_j + \theta_3 \sum_{j \in J} \sum_{i \in W_j(r)} \tilde{r}_{ij}^e p_i x_{ij} \tag{1.1}$$

$$\text{s.t.} \quad \sum_{i \in W_j(r)} p_i x_{ij} \leq q_j y_j, \quad j \in J \tag{1.2}$$

$$\sum_{j \in V_i(r) \cap J} x_{ij} \leq 1, \quad i \in I \tag{1.3}$$

$$\sum_{j \in J} c_j y_j \leq B \tag{1.4}$$

$$x_{ij} \geq 0, \quad i \in I, j \in J \tag{1.5}$$

$$y_j \in \{0, 1\}, \quad j \in J. \tag{1.6}$$

The objective (1.1) consists of minimizing the total risk consisting of the population risk (first term), the shelter risk (second term), and the evacuation risk (third term). The parameters θ_1, θ_2, and θ_3 represent the weights associated with each term. Constraints (1.2) impose the maximal shelter capacity. Constraints (1.3) ensure that the number of people assigned from population point i does not exceed its population in need of shelter, i.e., the proportion is at most one. Constraint (1.4) impose the maximal budget B to locate new shelters. Constraints (1.5) and (1.6) define the variable domain. Table 1 presents a summary of the sets, parameters and decision variables used in Model 1. (see Appendix 3.5).

1.4 Risk Identification and Assessment

Uncertainty refers to situations involving imperfect or unknown information and is typically quantified using probability functions [Dönmez et al., 2021]. Disasters are characterized by multiple uncertainties, which encompass not only their sources but also their highly erratic potential impacts over time. Neglecting to account for uncertainty in decision-making can lead to inefficient solutions. However, when predicting disasters that have not yet occurred, especially those with low-probability high-consequence outcomes, there is no historical distribution of previous events from which to extrapolate. Even for more frequently occurring disasters in some areas, including floods, it is essential to assess whether the background conditions under which past events were recorded have remained stable or changed, possibly due to climate or socio-economic changes. In such circumstances, probabilities cannot be precisely calculated but have to be estimated.While stochastic programming offers an efficient framework for optimizing problems involving uncertainty, it assumes a priori knowledge of the probability distributions of uncertain parameters, often represented by discrete realizations as approximations to real probability distributions. This representation of uncertainty may not be suitable for shelter network design in flood-prone areas in developing countries with limited historical data. One potential solution for addressing disaster-related uncertainty is to incorporate risk measures into the parameterization of an optimization model. This implies that risk must be assessed and measured for the elements of the graph representing the network to be optimized (e.g., population points, shelter locations and infrastructure, as well as evacuation paths).

Risk assessment is a process that aims to systematically identify, analyze, and evaluate potential threats that could have adverse consequences on an entity to enable effective management of uncertainty and inform decision-making. It relies on a rigorous understanding of the determinants of risk and the appropriate measurement of these determinants. This section aims to provide such an understanding by discussing the important elements to take into consideration when evaluating these determinants used to measure the risk associated with shelter networks in flood-prone areas.

The importance of considering risks in disaster management is acknowledged in the literature [Heckmann et al., 2015]. Risk analysis allows for the identification of the locations and population most likely to be affected by potential disasters, thereby assisting in managing preparedness and response to humanitarian crises. While there is no universally accepted definition of risk, disaster risk is widely understood as the result of the interaction between a hazard and the characteristics that make some locations vulnerable and exposed. In the literature, many authors [Arnette and Zobel, 2019, Heckmann et al., 2015] defined risk as:

$$Risk = Hazard \times Vulnerability \times Exposure,$$

where *hazard*, *vulnerability*, and *exposure* are the main determinants of risk [United Nations, 2016]. These determinants are defined and discussed below. The advantage of such formulation is to incorporate not only the likelihood and severity of a disaster, but also the characteristics of the affected population, buildings, and infrastructures that could be impacted by such an event.

Hazard The United Nations define hazard as "a process, phenomenon or human activity that may cause loss of life, injury or other health impacts, property damage, social and economic disruption or environmental degradation" [United Nations, 2016]. Similar definitions are also generally used in the scientific literature [Akgün et al., 2015, Arnette and Zobel, 2019]. In the context of floods, the probability of occurrence of flood [see Arnette and Zobel, 2019] and the flood water level [see Tran et al., 2009] have been used as estimates of hazard. Therefore, water depth in the event of a flood (referred to as flood depth) is an appropriate predictor of hazard in a specific location. However, estimating flood depth is not trivial and requires processing a large amount of data, including rainfall, water levels, water quantity, terrain elevation, and flood occurrences. High-resolution flood hazard maps, obtained using the outputs of complex flood models, provide valuable flood hazard estimates. In the case of Haiti, we benefit from such a high-resolution map that allowed the extraction of geolocalized flood depth indicators obtained through a reliable flood model (namely, HEC-RAS) and inputs [Heimhuber et al., 2015, World Bank, 2023].

Vulnerability The United Nations define vulnerability as "the conditions determined by physical, social, economic and environmental factors or processes which increase the susceptibility of an individual, a community, assets or systems to the impacts of hazards" [United Nations, 2016]. It can be seen as an internal risk factor and expressed by how the system will be affected by the hazard [Heckmann et al., 2015]. Within the context of disaster risk management, vulnerability indices have been used to measure the vulnerability of the different components of the system. These indices consider factors that determine the ability to resist and recover from the impacts of a disaster. One of the most common indices is related to social vulnerability which usually considers demographic and socioeconomic characteristics, health, coping capacity (e.g., housing conditions), and environmental factors [Alem et al., 2021, Arnette and Zobel, 2019, Rufat et al., 2015]. Vulnerability indices for buildings usually include its ability to resist and recover from the impacts of a disaster. In the context of flood-prone areas, it is important to estimate the vulnerability of the population as well as the infrastructure (e.g., shelters). In the case of Haiti, we benefit from a Wealth Index that accounts for several social vulnerability drivers derived by the World Bank in Haiti as well as a vulnerability index for shelter that accounts for their year of construction also provided by the World Bank.

Exposure The United Nations define exposure as "the situation of people, infrastructure, housing, production capacities and other tangible human assets located in hazard-prone areas" [United Nations, 2016]. The exposure does not depend on the vulnerability and susceptibility to the potential damages of a disaster, but rather on the degree, duration or extension of the system's contact with the hazard [Akgün et al., 2015, Arnette and Zobel, 2019]. Therefore, the exposure of a system to a flood can be estimated by determining the extent to which the components of this system are susceptible to being submerged by water. For example, for buildings such as shelters, two important elements to consider are the size of the building and whether it is located in a flood-prone area. A larger shelter will be more exposed to the same flood as a smaller shelter due to its size (area in contact with the flood). The flood area, measured in square meters, can be used as an indicator of exposure, and an area will be considered as flooded if its flood depth is larger than zero. In the case of Haiti, as for hazard, we benefit from the outputs of flood maps to estimate such exposure drivers in our area of interest, and this is done at a small aggregation level. Defining risk as a function of these determinants (i.e., hazard, vulnerability, and exposure) allows to distinguish the external risk factors (e.g., natural hazards) from internal risk factors that can be somewhat controlled (e.g., limiting the impacts of a natural hazard through robust infrastructure). Hence, risk arises from the interplay of uncontrollable external factors and the intrinsic characteristics of the system [Heckmann et al., 2015]. Hazard, vulnerability, and exposure mutually influence risk, and none of these elements can be considered in isolation. In the absence of a hazard, defining vulnerability to potential damages becomes meaningless. Similarly, a situation cannot be classified as a hazard for a system if it lacks both exposure and vulnerability to a potential event.

In Section 2.4, we provide a detailed description of how we overcame the challenges related to data availability to measure risk in the case of Haiti, utilizing different data sources at a small level of geolocalized aggregation.

1.5 Data Collection, Processing and Description in Haiti

The main goal of this study is to improve the shelter location process by providing a systematic tool that considers risk to guide the Government of Haiti as well as its funding partner, i.e., the World Bank. In existing work on facility location under uncertainty focusing on humanitarian settings, the main sources of uncertainty can be categorized under the three following components of a network: demand (i.e., the needs and locations of people affected), supply (i.e., availabilities at facilities involved in offered relief services), and network connectivity (i.e., conditions of the transportation links) [Dönmez et al., 2021]. In our context, this categorization can be translated into risk experienced at three components of a shelter network: population (demand), shelter (supply), and evacuation path (network). For each of these components, we have clarified the main goals, and identified operational constraints and standards in coverage of vulnerable populations.

Most of the data needed to capture the main elements of the problem under study have a spatial component, which represents an opportunity to use GIS [Mansourian et al., 2006, Rodríguez et al., 2012]. In fact, we have seen a significant increase in the application of GIS for modelling humanitarian logistics in recent years. In the specific context of flood disaster, Chang et al. [2007] used GIS to estimate the location of demand points and the quantities of required rescue equipment under different rainfall situations. Rodríguez-Espíndola and Gaytán [2015] employed raster GIS, which divides a study area into a regular grid of cells, each containing a single value, to create flood scenarios and identify water level in each scenario. Rodríguez-Espíndola et al. [2016] extended the procedure described by Rodríguez-Espíndola and Gaytán [2015] and introduced a method as a combination of raster and vector GIS. As opposed to raster GIS, vector GIS uses discrete line segments and points to represent locations, and can represent points, lines, and areas [Church, 2002]. In Rodríguez-Espíndola et al. [2016], vector GIS was used for data pre-processing and post-analysis, and raster GIS for analyzing potential flooding scenarios. Building upon Rodríguez-Espíndola and Gaytán [2015], Rodríguez-Espíndola et al. [2018] used vector GIS to locate suitable facilities and perform network analysis and raster GIS to consider different scenarios, discard facilities prone to flooding, and identify road failures.

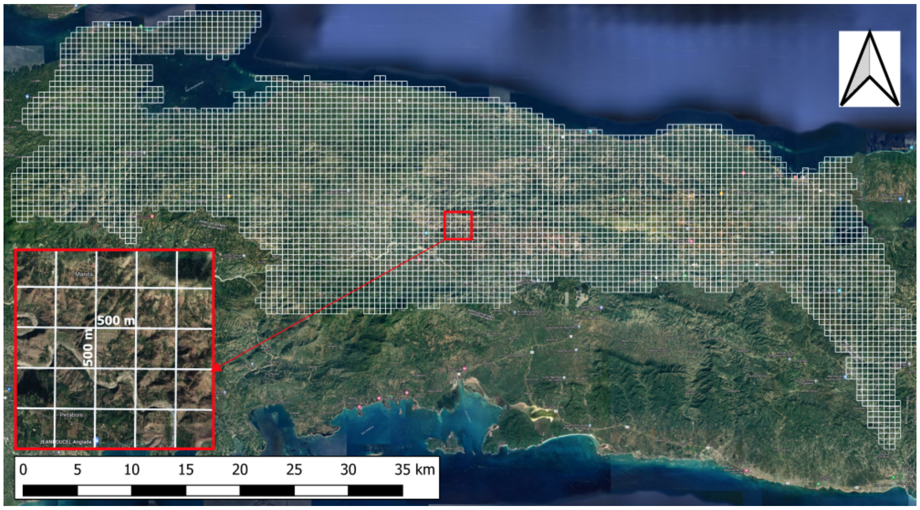

Fig. 1.2: Satellite image divided into 500 m × 500 m grids

In this study, we have collected reliable data such as geospatial information, high-resolution flood hazard maps, and socio-demographic information in order to properly parametrize the RB-SLP. These data included publicly available data from the World Bank and OSM, as well as data obtained through extensive discussions and interviews with different experts from the World Bank and the Government of Haiti. More precisely, we obtained GIS data from the World Bank which contained four layers: a *flood layer*, a *population layer*, an *existing shelter layer*, and a *new potential shelter layer*. The first layer is raster GIS, while the other three layers are vector GIS. Because raster GIS divides the study area into a regular grid of cells, with each cell (or pixel) containing a single value, while vector GIS uses polygons, discrete line segments, and points to represent locations [Church, 2002], the data were overlapped to conduct zonal statistics, thereby requiring extensive data processing. Note that we refer to a pixel in the GIS layer as a surface of 10m × 10m and a grid as a surface of 500m × 500m. The satellite image of the Nippes is shown in Fig. 1.2 along with the grid used to divide the region. In order to make network design, we discretize the continuous space of the department and aggregate data using grids.

In the following, we describe the data collected as well as the data processing. We first describe the *flood layer*, i.e., a flood hazard map. Then, we discuss the data related to the three components of a shelter network: population, shelters, and evacuation paths. For each, we also propose a risk measure. Each risk measure has also been normalized by using standard methods considering the interquartile range (IQR) and winsorizing to handle outlier values and then scaled to a [0, 1]-range (see Appendix 3.5 for detailed information). While our methodology is developed and tested using data from the Nippes Department of Haiti, it can also be implemented for any other flood-prone areas in the world.

1.5.1 Flood Hazard Map

A flood hazard map, referred to as the *flood layer*, was modelled by the World Bank team using the Hydrologic Engineering Center's River Analysis System (HEC-RAS) V5.0.6 [World Bank, 2019b]. HEC-RAS allows to perform one-dimensional steady flow, one- and two-dimensional unsteady flow calculations, sediment transport or mobile bed computations, as well as water temperature and water quality modeling [U.S. Army Corps of Engineers Hydrologic Engineering Center, 2023]. In this layer, the flood depth (in meters)

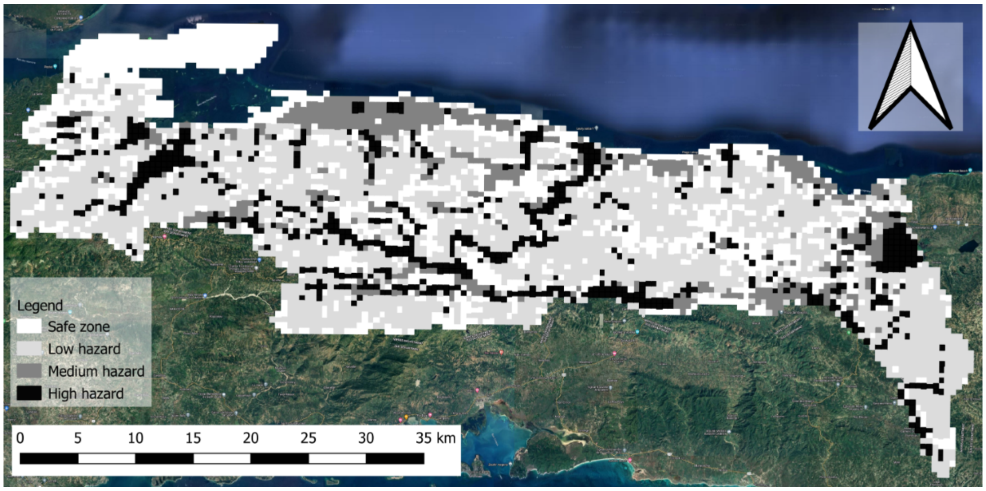

Fig. 1.3: Classification of flood hazard zone in Nippes

is available for each pixel. If the flood depth takes a positive value, then that pixel is said to be flooded. Figure 1.3 presents a map of the flood depth and flood area for the Nippes Department of Haiti, where the flood depth is measured in meters and the flood area is measured as the percentage of flooded pixels. For readability purposes, the data are aggregated in grids which are classified in four categories based on the classification used by the World Bank: i) safe zones with a flood area of at most 20% and flood depth of at most 2 meters; ii) low hazard zones with a flood area of at most 20% and flood depth of more than 2 meters; iii) medium hazard zones with flood area of more than 20% and flood depth of at most 2 meters; and iv) high hazard zones with a flood area of more than 20% and flood depth of more than 2 meters.

1.5.2 Population Data and Risk Assessment

In the following, we provide information about the specific population data provided by the World Bank, referred to as the *population layer*. Then, using that data, we detail how we have obtained the specific population parameters that are found in our mathematical formulation, that is, the population in need of shelter (p_i) according to the population data. Finally, using the *population layer* and the *flood layer*, we explain how risk is assessed and measured for every population point (r_i^p).

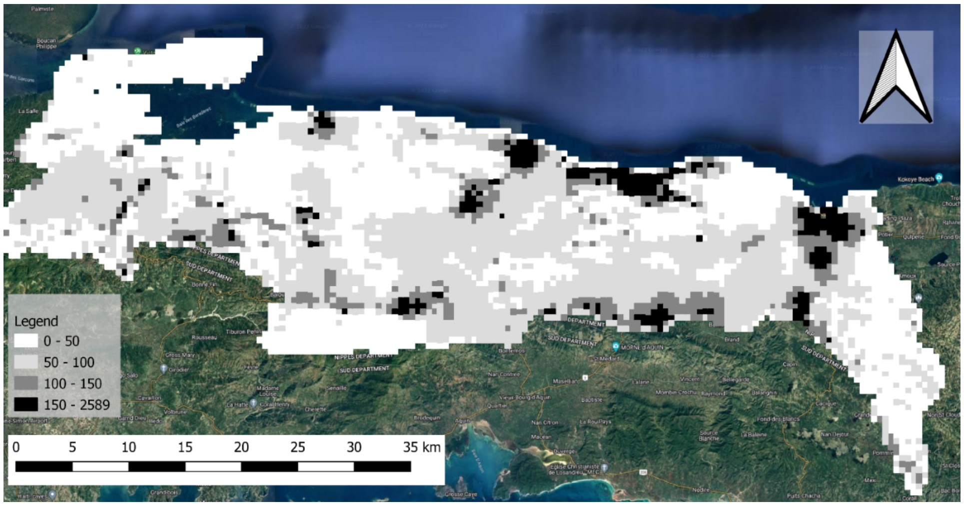

Fig. 1.4: Population of grids (population points) in Nippes

***Population layer* (vector GIS).** Specific data about population points, including the population and the wealth index of the population, were provided by the World Bank in the *population layer* (vector GIS). The spatial distribution of population in Haiti was produced based on the 2020 population census/projection-based estimates by WorldPop [Bondarenko et al., 2020]. This layer was discretized in grids, for a total of 5,331 grids. Each grid was then associated with exactly one population point (i.e., $|I| = 5,331$), and each population point i is located in the centroid of its associated grid. The data (population and wealth index) was then aggregated for each grid. The total population of Nippes is 347,461 people, and Figure 1.4 presents the grids (i.e., one grid is one population point) classified according to their population. The wealth index was specifically developed by the World Bank team for Haiti and considers three elements: (i) the physical assets (i.e., ownership of motorized means of transportation, durable goods, productive goods, and housing conditions); (ii) the human capital (i.e., education and health); and (iii) the financial assets (i.e., having a bank account). Figure 1.5 classifies the grids based on the wealth index, with higher values indicating greater wealth. This classification reveals that the western part of the Nippes Department has the lowest household wealth.

Population in need of shelter ($p_i, i \in I$). To determine the population in need of shelter, we conducted discussions with the H-SDRMCRP team who confirmed that only a small percentage of affected people evacuate toward shelters while others seek refuge in

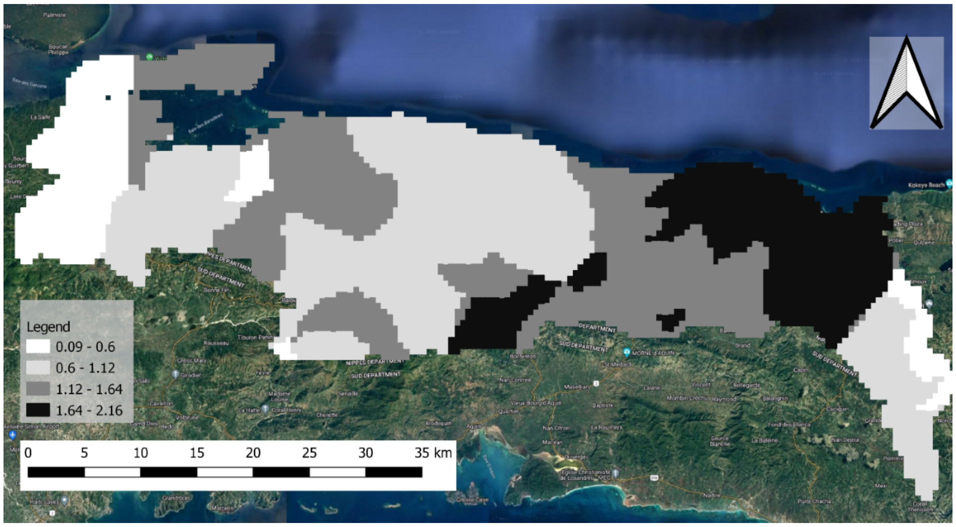

Fig. 1.5: Wealth index of grids (population points) in Nippes

different places. This is common in case of emergency where there are usually three groups: (i) those who leave early and travel to a location outside the danger zone; (ii) those who decide to shelter in refuge within the danger zone; and (iii) those who decide to stay at their houses (i.e., shelter-in-place). Therefore, the population in need of shelter, differed from the total population and had to be estimated. While there is no specific data for this in Haiti, different values have been used in the literature to determine the percentage of people which will evacuate toward shelters, e.g., Arnette and Zobel [2019] proposed a range between 2% and 50% and a fixed value of 14.7%, while Kılcı et al. [2015] used a fixed value of 12.5%. Mileti et al. [1992] found that when expert opinion is unavailable and there is insufficient historical data, then the constant sheltering need of 14.7% across all locations still provide a reasonable outcome. Therefore, in this paper, we consider a constant sheltering need of 14.7% in all grids, i.e., $p_i = 0.147 \times p'_i, \forall i \in I$, where p'_i is the total population of i.

Population risk assessment ($r^p_i, i \in I$). In accordance with the definitions of hazard, vulnerability, and exposure provided in Section 1.4, the population risk r^p_i of each population point $i \in I$ is computed as:

$$r^p_i = (f^d_i) \times (v^p_i) \times (f^a_i \times (1 - \tilde{p}_i/p_i)), \tag{1.7}$$

where f_i^d, the flood depth of population point i, represents hazard; v_i^p, the social vulnerability index of population point i, represents vulnerability; and f_i^a, the flood area of population point i, multiplied by $(1 - \tilde{p}_i/p_i)$, the percentage of uncovered people from population point i with existing shelters, represents exposure.

To determine the flood depth and flood area of each population point, we conducted zonal statistics by overlapping the *flood layer* with the *population layer*. We then obtained, for each grid, its average flood depth as well as the number of flooded pixels. Therefore, the flood depth of population point i (f_i^d) is set to the flood depth of its associated grid, and the flooded area of population point i (f_i^a) is calculated by multiplying the percentage of flooded pixels in its corresponding grid by the grid's area, which is $500m \times 500m$.

To determine a social vulnerability index, we determined that the inverse of the wealth index is a good estimate for the social vulnerability index because it includes the key factors of social vulnerability, that is, (i) demographic characteristics, (ii) socioeconomic status, (iii) health, (iv) coping capacity, and (v) environmental factors [see Rufat et al., 2015]. Therefore, the social vulnerability index of each population point is computed as:

$$v_i^p = \frac{1}{w_i},$$

where w_i represents the wealth index of population point i.

To determine the percentage of uncovered people with existing shelters, the value of $\tilde{p}_i$ was determined by solving a mathematical model (Model 3) that assigns the population in need of shelter to existing shelters (J') by minimizing the total risk. Appendix 3.5 presents additional details including this mathematical model.

Table 1.1 summarizes the data for the population points. The data related to the population points has a high variability, especially for the population, the flood area and the population risk.

1.5.3 Shelter Data and Risk Assessment

In the following, we provide information about the specific shelter data provided by the World Bank, referred to as the *existing shelter layer* and the *new potential shelter layer*. Then, using that data, we detail how we have obtained the specific shelter parameters that are found in our mathematical formulation, that is, the maximal shelter capacity (q_j), the

Table 1.1 Summary of the population data

Data	**Notation**	**Average**	**Std. Dev.**
Population in need of shelter	p_i	10.10	11.30
Flood depth (m)	f_i^d	1.90	0.80
Flooded area (m^2)	f_i^a	45,314.70	55,480.20
Social vulnerability index	v_i^p	1.40	1.40
Percentage of uncovered people in the existing network	$1 - \tilde{p}_i/p_i$	87.10	33.40
Population risk	r_i^p	59,452.50	62,848.40
Normalized population risk	$\tilde{r}_i^p$	0.30	0.30

cost of locating a shelter (c_j), the maximal coverage radius (r), and the maximal budget (B). Finally, using the *existing shelter layer*, the *new potential shelter layer* and the *flood layer*, we explain how risk is assessed and measured for every shelter (r_j^s).

***Existing shelter layer* and *new potential shelter layer* (vector GIS).** The specific data related to the shelters were provided by the World Bank and contained two layers (vector GIS): the *existing shelter layer* and the *new potential shelter layer*. The *existing shelter layer* contains data about the size and location of the existing shelters J'. The existing shelters comprise public buildings such as schools, auditoriums, and churches, which are primarily used for purposes other than sheltering. These buildings, not constructed according to current building codes, are more vulnerable to disasters and lack necessary sheltering infrastructure, such as appropriate utility spaces including kitchens and toilets. In addition, using these buildings for medium or long-term sheltering is not ideal, as it would require stopping their primary activities. While we refer to these building as existing shelters for readability purposes, it would be more appropriate to refer to them as potential existing shelters or as public buildings. The *new potential shelter layer* contains data about the location of new potential shelters J. The Government of Haiti in partnership with the World Bank decided to locate new potential shelters in the premises of existing public schools with road accessibility within 150 meters. Figure 1.6 shows the location of the 349 potential shelter locations and 144 existing shelters in Nippes. The map shows that many existing shelters, being inaccessible by road, are effectively unusable for sheltering needs.

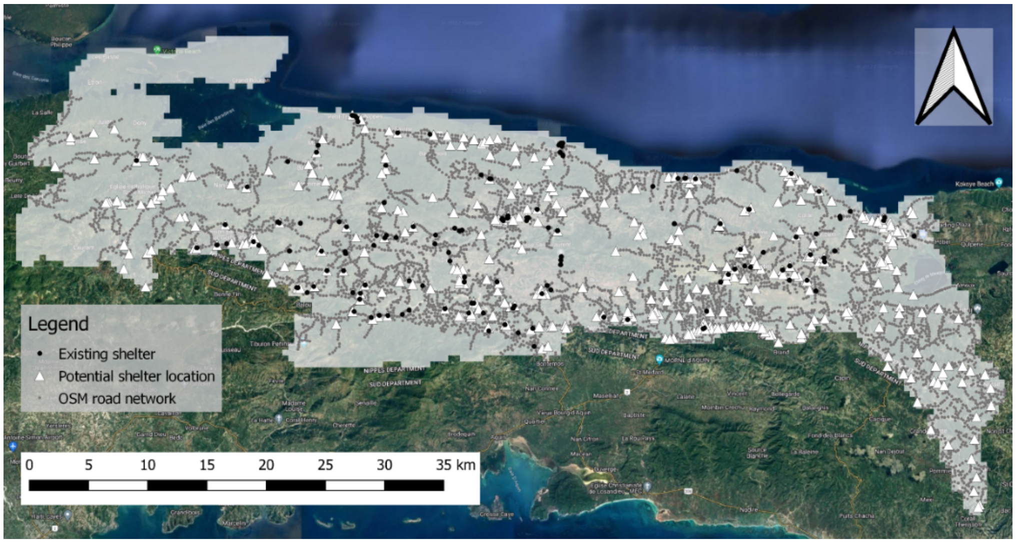

Fig. 1.6: Set of potential shelter locations J and existing shelters J' in Nippes

Shelter capacity ($q_j, j \in J \cup J'$). To determine the capacity of new potential shelters $q_j, j \in J$, government standards are used. The government imposes an area (living space) of 300 square meters per shelter, and we denote by s_j the size (living space in square meters) of the shelter, i.e., $s_j = 300, j \in J$. In addition, these standards also impose a living area of 3 square meters per person which limit the capacity of each new potential shelter to 100 people ($q_j = 100, j \in J$). For existing shelters, as previously explained, their size $s_j, j \in J'$ is available in the *existing shelter layer* data. Using the same government standards for the living area, we set the capacity of existing shelters to $q_j = \lfloor s_j/3 \rfloor, j \in J'$.

Cost of locating a shelter ($c_j, j \in J$). Our partners estimated that the cost of locating (building) a new shelter is 560,000 US dollars ($c_j = 560{,}000, \forall j \in J$). This cost represents the construction cost of a shelter and includes a fixed construction cost, as well as variable costs for land ownership, type of soil, and type of region.

Coverage radius (r). The maximal coverage radius needed to satisfy standards targeted by the government. In addition, it needed to allow foot-based evacuations. Therefore, after discussions with the H-SDRMCRP team, the maximal coverage radius of shelters was set to 3 km ($r = 3$), that is, only population points within a Euclidean distance of 3 km can be covered from a given shelter.

Budget (B). Given the H-SDRMCRP project appraisal document's budget [World Bank, 2019a], i.e., 35 million US dollars equally divided by 5 departments, a budget of 7 million US dollars ($B = 7{,}000{,}000$) was defined to build shelters in Nippes Department. This is an upper bound as it excludes unpredictable and fluctuating costs like training, field work, and logistics, which are inherent to the project. Therefore, given the estimated construction cost ($c_j = 560,000, \forall j \in J$), at most 12 new shelters can be built in the department.

Shelter risk assessment ($r^s_j, j \in J \cup J'$). According to the definitions of hazard, vulnerability, and exposure provided in Section 1.4, the shelter risk r^s_j of each shelter $j \in J \cup J'$ was computed as:

$$r^s_j = (f^d_j) \times (v^s_j) \times (f^a_j \times s_j), \tag{1.8}$$

where f^d_j, the flood depth of shelter j, represents hazard; v^s_j, the vulnerability index of shelter j, represents vulnerability; and f^a_j, the flooded area of shelter j multiplied by s_j, the size of shelter j, represents exposure.

To compute the flood depth and flooded area of each shelter, square buffers were defined in the *existing shelter layer* and the *potential new shelter layer* around each shelter in order to cover its entire area. The length of the side of this square buffer was computed as the square root of the area of the shelter and rounded up to its nearest integer, i.e., $\left\lceil \sqrt{s_j} \right\rceil, j \in J \cup J'$. By overlapping the *flood layer* with both the *existing shelter layer* and the *potential new shelter layer*, we obtained, for each shelter's surrounding square buffer, the average flood depth as well as the number of flooded pixels which was converted as a percentage of flooded pixels. Therefore, the flood depth of shelter j (f^d_j) was set as the flood depth of its corresponding square buffer, and the flooded area of shelter j (f^a_j) was computed by multiplying its corresponding buffer's percentage of flooded pixels with the area of the buffer (i.e., $\left\lceil \sqrt{s_j} \right\rceil^2, j \in J \cup J'$).

To determine the vulnerability index of each shelter, many discussions were conducted with the H-SDRMCRP team. The team confirmed that the new shelters will be constructed in compliance with the current government standards and construction codes, significantly reducing their vulnerability compared to existing shelters that do not meet these codes and are highly susceptible to various disasters. Therefore, each new shelter $j \in J$ was assigned a shelter vulnerability index of 0.1 ($v^s_j := 0.1$). In the *existing shelter layer* data, the age of each shelter was documented, indicating whether it was new or old. The H-SDRMCRP team determined that a building's age (new or old) served as a proxy for assessing the quality of its infrastructure and its vulnerability. Consequently, older existing shelters are more vulnerable than newer existing shelters. Therefore, the shelter vulnerability index ($v_j^s, j \in J'$) are set to 1 for older existing shelters, and to 0.5 for newer existing shelters.

Table 1.2 summarizes the data for the potential shelter locations and the existing shelters. Note that we present the flooded area as a percentage because the size of existing shelters vary, and it is easier to understand which shelters are in higher flood-prone areas than others. We do not present the shelter capacity and the vulnerability index for the potential shelter locations as all new shelters have a capacity of 100 people and a vulnerability index of 0.1. In addition, many existing shelters do not have road accessibility. The data shows a higher flood depth and flooded area for potential shelter locations than for existing shelters, but the methodology allows to determine where to locate the new shelters.

Table 1.2 Summary of the shelter data

Data	**Notation**	**Average**	**Std. Dev.**
Potential shelter locations $j \in J$			
Flood depth (m)	f_j^d	1.40	0.90
Flooded area (%)	f_j^a	26.70	36.70
Shelter risk	r_j^s	23.40	32.90
Normalized shelter risk	$\tilde{r}_j^s$	0.30	0.40
Existing shelters $j \in J'$			
Capacity (# people)	q_j	104.00	121.40
Flood depth (m)	f_j^d	0.20	0.50
Flooded area (%)	f_j^a	12.60	30.30
Vulnerability index	v_j^s	0.70	0.30
Shelter risk	r_j^s	21.90	80.40
Normalized shelter risk	$\tilde{r}_j^s$	0.10	0.20

1.5.4 Evacuation Path Data and Risk Assessment

In the following, we provide information about how we have used OSM to obtain a real-road network. Then, we detail how we have obtained the specific evacuation parameters that are found in our mathematical formulation, that is, how the travel distance of each edge has been computed ($d_{ij}, (i, j) \in E$). Finally, using the real-road network connected

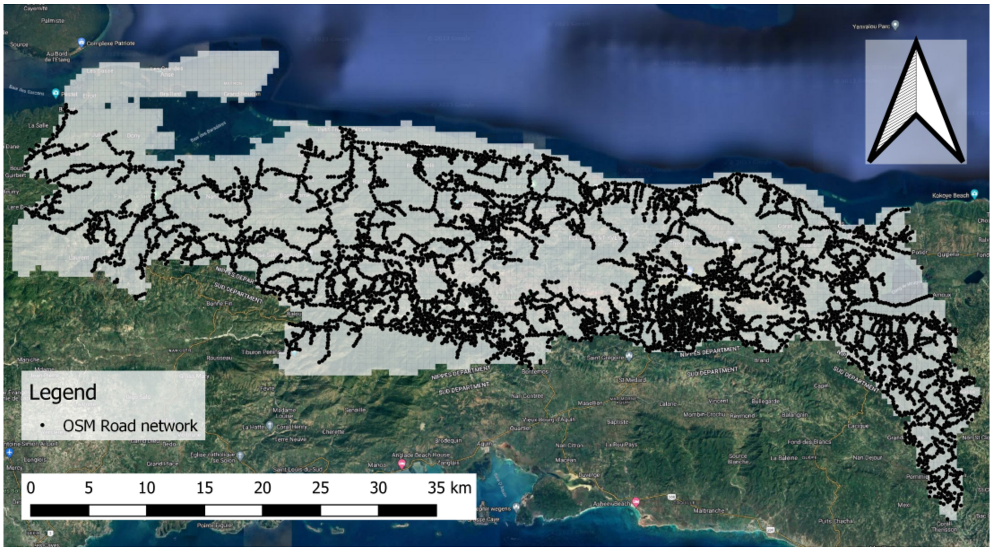

Fig. 1.7: OSM network $\mathcal{G} = (\mathcal{N}, \mathcal{A})$

with our GIS data, we explain how risk is assessed and measured for each path of network (r^e_{ij}).

Real-road network data. To determine the real-road distances, OSM was used. OSM has proven to be a valuable tool in data-limited environments. For a comprehensive framework on data estimation, refer to Sokat et al. [2018]. From OSM, a road-network consisting of single points and space, and road segments was extracted. Figure 1.7 illustrates the road network of Nippes which consists of 6,359 nodes and 7,351 arcs. Note that this data was converted as GIS vector data, referred to as the *OSM data.* This data was then connected with our network comprising population points and shelters to build a *road layer.* This required extensive data processing (see Appendix 3.5 for details).

Travel distance ($d_{ij}, (i, j) \in E$). As detailed in Section 1.5.3, the H-SDRMCRP team determined that shelters should cover population points within a radius of 3 km measured in Euclidean distance ($r = 3$km), as it allowed to take into account that people could walk on roads as well as off-road to reach a shelter. Therefore, to compute $d_{ij}, (i, j) \in E$, the latitude and longitude of each population point (i.e., the centroid of its grid) and each shelter was extracted from the *population layer*, *existing shelter layer* and *new potential shelter layer*. Recall that d_{ij} is only used to determine the set of population points that can be covered by shelters.

Evacuation risk assessment ($r_{ij}^e, i \in I, j \in J \cup J'$). By using the concepts of hazard, vulnerability, and exposure provided in Section 1.4, the evacuation risk represents the difficulty of travelling from one location to another following a flood. More precisely, the evacuation risk between population point $i \in I$ and shelter $j \in J \in J'$ is computed as:

$$r_{ij}^e = t_{ij}, \tag{1.9}$$

where t_{ij} represents the time to travel (exposure and vulnerability) from population point i to shelter j according to the flood water level (hazard) in the real-road network. Determining the value of t_{ij} required extensive data processing. To determine the speed of walking in flooded areas, many laboratory experiments have been conducted in open channels [see, e.g., Bernardini et al., 2020, Bernardini and Quagliarini, 2020]. On the other hand, these studies focus on flood depths with a maximum of 70 cm. By analyzing the data contained in the provided *flood layer*, we can see that many areas have a flood depth or more than 70 cm with a maximum flood depth of 2.5 meters (see Figure 1.3). Due to the dearth of studies with a flood depth of more than 70 cm, we computed the evacuation speed based on the experimental study of Bernardini et al. [2020]. Given that evacuation speed, we can then compute the shortest-path in terms of evacuation time, denoted by t_{ij}, between each population point $i \in I$ and shelter $j \in J \cup J'$ in the *road layer*. Appendix 3.5 presents more details on how the evacuation speed based on Bernardini et al. [2020] was computed.

Table 1.3 Summary of the evacuation data

Data	**Notation**	**Average**	**Std. Dev.**
# of accessible potential new shelter locations	$\lvert V_i(r) \cap J \rvert,\ i \in I$	6.50	4.50
# of accessible existing shelters	$\lvert V_i(r) \cap J' \rvert,\ i \in I$	2.80	3.20
Evacuation risk to new potential shelters	$r_{ij}^e,\ i \in I,\ j \in V_i(r) \cap J$	1.70	1.30
Evacuation risk to existing shelters	$r_{ij}^e,\ i \in I,\ j \in V_i(r) \cap J'$	1.60	1.20
Normalized evacuation risk to new potential shelters	$\tilde{r}_{ij}^e,\ i \in I,\ j \in V_i(r) \cap J$	0.40	0.30
Normalized evacuation risk to existing shelters	$\tilde{r}_{ij}^e,\ i \in I,\ j \in V_i(r) \cap J'$	0.30	0.30

Table 1.3 summarizes the evacuation data. The data presents the number of accessible shelters (new potential shelters and existing shelters) within the coverage radius (r = 3km)

of population points. The data shows that there are more potential new shelter locations within the coverage radius of population points, than existing shelters. In addition, there is a higher evacuation risk to potential new shelters compared with existing shelters which can be explained by the fact that the location of the potential new shelters can be in higher flood-prone areas.

1.6 Computational Results and Analyses

In this section, we conduct thorough computational analyses to derive appropriate managerial insights. Our model was coded in Python and solved with Gurobi 9.0.2. All the solutions were obtained within five seconds of computational time. First, we solve our problem with different weight settings to analyze their impacts on the solution. Second, using only the weight-vector setting where $\theta_1 = \theta_2 = \theta_3 = 0.33$, we compare our solution with an alternative solution approach, which relies on a typical shelter location problem where the objective function aims to maximize the number of covered people. Third, we conduct sensitivity analysis on the shelter construction cost. Finally, we compare our solution with the one provided by the H-SDRMCRP team and the Government of Haiti. Note that in all our tables, for a solution, we denote its average normalized population risk as PR, its average normalized shelter risk with SR, and its average normalized evacuation risk with ER. In addition, we denote the percentage of the covered population with new and existing shelters with % Pop. To obtain this value, we first solve Model 1 which only considers the new potential shelters. Then, we solve Model 3 which only considers the existing shelters, but this time only taking into account the population that is not covered with the new shelters obtained by solving Model 1. Therefore, % Pop corresponds to the sum of the covered population obtained in these two steps.

1.6.1 Analysis of the Weights Given to the Population Risk, Shelter Risk, and Evacuation Risk

In this section, we present a detailed analysis on the impact of the weight-vector settings (θ_1, θ_2, θ_3) on the solution. While working on this project, the COVID-19 pandemic and the inflation it has caused on construction costs have led to variation with respect to the cost of locating shelters (c_j). In our model, while the initial estimated shelter construction cost and budget ($c_j = 560,000, \forall j \in J$ and $B = 7,000,000$) allowed for the building of 12 new shelters, our partners ended up recommending to test the model with 6 new shelters due to an increase in costs. Therefore, in this section, we discuss the impacts of the weight-vector settings according to different number of new shelters. Our methodology was tested using different values between 6 and 12 new shelters, and our results remained consistent, i.e., the choice of weight-vector was consistent to the number of shelters. For conciseness reasons, we only present the results with 6 and 12 new shelters. The weight-vector settings are classified in two categories: i) extreme weight-vector settings where at least one weight is equal to 0; and ii) non-extreme weight-vector settings where all weights are greater than 0. Note than when setting $\theta_1 = 0$, constraints (1.2) and (1.4) are modified to impose equality as otherwise no population points are assigned. In Table 1.4, we first report the tested weight-vector settings (θ_1, θ_2, θ_3). Then, we present the PR, SR, ER, % Pop.

On the one hand, the results indicate that regardless of the weight-vector setting, the percentage of the population in need of shelter covered by new shelters consistently stands at 1.1% with 6 new shelters and 2.2% with 12 new shelters. This is due to the maximal shelter capacity (i.e., 100 people per shelter), which is always reached. On the other hand, % Pop varies because the percentage of the covered population with existing shelters does. In fact, when solving the risk-based model using existing shelters (Model 3), putting more weight on population risk results in the selection of riskier shelters, consequently covering a higher percentage of the population. Therefore, while the existing shelter capacity could cover 14,439 people, the average is 10,351 people. Note that a large portion of the population in need of shelter (more than 70%) remains uncovered, as many grids either lack a public school with road accessibility or have no existing shelters within a 3 km radius. This does not imply that people could not walk more than 3 km in practice to reach a shelter. Instead, it indicates that in our shelter network design, people are considered covered only if there is a shelter located within a 3 km radius.

Second, by analyzing the three risk measures obtained with the different weight-vector settings, their performance is less variable for the non-extreme weight-vector settings. With 12 shelters, the population, shelter, and evacuation risks have an average of 0.99, 0.01, and 0.07 with a standard deviation of 0.01. On the contrary, when considering extreme weight-

Table 1.4 Average normalized values with different weight-vector settings with 6 and 12 shelters

Weight-vector setting	**6 shelters**				**12 shelters**			
$(\theta_1, \theta_2, \theta_3)$	PR	SR	ER	% Pop	PR	SR	ER	% Pop
Non-extreme weight-vector settings								
(0.15, 0.15, 0.70)	0.98	0.05	0.04	11.40	0.97	0.03	0.05	12.50
(0.15, 0.30, 0.55)	0.98	0.00	0.06	12.40	0.98	0.02	0.06	13.50
(0.15, 0.45, 0.40)	0.98	0.00	0.06	13.30	0.98	0.00	0.07	14.40
(0.30, 0.60, 0.10)	0.99	0.00	0.07	18.30	0.99	0.00	0.09	19.40
(0.33, 0.33, 0.33)	0.99	0.00	0.06	16.00	1.00	0.00	0.07	16.50
(0.45, 0.25, 0.30)	1.00	0.00	0.07	19.50	0.99	0.02	0.07	24.00
(0.45, 0.30, 0.25)	1.00	0.00	0.07	19.70	0.99	0.00	0.08	20.70
(0.50, 0.10, 0.40)	1.00	0.03	0.05	24.00	0.99	0.03	0.06	25.10
(0.50, 0.25, 0.25)	1.00	0.00	0.07	21.10	0.99	0.01	0.07	21.90
(0.50, 0.40, 0.10)	1.00	0.00	0.07	20.70	0.99	0.00	0.09	21.70
(0.60, 0.10, 0.30)	1.00	0.03	0.05	26.30	0.99	0.03	0.06	27.00
(0.60, 0.25, 0.15)	1.00	0.00	0.07	23.00	0.99	0.00	0.09	24.20
(0.75, 0.10, 0.15)	1.00	0.00	0.07	27.40	0.99	0.02	0.07	28.40
(0.75, 0.15, 0.10)	1.00	0.00	0.07	27.60	1.00	0.00	0.09	28.70
(0.90, 0.05, 0.05)	1.00	0.00	0.07	27.80	1.00	0.01	0.08	28.90
Average	0.99	0.01	0.06	20.60	0.99	0.01	0.07	21.80
Std. Dev.	0.01	0.02	0.01	5.50	0.01	0.01	0.01	5.60
Extreme weight-vector settings								
(0.30, 0.00, 0.70)	0.99	0.43	0.03	21.40	0.99	0.28	0.05	22.50
(0.30, 0.70, 0.00)	1.00	0.00	0.30	19.40	1.00	0.00	0.25	20.50
(0.45, 0.00, 0.55)	1.00	0.44	0.03	23.60	0.99	0.28	0.04	24.50
(0.60, 0.40, 0.00)	1.00	0.00	0.23	22.00	1.00	0.00	0.23	23.00
(0.75, 0.00, 0.25)	1.00	0.44	0.03	26.80	0.99	0.28	0.05	27.80
(0.90, 0.00, 0.10)	1.00	0.44	0.03	27.70	1.00	0.32	0.05	28.70
(0.90, 0.10, 0.00)	1.00	0.00	0.30	28.10	1.00	0.00	0.25	29.20
(1.00, 0.00, 0.00)	1.00	0.42	0.29	28.10	1.00	0.30	0.18	29.20
(0.00, 1.00, 0.00)	0.54	0.00	0.26	1.10	0.35	0.00	0.18	2.20
(0.00, 0.00, 1.00)	0.23	0.19	0.00	1.10	0.22	0.17	0.01	2.20
Average	0.88	0.24	0.15	19.90	0.85	0.16	0.13	21.00
Std. Dev.	0.27	0.22	0.13	10.40	0.30	0.15	0.10	10.40
Average all	0.95	0.10	0.10	20.30	0.93	0.07	0.10	21.50
Std. Dev. all	0.18	0.18	0.09	7.60	0.20	0.12	0.07	7.70

vector settings with 6 shelters, then the solutions can have higher values of risk which can reach 0.19, 0.44, and 0.30 for the population, shelter, and evacuation risks. There is also more variability in the results, i.e., with 12 shelters, the population, shelter, and evacuation risks have an average of 0.85, 0.16, and 0.13 with a standard deviation of 0.30, 0.15, and 0.10. Therefore, the risk measures obtained with non-extreme weight-vector settings are more consistent.

1.6.2 Comparison with a Standard Objective Function

One of the most common objective functions considered in humanitarian logistics is to maximize coverage [Gutjahr and Nolz, 2016]. This objective is also common in shelter location problem. In our context, this would correspond to maximizing the covered population in need of shelter (Model 2). In order to assess the value of considering a risk-based model, this section compares our solutions with the corresponding population, shelter, and population risks resulting from solving Model 2. Given the preference of our partners and the results obtained with non-extreme weight vectors, we then compare the results obtained with the weight-vector (0.33, 0.33, 0.33) which was selected for our proposed objective function (1.1).

Model 2

$$\text{Maximize} \quad \sum_{j \in J} \sum_{i \in W_j(r)} p_i x_{ij} \tag{1.10}$$

$$\text{s.t.} \quad (1.2) - (1.6). \tag{1.11}$$

Table 1.5 reports the value of PR, SR, ER, % Pop. Note that when using the objective function (1.10), multiple solutions have the same optimal value. However, the results of some analyses showed that the initial solutions obtained by means of Gurobi are similar to the other optimal solutions. Therefore, for conciseness reasons, we only report that solution. By comparing our risk-based objective function with a traditional covering objective function (Model 2), we observe that the obtained solution allows to greatly reduce all three measures of risk. In fact, with the objective function (1.10), we have population, shelter, and evacuation risks of 0.39, 0.20, and 0.17 compared with 0.99, 0.01, and 0.07 with our more complex objective function. When analyzing the covered population in need of shelter within 3 km, we cover more people when considering the objective function (1.10) (29.2% compared with 16.5%). In addition, for both objective functions, new shelters always cover 2.2% of the population implying that 27.0% of the population is covered with existing shelters using objective function (1.10). This can be explained by the fact that upon solving the risk-based model, it is sometimes better not to assign population points to shelters which would be too risky. This issue could be solved by imposing equality in constraints (1.2). We can conclude that considering a risk-based objective function is important as it helps to find solutions with a very low risk for each risk measure, compared with a more general approach which does not consider risk at all.

Table 1.5 Performance of the solutions obtained with 12 shelters and the weight-vector $(0.33, 0.33, 0.33)$

Performance indicator	Model 1	Model 2
PR	0.99	0.39
SR	0.01	0.20
ER	0.07	0.17
% Pop	16.50	29.20

1.6.3 Impact of the Number of Shelters

In this section, we analyze the impact on the number of shelters on the three risk measures as well as the percentage of the population covered by new and existing shelters. This analysis is important, because in practice, two things could happen: i) the cost of the shelters c_j might be higher (or lower) than expected; and ii) the available budget B might be higher or lower than expected.

By modifying constraint (2.5) and with $(\theta_1, \theta_2, \theta_3) = (0.33, 0.33, 0.33)$, Table 1.6 reports for each number of shelters (*# Shelters*) its resulting PR, SR, ER, and %Pop. While one could expect a risk-decrease upon increasing the number of shelters, our results show the opposite. In fact, the trend shows that when increasing the number of new shelters, riskier population is covered, and there is an increase in the shelter and evacuation risks. In particular, by going from 4 to 20 shelters, the population, shelter, and evacuation risks go from 0.99 to 1.00, from 0.00 to 0.03, and from 0.05 to 0.08. This is due to two important elements. First, when more shelters are available, a higher population in need of shelter

Table 1.6 Impact of the number of shelters on the average normalized risks obtained with the weight-vector $(0.33, 0.33, 0.33)$

# Shelters	PR	SR	ER	% Pop
4.00	1.00	0.00	0.05	15.60
5.00	0.99	0.00	0.06	15.80
6.00	0.99	0.00	0.06	16.00
7.00	0.99	0.00	0.07	16.20
8.00	1.00	0.00	0.07	16.40
9.00	1.00	0.00	0.07	16.60
10.00	1.00	0.00	0.07	16.80
11.00	1.00	0.00	0.07	17.00
12.00	1.00	0.00	0.07	17.10
13.00	1.00	0.00	0.07	17.30
14.00	1.00	0.01	0.07	17.50
15.00	1.00	0.01	0.07	17.70
16.00	1.00	0.02	0.08	17.90
17.00	1.00	0.02	0.08	18.10
18.00	1.00	0.02	0.08	18.30
19.00	1.00	0.03	0.08	18.40
20.00	1.00	0.03	0.08	18.60

can be covered which results in covering riskier population points. Second, when locating a few number of shelters (e.g., four), these shelters tend to be located in less risky area and to cover less risky population points thus resulting in a lower shelter and evacuation risks. In general, for all three risk-measures, our solution approach is robust to an increase (or a decrease) on the number of shelters which could be due to a decrease (or an increase) on the construction costs or to an increase (or a decrease) on the available budget. Finally, when increasing the number of new shelters, we increase the population covered by the new shelters and always use the total capacity of these shelters.

1.6.4 Comparison with Our Partners' Solution

During our work on this project, there was some uncertainty on the final shelter construction cost c_j. Therefore, the H-SDRMCRP team decided to be conservative and select 6 new shelter locations and gave its recommendation to the Government of Haiti. To identify these shelters, the H-SDRMCRP team started spatial assessments in 2019 which were conducted as follows. First, public schools with land availability and road accessibility within 150 meters were identified. Second, for each of these public schools, the number of existing shelters in a 150-meter radius, the number of people in a 3-km radius, and the number of people living in flood-prone areas in a 3-km radius have been computed. Third, final field visits were conducted to gather more information, and recommendations have been made in order to determine where to locate these new shelters. With these recommendations, the Government of Haiti can analyze the possibility of building the shelters in the selected areas. Therefore, in this section, we compare the solution recommended by our optimization approach (i.e., solving the RB-SLP) with the solution provided by the H-SDRMCRP team. This allows us to determine the importance of developing a sophisticated mathematical model that can consider risk in the objective function in a more holistic way and evaluate all possible alternative as opposed to a more manual process. The solution provided by the H-SDRMCRP team along with our risk-based model's solution obtained with the weight-vector setting (0.33, 0.33, 0.33) are depicted in Figure 1.8. Table 1.7 reports the value of PR, SR, ER, % Pop for these two solutions. In both solutions, the maximum number of people is covered with new shelters, representing 1.1% of the covered population in need of shelter. In addition, our results show that for all risk measures, our solution approach outperforms the solution provided by our partners. This is the most important for the population risk which goes from 0.64 to 0.99, which implies that our solution approach allows to select the population points with the higher risk and assigned them to shelters. The shelter risk also decreases from 0.03 to 0 which implies that less risky shelters are selected. Finally, the evacuation decreases from 0.24 to 0.06 which allows the population to evacuate using safer paths. This shows the effectiveness of our approach.

Table 1.7 Performance of our partners' solution and our approach with 6 shelters and the weight-vector $(0.33, 0.33, 0.33)$

Performance indicator	Partners	Our
PR	0.64	0.99
SR	0.03	0.00
ER	0.24	0.06
% Pop	28.00	16.00

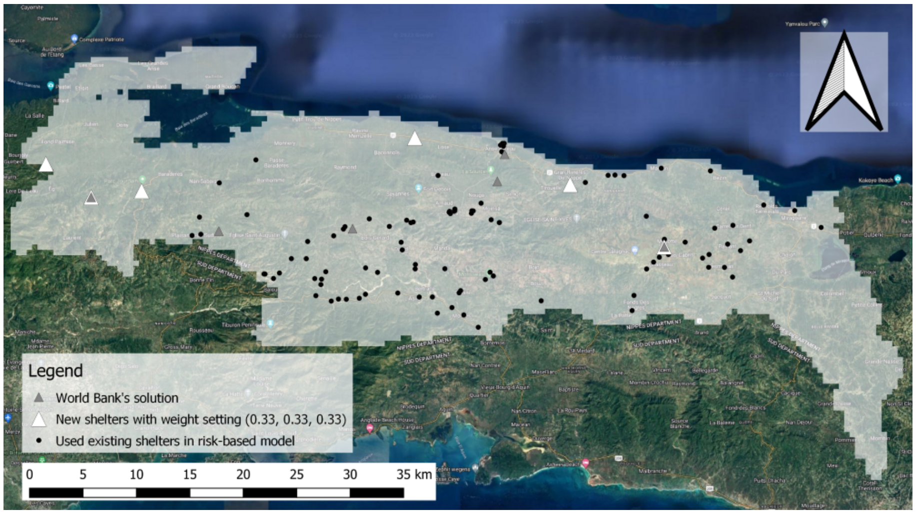

Fig. 1.8: The H-SDRMCRP team's solution versus the risk-based model's solution with (0.33, 0.33, 0.33)

1.7 Conclusions

Lack of access to shelters is one of the most important humanitarian and development problems in remote areas of developing countries. Addressing shelter needs during and after a disaster remains a serious challenge for governments and humanitarian agencies. In this paper, we have solved a shelter network design problem motivated by the need to reconstruct the shelter network of flood-prone regions in Haiti. We have proposed a risk-based approach to assess and measure the inherent risks of the shelter network. In particular, three risk measures (population risk, shelter risk, and evacuation risk) have been defined to represent the uncertain nature of demand, supply, and network. As a first attempt to study pedestrian-based evacuation in an optimization model, we have developed a new methodology inspired from empirical research to estimate the risk of evacuation in flood water.

Despite the scarcity of data in the humanitarian sector, we succeeded in gathering data from various sources (e.g., geospatial information, high-resolution flooding maps, socio-demographic data, road network). In particular, our collaboration with the World Bank and the Government of Haiti allowed the formulation of a well-defined and realistic problem, adequately parameterized using real data. This collaboration also allowed us to fully understand the context and determine the decisions, constraints, objectives, and particularities of stakeholders (e.g., Haitian Government) to define and solve the problem.

We have conducted extensive numerical analyses to ensure robustness and correctness, while demonstrating the efficacy of our risk-based methodology. We also proposed different performance indicators adapted for this context that allows to evaluate the solutions on several dimensions. Our results showed that while different solutions are obtained according to the weight given to each risk measure, if we do not use extreme values, our model is robust in terms of solution quality. In addition, by comparing our methodology to a standard methodology where we maximize the covered population in need of shelter and with the current solution of the H-SDRMCRP team, we showed the need for risk-based models.

The solution approach was validated by our partners and our method have been extended to make recommendations on possible shelter locations in another department of Haiti, namely Nord-Ouest Department, which have been used for further field investigation by the Government. This collaboration proved advantageous for our partners as they recognized the approach as an innovative tool that can be applied to different departments and different fields of investment. While we have focused on a particular district of Haiti, the proposed methodology is of general applicability and can be adapted to other regions of the world. This study contributes to the advancement of the UN Sustainable Development Goals 11, 13, and 17, which focus on sustainable cities and communities, climate action, and partnerships for goals.

While this study provides valuable insights into flood evacuation planning, certain areas could be further explored in future research. First, our current model employs a single-level optimization framework, assuming centralized control of evacuee movements. A potential extension could involve developing a bi-level approach to model decentralized user behavior. This would allow authorities to anticipate and incorporate evacuees' behaviors when setting policies and determine potential shelter sites. Second, our focus in this study was primarily on pedestrian-based evacuation. An interesting avenue for future research could be the consideration of multi-modal evacuation transportation that would account for various transportation methods available during emergencies. Moreover, we recognize that data availability can be context-dependent. While our model has proven effective in the current setting, applying it to different geographical or social contexts may require some modifications in data analysis and processing.

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Chapter 2

A Behavior-Driven Framework for Shelter Network Design and Evacuation Planning Problem: An Application to Evacuation Management in Haiti

Abstract

Effective evacuation planning during the preparedness phase necessitates consideration of dynamic factors such as evacuee behaviors and the evolving nature of disasters during the response phase. This study introduces a bi-level optimization model as a decentralized tool that captures the hierarchical interactions between authorities and evacuees. The model frames the shelter network design as a Stackelberg game, where authorities (leaders) decide on shelter locations, anticipating the optimal responses of evacuees (followers) who optimize their perceived utility in evacuation decisions. The utility function is designed based on the Fogg Behavior Model (FBM), incorporating empirical behavioral factors—motivation, ability, and triggers—that influence evacuee decisions to evacuate. We parameterize our

utility function using structural and behavioral barriers to the evacuation process in Haiti, derived from qualitative research conducted by the World Bank team. Our approach accounts for key dimensions where conflicts may arise between authorities and evacuees, such as the route choice, departure time, and destination choice. To assess how flood develops across different locations within the study area, we leverage GIS tools to incorporate key influential factors that contribute to flood evolution. By integrating regional characteristics and available spatial datasets, we estimate flood behavior and create a relative index—the Flood Evolution Index (FEI). This index allows the model to dynamically adjust to disaster evolution. We tested our behavior-driven bi-level optimization tool in the Nippes Department of Haiti. The computational results demonstrate the value of this decentralized, behavior-driven approach over centralized models which often overlook evacuee priorities and assumes centralized control over evacuation movements. The findings underscore the importance of integrating evacuee behavior into shelter network design, offering valuable managerial insights and a decision-support tool for policymakers to evaluate policies that improve the evacuation process.

2.1 Introduction

Between 2000 and 2019, over 7,348 major disasters were recorded, causing 1.23 million fatalities and affecting more than 4 billion individuals globally [CRED, 2020]. Effective evacuation strategies have therefore become more crucial than ever in our collective effort to protect communities from the increasing threats posed by natural disasters. The primary objective of evacuation is to save lives by moving individuals out of threatened zones and their reception in safe areas [Bayram and Yaman, 2024]. Central to effective evacuation planning is the design of shelter networks, which involves establishing potential shelter locations as accessible and safe facilities for accommodating people who cannot evacuate to other safe places [Sharbaf et al., 2025]. Evacuation planning must also account for the realities and challenges of evacuation modes, such as pedestrian-based evacuations, which are particularly prevalent in developing countries and regions with limited transportation access and infrastructures.

The design of shelter networks and evacuation planning involves two key decision-makers:

authorities who establish the shelter network during the preparedness phase, and evacuees who rely on this network and make evacuation decisions during the response phase [Afkham et al., 2022]. In self-evacuation contexts limited to a single mode of transportation, such as pedestrian-based evacuation, four main decision points can lead to conflicts between authorities and evacuees [Murray-Tuite and Wolshon, 2013, Bayram, 2016, Thompson et al., 2017]. First, the evacuate-or-stay decision may cause conflict when authorities prioritize protecting vulnerable populations while individuals face motivational barriers that influence their evacuation choices. These barriers stem from perceptions and interpretations of the threat's severity and immediacy, shaped by beliefs, attitudes, emotions, risk perception, personal attachments, social norms, and prior hazard experiences [Riad et al., 1999, Murray-Tuite and Wolshon, 2013, Thompson et al., 2017, Gupta and Gupta, 2019]. Second, evacuees' route preferences for the shortest paths, influenced by logistical barriers, may conflict with authorities' preferences for less risky routes. Logistical barriers arise from constraints related to demographics (e.g., health and mobility limitations), socioeconomic circumstances (e.g., financial constraints), and limited access to resources (e.g., transportation issues) that hinder an individual's ability to evacuate [Riad et al., 1999, Hamilton et al., 2020, Anyidoho et al., 2022]. Third, authorities' preferred evacuation timeline may overlook the varied behavioral responses to evacuation alerts influenced by warning barriers. These barriers result from issues in disseminating, communicating, and receiving emergency alerts, causing delayed responses or non-compliance with evacuation orders [Dash and Gladwin, 2007, Huang et al., 2016, Serulle and Cirillo, 2017, Rollason et al., 2018]. Finally, shelter assignments dictated by authorities might overlook evacuees' real-time ability to reach designated locations during a disaster, often disregarding barriers and accessibility challenges induced by logistical barriers.

Single-level optimization cannot adequately address this interplay between authorities and evacuees, as it tends to overly emphasize one decision-maker's objectives and constraints while ignoring the other's priorities. Formalizing these points of conflict into an interconnected decision-making process gives rise to hierarchical or bilevel optimization problems [Beck et al., 2023]. Although shelter network design and evacuation planning through bilevel optimization has gained attention [Kongsomsaksakul et al., 2005, Li et al., 2012, Afkham et al., 2022], less consideration has been given to the barriers (i.e., motivational, logistical, and warning barriers) that shape or impede evacuation decisions. Effectively addressing these barriers requires a deep understanding and accurate modeling of evacuee behavior [Amideo et al., 2019]. The psychology and behavior of people during evacuation are highly complex [Chang et al., 2024], and failing to account for the complex dynamics of human responses and interactions during emergencies can significantly undermine evacuation effectiveness. Yet, a critical component frequently under-addressed in optimization-based approaches is human behavior [Haghani and Yazdani, 2024]. Successfully capturing the different dimensions of evacuee behavior also requires estimating the disaster's evolution over time to understand how it influences decisions across various time periods [Serulle and Cirillo, 2017]. However, evacuation decision-support models typically do not incorporate uncertainties around disaster evolution dynamics [Yang et al., 2019]. The aim of this paper is to introduce a systematic optimization tool to assist decision makers in designing an effective shelter network (i.e., determine the location of new sheltering facilities) that accounts for the behavior of evacuees and assess its impacts. We propose an interdisciplinary approach, integrating optimization with other disciplines such as behavioral science, economics, and hydrology, to create a holistic approach that enhances the overall efficacy and responsiveness of shelter network design and evacuation planning process. In this optimization framework, authorities design the shelter network during the preparedness phase, anticipating the behavior of evacuees during the response phase, who optimize their perceived utility in evacuation decisions. This utility of evacuation is developed by integrating empirical insights within a comprehensive behavioral model, aiming to reflect and address the barriers to evacuation. To model the evolution of the disaster over time, we leverage Geographic Information System (GIS) tools to incorporate key influential factors and create the Flood Evolution Index (FEI), which enables the model to dynamically adjust to disaster evolution over the evacuation planning horizon. To ensure the validity and practical applicability of our decision-support tool, we collaborated with the World Bank and the Government of Haiti as part of a project aimed at strengthening disaster response capacity in Haiti. This project, titled "Using behavioral insights to improve disaster preparedness, early warning, and response mechanisms in Haiti", focuses on understanding structural and behavioral barriers affecting evacuation decisions in Haiti [Llopis Abella et al., 2020].

2.1.1 Problem Description, Research Design, and Context of This Study

Developing countries face significant challenges due to insufficient disaster response capacities and inadequate local shelter networks, compounded by structural barriers and behavioral obstacles that hinder the evacuation process during disasters. We develop a hierarchical decision-making framework that captures the interactions between two key decision makers in the shelter network design and evacuation planning problem. We coin the problem as the *Risk-Based Behavior-Oriented Shelter Location and Evacuation Planning Problem (RBBO-SLEPP)*, and model it as a bilevel optimization program. In the upper-level decision problem, authorities aim to locate permanent sheltering facilities that provide safety, protection, and services to affected communities. Their objective is to maximize the coverage of high-risk populations by providing shelters to those most exposed and vulnerable to hazards, and minimize the evacuation risk encountered by the population when they evacuate toward the shelters. The design of upper-level shelter network decisions is subject to shelter risk and budget constraints. Measures of population risk and shelter risk are estimated based on the interaction between hazard, exposure, and vulnerability, while evacuation risk estimates the difficulty associated with walking in flooded network [Sharbaf et al., 2025]. In the lower-level decision problem, evacuees decide about their departure time choice, route choice, and destination choice to maximize their perceived utility. Their behavior is derived as the optimal solution of the lower-level problem, grounded in the assumption from economics and decision theory that individuals act to maximize their utility [Fishburn, 1968]. The utility that evacuees optimize is modeled using the Fogg Behavior Model (FBM) [Fogg, 2009], which incorporates motivation, ability, and triggers to effectively capture the benefits and barriers to evacuation. By changing the location patterns and design of the shelter network, authorities can influence but cannot control evacuees' choices. The evacuation planning horizon is divided into multiple time periods, during which the state of the network varies at each interval, depending on the characteristics and evolving nature of the disaster. As disaster propagation varies across different locations and time periods, the evacuation risk associated with moving through the network and utility of evacuation changes accordingly. Lower-level evacuation decisions are subject to shelter capacity constraints.

For this study, we parameterized and tested the RBBO-SLEPP to enhance the shelter network and evacuation planning in the Nippes Department of Haiti. Haiti's high exposure to multiple hazards, particularly floods, combined with its pre-existing sociopolitical vulnerabilities and fragility, makes the nation highly susceptible to the impacts of disasters [Llopis Abella et al., 2020]. The country faces insufficient shelter capacity, necessitating the expansion of its shelter network. Beyond the lack of shelter capacity, Haiti suffers from inadequate disaster response mechanisms during evacuations. Structural obstacles and behavioral barriers limit the desired evacuation behavior, including lack of proper dissemination and communication of warning, lack of access to the resources needed for evacuation, and insufficient knowledge and internalization of risk [Canavire-Bacarreza et al., 2023]. By tailoring our model to the conditions and needs of Nippes department, we aim to support the Government of Haiti and the World Bank by providing practical solutions that can be implemented in practice.

2.1.2 Contributions and Organization of This Paper

In this section, we highlight the key contributions of our research and present the general organization of this paper. The development of our decision support tool required an interdisciplinary approach integrating operations research with other disciplines, including social science, economics, and hydrology. The overall methodology, as illustrated in Fig. 2.1, consists of five interconnected components and makes several key contributions to the field of humanitarian operations and crisis management. We propose a novel bilevel optimization tool that optimizes the design of a shelter network and the evacuation process by directly modeling the behavior of its most crucial element, i.e., the individuals involved. This framework represents a significant shift from traditional car-based evacuation research methodologies, which predominantly concentrate on modeling driver routes considering system traffic in large-scale highway-based evacuations but overlook the complexity of human behavior and its effects on evacuation decisions [Li et al., 2012, Yi et al., 2017, Afkham et al., 2022] (component 1, Fig. 2.1). To assess the risks within the elements of the shelter network (i.e., population points, shelter locations, and evacuation paths), we incorporate risk measures, derived from the interaction between hazard, exposure, and vulnerability, into the parameterization of our optimization model (component 2, Fig. 2.1). Moreover, understanding the temporal evolution of disasters is critical for accurately modeling human behavior during evacuation [Amideo et al., 2019]. To achieve this, we model the progression of flood disasters over time at a disaggregated and small geographical scale, a process that required extensive data processing and analysis. Building upon a comprehensive review of hydrological literature, we integrate various geospatial data sources (i.e., elevation, slope, precipitation, land use/land cover, and flow accumulation) to develop the FEI, which captures the dynamic nature of flood progression over time (component 3, Fig. 2.1).

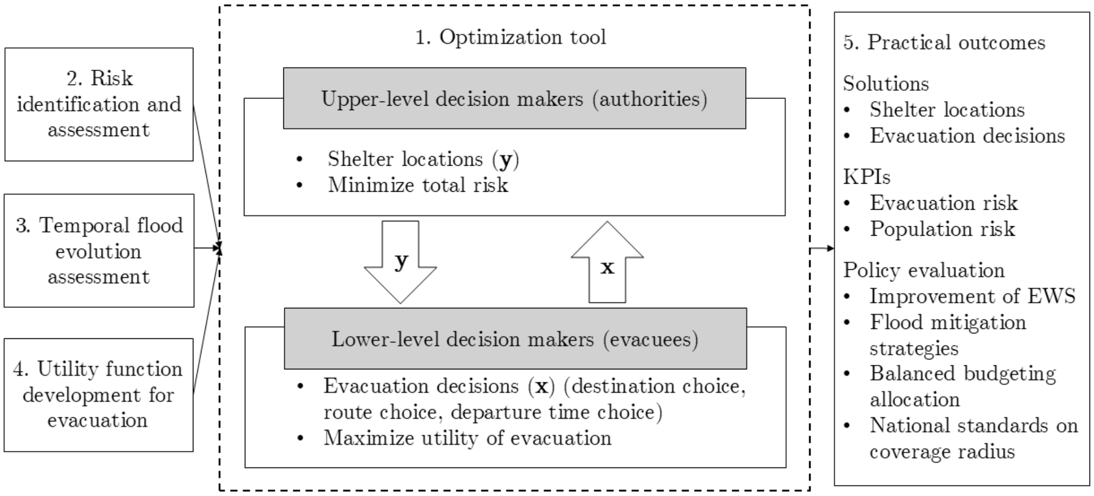


Fig. 2.1: The five components of our decision-support tool

The most distinct contribution of our study lies in the development of a novel utility function that integrates empirical insights and knowledge from behavioral science, economics, and hydrology to model evacuees' behavior during evacuation (component 4, Fig. 2.1). This utility function is systematically incorporated into an optimization tool and explicitly accounts for evacuees' reactions to authorities' decisions, bridging the gap between lower-level behavioral responses and upper-level planning. The literature emphasizes the importance of incorporating evacuees' behavior in shelter network design and evacuation planning and highlights the need to incorporate insights from social science to better understand human reactions in disaster scenarios [Bayram, 2016, Amideo et al., 2019]. Understanding the rationale behind evacuation decisions requires innovative analysis that is difficult to obtain, as individual-level data from these events are not commonly available. To develop our comprehensive utility function, we conducted an extensive study of established behavioral models and theories, as well as empirical research on human behavior during disasters. These were further enriched through extensive discussions and interviews with behavioral and social scientists from the World Bank and the Government of Haiti, which deepened our understanding of evacuees' behavior. Building on these investigations, we adopted the FBM as the foundation for our utility function. The key elements of this behavioral model (i.e., motivation, ability, and triggers) align well with the benefits and barriers to evacuation identified in empirical studies on evacuation decisions. By synthesizing empirical insights and interdisciplinary knowledge, our study represents a significant theoretical advancement in evacuation modeling.

Our computational results demonstrate the value of our decentralized, behavior-driven framework over centralized approach. This novel approach of behavioral modeling in evacuation planning presents several advantages over traditional methods. First, it recognizes the significance of human behavior in the evacuation process, addressing a critical gap in existing strategies. Furthermore, it also offers a more adaptable, versatile, and pragmatic solution, as behavioral strategies can be easily communicated and implemented in practice. In addition, our decision-support tool can inform managerial insights based on a set of KPIs (i.e., evacuation risk, population risk) and quantify the impact of different policies in several key areas, including assessing the potential effectiveness of improving Early Warning Systems (EWS) on evacuation processes, analyzing the implications of balanced budgeting allocation across different administrative levels for public financial management, evaluating the efficacy of various flood mitigation strategies during the construction of new shelters, and examining the consequences of changing national standards on the required travel distance between residential areas and the nearest emergency shelter to ensure timely access to safety (component 5, Fig. 2.1).

The remainder of this paper is organized as follows. In section 2.2 we review the relevant literature and position our contributions within the existing literature. In section 2.3, we describe the problem and our methodology. In section 2.4, we present Haiti's evacuation barriers and explain how we parametrize the utility function using empirical data and qualitative research insights. We present our numerical analysis and results in section 2.5.

Finally, we conclude and discuss future work in section 2.6.

2.2 Literature Review

In the context of emergency response, network design decisions are of critical importance, as they set the foundation for all subsequent post-disaster operations during the response stage of the disaster management life-cycle [Erbeyoğlu and Bilge, 2020]. The decision-making process involved in network design problem is hierarchical in the sense that the realized outcome of any decision taken by the network planners (leaders) is affected by the behavior of network users (followers), who will seek to optimize their own outcomes [Ben-Ayed et al., 1988]. The relevance of bilevel optimization in emergency response network design therefore stems from the involvement of various heterogeneous stakeholders (e.g., governments, organizations, local communities, affected population) in humanitarian logistics, each with different perspectives, interests, and priorities where the strategies of authorities influence, and are influenced by, the behavior of the affected populations [Paciarotti and Valiakhmetova, 2021]. Thus, adapting methods to account for the diversity of stakeholders and their behaviors represents an important research avenue [Starr and Van Wassenhove, 2014]. Although the potential of bilevel programming techniques to model the hierarchical nature of decisions in humanitarian operations has been investigated [e.g., Sahinyazan et al., 2021, Afkham et al., 2022], there are still research gaps for new attempts to extend this method in the context of emergency response. To the best of our knowledge, incorporating network users' behaviors into emergency response network design has been largely overlooked. While significant benefits can be derived from integrating human behavior into humanitarian network design decisions, this remains unexplored. Our study bridges this gap by integrating behavioral theories and social science insights into a shelter network design problem, informing a bilevel optimization model that effectively captures the dynamic interplay between the strategic decisions of authorities and the responsive behavior of evacuees.

In this section, we review the relevant literature in two key areas: evacuation planning and human behavior in disaster environments. We then highlight the distinction between our paper and the existing literature.

2.2.1 Evacuation Planning

The bilevel programming approach enhances evacuation planning by modeling decentralized user behavior, enabling authorities to account for evacuees' reactions when setting policies, thereby addressing the conflict between stakeholders and achieving solutions that are optimal for both parties. Bilevel optimization literature on evacuation planning has traditionally focused on car-based large-scale evacuations on highways, examining the routing behavior of drivers and overall traffic flow within the system. In these car-based evacuation settings, the upper-level decision maker is the government or emergency authority who is responsible for managing the evacuation process and balancing traffic flow across the network. The lower-level decision makers are typically drivers (i.e., network users) who, while being evacuated, make decisions based on the instructions provided by the leader. The leader's decisions involve, e.g., locating relief centers [Kongsomsaksakul et al., 2005, Li et al., 2012, Hammad et al., 2019, Afkham et al., 2022], relief centers' assignment [Ng et al., 2010, Li et al., 2012], managing road equipment [Afkham et al., 2022], determining when and where to issue evacuation orders [Yi et al., 2017], and implementing signals and uninterrupted flow intersections [Liu and Luo, 2012]. The followers' decisions range from destination choice [Kongsomsaksakul et al., 2005, Yi et al., 2017, Hammad et al., 2019, Afkham et al., 2022], to route choice [Kongsomsaksakul et al., 2005, Ng et al., 2010, Li et al., 2012, Yi et al., 2017, Hammad et al., 2019, Afkham et al., 2022], and departure time choice [Yi et al., 2017]. While emergency authorities typically aim to minimize total evacuation time at the upper-level, modeled with flow-dependent travel times on congested roads, the lower-level problem is indicative of a user equilibrium assignment that describes the road selection behavior of users aiming to minimize their own travel times.

2.2.2 Human Behavior in Disaster Environment

Understanding what drives human behavior is a complex process that requires deep insights from behavioral science. Various behavioral models and theories have been developed across multiple disciplines (e.g., psychology, sociology, and economics) to provide insights into the mechanisms behind human actions and decision-making processes. Widely applied models across different fields are Theory of Planned Behavior (TPB) [Ajzen, 1991], Health Belief Model (HBM) [Janz and Becker, 1984], Social Cognitive Theory (SCT) [Bandura, 1977], Fogg Behavior Model (FBM) [Fogg, 2009], Protective Action Decision Model (PADM) [Lindell and Perry, 2012], Community Engagement Theory (CET) [Head, 2007], Protection Motivation Theory (PMT) [Rogers, 1975], Extended Parallel Process Model (EPPM) [Witte, 1992], and Discrete Choice Models (DCM) [Bierlaire, 1998]. A number of these behavioral models and theoretical frameworks have been applied to explain disaster preparedness behavior and protection action decisions (e.g., store water, make an emergency plan, home insurance) in adjusting to hazards. Terpstra and Lindell [2013] applied PADM to explain flood preparedness intentions in the Netherlands. According to PADM, attributes that people consider when adopting hazard adjustments can be categorized into hazard- and resources-related attributes. PMT captures two main cognitive processes that individuals undergo when faced with a threat, namely, threat appraisal and coping appraisal. Applying PMT, research by Zaalberg et al. [2009] showed that coping appraisal is a strong predictor of people's flood preparedness behavior. EPPM details how fear appeals shape behavioral responses. Research by Li et al. [2024] found that households with high perceived threat adopt more protective hazard adjustments. TPB proposes that the primary determinant of a given behavior is intention to do that behavior. It has been applied to understand risk-mitigating behaviors in natural hazards, particularly in bushfire [Morrison et al., 2014], and wildfire preparation [Bates et al., 2009]. We refer the reader to Ejeta et al. [2015] and Ryan et al. [2020] for the application of behavioral theories to disaster and emergency health preparedness.

In addition to behavioral theories and frameworks, a substantial body of empirical studies have employed various methods, such as interviews, surveys, experiments, and virtual reality [Savage and Torgler, 2021], to collect data and address the questions of "who evacuates?" and "what factors influence the evacuation decision?" [Murray-Tuite and Wolshon, 2013, Thompson et al., 2017, Wang et al., 2021]. Empirical evidence derived from these studies offers insights into various influential factors on evacuation/stay decision, broadly divided into six main categories: risk perception, information and communication, access to resources, demographic factors and socioeconomic status, historical context, and environmental cues. We refer the reader to Bayram [2016], Hamilton et al. [2020], Murray-Tuite and Wolshon [2013], Serulle and Cirillo [2017], Thompson et al. [2017], Wang et al. [2021], Yazici and Ozbay [2008] for reviews on factors affecting evacuation decision. These factors have different likelihood effects on evacuation decision. Apart from the individual likelihood effect of each factor (i.e., increase, decrease, mixed), the effectiveness of these factors on evacuation decision is deeply interconnected. These factors do not operate in isolation, but rather their combined and interrelated influence determines the ultimate decision to evacuate. For instance, warnings alone are insufficient to prompt evacuation unless they are accompanied by a clear perception of risk [Dash and Gladwin, 2007]. Moreover, even if individuals are aware of the risk and receive timely warnings, the absence of necessary resources, such as transportation options or proximity to shelters, can significantly hinder their ability to evacuate [Murray-Tuite and Wolshon, 2013, Bayram, 2016]. Recognizing the deeply interconnected effects of these factors, a comprehensive understanding of evacuation behavior must account for how these elements work together to shape the ultimate choice of evacuation. Insights from barriers to evacuation in disaster context [Llopis Abella et al., 2020] suggest that effective evacuation strategies must integrate three important aspects of evacuation: (i) motivating people to want to leave; (ii) ensuring they have the means to do so; and (iii) providing timely triggers to initiate the action.

2.2.3 Positioning of Our Study Among the Related Literature

Table 2.1 provides a summary of bilevel studies on evacuation planning and highlights the positioning of our study within the existing body of literature. While previous research has predominantly focused on car-based evacuations and emphasized minimizing flow-dependent travel times on congested roads at the upper-level, our study shifts the focus to a pedestrian-based evacuation context with a risk-based approach that prioritizes minimizing the total risk of the network while maximizing coverage for those most exposed and vulnerable to hazards, more effectively aligning with the real-world objectives of authorities. Additionally, previous studies have primarily focused on users' road selection behavior at the lower level, with the goal of minimizing individual travel times. In contrast, our study adopts a behavior-driven framework that incorporates evacuee behaviors and optimizes their utility in evacuation decisions.

Our approach distinguishes itself further by comprehensively analyzing key decisions in self-evacuation context (i.e., evacuate-or-stay, route choice, departure time, and destination selection) through a social science lens that accounts for varied socioeconomic and demographic backgrounds, risk perceptions, and behavioral responses to warnings and real-time information. This multifaceted perspective highlights the potential points of conflict between authorities and evacuees and addresses challenges such as accessibility limitations, delayed warning reception, and evacuees' capabilities. Our study is the first to use the FBM as a theoretical foundation to construct a utility function that explicitly accounts for the three critical evacuation barriers: motivational, logistical, and warning barriers. This unified framework allows us to mathematically represent how these elements work together to influence evacuation decisions, rather than treating them as isolated factors.

Table 2.1 Bilevel studies in evacuation planning

			Evacuee behavior dimension				Evacuation mode		
Reference	Decision(s)	Objective(s)	E/S	DC	RC	DT	CB	PB	Disaster type
Kongsomsaksakul et al. [2005]	UL: Shelter location LL: Shelter selection, route selection	UL: Travel time LL: Travel time		✓	✓		✓		Flood
Ng et al. [2010]	UL: Shelter assignment LL: Route selection,	UL: Travel time LL: Travel time			✓		✓		General
Li et al. [2012]	UL: Shelter location, shelter assignment LL: Route selection	UL: Travel time, unmet demand LL: Travel time			✓		✓		Hurricane
Yi et al. [2017]	UL: Evacuation plan, LL: Shelter selection, route selection, time period selection	UL: Travel time LL: Travel time		✓	✓	✓	✓		Hurricane
Hammad et al. [2019]	UL: Shelter location LL: Shelter selection, route selection	UL: Travel time, construction cost LL: Travel time		✓	✓		✓		General
Afkham et al. [2022]	UL: Shelter location, road equipment LL: Shelter selection, route selection	UL: Travel time LL: Travel time		✓	✓		✓		Bushfire
This study	UL: Shelter location, budget allocation LL: Evacuate or not, shelter selection, route selection, time period selection	UL: Risk LL: Utility of evacuation	✓	✓	✓	✓		✓	Flood

UL: Upper-level, LL: Lower-level

E/S: Evacuate or stay, DC: Destination choice, RC: Route choice, DT: Departure time

CB: Car-based, PB: Pedestrian-based

Moreover, none of the evacuation planning studies consider the dynamic nature of disasters in their modeling [Fahad et al., 2019, Yang et al., 2019]. By leveraging regional characteristics (e.g., weather conditions, topography) and available spatial datasets, we capture the temporal evolution of flood disasters over time and integrate this dynamic aspect into our optimization framework. This integration ensures that evacuation strategies remain robust and adaptable to the evolving characteristics of disaster, thus addressing a critical gap in the literature.

We are also among the first studies to focus on evacuation behavior in developing countries, addressing a critical research gap highlighted in the literature. While previous data-driven studies on human behavior during disasters have primarily concentrated on large-scale evacuations in developed countries such as the Netherlands and the United States [Lim et al., 2016], our research extends this focus to developing countries. Influenced by factors such as data availability, complexity of disasters, and uniqueness of transportation infrastructures, studies of developing countries are far less common than those conducted in developed countries. In developing nations, natural disasters are often interpreted as acts of god, which can result in lower intentions for evacuation. This is evident when comparing evacuation rates between developed and developing countries; for example, evacuations during flood events are generally more prevalent in developed countries like Australia than in developing ones like Nigeria [Hamilton et al., 2020]. This difference in evacuation rates underscores the necessity of more research in developing countries, as pointed out by Thompson et al. [2017], to better understand the differences in their evacuation behavior.

2.3 Methodology

This section aims to present the RBBO-SLEPP, our risk assessment methodology, and the development of the utility function for evacuation.

2.3.1 Mathematical Formulation

The problem tackled in this paper involves designing a shelter network that accounts for the behavior of evacuees. The objective is to strategically locate shelters to maximize coverage of populations with high risk, while minimizing evacuation risks based on the optimal reactions of evacuees, who are assumed to maximize their perceived benefits (utility of evacuation).

The evacuation planning horizon is divided into $t \in T$ time periods, during which the state of the network varies at each interval, depending on the characteristics and evolving nature of the disaster. The RBBO-SLEPP is defined on an undirected graph $G = (V, E)$, where V is the set of vertices and E the set of edges. $V = I \cup J \cup J'$ comprises the set of population points I, the set of potential shelter locations J, and the set of existing shelters J'. Each population point $i \in I$ is associated with a population in need of shelter d_i and a normalized population risk $\tilde{r}_i^p$. Each shelter $j \in J \cup J'$ is associated with a capacity q_j representing the maximal number of people that can be evacuated to that shelter, and with its normalized shelter risk $\tilde{r}_j^s$. In addition, each potential shelter $j \in J$ has a cost $c_j \geq 0$, representing the cost of locating (building) a shelter in location j. Each edge $(i, j) \in E, i \in I, j \in J \cup J'$ in time period $t \in T$ is associated with its travel distance d_{ij} and its normalized evacuation risk $\tilde{r}_{ijt}^e$. For evacuees in population point $i \in I$, the utility of evacuating to shelter $j \in J$ during time period $t \in T$ is denoted as U_{ijt}. The maximal budget to locate (build) new shelters is B. The RBBO-SLEPP can be formulated as follows:

$$\min_{y_j,\, \mathbf{x}} \quad \sum_{j \in J} \sum_{i \in I} \sum_{t \in T} (\tilde{r}_{ijt}^e - \tilde{r}_i^p)\, x_{ijt} \tag{2.1}$$

$$\text{s.t.} \quad \sum_{j \in J} c_j y_j \leq B \tag{2.2}$$

$$y_j \in \{0, 1\}, \quad j \in J \tag{2.3}$$

$$\mathbf{x} \in \arg\max_{\overline{\mathbf{x}}} \quad \sum_{j \in J} \sum_{i \in I} \sum_{t \in T} U_{ijt}\, \overline{x}_{ijt} \tag{2.4}$$

$$\text{s.t.} \quad \sum_{j \in J} \sum_{t \in T} \overline{x}_{ijt} \leq d_i, \quad i \in I \tag{2.5}$$

$$\sum_{i \in I} \sum_{t \in T} \overline{x}_{ijt} \leq q_j y_j, \quad j \in J \tag{2.6}$$

$$\overline{x}_{ijt} \geq 0, \quad i \in I, j \in J, t \in T \tag{2.7}$$

In the RBBO-SLEPP, the decision variables are divided between two distinct decision makers. The upper-level decision maker (authorities) decides on opening new shelters, while the lower-level decision makers (evacuees) make decisions about evacuation (i.e., evacuate-or-stay, destination choice, route choice, departure time choice). Consequently, this model includes two sets of decision variables. The first set, y_j is a binary variable that is set to one if a new shelter is established at vertex $j \in J$, and zero otherwise. The second set is $\mathbf{x}$, whose components x_{ijt} represents the number of people evacuating from population from $i \in I$ to shelter $j \in J$ during the time period $t \in T$:

$$\mathbf{x} := \left(x_{ijt}\right)_{i \in I,\, j \in J,\, t \in T} \quad , \qquad \overline{\mathbf{x}} := \left(\overline{x}_{ijt}\right)_{i \in I,\, j \in J,\, t \in T}.$$

The upper-level's objective function (2.1) aims to minimize the total risk associated with evacuation, which includes evacuation risk incurred during walking on the flooded road network (first term) and covered population risk (second term). While evacuees might prioritize shorter routes over safer ones, often ignoring the actual risks of navigating through flood-affected network paths, authorities' main goal is to minimize these risks through strategic shelter network design. By modifying the location patterns and design of the shelter network, authorities can influence but cannot control the choice behavior of users. Constraint (2.2) impose the maximal budget B to locate new shelters. Constraints (2.3) define the domain for the binary variables.

The lower-level's objective function (2.4) aims to maximize the total utility associated with evacuation of people evacuating from population point $i \in I$ to shelter $j \in J$ during the time period $t \in T$. Section 2.3.3 describes the behavioral model used to assess utility of evacuation. Constraints (2.5) ensure that the number of people evacuated from population point i does not exceed its population in need of shelter. Constraints (2.6) impose the maximal shelter capacity. Constraints (2.7) define the domain for the continuous variables. We exploit the fact that our lower-level problem is a linear program. By constructing the Karush–Kuhn–Tucker optimality conditions of this lower-level problem, we obtain a single-level problem that is equivalent to the original one and can be solved by an efficient commercial solver. E-Companion section A provides the details.

2.3.2 Risk Identification and Assessment

The importance of incorporating risk considerations into disaster management is well-documented in the literature [Heckmann et al., 2015]. Disaster risk is defined as follows [Arnette and Zobel, 2019]:

$$Risk = Hazard \times Vulnerability \times Exposure.$$

Hazard is defined as “a process, phenomenon or human activity that may cause loss of life, injury or other health impacts, property damage, social and economic disruption or environmental degradation”. *Vulnerability* is “the conditions determined by physical, social, economic and environmental factors or processes which increase the susceptibility of an individual, a community, assets or systems to the impacts of hazards”. *Exposure* is defined as “the situation of people, infrastructure, housing, production capacities and other tangible human assets located in hazard-prone areas” [United Nations, 2016]. These three elements are the main determinants of risk.

Defining risk as a function of these determinants allows to distinguish the external risk factors that are not really controllable (e.g., natural hazards) from internal risk factors that can be somewhat controlled (e.g., limiting the impacts of a natural hazard through robust infrastructure) [Arnette and Zobel, 2019]. It also allows for the identification of the locations and population most likely to be affected by potential disasters, thereby assisting in managing preparedness and response to humanitarian crises. Hazard, vulnerability, and exposure mutually influence risk, and none of these elements can be considered in isolation. In the context of flood disasters, each element (hazard, exposure, and vulnerability) is thoroughly assessed for population points and potential shelter locations, and their interaction is then used to derive population risk and shelter risk measures. Additionally, in pedestrian-based self-evacuation scenarios, evacuation risk calculates the difficulty of traveling from population points to shelters in different flood depths, incorporating insights from empirical research. For a detailed assessment of these risk measures, we refer the reader to Sharbaf et al. [2025].

2.3.3 Utility Function for Evacuation

Utility, a fundamental concept in both decision theory and economics, quantifies the satisfaction, benefit, or value an individual derives from various outcomes [Fishburn, 1968]. In decision theory, it is conceptualized as a quantitative representation of the value individuals assign to various choices, reflecting their preferences and the perceived benefits of those choices. It represents a numerical expression of how individuals prioritize and choose between different options based on perceived levels of benefit [Arrow, 1958]. Similarly, in economics, it is a measure of satisfaction or well-being that a decision maker attempts to maximize, taking into account the trade-offs in consumption across goods or alternative uses of resources (e.g., time and income). The utility function, a classic econometric tool, helps decision makers account for these trade-offs [Apte et al., 2020].

In emergency situations, utility functions could serve as a tool for predicting beneficiary preferences, even when direct preference solicitation is impractical. However, the diverse and context-specific nature of emergencies often leads to varied preferences among beneficiaries, reflecting different community impacts and personal experiences, which complicates the application of a universal utility function across different emergency scenarios [Gralla et al., 2014]. Several studies in humanitarian operations management develop utility functions to assist decision makers in balancing trade-offs. Apte et al. [2020] develop a utility function to guide the deployment of assets, such as ships, for humanitarian assistance and disaster relief operations, enabling decision makers to evaluate and prioritize assets based on their capabilities, proximity to the disaster area, and associated costs. Yoo et al. [2020] establish a utility function to assess why users decide to follow a humanitarian organization on social media after seeing their content, by evaluating whether the perceived benefits of following exceed the associated costs. A utility function is introduced by Park and Berenguer [2020] as quantitative measure to prioritize resource distribution in non-profit settings by addressing both the geographic disparities and varying individual needs within the same location. Gralla et al. [2014] develop a piece-wise linear utility function, based on a conjoint survey involving experts' opinions, to use as the objective of optimization models for humanitarian resource allocation problems across beneficiaries. Sahinyazan et al. [2021] formulate a utility function to model the spending choices and preferences of beneficiaries in food aid programs, determining which aid modality (cash, vouchers, or in-kind) is most effective.

In the context of evacuation decision-making, utility captures the perceived benefits and opportunity costs associated with the decision to evacuate versus not evacuating in the face of a disaster. These benefits and costs are shaped by a range of behavioral factors and evacuation barriers, derived from empirical insights into human behavior during evacuations. To develop a realistic and applicable utility function for evacuation, it is essential to employ a behavioral framework that effectively integrates both the benefits and barriers of evacuation, providing a comprehensive view of the decision-making process. The Fogg Behavior Model (FBM), developed by Fogg [2009], is a psychological framework that outlines the essential elements required for behavior change. According to the FBM, an individual must be motivated to perform the behavior, have the ability to perform it, and be triggered or prompted to perform it. A behavior is therefore the product of three principal factors: the motivator (Motivation), the simplicity factor (Ability), and the prompt (Trigger). These three factors must occur at the same moment, else the behavior will not happen. Leveraging the FBM framework (see Fig. 2.2), we develop the utility function for evacuation as:

$$Utility = Motivation \times Ability \times Trigger = f_m(\cdot) \times f_a(\cdot) \times f_t(\cdot),$$

where *Motivation*, *Ability*, and *Trigger* are the main drivers of the utility of evacuation. This formulation is a mathematical representation of the overall value, usefulness or benefit of evacuation which is determined by the interaction of three functions. The function $f_m(\cdot)$ represents motivation, reflecting the perceived necessity or benefit of taking action to evacuate. The function $f_a(\cdot)$ represents ability, capturing the extent to which physical and resource-based capabilities facilitate or hinder evacuation efforts. The function $f_t(\cdot)$ represents triggers, which serve as the cues or prompts that initiate the actual decision to evacuate. Together, these functions define the utility framework, where the overall utility is determined by the interdependent contributions of motivation, ability, and trigger. For evacuation to have high utility, all three components must be sufficiently strong, as a deficiency in any one of them can significantly reduce the likelihood of evacuation. The exact nature of these functions would need to be defined based on disaster context, attributes of hazard, empirical data, and regional characteristics. In section 2.4 we explain how we leverage insights from research on evacuation barriers in Haiti to develop these function and parameterize key elements of the utility function.

Although not originally designed for disaster contexts, the FBM's core elements align closely with factors influencing evacuation decisions identified in the literature (see Section 2.2.2). The model's three elements are interconnected, reflecting the interplay observed among key empirical factors affecting evacuation behavior. FBM's applicability is supported by its success in various behavior-change interventions, including health promotion

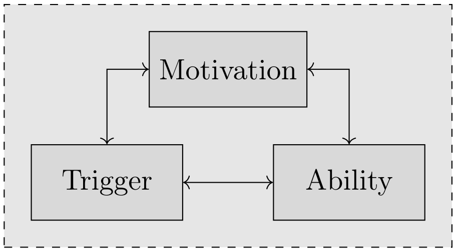


Fig. 2.2: Elements of Fogg Behavior Model (FBM)

[Agha et al., 2024] and education [Jyothy et al., 2024]. Within the evacuation context, the motivation element closely relates to risk perception and historical context, as both shape an individual's willingness to leave. The prompt element corresponds to environmental cues and information dissemination strategies, where immediate warnings or visible danger signs serve as triggers. The ability component maps to access to resources and demographic/socioeconomic conditions, capturing the practical constraints that determine whether a motivated individual can actually evacuate.

Alongside empirical evidence, FBM offers distinct advantages over other behavioral models for developing evacuation utility function. It provides a straightforward, adaptable framework for both qualitative and quantitative analysis, unlike more intricate models (e.g., SCT, PADM) that can impede rapid application. FBM also minimizes biases found in self-report–dependent models (TPB, HBM, PMT, SCT, EPPM) by focusing on observable behaviors rather than subjective appraisals. Crucially, it integrates immediate triggers essential for initiating rapid behavior change in emergency scenarios, a feature that is lacking in EPPM, SCT, HBM, and CET. Additionally, FBM's focus on ability addresses practical constraints, guiding targeted interventions for efficient evacuation. In contrast, models like TPB and HBM center on intentions or perceived barriers, which may not translate into swift action. Consequently, FBM emerges as a robust, adaptable framework that captures structural and behavioral barriers in evacuation decisions.

2.4 Parametrization of the Utility Function: the Case of Haiti

Haiti, ranking third among countries most affected by weather-related disasters, is one of the world's poorest nations. The country faces multiple hazards, with over 96% of the population exposed to two or more, including floods, hurricanes, earthquakes, and landslides. When facing natural hazards, Haitians encounter multiple barriers that interfere with evacuation decision-making. In an effort to understand the structural and behavioral barriers limiting evacuation decisions in Haiti, a World Bank team comprising behavioral scientists, economists, social scientists, and disaster risk management specialists conducted a qualitative research project in Haiti [Llopis Abella et al., 2020]. The purpose of this research was to examine, through a behavioral approach, the psychological, structural, and social factors limiting people's ability to evacuate. These details were further enriched by insights and information we documented through extensive discussions and interviews with experts from both the World Bank and the Government of Haiti. Here, by translating qualitative observations and empirical data from Haiti into quantifiable parameters for the FBM, we develop three functions (i.e., motivation, ability, and trigger) of the evacuation utility. Figure 2.3 depicts the conceptual framework for this utility. These functions could be adapted or developed for other contexts, including different types of disasters, regions, or evacuation scenarios.

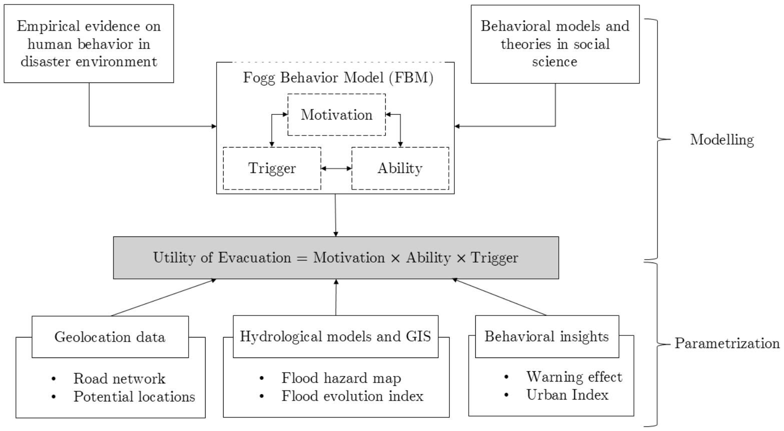


Fig. 2.3: Modeling and parameterization of utility function

Motivation function $f_m(\cdot)$**.** This function is constructed by modeling the temporal evolution of flood disaster, leveraging the progressive visibility of floodwater volume as a real-time risk indicator. This approach directly addresses the unique motivational barriers observed in Haiti, particularly the population's requirement for tangible evidence before taking action. Social science literature describes this phenomenon as "observational confirmation", wherein individuals typically need personal observations, such as directly assessing river water levels, to validate warnings and confirm the necessity of evacuation [Drabek, 1969]. In populations unfamiliar with hazards or lacking simulation training, the gradual visibility of rising waters serves as a practical, real-time learning experience, transforming abstract threats into tangible, immediate risks. Modeling the temporal dynamics of flood evolution in our context poses several challenges, including limited access to advanced technologies like remote sensing techniques and satellite imagery, a lack of real-time data, and non-existent historical records of past disasters. To address these limitations, we leveraged regional characteristics and available spatial datasets to model the temporal evolution of flood disasters. Drawing on a comprehensive review of hydrological literature, we integrated geospatial data sources, such as elevation, slope, precipitation, land use, and flow accumulation, to develop the Flood Evolution Index (FEI), which captures the dynamic progression of floods over time. These factors were selected based on their importance in influencing flood evolution [Shafapour et al., 2017, Malczewski, 2006, Kourgialas and Karatzas, 2011, Tehrany et al., 2014] and the availability of data for the region. ArcGIS Pro 3.3.0 was used to manage and process all spatial data in the development of the FEI. Detailed methodology for the development of this index is provided in the E-Companion section B. The resulting FEI map (Figure 3) provides a spatial representation of the relative potential for flood evolution across different locations in the study area, serving as a relative measure quantifying how quickly the flood hazard approaches maximum levels in each grid.

Building on the development of the FEI, we model the temporal evolution of flood disaster over time. Based on established flood behavior patterns, in the early stages of a flood event, runoff patterns show a dramatic rise as rainfall adds to water accumulation, reaching a peak when the flow rate is at its maximum [Wooding, 1965, Benito et al., 2023]. To capture this behavior of water movement across a landscape during a flooding event, we leverage

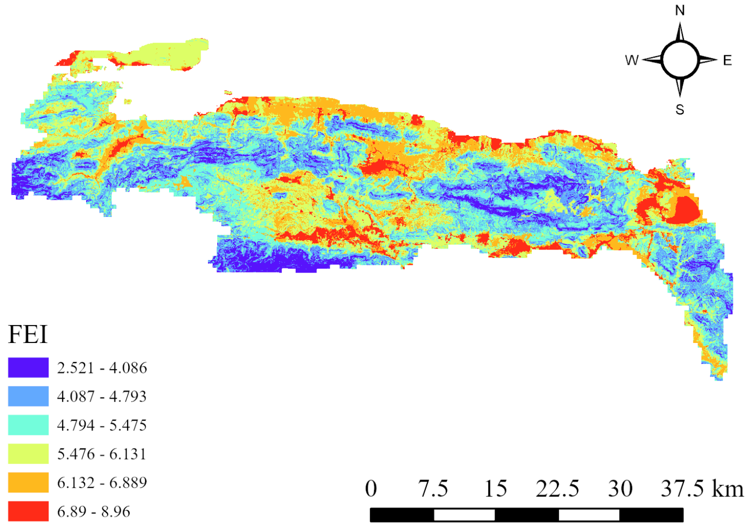


Fig. 2.4: Flood Evolution Index

exponential growth function, as a fair approximation to describe the initial rapid increase in water flow, followed by a slower approach to peak flow conditions. Then, for people living in grid i at the time t, the motivation function is approximated as the flood hazard of grid i at the time t, denoted as:

$$f_m(h_{it}) = h_i^{\max} \times \left(1 - e^{-\mathrm{FEI} \times t}\right) \tag{2.8}$$

where $h_i^{\max}$ represents maximum flood hazard of grid i at time t obtained from raster flood maps.

Ability function $f_a(\cdot)$**.** This function is formulated to incorporate two critical logistical barriers to evacuation in Haiti. These barriers include the scarcity of emergency shelters and the sparsity of road networks. The empirical evidence revealed that evacuation in Haiti mainly relies on foot travel, with individuals typically relying on road networks to reach the nearest shelter. However, due to the scarcity of roads, evacuees often face a complex evacuation. In many cases, they must first traverse various types of challenging terrain, such as swampy bogs, dense bushes, or forested areas, before they can access the road network. Once on the road, they then proceed along the shortest available path to reach a shelter. To address these challenges and construct an ability function based on these circumstances, we propose a composite measure that combines two key factors: road network accessibility and shelter availability. This composite measure provides an assessment of mobility constraints during emergency evacuations, capturing the complex geographical and infrastructural challenges that significantly impede evacuation efforts in Haiti. For people living in population point i to evacuate to a particular shelter at j, the ability function is approximated as the distance of evacuation between population point i and shelter j, denoted as $f_a(d_{ij})$. To account for the sparsity of the road network in Haiti, which requires people to travel across different types of terrain, a more nuanced approach is needed to calculate the effective distance d_{ij}. Research by Soule and Goldman [1972] demonstrates that walking on paved roads requires significantly less energy compared to navigating through other types of terrain. Addressing this difference, we incorporate data from their empirical study on the relative energy expenditure associated with walking across different land cover types. The evacuation distance d_{ij} from population point i and shelter j is then calculated as follows:

$$d_{ij} = (\lambda \cdot d_{ij}^{u}) + d_{ij}^{r} \tag{2.9}$$

where d_{ij} represents the total weighted distance between points i and j; λ is a factor that adjusts for the increased difficulty of walking through bush or other off-road terrain compared to walking on a road; d_{ij}^{u} is the Euclidean distance across unpaved terrain and d_{ij}^{r} is the distance along the paved road network. Using this effective distance, we then define the ability function as an exponential decay function. This means that as the effective distance increases, the ability to evacuate to shelter j decreases. The exponential nature of this function reflects that the difficulty of evacuation increases more rapidly as distances become greater. For the ability function f_a based on the distance d_{ij}:

$$f_a(d_{ij}) = \begin{cases} ce^{-kd_{ij}} + b & \text{if } d_{ij} \leq 3 \text{ km} \\ ce^{-k'(d_{ij}-3)}e^{-k\times 3} + b & \text{if } d_{ij} > 3 \text{ km} \end{cases} \tag{2.10}$$

where c is the initial ability, b is the baseline ability, k is the decay constant for $d_{ij} \leq 3$, and k' is the decay constant for $d_{ij} \geq 3$. The adoption of a 3-kilometer threshold in this ability function aligns with Haitian government standards for the maximum coverage radius permitted for foot-based evacuations and can be modified depending on the context. This threshold marks a critical point where the ability to evacuate begins to decline more steeply due to increased physical fatigue, resource depletion, and psychological barriers associated with longer distances.

***Trigger function* $f_t(\cdot)$.** This function is designed to reflect the unique warning barriers in Haiti. The warning dissemination process in Haiti evolves from public channels to more personal and private means of communication. This progression aligns with the concept of "degree of personalization" described in empirical literature on evacuation behavior [Drabek, 1969]. As warnings transition from public to more personal channels, their effectiveness gradually increases. Therefore, Haiti's warning dissemination process, which moves from public to private channels over time, exhibits a corresponding increase in both the degree of personalization and the overall effectiveness of the warnings. However, several inefficiencies hinder effective communication during evacuation in Haiti (e.g., lack of standardized warning processes, confusion from multiple communication channels, public distrust in authorities, and poorly adapted information). These inefficiencies contribute to a phenomenon known as "warning fatigue" where people become increasingly indifferent to warnings over time. As Drabek [1969] notes, prolonged exposure to warnings without experiencing the immediate impact of the predicted event can lead to desensitization. This desensitization ultimately results in a decrease in the perceived urgency and credibility of subsequent warnings, potentially compromising the effectiveness of the EWS. These two characteristics (increasing personalization and warning fatigue) can be conceptualized as sequential processes influencing the warning effect. Initially, the warning effect intensifies over time due to the increasing degree of personalization, reaching a peak within a given area. Subsequently, this is followed by a gradual decline attributed to the warning fatigue phenomenon. To account for these dynamics, we employ a Gaussian function to represent warning effect over time mathematically. Its bell-shaped curve and smooth transitions make it an appropriate approximation for capturing the nuanced changes in warning impact over time. This representation effectively encapsulates both the initial surge in warning effectiveness (corresponding to increased personalization) and the ensuing decrease (resulting from warning fatigue). Given these considerations, we parameterize the trigger function $f_t(w_{it})$ as follows:

$$f_t(w_{it}) = ae^{-\frac{(t-b)^2}{2c^2}} \tag{2.11}$$

where a is the curve's peak, b is the center of the peak, and c is the standard deviation. In addition to the previously mentioned factors, there is a difference in warning reception between urban and rural areas. Urban residents typically receive warning communications sooner than their rural counterparts due to more immediate and efficient access to communication channels. To incorporate these varying impacts of warning systems across different settlement types, we developed an Urban Index (UI). This index considers two crucial elements: population density and infrastructure (i.e., road network) density. The detailed methodology for developing the UI is provided in the E-Companion section C. Based on this index, we categorize our study region into four distinct areas: urban, suburban, rural, and remote. To account for the difference in warning reception between urban and rural areas, we further refine our parametrization by adjusting the Gaussian function. Specifically, we shift the peak of the function to occur earlier in urban areas compared to rural regions, thereby reflecting the more rapid dissemination of warnings in urban settings.

2.5 Computational Results and Analyses

Given the high flood hazard in the Nippes Department of Haiti, it serves as a crucial case for testing and validating our methodological approach. Nippes has a total population of 347,461 people distributed across 5,331 population points (grids of 500 m × 500 m), with a road network comprising 6,359 nodes and 7,351 arcs. The region includes 144 public buildings, such as schools and auditoriums, which are used as emergency shelters. These existing shelters do not comply with current building codes and standards, are structurally vulnerable to disasters, and often lack essential sheltering infrastructure. In some cases, these shelters are even situated within flood-prone areas. In response to these challenges, the Government of Haiti, in partnership with the World Bank, has initiated a project to construct 12 new shelters within the available budget. These new shelters will be built on the premises of public schools that have road accessibility within 150 meters. This criterion has identified 349 potential shelter locations throughout the region, providing a range of options for strategic placement of the new facilities. E-Companion section E presents more details on data of Nippes department.

In this section, we first assess the value of our decentralized, behavior-driven framework, followed by an evaluation of policies to improve evacuation management. Our model was coded in Python and solved with Gurobi 10.0.1.

2.5.1 Value of the Decentralized Decision-Making Approach

In this section, we analyze the benefits of employing a decentralized decision-making approach (i.e., bilevel optimization) compared to a centralized one (i.e., single-level optimization), particularly when dealing with two levels of hierarchical decision makers, each having their own constraints, objectives, and decision variables. Specifically, our objective is to assess the potential drawbacks that arise when the upper-level decision maker ignores the hierarchical nature of the problem and disregards the objectives of the lower-level decision maker, in our context, the evacuees. By evaluating the outcomes resulting from the authority's use of a centralized approach, one that fails to consider the preferences, barriers, or utility of evacuees, we seek to measure the extent to which such a decision-making process could lead to suboptimal results. Central to this analysis is the concept of High-Point Relaxation (HPR) [Kleinert et al., 2021], which establishes a theoretical benchmark to compare the performance of decentralized against centralized decision-making approach. E-Companion section D provides details on how we estimate the value of decentralized decision-making (V_{DDM}) by analyzing the outcomes of the High-Point Relaxation (HPR) approach and its comparison with the bilevel optimization framework.

Table 2.2 quantifies the value of decentralized versus centralized decision-making approach. For each configuration of number of shelters (# Shelters) contingent upon available budget, this table reports the objective function value (Obj_{BL} for bilevel and $\text{Obj}_{\text{HPR-LL}}$ for HPR-LL), its breakdown into evacuation risk (ER) and population risk (PR) along with the percentage of improvement (Improvement (%)) when using the bilevel optimization approach compared to the centralized HPR-LL approach.

As seen in the results, the significant improvement in the leader's objective function when using the bilevel optimization approach compared to the centralized HPR-LL model is

Table 2.2 Value of decentralized compared to centralized decision-making

	Decentralized DM			Centralized DM			Improvement (%)		
# Shelters	Obj_{BL}	ER	PR	$\text{Obj}_{\text{HPR-LL}}$	ER	PR	Obj.	ER	PR
1	96.10	3.90	100.00	84.50	15.50	100.00	13.60	74.70	0.00
2	190.90	9.10	200.00	172.50	25.20	197.70	10.70	63.80	1.20
3	285.00	15.00	300.00	262.20	35.50	297.70	8.70	57.80	0.80
4	379.80	20.20	400.00	356.20	41.50	397.70	6.60	51.30	0.60
5	475.80	24.20	500.00	448.10	49.60	497.70	6.20	51.10	0.50
6	570.50	29.50	600.00	542.30	55.40	597.70	5.20	46.80	0.40
7	664.50	35.50	700.00	634.20	63.50	697.70	4.80	44.20	0.30
8	758.10	41.90	800.00	719.00	77.80	796.80	5.40	46.20	0.40
9	850.70	49.10	899.80	816.50	80.30	896.80	4.20	38.90	0.30
10	943.00	56.70	999.80	908.70	84.30	992.90	3.80	32.70	0.70
11	1035.20	60.70	1095.90	1002.90	90.10	1092.90	3.20	32.60	0.30
12	1126.50	69.40	1195.90	1093.10	97.40	1190.50	3.00	28.80	0.40
13	1218.00	77.80	1295.90	1183.70	104.10	1287.80	2.90	25.20	0.60
14	1309.40	86.50	1395.90	1271.20	111.80	1383.00	3.00	22.70	1.00
15	1400.40	92.80	1493.20	1367.30	115.70	1483.00	2.40	19.80	0.70
16	1490.70	100.20	1590.80	1460.50	122.50	1583.00	2.10	18.20	0.50
17	1580.60	103.50	1684.10	1553.60	129.10	1682.70	1.70	19.80	0.10
18	1670.10	114.00	1784.10	1629.70	145.00	1774.70	2.50	21.40	0.50
19	1757.90	126.20	1884.10	1716.80	152.90	1869.70	2.40	17.50	0.80
20	1842.40	141.70	1984.10	1812.80	156.90	1969.70	1.60	9.70	0.70

primarily due to the substantial reduction in evacuation risk (ER). For instance, with one shelter, there is a 74.7% improvement in ER, which contributes to a 13.6% improvement in the overall objective function. This can be explained by the different and conflicting objectives of the authorities and the evacuees. Authorities have a comprehensive understanding of the flood risks across the network in different time periods, while evacuees lack full awareness of the actual risk levels ahead and base their decisions on personal perceptions and immediate circumstances. To delve deeper, authorities prefer that evacuations take place via the least risky routes, but the *ability* component of the evacuees' utility function leads them to choose shorter, more familiar routes that are not necessarily the less risky paths. This preference for shorter paths increases their exposure to higher evacuation risks. Furthermore, while authorities aim for evacuations to occur promptly, evacuees may delay evacuation until they receive a direct trigger, such as an official warning (*trigger*) or visible signs of danger (*motivation*). This delay can result in evacuations occurring during later time periods when the network is more severely flooded, further increasing evacuation risk.

The slight improvement in population risk (PR) between the centralized and decentralized approaches can be attributed to the widespread distribution of high-risk populations across the network. Since the demand for shelter among high-risk population is consistently high throughout the Nippes department, the model inherently targets these populations regardless of the decision-making approach. Therefore, the potential for significant reductions in population risk through shelter location decisions alone is limited. The results of Table 2.2 also shows that as the number of shelters increases, the percentage of improvement in evacuation risk (ER) decrease. This trend can be explained by the fact that with more open shelters, the possibility increases that some of the shorter paths taken by evacuees will coincide with the less risky paths favored by authorities. Additionally, people with better access to communication channels (less risky people) are more likely to be targeted. As a result, evacuation can occur earlier, reducing the tendency of evacuees to postpone their departure to later periods. This earlier evacuation aligns more closely with the authorities' preferences, ensuring that the evacuation process is more orderly and effective. This comparative analysis shows the importance of integrating evacuees' preferences into the strategic planning process, thereby mitigating potential inefficiencies and enhancing overall system performance.

2.5.2 Policy Evaluation

In this section, we evaluate various policies to provide insightful recommendations for effective evacuation planning and management.

2.5.2.1 Improvement of Early Warning Systems (EWS)

Here, we aim to evaluate the potential impact and effectiveness of improving EWS as a policy intervention for evacuation process and analyze the results. The United Nations has emphasized the importance of EWS, with the UN Secretary-General calling for every person on Earth to be protected by EWSs by 2027 [The United Nations, 2022]. Advances in EWS have saved tens of thousands of lives and hundreds of billions of dollars, making them one of the best-proven and cost-effective methods for reducing disaster deaths and losses. However, as of 2022, only half of the countries globally are protected by multi-hazard

EWS, and the numbers are even lower in developing countries [The United Nations, 2022]. Developing countries, despite similar technical capabilities, still face higher casualties and economic losses compared to developed countries, indicating a need for improvement in the communication and timely response components of EWSs [Cools et al., 2016, Fernández-Nóvoa et al., 2024]. This underscores the need to improve EWS, especially in remote and rural areas where people often receive warnings later than those in urban regions [Llopis Abella et al., 2020].

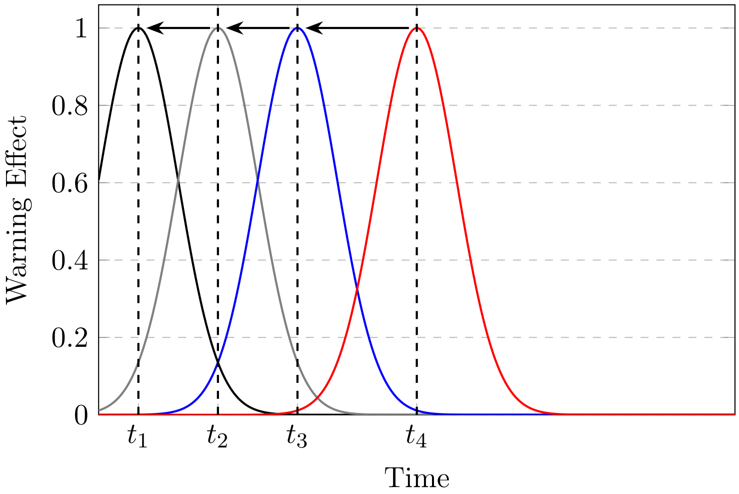


Fig. 2.5: Adjustment of trigger function

To translate the improvement of EWS into our model, we focus on adjusting the trigger function that represents the effectiveness of EWS over time (see Fig. 2.5). To investigate the effectiveness of this improvement in EWS, we adjust the trigger function for a subset of evacuees living in remote areas. Specifically, we randomly select 50% of grids in remote regions and shift the center of their trigger function to occur earlier in evacuation process. This adjustment reflects the enhanced capability of the EWS to deliver timely and effective warnings to populations in remote areas. By shifting the trigger function peak earlier, we model the anticipated increase in the warning effect due to improvements in the EWS. We then evaluate the impact of this adjustment on two performance criteria: the percentage of people who evacuate earlier, which measures the proportion of the population in remote areas who initiate evacuation actions sooner due to the earlier peak in the trigger function, and the percentage improvement in total evacuation risk, which quantifies the reduction in overall evacuation risk resulting from the earlier evacuation of people, as they

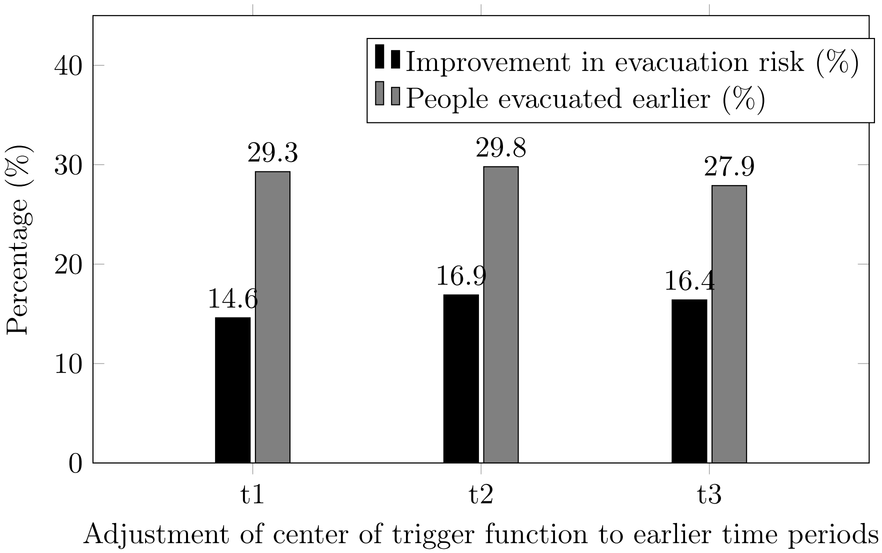


Fig. 2.6: Effect of improvement of EWS for some remote areas

have reached safety sooner and were less exposed to flood hazard when evacuating through potentially hazardous network. Figure 2.6 illustrates the impact of enhancing EWS in 50% of remote areas within our study region. The results reveal that even a modest improvement in the EWS, such as issuing evacuation warnings one time period earlier (from t_4 to t_3), leads to 27.9% of the population evacuating earlier. This adjustment leads to a substantial 16.4% improvement in the total evacuation risk. These findings demonstrate that advancing the timing of warnings by even a single time period can significantly influence evacuation behavior. Further adjustments to the warning timing provide additional insights. Issuing evacuation warnings at the second time period (t_2) yields a slight increase in early evacuations, with 29.8% of people evacuating sooner, and marginally improves the total evacuation risk to 16.9%. However, issuing warnings at the earliest time period (t_1) appears less effective.

These results highlight a nuanced relationship between the timing of warnings and their effectiveness. The diminished impact of warnings issued at (t_1) suggests that while early warnings are crucial, they must coincide with the population's perception of risk to be effective. In the initial stages of a potential flood, the absence of visible signs, such as rising water levels, may lead individuals to underestimate the urgency of the situation. Consequently, warnings issued too early may not prompt the desired evacuation response due to a lack of tangible evidence reinforcing the need for immediate action. This phenomenon underscores the critical role of motivation in the decision-making process during evacuations. People often rely on visual cues and without observable indicators of danger, early warnings may fail to trigger the necessary sense of urgency. The findings suggest that effective policy interventions should aim for timely and strategic dissemination of warnings. In parallel, there is a critical need for public education and awareness programs that elucidate the dangers of delayed evacuation and stress the importance of responding to early warnings. Moreover, enhancing risk perception through effective communication strategies that convey the severity and immediacy of potential hazards is vital.

2.5.2.2 Balanced Budgeting Allocation

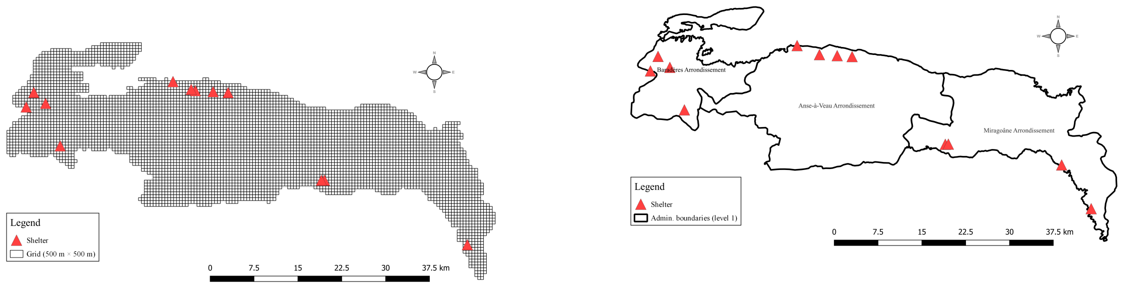
In the context of public financial management and government budgeting, the allocation of resources across different administrative levels and geographical areas is a crucial consideration. The literature on national and subnational government budgeting emphasizes the importance of a well-balanced approach to resource allocation [Wildavsky, 1986]. This is particularly relevant when it comes to the placement of critical infrastructure, such as emergency shelters, which can have significant implications for public safety and well-being [Lassa et al., 2019]. When the objective is to maximize coverage of high-risk populations, regardless of the employed methodology to determine shelter locations (e.g., optimization models or manual selection methods), it is natural for the solution to allocate resources to areas with the highest concentration of at-risk individuals. While this is efficient from a risk-reduction standpoint, it may not align with broader governmental objectives that include administrative balance and regional development goals [Rubin, 2019]. To address the need for a more geographically balanced allocation of shelters, we introduce an administrative budget constraint into our optimization model, formulated as:

$$\sum_{j\in k} y_j \leq \left\lceil B\frac{\sigma_k}{\sum_{k'}\sigma_{k'}}\right\rceil, \quad \forall k \tag{2.12}$$

where B is the total budget, y_j is the binary variable indicating whether shelter j is opened, areas are denoted by k, and σ_k represents the population density of area k. This constraint limits the number of shelters that can be opened in each administrative area based on its population density. Specifically, we allocate the total budget proportionally across areas, preventing the over-concentration of shelters in a single area and ensuring that each area receives funding aligned with its share of the total population.

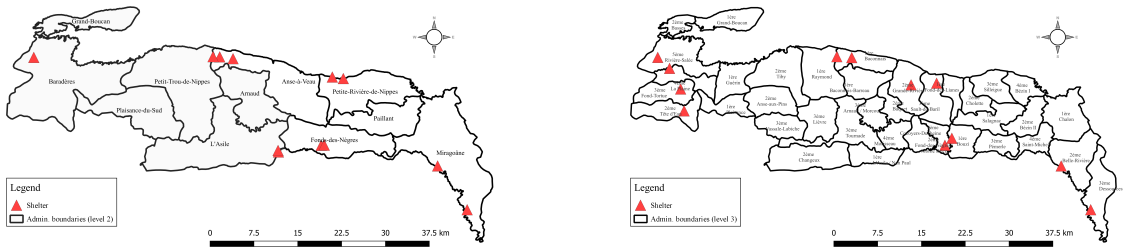
We evaluate the impact of the administrative budget constraint by solving four different versions of the model, with results depicted in Figure 2.7. The four cases include: a) *without budget constraint per area*: shelters are concentrated in high-risk areas, resulting in multiple shelters being opened close to each other. This case serves as the base case for comparison; b) *budget constraint proportional to 1st level administrative boundaries*: applying the budget constraint at the arrondissement level, where the Nippes department is divided into three arrondissements, distributes shelters according to each arrondissement's population density. This approach leads to a 0.5% deterioration in total risk compared to the base case; c) *budget constraint proportional to 2nd level administrative boundaries*: at the commune level, with eleven communes in the Nippes department, shelters are distributed based on each commune's population density. This finer administrative division results in a 22.2% increase in total risk compared to the base case; d) *budget constraint proportional to 3rd level administrative boundaries*: implementing the budget constraint at the most granular level of thirty-seven section communales in the Nippes department leads to shelters being allocated according to each section communale's population density. This results in a 3.0% deterioration in total risk compared to the base case.

The results indicate that introducing administrative budget constraints promotes a more geographically balanced distribution of shelters, as shown in Figure 2.7. However, this approach results in a deterioration of overall risk compared to the unconstrained model. Since budget allocation is inherently a political decision, we cannot recommend a specific solution. Instead, our decision-support tool enables governments to balance the benefits of achieving a politically and administratively acceptable shelter distribution against the associated increase in total risk. Additionally, the maps reveal that certain shelter locations remain consistent across all scenarios, highlighting areas of critical importance due to high risk and population density. These consistent locations underscore their necessity in the overall evacuation strategy, regardless of the administrative constraints.



(a) No administrative boundaries

(b) Administrative boundaries level 1



(c) Administrative boundaries level 2

(d) Administrative boundaries level 3

Fig. 2.7: Geographic distribution of shelter locations under different administrative-level budget constraints

2.5.2.3 Evaluation of Flood Mitigation Strategies

Emergency service facilities like shelters must remain operational during floods to provide safe refuge for affected populations. Implementing flood mitigation strategies during the construction of new shelters is crucial, particularly in areas where alternative flood prevention methods (e.g., dikes and levees) are unavailable [Jha et al., 2012]. While the ideal solution is to build shelters outside flood-prone zones, this is not always practical or optimal. Many potential shelter locations are situated in areas at risk of flooding and excluding them from candidate locations may decrease overall coverage of high-risk population and leave vulnerable communities without accessible refuge. To address this challenge, flood mitigation strategies can be implemented during the construction of new shelters. According to a comprehensive flood risk management guide developed by the World Bank [Jha et al., 2012], there are three main building design solutions. i) Flood resilience (wet proofing): This approach allows floodwater to enter the building but minimizes damage by using flood-resistant materials and construction techniques. For example, walls can be constructed with materials less susceptible to water damage, and services like electrical systems can be elevated above expected flood levels. ii) Flood resistance (dry proofing): This method aims to prevent floodwater from entering the building entirely. Techniques include sealing walls and foundations, installing flood barriers or shields over openings, and ensuring all entry points are watertight. iii) Flood avoidance: This strategy involves elevating the building above expected flood levels, either by raising the land or constructing the building on stilts or piers. By physically removing the building from the flood zone, the risk of flood damage is significantly reduced. This guide provides advice on when and where different flood proofing measures are appropriate. The suitability of each approach depends on flood characteristics (e.g., flood depth, velocity), site characteristics (e.g., location, soil type), and building characteristics (e.g., construction materials).

To evaluate the potential benefits of implementing flood mitigation strategies, we adjust our optimization model to consider all potential shelter locations, including those previously excluded due to higher flood risks. Initially, we preselected shelters based on strict flood risk criteria to ensure safety, in accordance with the standards set by the Government of Haiti. The criteria were: (i) flood area $\leq$ 50% and flood depth $\leq$ 0.8 meters; or (ii) flood area $\leq$ 20% and flood depth $\leq$ 2 meters. By incorporating flood mitigation measures, potential shelter locations in areas with higher flood risks can be considered for building new shelters. This allows us to relax the preselection constraints and include a broader set of potential shelter locations in the model. By relaxing the preselection constraints, 93 additional potential shelter locations were included as candidates for new shelter construction. After solving the model, we observed a 0.5% improvement in total population risk and a 13.0% improvement in total evacuation risk.

While the inclusion of additional shelter locations and the implementation of flood mitigation strategies show improvements in risk metrics, more exhaustive cost-benefit analysis is necessary to evaluate the benefits of implementing these mitigation strategies during construction versus investing in broader flood protection infrastructure, such as dikes and levees, or modifications to coastal land elevation [Jenkins et al., 2024]. For instance, instead of constructing 12 shelters without mitigation measures, the budget might only allow for 11 flood-resistant shelters with mitigation measures. Comparing the model results, we find that this will lead to an approximate 8.1% reduction in population risk coverage. This suggests that if flood mitigation strategies result in fewer shelters being built, the decrease in population risk coverage may not justify their implementation.

Building on these insights, our model provides a comprehensive framework to evaluate the trade-offs between investing in individual shelter flood mitigation and broader flood risk reduction measures. It allows decision-makers to assess how higher construction costs associated with mitigation strategies could influence the total number of shelters feasible within a given budget. By integrating these factors, the model delivers a clear cost-benefit analysis, guiding stakeholders toward optimal resource allocation – whether that means building more non-mitigated shelters or fewer, yet more resilient, flood-resistant ones – to achieve the greatest possible risk reduction.

2.5.2.4 National Standards

The required travel distance to reach safety (i.e., distance between where people live and the nearest emergency shelter) is one of the most important factors in determining the mode of transportation taken to evacuate [Murray-Tuite and Wolshon, 2013]. This critical aspect plays a crucial role in shaping evacuation behavior and ultimately influences the success of emergency response efforts. Despite its importance, international humanitarian standards lack clear guidance on appropriate evacuation distances for various transportation modes. For example, according to the Sphere standards [Sphere Association, 2018] which are internationally recognized quantifiable minimum standards for humanitarian responses, there are guidelines for the distance between shelters and service facilities such as water points, distribution points, and health centers. However, to the best of our knowledge, there are no international minimum standards for walking distance between population points and shelters. This lack of a universally accepted standard has led to disparities in national guidelines, such as the 3 km radius set by the Haitian government. However, the practicality and effectiveness of such standards are questionable, particularly in flood scenarios where walking up to 3 km through water may be difficult, not feasible, or extremely hazardous. Assuming this coverage radius, we might overestimate the population risk that can be covered by set of new shelters. Empirical data on factors affecting pedestrian evacuation show different numbers. A study by Paul [2012] examines the responses of Sidr victims to cyclone warnings in Bangladesh, revealing that distance to

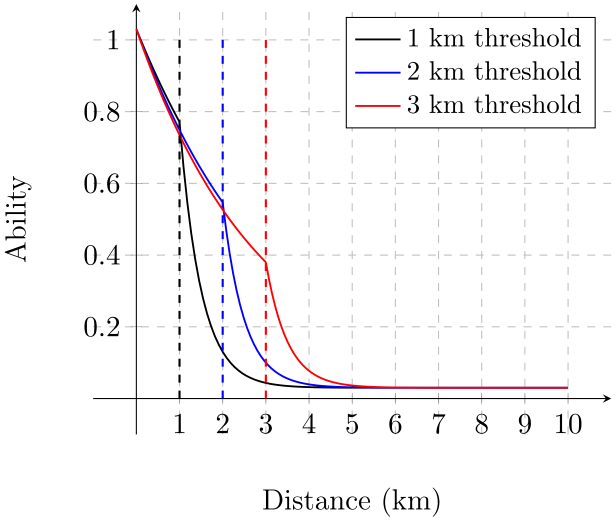


Fig. 2.8: Examples of ability function with different threshold for evacuation distances

shelter is the most significant factor, with residents unwilling to travel more than 1.6 km to public shelters during emergencies. Another study by Lim et al. [2016] seeks to identify and understand the effects of determinants on the behavior of households by mode choice in the Philippines and finds that traveling more than 200 meters reduces the chances of walking by 64.2%. These findings underscore the importance of considering realistic travel distances in evacuation planning and suggest that current standards may overestimate the population's ability to reach distant shelters.

To translate this into our model, we performed a sensitivity analysis on the 3 km radius in the ability function (see Fig. 2.8), solving the model with different values of 2.5, 2, 1.5, 1, and 0.5 (see Fig. 2.9). The results show that as we decrease radius (k), the sum of population risk decreases, meaning that fewer people at risk will be covered. However, the difference is not substantial. In addition, the sum of the evacuation risk also decreases. By decreasing k to smaller values, people closer to shelters have more utility than those farther away, so they are more likely to evacuate. As a result, both the sum of population risk and evacuation risk decrease. This analysis emphasizes the need for further research and data collection to establish evidence-based national standards for walking distances to shelters, taking into account local contexts and the specific challenges faced by communities during disasters. By refining these standards and incorporating them into disaster management plans, policymakers and humanitarian organizations can improve the

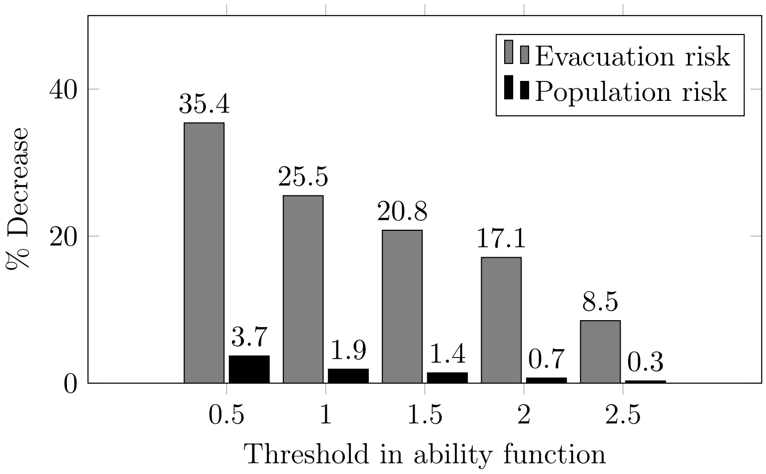


Fig. 2.9: Percentage of decrease in sum of population risk and evacuation risk in different coverage radius compared to base case ($r = 3$ km)

effectiveness of evacuation efforts and ultimately save more lives.

2.6 Conclusions

This study has introduced a novel, interdisciplinary decision-support framework for shelter network design and evacuation planning, advancing both theory and practice in humanitarian operations. By integrating operations research, social science, economics, and hydrology, the proposed bilevel optimization tool models shelter network design and evacuation processes as a Stackelberg game between authorities and evacuees. This approach captures the hierarchical interactions and potential conflicts that may arise, marking a fundamental distinction from conventional car-based evacuation studies that often overlook the nuanced complexity of human behavior.

Methodologically, this tool unifies five interconnected components while embedding risk measures derived from hazard, exposure, and vulnerability, along with a dynamic representation of flood progression. By handling disaster evolution at high resolution and over time, it more accurately reflects the urgency and variability of real-world evacuations. A central theoretical contribution of this work lies in its novel utility function, grounded in the Fogg Behavior Model and enriched by inputs from behavioral science, economics, and hydrology. Explicitly incorporating evacuees' motivation, ability, and triggers allows the model to better capture how people respond to different strategies proposed by decision-makers, thus bridging the gap between lower-level behavioral responses and high-level planning decisions.

Practically, the model supports decision-makers by providing quantitative metrics such as evacuation risk and population risk coverage, enabling them to assess various policy interventions. It offers actionable insights into designing or upgrading shelter networks, improving Early Warning Systems, and evaluating the cost-effectiveness of flood mitigation strategies. Moreover, the model accounts for budgetary constraints and administrative considerations, such as national standards for travel distance to shelters, to guide resource allocation decisions.

Finally, this research aligns with and supports the advancement of the United Nations Sustainable Development Goals 11, 13, and 17, emphasizing sustainable cities and communities, climate action, and partnerships for shared objectives. Throughout its development, the framework has been guided by the needs of the Government of Haiti and the World Bank, demonstrating its potential for real-world impact. By integrating diverse insights from multiple disciplines and empirical data, the proposed optimization model marks a significant step forward in evacuation planning, offering a robust, behavior-driven alternative to traditional approaches and providing a valuable tool for decision-makers in crisis management worldwide.

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Chapter 3

Analysis and Optimization of Post-Disaster Temporary Housing Solutions: An Application to Hurricane Response in Louisiana

Abstract

As disasters have become more frequent and severe, their impacts on households and homes have intensified accordingly. Addressing post-disaster housing remains a persistent challenge facing America's emergency management community. This research addresses the critical question of how state governments can optimally plan housing resources to accommodate displaced population effectively throughout the 18-month post-disaster recovery period, which is divided into three phases of varying duration: immediate response, transitional recovery, and stabilization. The study develops an optimization tool to maximize the expected well-being of displaced households throughout the designated temporary housing period. Five categories of housing types are considered: congregate shelters, third-party lodging (hotel rooms), and mobile units including trailers, Manufactured Housing Units (MHUs) and Alternative Transportable Temporary Housing Units (ATTHUs). Central to this research is the incorporation of households' utility function that quantify preferences based on displacement distance, housing type attributes, and temporal considerations across recovery phases, recognizing that housing preferences evolve over time. The framework addresses two procurement stages: pre-disaster and post-disaster. Pre-disaster procurement involves purchasing physical housing units for central stockpiling and contracting capacities with suppliers or hotel chains to reserve post-disaster acquisition options. Post-disaster procurement focuses on activating existing contracts as well as acquiring additional housing units when pre-disaster resources prove insufficient. We characterize the uncertainties regarding the location and severity of disaster by means of a discrete set of scenarios and formulate the problem using a two-stage stochastic programming approach. First-stage decisions encompass all pre-disaster procurement activities, including stockpiling quantities and supplier contracts. Second-stage decisions, made once a disaster strikes and a scenario is realized, include post-disaster procurement activities, deployment quantities across different regions and phases, and accommodation variables that map households' journeys throughout the temporary housing period. This two-stage stochastic optimization tool balances pre-disaster preparedness with post-disaster response, while maximizing total expected utility subject to budgetary and operational constraints. Through a case study of Louisiana's hurricane response, we assess the tool's performance across multiple analytical dimensions. The analysis examines budget allocation trade-offs between pre-disaster and post-disaster phases, compares planning portfolios with and without extreme events like hurricane Katrina, evaluates the impact of expanding supplier capacity and third-party lodging availability, and explores needs-based post-disaster funding approaches. The tool serves as a conceptual model to build intuition for decision-makers, enabling them to explore and evaluate the impacts of different housing solution options, procurement strategies, and resource allocation decisions.

Keywords: Post-disaster temporary housing, Housing preference dynamics, Resource allocation, Capacity planning, Two-stage stochastic programming, Louisiana hurricane recovery, Disaster recovery planning.

3.1 Introduction

The aftermath of large-scale disasters often results in substantial damages to housing infrastructure, leaving numerous homes uninhabitable and countless individuals in need of temporary accommodations. Temporary housing plays a critical role in disaster response and recovery by providing displaced population a place to reside and resume pre-disaster life activities before returning to permanent residences [Perrucci and Baroud, 2020]. The literature on post-disaster temporary housing emphasizes a critical distinction between "sheltering" and "housing". Sheltering refers to a place to stay during the immediate aftermath of a disaster, suspending daily activities, whereas housing denotes a return to household responsibilities and normal routines [Félix et al., 2013]. Practice and policy typically divide the temporal dimension of post-disaster housing into three phases of immediate response, transitional recovery, and stabilization, with needs evolving from urgent emergency accommodations such as shelters and hotels in the first phase, to more sustainable solutions like mobile homes or modular units in the second and third phases [Chen et al., 2013]. Different housing types offer differing attributes, including privacy level, comfort level, cultural appropriateness, and suitability for different durations of stay. Survivors' needs and preferences also change over time during recovery phases, making it essential to recognize housing types based on their functions at different phases [Chen et al., 2013]. Addressing temporary housing needs in these phases remains a persistent preparedness challenge for governments and humanitarian agencies. Despite this critical need for proactive management and capacity planning, the literature reveals that the concept of temporary housing has received limited attention from the operations research community, particularly regarding strategic planning approaches that can enhance cost-effective and survivor-centered disaster housing policy and practice [Perrucci and Baroud, 2020].

In the United States, planning for post-disaster housing is a persistent challenge facing emergency management community [Windle et al., 2019, Finegan et al., 2024]. This challenge is illustrated by the 2023 National Preparedness Report, which identifies "Housing" as one of the lowest achieving core capabilities (bottom 5) across all communities [FEMA, 2023b]. The Federal Emergency Management Agency (FEMA) defines the "Housing Core Capability" as implementing housing solutions that effectively support the needs of the whole community and contribute to its sustainability and resilience [FEMA, 2023a]. To achieve this capability, temporary housing programs are designed to provide accommodations for up to 18 months for survivors who qualify for this program. Housing programs in the United States are federally resourced, state managed and locally executed. Planning for disaster housing should occur at all levels of government before a disaster strikes [FEMA, 2025]. In this structure, FEMA plays a significant role in assisting states by providing necessary financial support [Windle et al., 2019]. However, it is ultimately the responsibility of states to request assistance from FEMA and make strategic decisions about resource allocation. Thus, the state acts as a centralized decision-maker regarding housing capacity placement that is supported financially by FEMA [Finegan et al., 2024].

The complexity of this decision-making process motivates the main research question we want to answer: "Considering survivors' preferences, what types of housing options should federal and state governments plan for, what procurement strategies are needed, and in which locations or regions should these resources be allocated to accommodate displaced population effectively over the 18-month post-disaster period?" Put differently, how well does a chosen deployment of housing capacity meet the preferences and utility of the survivors? Addressing this research question presents two primary challenges: first, the need to quantify survivors' preferences (utility) for different housing types and characterize how these preferences evolve throughout post-disaster recovery phases; and second, the challenge of addressing stochasticity stemming from uncertainty in both the location and magnitude of disasters. To tackle the first challenge, we conduct a comprehensive analysis of previous housing responses in major U.S. disasters to understand typical housing options, their characteristics, their alignment with household preferences, and how these preferences evolve across the three recovery phases. For the second challenge, we employ two-stage stochastic programming, which provides a robust framework for incorporating multiple disaster scenarios and their associated probabilities, allowing for the development of flexible and resilient housing strategies.

The aim of this study is to develop an optimization tool informed by empirical insights to help state and FEMA decision-makers explore, understand, and evaluate the impacts of different housing solution options, procurement decisions, and resource allocation strategies throughout the designated temporary housing period which is further divided into three phases of immediate response, transitional recovery, and stabilization. We consider three main categories of sheltering and housing types: i) congregate shelters, ii) third-party lodging (hotel rooms), and iii) mobile homes including travel trailers, Manufactured Housing Units (MHUs) and Alternative Transportable Temporary Housing Units (ATTHUs). To capture household preferences for these options, we translate qualitative insights and empirical evidences coming from previous housing responses to inform a utility function that quantifies preferences based on housing type attributes, displacement distance, and temporal considerations across recovery phases.

The problem is defined over two sets of geographical boundaries: the set of demand points (e.g., census tracts) that characterize household populations and demand, and the set of political jurisdictions (e.g., counties, parishes) that represent broader administrative regions for strategic capacity planning and resource allocation. Two parameters are scenario-dependent and vary based on the location and severity of the disaster: the demand (the number of households in each demand region requiring temporary housing) and the operational capacity of jurisdictions (the ability of a jurisdiction to accommodate certain housing types following a disaster). For instance, a disaster could reduce the available capacity of hotels or eliminate viable sites suitable for deploying mobile homes, thus limiting housing strategies within a jurisdiction, potentially forcing households to be displaced to other jurisdictions.

Recent natural disasters have underscored the critical importance of securing housing resources before disasters strike to enable rapid deployment of solutions post-disaster [Finegan et al., 2024]. To this aim, the model considers two stages of procurement: pre-disaster and post-disaster. Pre-disaster procurement involves two main strategies: (i) purchasing physical housing units that are centrally stockpiled with no particular location constraint, making them available to all jurisdictions once a disaster occurs, and (ii) contracting capacities with suppliers, which reserves the option to acquire housing capacities post-disaster. The stockpiling strategy ensures immediate resource availability during the initial response phase but requires substantial allocation from the state's pre-disaster budget. In contrast, contracting capacities requires a smaller portion of the pre-disaster budget since agreement fees are lower than outright purchasing costs. However, contracted capacities are unavailable in the initial response phase, becoming accessible only in the second or third phases depending on the supplier's capacities in different phases. Post-disaster procurement focuses on activating existing contracts and acquiring additional housing units from the spot market if pre-disaster resources prove insufficient. Expenses associated with post-disaster procurement are funded through the state's dedicated post-disaster budget.

We formulate this problem using a two-stage stochastic programming framework. First-stage decisions encompass all pre-disaster procurement activities, including stockpiling quantities for each type of housing and supplier selection for contracts, and are constrained by the available pre-disaster budget. Second-stage decisions, made once a disaster strikes and a scenario is realized, include post-disaster procurement activities, resource allocation, deployment quantities across different regions and phases, and accommodation variables that map households' journeys throughout the temporary housing period; these decisions are subject to the post-disaster budget. The objective function maximizes total expected utility across all disaster scenarios while minimizing the expected transition burden incurred by households when relocating between different housing options across recovery phases.

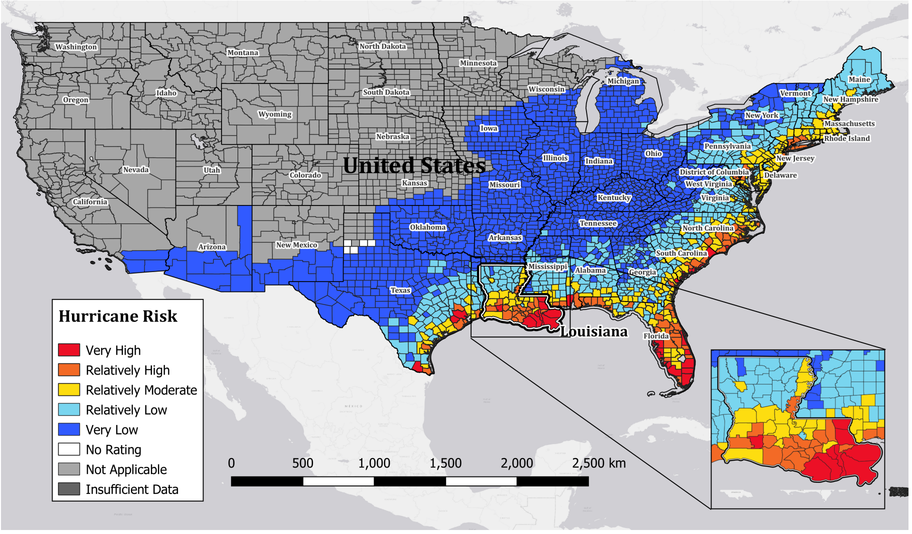


Fig. 3.1: Hurricane National Risk Index across the U.S.

While our model is adaptable to other contexts, we tested its application in the State of Louisiana's hurricane response. Louisiana's geography and climate make it one of the most disaster-prone states in the United States, especially with regard to hurricanes. The state sits on the northern Gulf of Mexico, directly in the typical path of Atlantic tropical cyclones that move west-northwest under the Bermuda–Azores high pressure system [NOAA, 2020]. Much of coastal Louisiana is low-lying delta land; portions of New Orleans and other communities even lie below sea level, protected only by levees and pumps [EPA, 2016]. These geographic factors, combined with the Gulf's warm waters (fueling intense storms), expose Louisiana to frequent and severe hurricane strikes. Historically, the state experiences about one hurricane landfall every 3 years on average [NWS, 2024]. In fact, from 1851 to 2004, Louisiana saw 49 hurricanes make direct landfall, the third-highest of any state (trailing only Florida and Texas). This includes 18 major hurricanes (Category 3–5) in that period [NHC, 2024]. Louisiana's long history of devastating hurricanes underscores why it is an appropriate and compelling case study for post-disaster housing solutions. Figure 3.1 shows National Hurricane Risk Index, which represent each community's relative risk of Hurricanes compared to the rest of the United States [FEMA, 2024d].

To the best of our knowledge, this is the first study in the temporary housing literature to integrate the temporal evolution of survivors' preferences into a comprehensive optimization model for capacity planning. We achieve this by conducting empirical analysis of historical housing responses to inform a utility function that quantifies household preferences, which are then embedded within a two-stage stochastic optimization model for pre-disaster planning that aligns housing solutions with survivor needs throughout the recovery period. The optimization tool serves as a conceptual model to build intuition for decision-makers and enhance strategic planning capabilities. This research advances disaster housing policy and practice by providing decision-makers with a systematic, data-driven approach that prioritizes survivor preferences while managing the inherent uncertainties and resource constraints of disaster response.

3.2 Literature Review

3.2.1 Temporary Housing Solutions and Preference Analysis in the United States

After major disasters in the United States, housing recovery typically progresses through phases from emergency sheltering to temporary housing and finally to permanent housing

[FEMA, 2009a]. The nature and magnitude of an incident drives the size, scope, and scale of housing needs and the duration of assistance required [FEMA, 2025]. The scope of this study focuses on sheltering and temporary housing phases. FEMA uses a combination of sheltering and temporary housing options to support disaster survivors on their road to recovery. Survivors' preferences for different housing options can greatly influence the success of recovery efforts. While there is no published preference ranking of displaced population from different housing options, empirical evidence from previous housing responses in major disasters shows findings on utilization rates, request patterns, and temporal changes. This section reviews five common post-disaster sheltering and housing solutions used to support disaster survivors on their road to recovery in the United States.

Congregate shelters are typically the first line of response in providing immediate, very short-term solutions for individuals displaced by a disaster. These facilities are often established in pre-identified public buildings such as schools and community centers which are quickly repurposed to accommodate large numbers of people together [FEMA, 2025]. The deployment process for congregate shelters is designed for rapid activation, leveraging existing infrastructure to the extent possible. The accommodation provided involves setting up sleeping areas, communal dining facilities, and basic sanitation amenities. The management of these shelters often involves a collaborative effort between government agencies, non-profit organizations like the American Red Cross, and community volunteers who provide essential services and support [HCDD, 2019]. Utilization is very high initially (hundreds of thousands across disasters) but declines rapidly; for example in 2017 Hurricane Season, Florida supported a peak of 191,764 people in nearly 700 shelters across the state, but within 1–2 months essentially all had transitioned out [FEMA, 2018]. While congregate shelters are crucial for immediate lifesaving, their suitability for extended stays is limited due to lack of privacy, overcrowding, and resource strain. For example, during Hurricane Sandy (2012), shelter occupants experienced intensified anxiety, frustration, depression and exhaustion, partly due to impersonal environments and limited services [Basile, 2020].

Hotel lodging under FEMA's Transitional Sheltering Assistance (TSA) program provides survivors with short-term hotel or motel stays paid by FEMA. This is considered non-congregate sheltering, an alternative to group shelters that still falls under emergency sheltering category, but with the privacy of a hotel room. FEMA contracts with corporate lodging consultants to administer this program through a nationwide network of participating hotels [DHS, 2020b]. TSA can be launched within days or weeks post-disaster subject to availability of participating hotels nearby. Hotels offer high immediate comfort (e.g., beds, climate control, housekeeping service), providing survivors with a private space and sense of normalcy and safety immediately post-disaster. However, the utility of hotels as a housing solution tends to decline over extended displacement periods. Over time, issues such as lack of space, absence of cooking facilities, family separation (if multiple rooms needed), and uncertainty about duration of stay begin to erode their usefulness. While these conditions are tolerable for weeks, they become increasingly frustrating when extended to many months, leading survivors to seek more home-like accommodations such as FEMA temporary units where they can cook and experience less transient living conditions [FEMA, 2018, DHS, 2020b, 2021]. Additional challenges can arise when TSA-participating hotels are located far from survivors' communities, as evidenced after Hurricane Harvey when the nearest FEMA-approved hotel in Victoria, Texas was 100 miles away, forcing displaced residents to choose between long commutes or job loss [THS, 2017]. TSA occupancy typically peaks early (within weeks of the disaster) and then gradually declines as people transition to FEMA units or the program eligibility ends. However, if recovery is slow, significant numbers can still be in hotels after 6 months. For example, after Hurricane Harvey hit Texas in 2017, some survivors stayed in the TSA program for almost a year, well beyond its intended duration [Windle et al., 2019].

Transportable Temporary Housing Units (TTHUs) are readily-fabricated dwellings provided by FEMA to eligible applicants for use as temporary housing placed on private site (i.e., the survivor's own land), commercial parks, or FEMA-established group sites [FEMA, 2020]. TTHUs are further divided into the two categories of travel trailers and Manufactured Housing Units (MHUs). Travel trailers, also known as Recreational Vehicles (RVs) are designed to provide temporary living quarters mounted on wheels for recreational purposes. They are not built to full housing code, have not motor (tow only), and provide at least 200 square feet of space equipped with basic living amenities such as one separate sleeping area, a small kitchen, and a bathroom [DHS, 2013, FEMA, 2020]. FEMA procures them via pre-established contracts with multiple RV manufacturers, and holds a modest inventory of new trailers at storage yards. Because of their ample availability in the commercial market, and to avoid maintaining a large inventory of RVs in storage, FEMA may purchase them from commercial dealers in the local area after disaster [FEMA, 2020]. Trailers are intended for short-term temporary housing (months, not years) and FEMA now does not consider them appropriate for long-term use as a dwelling [FEMA, 2009c]. From a household perspective, RVs offer more privacy and autonomy than congregate shelters or hotel rooms and a sense of "home" but the living quarters are often cramped, especially for larger families, and the quality of construction may not be as robust as other options like MHUs. For example, high winds in some areas destroyed trailer foundation skirting. They were also the source of many of the previous health and safety problems after Hurricanes Katrina and Rita [DHS, 2013].

MHUs are manufactured homes regulated by U.S. Department of Housing and Urban Development (HUD) Code, which is a federally accepted building code for permanent housing. They typically come in one to three-bedroom configurations (12 to 14 feet wide and 40 to 64 feet long), depending on the household's size and composition, and are intended for use when temporary housing is needed for longer periods, often exceeding six months and up to 18 months [DHS, 2013]. FEMA maintains a baseline stockpile of MHUs at its storage sites and also pre-arranges Indefinite Delivery, Indefinite Quantity (IDIQ) contracts with several mobile home manufacturers. When the national MHU inventory cannot support the MHU needs of the housing mission, FEMA generally uses existing production contracts to acquire additional MHUs [DHS, 2020a]. Logistically, MHUs are more complex and costly to deploy than travel trailers due to their larger size, weight, and the need for more extensive site preparation and utility connections. However, they can be equipped with accessible features like exterior ramps to accommodate individuals with disabilities [FEMA, 2009c]. From a household perspective, the additional living space, full-size kitchens and bathrooms, more windows and the outside space provided by the porch were reported to contribute substantially to occupants' well being. Improvements to mental health were mentioned by occupants more frequently than improvements to physical health. Living in a unit that "feels more like home" and being able to resume pre-disaster activities, such as inviting family and friends over, created a sense of normality that was greatly valued by program participants [FEMA, 2009c].

Alternative Transportable Temporary Housing Units (ATTHUs) represent a higher-quality form of factory-built temporary housing. These units are often constructed in sections (modules) and then transported to the site for assembly on a permanent foundation. They come in one to three-bedroom configurations (14 feet wide and 35 to 70 feet long) and are designed to be more aesthetically pleasing, durable, and energy-efficient than MHUs or RVs. The duration of use for modular units can be similar to MHUs, potentially up to 18 months or longer, and in some cases, these units were designed for eventual conversion to permanent housing or for reuse in future disasters [FEMA, 2024c]. ATTHUs are rarely used and the terminology "ATTHU" came to prominence with the 2023 Maui wildfire recovery, where FEMA sought alternative units suitable for the local context (shipping to Hawaii, culturally appropriate design, more closer to permanent house etc.). The units arriving at Kilohana were prefabricated, furnished and met all county, state, and federal requirements. FEMA procured modular units from three different vendors. Units were designed to meet Americans with Disabilities Act/Uniform Federal Accessibility Standards requirements and can be modified as needed by occupants with access and functional needs. The modular units have been built to last at least 30 years. When they are no longer used for temporary housing purposes, FEMA may sell or reallocate them to Maui residents so that they contribute to the island's housing stock [FEMA, 2024b, Maui News, 2025, FEMA, 2024a]. Logistically, modular units can be more expensive initially and require more time for production and installation compared to MHUs or RVs. However, their potential for longer lifespan, better energy performance, and higher occupant satisfaction can offset some of these initial costs and challenges.

3.2.2 Capacity Planning and Resource Allocation in Humanitarian Operations

In the disaster relief world, capacity planning is the set of strategic decisions that determine the amount, type, location and readiness of resources, infrastructures, and capabilities a humanitarian organization can draw on once a disaster strikes [Vanajakumari et al., 2016, Acimovic and Goentzel, 2016, Duran et al., 2012]. Typical decisions include facility siting, sizing or expansion of warehouses and regional hubs [Dufour et al., 2018, Charles et al., 2016, Vanajakumari et al., 2016], pre-positioning or stockpiling of multi-commodity inventories [Duran et al., 2012, Eftekhar et al., 2022], and reservation of production, transportation (fleet size) or supplier capacity through advance contracts or flexible agreements [Eftekhar et al., 2014, Huang et al., 2016, Guo and Zhu, 2023]. Once these capacities are established, resource allocation involves the tactical and operational decisions about mobilization, prioritization and deployment of those resources across different locations, time periods, and beneficiary populations to maximize humanitarian impact. Typical decisions include distributing and routing of relief flows from depots to points of distribution [Vanajakumari et al., 2016] and replenishment and local procurement to close residual gaps [Guo and Zhu, 2023, Eftekhar et al., 2022]. Capacity planning therefore sets the envelope within which resource allocation can take place.

The uncertain nature of disasters in terms of location, timing, and impact necessitates modeling these decisions under uncertainty. A natural modeling framework is two-stage stochastic optimization, where the first stage commits to capacity and the second stage decides how to use that capacity once the uncertain parameters are revealed [Grass and Fischer, 2016, Sabbaghtorkan et al., 2020]. Several studies have employed this approach to link pre-disaster capacity planning with post-disaster resource allocation. Alem et al. [2021] propose a multi-period, two-echelon network design model where the first-stage variables decide where and how large warehouses should be located and expanded over macro-time periods, while the second-stage variables then assign relief centers to affected areas, procure additional supplies locally and route inventory flows under each disaster scenario. Guo and Zhu [2023] develop a framework that integrates pre-positioning decisions and supplier capacity reservations under flexible contracts in the first stage, while the second stage chooses reactive procurement, inventory movements and routing under revealed demand scenarios. Rawls and Turnquist [2010] present a model where preparedness decisions involve selecting facility sites and sizes along with determining initial stock quantities of essential supplies, while response decision include routing available stock through potentially degraded networks. Balcik et al. [2019] propose a collaborative approach where first-stage decisions include selecting the number and location of regional warehouses, determining pre-positioned quantities of relief supplies, and establishing country-specific insurance-style premiums to cover system costs. The second-stage decisions involve flowing supplies from warehouses to affected countries through different response-time tiers while allowing for in-season replenishment of warehouses. These studies collectively demonstrate how two-stage stochastic optimization can effectively integrate strategic capacity planning decisions with operational resource allocation responses under disaster uncertainty.

3.2.3 Procurement Strategies in Humanitarian Operations

Procurement of products (e.g., medicines, food, or non-food-items) and services (e.g., transportation, warehousing) is a critical activity for humanitarian organizations, accounting for approximately 65% of the costs of relief operations. Pre-positioning relief supplies is a critical proactive procurement strategy in humanitarian operations, aimed at reducing response times and ensuring the immediate availability of essential items when a disaster strikes [Acimovic and Goentzel, 2016]. However, because of the unpredictability of disasters, high inventory holding cost, and donor preferences, it is nearly impossible to preposition the right items at the right quantity [Eftekhar et al., 2022]. To address this, humanitarian organizations can decide to use a mix of pre-positioning, framework agreements, option contracts, capacity reservation, or spot purchasing to streamline procurement of relief items.

Eftekhar et al. [2022] consider a mix of pre-positioning and local purchasing in the presence of demand, budget, and local supply uncertainties, and propose policies to determine optimal pre-positioned stock levels. Hu and Dong [2019] emphasize the importance of integrating supplier selection into the pre-positioning strategy and consider price discounts offered by suppliers as well as supplier physical inventory as supplier selection criteria. Aghajani et al. [2020] integrate option contracts into supplier selection and inventory prepositioning and propose a two-stage stochastic programming model. First-stage decisions involve inventory prepositioning levels, supplier selection, and capacity reservations, while second-stage decisions determine the timing and quantities of exercised options. Shamsi et al. [2018] explore the use of option contracts for vaccine procurement from suppliers in response to potential epidemics. These contracts allow humanitarian organizations to secure the right, but not the obligation, to purchase relief supplies at a predetermined price (exercise price) after paying an initial fee (option price) to the supplier. Hu et al. [2024] propose a supplier selection problem with consideration of the option contract, in which all-unit quantity and incremental quantity discounts are integrated. They formulate a multiobjective stochastic programming model with the objectives of minimizing the cost of the relief agency and maximizing the profit of suppliers. Balcik and Ak [2014] consider the supplier selection problem of a relief organization that wants to establish framework agreements with a number of suppliers and focus on a quantity flexibility contract in which the relief organization commits to purchase a minimum total quantity from each framework supplier over a fixed agreement horizon, and, in return, the suppliers reserve capacity for the organization and promise to deliver items according to pre-specified agreement terms. Wang et al. [2019] argue that although a fixed framework agreement provides a platform to secure relief supplies before a disaster, the nature of these agreements with predetermined terms does not motivate suppliers to improve their services. Therefore, they suggest complementing fixed framework agreements with bonus contracts and assess the outcome of bonus contracts using deprivation cost, economic cost and cost-effectiveness of the relief operation. While contracting is essential for achieving agreement and implementing capacity reservation, such collaboration contracts cannot follow a one-size-fits-all approach [Fan et al., 2024]. Effective sourcing strategy depends on the specific nature of the crisis, product types, objectives, and available funding. Despite this recognized need for customization, the majority of research on contract design are not developed in collaboration with humanitarian organizations and relies instead on hypothetical assumptions and data [Moshtari et al., 2021].

3.2.4 Positioning of This Study in Related Literature

The existing body of research on post-disaster temporary housing explores a broad array of issues worldwide. A significant portion of the literature examines design strategies including innovative architectural solutions, sustainable materials, and rapid construction techniques for temporary units [e.g., Hosseini et al., 2018, Perrucci et al., 2023, Johnson, 2007]. Another stream investigates sustainability of temporary housing units including evaluation of environmental, social, and economic dimensions [e.g., Atmaca and Atmaca, 2016, Song et al., 2016]. Some studies emphasize health impacts and cultural considerations of temporary housing units [Sukhwani et al., 2021, Watanabe and Maruyama, 2021]. The literature also addresses logistical complexities such as site selection and occupant assignment, though the latter is often approached from a logistical or needs-based perspective rather than a comprehensive preference-based one [Chen et al., 2024, Perrucci and Baroud, 2020]. These efforts have advanced the understanding of temporary housing challenges. However, to the best of our knowledge, the capacity planning and allocation of temporary housing resources while accounting for households' preferences have largely been ignored by the operations research community. This study aims to bridge this gap by developing a two-stage stochastic programming approach that considers pre-disaster procurement and post-disaster allocation of diverse housing types by explicitly accounting for survivor preferences into the core of the strategic and operational planning process. This framework considers the evolution of housing preferences across recovery phases, acknowledging that what is acceptable immediately after a disaster may change as recovery progresses. By embedding a utility function that captures survivor preferences based on attributes of different housing types, displacement distance, and temporal considerations across recovery phases, this research contributes to more effective and survivor-centered disaster housing policy and practice. While our focus is on U.S.-based case study and FEMA housing programs, the modeling approach is generalizable to other countries and disaster contexts.

3.3 Methodology

3.3.1 Problem Definition

We define the problem using several key sets that characterize the spatial, temporal, and operational dimensions of post-disaster housing planning. Spatially, we consider two sets of geographical boundaries: the set of demand points I, and the set of political jurisdictions J representing broader administrative regions. Let K denote the set of all housing types. We partition K into three mutually exclusive subsets: K^s (congregate shelters), K^h (hotels), and K^m (mobile units, including trailers, MHUs, and ATTHUs). A generic housing type is indexed by $k \in K$. The temporal dimension is captured by the set of phases T where

$t \in \{1, 2, 3\}$ corresponds to the three post-disaster recovery periods of varying duration (i.e., immediate response, transitional recovery, and stabilization), each characterized by different operational constraints. The set of candidate suppliers S represents potential entities capable of providing housing units through contractual agreements. Finally, the set of disaster scenarios Ω captures the inherent uncertainty surrounding disaster, including the unpredictability of its location, severity, and impact. Each scenario is associated with a distinct occurrence probability of p^{ω}.

The demand for temporary housing is captured by parameter $d_{i\omega}$, representing the number of households in region $i \in I$ who qualify by FEMA for assistance eligibility and require housing assistance under scenario ω. The demand of each region is assumed to be at the center of the region. Each jurisdiction $j \in J$ has housing capacity under scenario $\omega \in \Omega$ that depends on the housing category. For congregate shelters and hotels, capacity is denoted by $q_{kj\omega}$ for housing type $k \in (K^s \cup K^h)$; specifically, $q_{kj\omega}$ represents the number of shelter spaces (households) that can be accommodated when $k \in K^s$, and the number of available hotel rooms when $k \in K^h$. For mobile housing, capacity is determined by the availability of commercial sites and is shared across all mobile-unit types; we denote this by $\bar{q}_{j\omega}$, the total number of mobile-unit sites available in jurisdiction j under scenario ω, which applies jointly to all $k \in K^m$ (i.e., trailers, MHUs, ATTHUs). Available capacity of each jurisdiction is assumed to be at the center of the jurisdiction.

Household preferences are quantified through utility parameter u_{ikjt}, which measures the utility that households from region $i \in I$ derive from occupying housing type $k \in K$ in jurisdiction $j \in J$ during phase $t \in T$. To capture the burden of transitions between housing types, we introduce the transition disutility parameter $\beta_{kk't}$, which represents the disutility (in utility units) incurred when a household changes from housing type $k \in K$ in phase $t-1$ to housing type $k' \in K$ at phase t. This parameter structure is asymmetric by design: upgrades incur minimal friction, while downgrades face substantially higher penalties, discouraging quality deterioration in household accommodations throughout the recovery period.

The cost structure reflects three procurement pathways with distinct pricing mechanisms. Pre-disaster stockpiling costs are represented by $c_k^{(\text{stock})}$, the unit price for purchasing and stockpiling mobile housing type $k \in K^m$ before a disaster occurs. For supplier agreements, the cost structure includes two components: $c_{sk}^{(\text{fixed})}$ captures the fixed agreement fee charged by supplier $s \in S$ for the right to procure housing type $k \in K^m$ post-disaster, while $c_{skt}^{(\text{unit})}$ represents the unit purchase price from that supplier in phase $t \in T$ once the contract is activated. Each supplier $s \in S$ is type-specific (e.g., trailer suppliers are distinct from MHU suppliers) and has a maximum delivery capacity α_{skt} for housing type $k \in K^m$ in phase $t \in T$. For emergency spot market purchases made entirely post-disaster without prior arrangements, $c_k^{(\text{spot})}$ represents the unit purchase price of housing type $k \in K^m$. The purchase cost and availability of mobile housing units depend on procurement strategies: stockpiled units purchased before the disaster are the least expensive per unit and immediately deployable without lead times; pre-disaster contracted capacities are more costly per unit and become available in later phases; and units procured entirely after the disaster (without prior arrangements) are the most expensive and subject to considerable lead times. For mobile housing types, a deployment cost $c_k^{(\text{dep})}$ is included to cover site preparation and unit installation. For non-mobile housing types (i.e., shelters and hotels), $c_{kt}^{(\text{opr})}$ represents the operational cost of housing type $k \in K^s \cup K^h$ throughout phase $t \in T$, which depends on the length of phase t. To accommodate these different costs, the available funding is strategically divided between pre-disaster budget b_0 and post-disaster budget b_1, reflecting the distinct financial requirements at each stage of disaster management cycle.

The model incorporates both first-stage (pre-disaster) and second-stage (post-disaster) decision variables. First-stage decisions include X_k, representing the number of mobile housing units of type $k \in K^m$ to purchase and stockpile before a disaster, and Y_{sk}, a binary variable equal to 1 if supplier $s \in S$ is selected (contracted) to supply housing type $k \in K^m$ post-disaster, and 0 otherwise. Second-stage decisions, made after a disaster occurs and scenario $\omega \in \Omega$ is realized, include: (i) the contracted purchase quantity $Q_{sk\omega t}$ of mobile housing type $k \in K^m$ from pre-selected supplier $s \in S$ in phase $t \in T$; (ii) the spot-market purchase quantity $O_{k\omega t}$ for $k \in K^m$ in phase $t \in T$; (iii) the deployment quantity $V_{kj\omega t}$ of mobile housing type $k \in K^m$ to jurisdiction $j \in J$ in phase $t \in T$; (iv) the accommodation variable $Z_{ikj\omega t}$, which tracks the number of households from demand point $i \in I$ assigned to housing type $k \in K$ in jurisdiction $j \in J$ during phase $t \in T$; and (v) the transition flow variable $F_{ikk'\omega t}$, which tracks the number of households from $i \in I$

that move from housing type $k \in K$ in phase $t-1$ to housing type $k' \in K$ in phase t, for $t \in \{2, 3\}$.

The resulting two-stage stochastic optimization framework balances pre-disaster preparedness with post-disaster response flexibility, capturing uncertainties in disaster occurrence, magnitude, and impact while aiming to maximize total expected utility subject to budgetary and operational constraints.

3.3.2 Mathematical Formulation

We next present the notation to formulate the problem.

Indices and index sets

I : set of demand points, $i \in I$

J : set of political jurisdictions, $j \in J$

K: set of housing types, $k \in K$, where $K = K^s \cup K^h \cup K^m$

T : set of post-disaster phases, $t \in \{1, 2, 3\}$

S : set of candidate suppliers, $s \in S$

Ω : set of disaster scenarios, $\omega \in \Omega$.

Parameters

$d_{i\omega}$: number of households in region i in need of housing under scenario ω

$q_{kj\omega}$: capacity in jurisdiction j under scenario ω for housing type $k \in (K^s \cup K^h)$

$\bar{q}_{j\omega}$: capacity of mobile-unit sites available in jurisdiction j under scenario ω (shared across all $k \in K^m$)

u_{ikjt} : utility of households in region i using housing type $k \in K$ in jurisdiction j during phase t

$c_k^{(\text{stock})}$: unit stockpiling price of housing type $k \in K^m$ for fully pre-disaster purchasing

$c_{sk}^{(\text{fixed})}$: fixed contract fee of supplier s for supplying housing type $k \in K^m$

$c_{skt}^{(\text{unit})}$: unit purchase price of housing type $k \in K^m$ from supplier s in phase t

$c_k^{(\text{spot})}$: unit spot market price of housing type $k \in K^m$ for fully post-disaster purchasing

$c_k^{(\text{dep})}$: unit deployment cost of housing type $k \in K^m$ including site preparation and installation

$c_{kt}^{(\text{opr})}$: unit operational cost of housing type $k \in K^s \cup K^h$ throughout phase t

α_{skt} : delivery capacity of supplier s for housing type $k \in K^m$ in phase t

$\beta_{kk't}$: transition burden incurred by one household when moving from housing type k at phase $t-1$ to k' at phase t

b_0 : total available pre-disaster budget

b_1 : total available post-disaster budget

p_ω : probability of scenario ω occurring.

First-stage decision variables

X_k: number of housing type $k \in K^m$ to be stockpiled pre-disaster

Y_{sk}: 1 if supplier s is selected for supplying housing type $k \in K^m$ post-disaster; 0 otherwise.

Second-stage decision variables

$Q_{sk\omega t}$: number of housing type $k \in K^m$ purchased from supplier s in phase t under scenario ω

$O_{k\omega t}$: number of housing type $k \in K^m$ purchased from the spot market in phase t under scenario ω

$V_{kj\omega t}$: number of housing type $k \in K^m$ deployed to jurisdiction j in phase t under scenario ω

$Z_{ikj\omega t}$: number of households from region i using housing type $k \in K$ in jurisdiction j during phase t under scenario ω

$F_{ikk'\omega t}$: flow of households from region i that move from housing type $k \in K$ at phase $t-1$ to $k' \in K$ at phase t under scenario ω.

The problem can be formulated as follows:

$$\max \quad \sum_{\omega\in\Omega} p_\omega \left[\sum_{i\in I}\sum_{k\in K}\sum_{j\in J}\sum_{t\in T} u_{ikjt}\; Z_{ikj\omega t} - \sum_{i\in I}\sum_{k\in K}\sum_{k'\in K}\sum_{t\in 2,3} \beta_{kk't}\; F_{ikk'\omega t} \right] \tag{3.1}$$

$$\sum_{k\in K}\sum_{j\in J} Z_{ikj\omega t} \;\leq\; d_{i\omega} \quad , \quad \forall\, i,\; \omega,\; t \tag{3.2}$$

$$\sum_{i\in I} Z_{ikj\omega t} \;\leq\; q_{kj\omega} \quad , \quad \forall\;\; k\in (K^s\cup K^h),\; j\;,\; \omega\;,\; t \tag{3.3}$$

$$\sum_{i\in I}\sum_{k\in K^m} Z_{ikj\omega t} \;\leq\; \bar{q}_{j\omega} \quad , \quad \forall\, j,\; \omega\;, t \tag{3.4}$$

$$\sum_{i\in I} Z_{ikj\omega t} \;\leq\; \sum_{\tau=1}^{t} V_{kj\omega\tau} \quad , \quad \forall\, k\in K^m,\; j,\; \omega,\; t \tag{3.5}$$

$$Q_{sk\omega t} \;\leq\; \alpha_{skt}\; \cdot\; Y_{sk} \quad , \quad \forall\, s, k\in K^m, \omega, t \tag{3.6}$$

$$\sum_{\tau=1}^{t}\sum_{j\in J} V_{kj\omega\tau} \;\leq\; X_k \;+\; \sum_{s\in S}\sum_{\tau=1}^{t} Q_{sk\omega\tau} \;+\; \sum_{\tau=1}^{t} O_{k\omega t} \quad , \quad \forall\, k\in K^m, \omega, t \tag{3.7}$$

$$\sum_{k'\in K} F_{ikk'\omega t} \;=\; \sum_{j\in J} Z_{ikj\omega, t-1} \quad , \quad \forall\, i, k\in K,\; \omega,\; t\in 2,3 \tag{3.8}$$

$$\sum_{k\in K} F_{ikk'\omega t} \;=\; \sum_{j\in J} Z_{ik'j\omega t} \quad , \quad \forall\, i, k'\in K,\; \omega,\; t\in 2,3 \tag{3.9}$$

$$\sum_{k\in K^m} c_k^{(\text{stock})}\, X_k \;+\; \sum_{s\in S}\sum_{k\in K^m} c_{sk}^{(\text{fixed})}\, Y_{sk} \;\leq\; b_0 \tag{3.10}$$

$$\sum_{k\in K^m, t}\left[\sum_{s\in S} c_{skt}^{(\text{unit})}\, Q_{sk\omega t} + c_k^{(\text{spot})}\, O_{k\omega t}\right] + \sum_{k\in K^m, t, j} c_k^{(\text{dep})}\, V_{kj\omega t} + \sum_{k\in (K^s\cup K^h), i, t, j} c_{kt}^{(\text{opr})}\, Z_{ikj\omega t} \leq b_1, \quad \forall\omega \tag{3.11}$$

$$X_k \geq\; 0 \quad , \quad \forall\, k\in K^m \tag{3.12}$$

$$Y_{sk} \;\in\; \{0,1\}, \quad \forall\, s, k\in K^m \tag{3.13}$$

$$Q_{sk\omega t} \geq\; 0 \quad , \quad \forall\, s, k\in K^m, \omega, t \tag{3.14}$$

$$O_{k\omega t} \geq \ 0 \quad , \quad \forall\, k \in K^m, \omega, t \tag{3.15}$$

$$V_{kj\omega t} \geq \ 0 \quad , \quad \forall\, k \in K^m, j, t, \omega \tag{3.16}$$

$$Z_{ikj\omega t} \geq \ 0 \quad , \quad \forall\, i, k \in K, j, t, \omega \tag{3.17}$$

$$F_{ikk'\omega t} \geq \ 0 \quad , \quad \forall\, i, k \in K, k' \in K, t, \omega \tag{3.18}$$

The first term of the objective function (3.1) maximizes the expected utility (preference) of households across all disaster scenarios. The second term in (3.1) minimizes the disutility of transition incurred by households when relocating between different housing types. Constraints (3.2) ensure that in each phase, the total evacuated households from region i to all types of housing in all jurisdictions, do not exceed demand of the region. Constraints (3.3) and (3.4) ensure that household assignments do not exceed the available housing capacity in each jurisdiction across all scenarios. Constraints (3.5) ensure that the total number of accommodated households in phase t cannot exceed the total number of units deployed in current and previous phases, reflecting the fact that once a unit is deployed, it remains installed and available for subsequent phases. Households may either remain in their previously assigned units or relocate to newly deployed units that offer higher utility. The model does not track vacated units once households have moved out of them. Constraints (3.6) ensure that contracted purchases can only be made from pre-selected suppliers ($Y_{sk} = 1$) and cannot exceed the supplier's maximum capacity for that specific phase (α_{skt}). Constraints (3.7) is a generalized inventory constraint that links deployment to available supply sources across all phases. Constraints (3.8) and (3.9) are flow conservation constraints. Constraint (3.10) ensures that all up-front (pre-disaster) costs of stockpiling and agreement, do not exceed from the pre-disaster budget. Constraint (3.11) ensures that all post-disaster costs of purchasing (from contracted suppliers), spot purchasing, deployment, and operating are covered by the post-disaster budget. Constraints (3.12), (3.13), (3.14), (3.15), (3.16), (3.17), and (3.18) define the variable domain.

3.3.3 Utility Identification and Assessment

The success of post-disaster recovery efforts depends greatly on how well temporary housing solutions align with survivors' preferences and needs [Finegan et al., 2024]. To operationalize these considerations within our optimization framework, we develop a utility function that quantifies household preferences across different recovery phases. This utility function serves as the foundation for measuring expected household well-being and guides the optimal allocation decisions in our model. Rather than relying solely on prescriptive standards or supply-side constraints, our approach prioritizes demand-side preferences by systematically translating qualitative insights and empirical evidence from previous disaster housing responses into a quantifiable preference structure.

To understand the utility (i.e., satisfaction or usefulness to survivors) of each housing option across recovery phases, we conducted extensive analysis of official reports and authoritative sources (e.g., FEMA, GAO (U.S. Government Accountability Office), and DHS (U.S. Department of Homeland Security)) from previous disaster-housing responses in the U.S. to address several key questions: "which housing types were most or least preferred in each phase?", "how did preferences shift over time?", "what factors (privacy, space, location, services) drove those preferences?", and "how did housing type interact with displacement distance (local versus far relocation)?". Results of this analysis can inform the development of a utility function that measures survivor preferences for different housing types while incorporating the critical factor of displacement distance.

The utility that household in census tract i derives from being accommodated to housing type $k \in K$ in jurisdiction j during recovery phase t is expressed as:

$$u_{ikjt} = \bar{u}_{kt} \; . \; g\ (d_{ij}) \quad , \quad 0 < \alpha \leq g(.) \leq 1 \ , \tag{3.19}$$

where $\bar{u}_{kt}$ represents the base (distance-neutral) utility of housing type $k \in K$ in phase t, and $g\ (d_{ij})$ is a logistic distance decay function that affects this base utility based on the displacement distance d_{ij} between the household's origin census tract i and destination jurisdiction j. This utility-based framework enables us to balance competing objectives such as proximity to pre-disaster locations versus housing quality, while explicitly recognizing that household preferences evolve as recovery progresses from immediate emergency response to longer-term stabilization.

Base utility ($\bar{u}_{kt}$). The base utility component captures the intrinsic desirability of each housing type and how these preferences shift across recovery phases. This component aggregates household valuations of various housing attributes including privacy, space adequacy, kitchen facilities, autonomy, and the degree to which the accommodation resembles permanent housing. Figure 3.2 depicts base utilities by housing type across recovery phases.

Shelters. Congregate shelters are multi-household facilities that represent the most basic form of temporary accommodation, providing essential life-saving shelter but minimal comfort or privacy. While crucial for immediate response with their principal advantages of speed and scale, shelters quickly become unsuitable for extended stays. The open, communal spaces with virtually absent privacy, continuous lights and noise, and uncertain security of belongings create an environment where survivors experience intensified anxiety, exhaustion, and profound loss of autonomy [HCDD, 2019]. In the broader picture, the lesson learned is that rapidly transitioning survivors out of mass shelters is crucial to reduce trauma. This explains the rapid decline in base utility from 2.0 in phase 1 to 1 in phase 2 and 0.5 in phase 3. Evidence from Hurricane Sandy demonstrates that residents left shelters as soon as any alternative became available, reflecting their unsustainability beyond immediate emergency response [Basile, 2020].

Hotels. In the immediate aftermath of disasters, hotels offer a marked improvement over shelters with immediate comfort features including beds, climate control, and housekeeping services, providing survivors with private space and a sense of normalcy, justifying their phase 1 utility of 4.0, two times that of shelters. The privacy and autonomy that families greatly value make hotels particularly appealing initially [DHS, 2021]. However, the absence of cooking facilities, limited space for family activities, and potential family separation across multiple rooms progressively erode their usefulness, causing utility to decline to 3.0 in phase 2 and 2.0 in phase 3. Many survivors would rather stay in a hotel far away than in a crowded shelter near home during phase 1, but by phase 3 this often flips, they'd prefer a temporary home nearer their community even if it's less luxurious than a distant hotel.

Trailers. Also known as RVs, are not built to full housing code, but designed to provide temporary living quarters mounted on wheels. Trailers provide a significant step toward

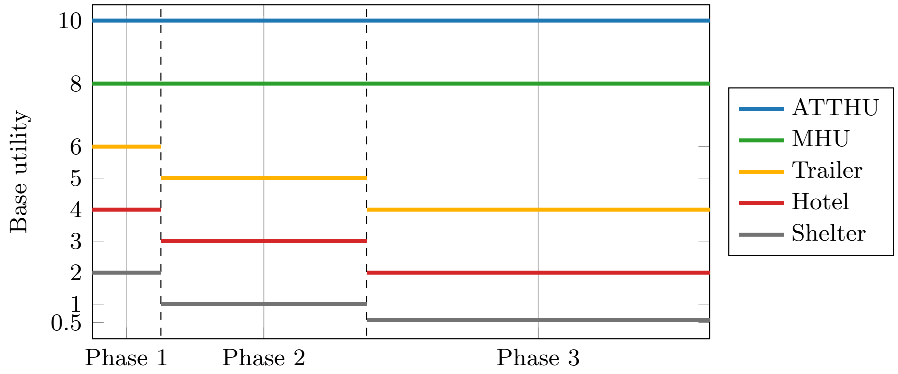


Fig. 3.2: Piecewise-constant base utilities by housing type across phases

normalcy with basic living amenities including separate sleeping area, small kitchen, and a bathroom, offering substantially more privacy and autonomy than both shelters and hotels [FEMA, 2020]. This "home" quality, however humble, explains their initial utility of 6.0, 50% higher than hotels. Trailers enable families to maintain community continuity while having their own space. Yet their limitations become increasingly apparent over time: the typically small, one-bedroom units not designed for long-term family living lead to crowding and maintenance problems. Post-Katrina evidence shows that what felt acceptable as an emergency stopgap became frustrating over months, with survivors unable to resume normal activities like hosting family gatherings [DHS, 2013]. This progressive dissatisfaction drives the utility decline from 6.0 to 5.0 in phase 2 and 4.0 in phase 3, though trailers consistently maintain higher utility than hotels due to their superior autonomy and cooking capabilities.

MHUs. These are manufactured homes regulated by U.S. Department of Housing and Urban Development (HUD), typically 2–3 times the size of a trailer. MHUs represent a qualitative jump in temporary housing, offering full-size kitchens and bathrooms, more windows, and sturdy construction that closely approximates real houses [DHS, 2013]. Their consistent utility of 8.0 across all phases reflects their ability to meet household needs throughout recovery. Mississippi's Katrina Cottages evaluation found clear consensus that the Cottages are a far better solution for long-term temporary housing than trailers, with features like additional living space, higher ceilings, and outdoor porches contributing substantially to occupants' sense of well-being [FEMA, 2009c]. Unlike the declining utility of trailers, MHUs enable survivors to resume normal routines (e.g., hosting family gatherings, cooking meals, and maintaining social activities) creating a sense of normality unavailable in trailers. This home-like environment, linked to improved mental health outcomes, justifies MHUs' stable high utility that is double that of trailers by phase 3.

ATTHUs. These highest-quality factory-built units, constructed in modules and assembled on permanent foundations, offer all the benefits of MHUs with additional advantages including better energy performance, potential for customization to local preferences, and enhanced durability [FEMA, 2024b,a]. Evidence from Maui's Kilohana site demonstrates that residents expressed such high satisfaction that many advocated to purchase units for permanent housing, blurring the line between temporary and permanent accommodation [Maui News, 2025]. ATTHUs represent the pinnacle of temporary housing solutions, achieving the maximum utility of 10.0 across all phases. The 25% utility premium over MHUs reflects ATTHUs' superior construction quality, customization potential, and ability to fully restore pre-disaster living standards while maintaining community connections.

Distance decay function ($g\ (d_{ij})$). The distance multiplier accounts for the critical role of geographic displacement in household well-being. Displacement distance affects daily commuting to employment, children's access to schools, maintaining social networks, and psychological attachment to pre-disaster communities. We model this relationship using a logistic decay function:

$$g\ (d_{ij}) = \alpha\ + \frac{1-\alpha}{1+e^{\beta\ (d_{ij}\ -\ \gamma)}}, \tag{3.20}$$

where α represents the minimum utility retention factor (the lower bound on utility even at extreme distances), β controls the steepness of utility decline with distance, and γ represents the inflection point distance at which utility decay accelerates. Long displacement distances reduce utility as survivors must maintain daily connections to employment, schools, healthcare providers, and social networks, connections that become increasingly difficult and costly to sustain as distance grows. This consideration aligns with established disaster housing policy principles. FEMA's evacuation planning considerations establishes the planning baseline to "move as few people as needed the shortest distance to safety"

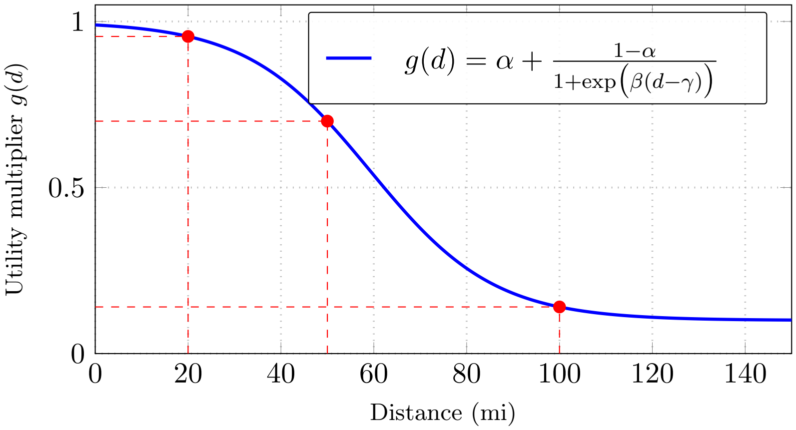


Fig. 3.3: Logistic distance decay function

[FEMA, 2019]. Similarly, the national disaster housing strategy specifies that community sites "should be located within, or in close proximity to, the affected community to allow victims to return to their communities and promote recovery" [FEMA, 2009b]. Historical evidence from Hurricane Katrina demonstrates the consequences of inadequate consideration of displacement distance, where thousands of travel-trailer households were placed in group sites lacking essential services and infrastructure, leading to isolation and increased costs and time for accessing employment and childcare [GAO, 2008].

We model this relationship using a logistic decay function with parameters calibrated to reflect the practical realities of daily commuting and the impacts of displacement distance on recovery outcomes. Specifically, we set $\alpha = 0.10$, $\beta = 0.075$, and $\gamma = 50$ miles (see Figure 3.3). These values encode a meaningful distance-utility relationship: at a displacement distance of 50 miles (representing a 100-mile daily round-trip commute), the utility multiplier equals approximately 0.7, indicating that base utility decreases by 30 percent. This threshold reflects the boundary at which daily commuting becomes substantially burdensome for households attempting to maintain employment, school attendance, and community ties. Beyond this inflection point, utility declines more sharply; at 100 miles of displacement, the multiplier drops to approximately 0.1, retaining only 10 percent of the base utility. This dramatic decrease captures the reality that such extreme displacement effectively severs households from their pre-disaster communities, making it prohibitively difficult to sustain employment, continue children's education in familiar schools, or maintain essential social support networks.

3.3.4 Transition Burden Assessment

Beyond the direct utility derived from housing accommodations, post-disaster recovery planning must consider the disruption caused by relocation between different housing types across recovery phases [Finegan et al., 2024]. Each transition imposes significant burden on displaced households (e.g., packing belongings, completing administrative paperwork, disrupting children's schooling, interrupting work routines, and losing established social connections and support networks). These transition costs represent a critical but often overlooked component of survivor well-being during recovery. The magnitude of transition burden depends on the direction of housing quality change. We establish an ordered hierarchy of housing types based on quality and amenities:

$$shelter < hotel < trailer < MHU < ATTHU \tag{3.21}$$

This ordering reflects the progressive improvement in privacy, space, autonomy, and home-like features across housing types, as established through the base utility assessment. Within this framework, transitions are classified as either downgrades (moves to lower-quality housing) or upgrades (moves to higher-quality housing). Downgrades impose particularly severe burden on households. Consider a household that has lived in a trailer for eight months through phases 1 and 2, establishing routines, personalizing their space, and achieving a sense of "home" despite the trailer's limitations. For this family, moving to a hotel in phase 3 would mean losing their private kitchen, reducing their living space, and potentially separating family members across multiple rooms. Conversely, when the same family moves from a trailer to an MHU, they experience the inconvenience of packing and moving but gain additional bedrooms, a full kitchen, and improved construction quality. The anticipation of improved living conditions partially offsets the disruption costs, resulting in a lower overall transition burden. To capture these effects, the optimization model incorporates transition burden parameters $\beta_{kk't}$, representing the disutility incurred by one household when moving from housing type k at phase $t-1$ to type k' at phase t. Let $\Delta\bar{u}_{kk't} = \bar{u}_{k't} - \bar{u}_{kt}$ be the base utility gap between types in phase t. We define:

$$\beta_{kk't} = \begin{cases} \phi_{\uparrow}\, \Delta\bar{u}_{kk't} \ , & \text{if } \Delta\bar{u}_{kk't} > 0 \text{ (upgrade)} \\ \phi_{\downarrow}\, |\Delta\bar{u}_{kk't}| \ , & \text{if } \Delta\bar{u}_{kk't} < 0 \text{ (downgrade)} \\ 0 \ , & \text{if } \Delta\bar{u}_{kk't} = 0 \text{ (no transition)} \end{cases} \tag{3.22}$$

with unitless coefficients of upgrade friction $\phi_{\uparrow}$ and downgrade burden $\phi_{\downarrow}$. Thus $\beta_{kk't}$ is measured in the same unit as the utility term. We choose $\phi_{\uparrow} < \alpha$ (α is the lower bound in distance decay function) to ensure upgrades remain beneficial under any displacement distance, and a large $\phi_{\downarrow} > 0$ that discourages downgrades (so downgrades cannot be offset by upgrades of comparable sizes).

3.4 Case Study

We conduct a case study by evaluating the performance of the proposed framework on the State of Louisiana's hurricane response. Louisiana presents an illustrative case study for optimizing post-disaster temporary housing strategies due to its extreme hurricane exposure and documented housing response challenges. The state experiences hurricane landfalls approximately every 3 years, with 49 direct strikes between 1851-2004, including 18 major hurricanes (category 3-5) [NHC, 2024]. This persistent threat culminated in 2005. In particular, the 2005 hurricane season was unprecedented when hurricanes Katrina and Rita struck Louisiana within a single month, causing catastrophic damage across the region. Hurricane Katrina has been characterized by FEMA as "the single most catastrophic natural disaster in U.S. history", triggering the largest temporary housing mission ever in the United States (over 200,000 units including travel trailers and mobile homes only in Louisiana) [U.S. House Committee, 2015, U.S. Congress, 2010]. The 2020 hurricane season set a new record when five named storms made landfall in Louisiana, the highest number of landfalls any state has endured in a single season [NCEI, 2020]. Since 1980, Louisiana has sustained approximately $290 billion in damages from 27 billion-dollar tropical cyclone events, ranking third nationally in absolute losses [Smith, 2023]. This risk profile, combined with Louisiana's geographic characteristics (i.e., a low-elevation coastal plain within hurricane alley) creates recurring demand for temporary housing solutions across multiple recovery phases. For the purposes of our optimization tool, Louisiana's administrative structure provides a well-defined spatial framework. The state comprises 64 parishes (political jurisdictions, denoted as set $j \in J$ in our mathematical formulation) and 1,388 census tracts (demand regions, denoted as set $i \in I$ offering granular geographic units through which to analyze displacement patterns and housing resource allocation.

3.4.1 Experimental Setup and Parameter Estimation

We construct a detailed dataset using information from publicly available sources. All information used to conduct the experiments is presented below.

3.4.1.1 Impact Prediction and Demand Scenarios

FEMA provides recovery assistance through three programs: Individual Assistance (IA), Public Assistance (PA), and the Hazard Mitigation Grant Program (HMGP). The IA program assists individuals and households directly, while PA provides grants to affected state, territory, or tribal governments for disaster response and recovery, including debris removal, and permanent facility restoration. HMGP supports governments in protecting eligible public or private property through mitigation measures after a disaster declaration. Program authorization depends on disaster-specific needs [FEMA, 2021]. The Individuals and Households Program (IHP), a component of IA, provides financial assistance and direct services to eligible individuals and households with uninsured necessary expenses and serious needs. IHP assistance is limited to 18 months following the disaster declaration date and comprises two categories: Housing Assistance (HA) and Other Needs Assistance (ONA). HA is further divided into financial assistance and direct assistance. Figure 3.4 illustrates the complete structure of FEMA's IHP. FEMA determines appropriate HA types for household eligibility based on disaster-caused losses, access to life-sustaining services, cost-effectiveness, and other factors. Households who qualify (i.e., meet eligibility criteria) for temporary housing units under direct assistance program are those who define "demand" in our problem.

To construct demand scenarios, we focus on major hurricane disasters affecting Louisiana between 2002 and 2024. According to NOAA historical hurricane tracks, 22 Category 1-5

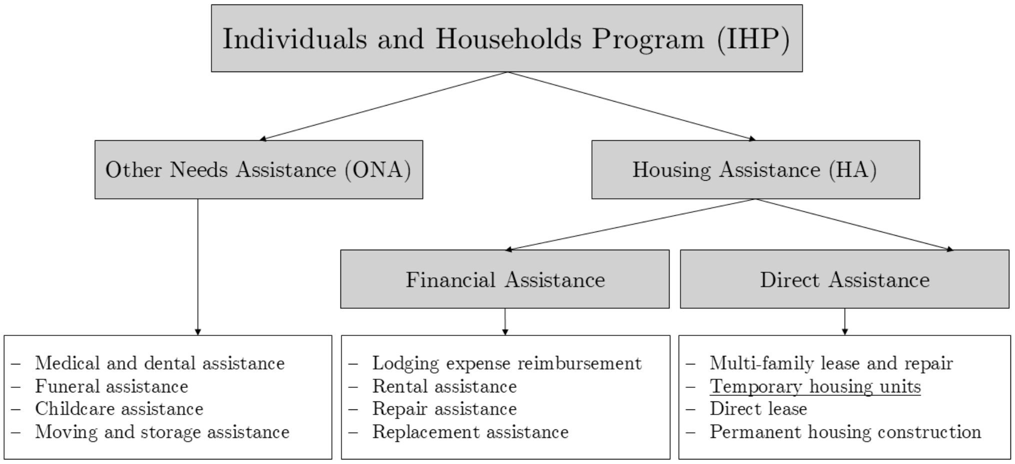
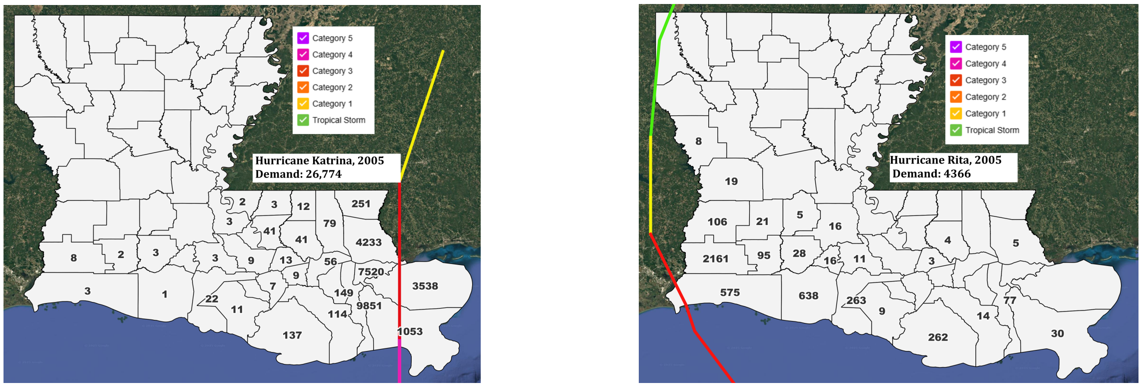


Fig. 3.4: The whole umbrella of Individual and Household Program (IHP) by FEMA

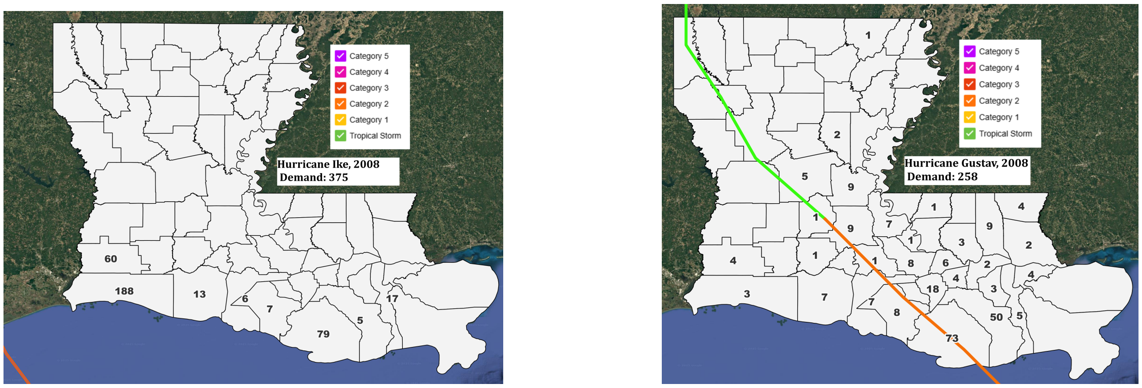
storms struck Louisiana during this period. Of these, 12 received major disaster declarations [FEMA]: Hurricane Ivan (2004), Hurricane Katrina (2005), Hurricane Rita (2005), Hurricane Gustav (2008), Hurricane Ike (2008), Hurricane Isaac (2012), Tropical Storm Harvey (2017), Hurricane Barry (2019), Hurricane Laura (2020), Hurricane Delta (2020), Hurricane Ida (2021), and Hurricane Francine (2024). However, Barry and Harvey did not activate FEMA IA, only PA was declared for these events. For Isaac and Ivan, FEMA approved only financial assistance and ONA. Consequently, we consider the remaining eight hurricanes as our scenario set. To characterize demand in each scenario, we utilized FEMA's IHP Valid Registrations dataset [FEMA], which contains applicant-level records for FEMA IA covering all major disasters since 2002 (approximately 25.6 million records). This dataset includes disaster declarations, disaster locations (state and parish level), applicant demographics, self-reported needs, and eligibility outcomes such as housing assistance details. From this dataset, we extracted parish-level demand for temporary housing in Louisiana across all eight major disasters. Figure 3.5 presents this data alongside hurricane tracks for the eight events that comprise our demand scenarios. Also, population and household counts at the parish and census tract levels were obtained from the U.S. Census Bureau's 2019–2023 ACS 5-year estimates [U.S. Census Bureau].

To establish baseline statewide capacity parameters, we begin with Louisiana's hotel inventory of approximately 98,877 rooms across roughly 1,033 properties [AHLA]. Assuming that 20 percent of the state's hotel stock could reasonably be made available for TSA during a major disaster, we set the baseline hotel capacity at 20,000 rooms. From this benchmark, we establish proportional baseline capacities for shelters at 60,000 spaces (three times hotel capacity) and commercial site capacity at 40,000 pads (twice hotel capacity). These statewide baseline capacities are then allocated to individual parishes proportionally based on each jurisdiction's share of the state's total household population, ensuring that capacity distribution reflects underlying demographic patterns and housing density. However, disaster impacts compromise the availability of these resources in affected areas. To capture this, we introduce a post-disaster availability factor ρ_ω that reflects the proportion of baseline capacity remaining operational in impacted parishes under scenario ω. This factor varies with disaster severity: low-impact events (Delta, Francine, Gustav) retain 90 percent of baseline capacity ($\rho_\omega = 0.90$). Hurricane Ike, with somewhat greater intensity, reduces availability to 80 percent ($\rho_\omega = 0.80$). Laura and Ida significantly compromise local capacity, leaving only 60 percent operational ($\rho_\omega = 0.60$). Hurricane Rita, one of the most intense storms in Louisiana's history, degrades capacity to 50 percent ($\rho_\omega = 0.50$). Finally, Hurricane Katrina, the most catastrophic event in our scenario set, reduces available capacity in impacted parishes to just 30 percent ($\rho_\omega = 0.30$). Critically, this availability factor applies only to parishes directly affected by each hurricane; non-impacted parishes retain their full baseline capacity.



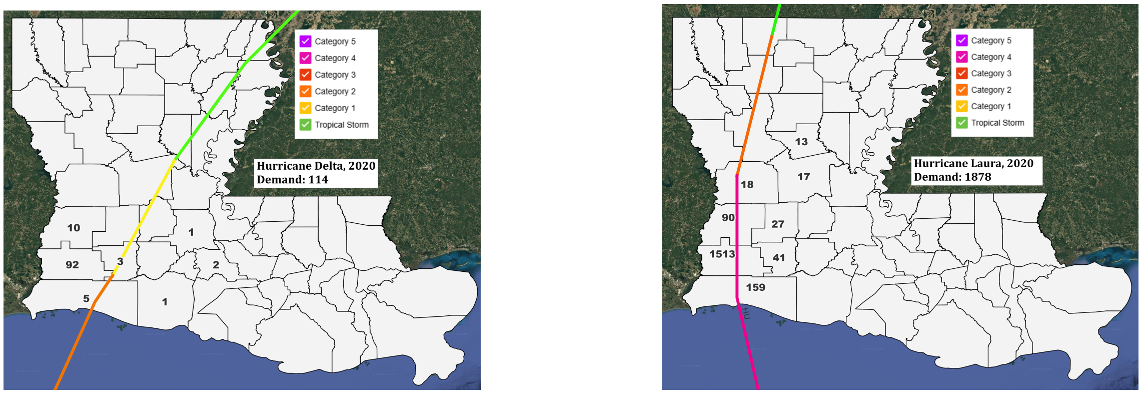
(a) Hurricane Katrina, 2005

(b) Hurricane Rita, 2005



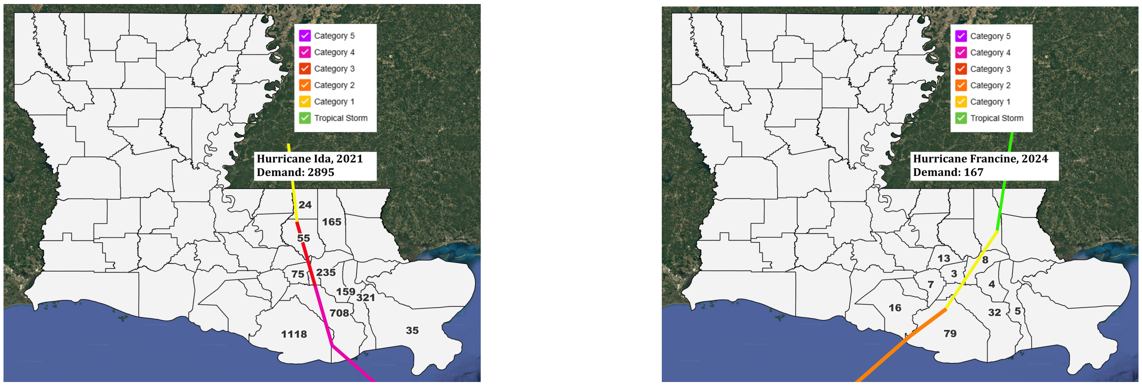
(c) Hurricane Ike, 2008

(d) Hurricane Gustav, 2008



(e) Hurricane Delta, 2020

(f) Hurricane Laura, 2020



(g) Hurricane Ida, 2021

(h) Hurricane Francine, 2024

Fig. 3.5: Louisiana's major hurricane tracks and their demand scenarios

3.4.1.2 Cost Structures and Supplier Setup

This section details the cost structure underlying our optimization model and describes the baseline supplier configuration. Table 3.1 presents the unit costs associated with each procurement strategy for mobile housing types. All monetary values are in USD per unit (one household placement). The cost structure follows a hierarchy:

$$c_k^{(\text{stock})} \leq c_{sk,3}^{(\text{unit})} < c_{sk,2}^{(\text{unit})} < c_k^{(\text{spot})} \quad \forall k \in k^m.$$

This hierarchy reflects the trade-off between advance planning and procurement flexibility, where early commitment reduces unit costs but requires upfront capital investment.

Table 3.1 Procurement costs for mobile housing units across different strategies ($ USD per unit)

$k \in k^m$	$c_k^{(\text{stock})}$	$c_{sk,2}^{(\text{unit})}$	$c_{sk,3}^{(\text{unit})}$	$c_k^{(\text{spot})}$
Trailer	20,000	40,000	30,000	50,000
MHU	50,000	70,000	60,000	100,000
ATTHU	90,000	110,000	100,000	180,000

In our baseline configuration, each supplier is specialized in providing only one type of mobile unit. Suppliers have time-dependent capacity constraints that reflect production lead times. Critically, no supplier can deliver units during phase 1 (immediate response), as manufacturing require minimum lead times that exceed this initial two-month window. Supplier capacity increases from phases 2 to 3, with phase 3 capacity approximately double that of phase 2, reflecting the additional time available for production. Table 3.2 summarizes these capacity constraints. The capacity structure also reflects the technical complexity factor across housing types. ATTHUs have the lowest supplier capacity due to their complex and longer production cycles. MHUs have intermediate capacity levels while trailers, which are the simplest mobile housing options, have the highest supply capacity.

Table 3.2 Supplier capacity limits by housing type and phase (units)

$k \in k^m$	α_{sk1}	α_{sk2}	α_{sk3}
Trailer	0	800	1,600
MHU	0	400	800
ATTHU	0	200	400

Each supplier contract carries a fixed agreement fee $c_{sk}^{(\text{fixed})} = \$100{,}000$ regardless of housing type. This cost represents the administrative efforts and staff time (rather than a payment to the supplier) required to establish formal procurement agreements, including legal review, contract negotiation, and vendor qualification processes. This agreement fee is an intangible but necessary cost that will be incurred whenever initiating a supplier relationship.

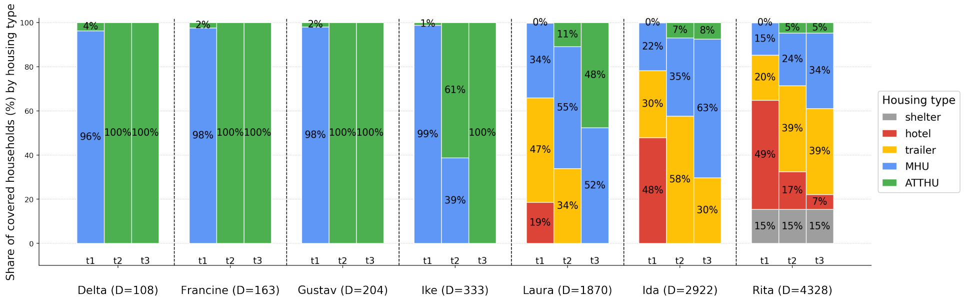
Deployment costs $c_k^{(\text{dep})}$ account for site preparation, unit installation, and connection to utilities. We assume all mobile unit deployments occur at commercial sites, specifically, units occupy pads in existing RV parks or mobile-home communities that FEMA leases from property owners. Deployment costs increase with unit complexity: trailers require \$10,000 per unit, MHUs require \$20,000, and ATTHUs require \$30,000 given their more permanent construction standards. Hotels and shelters incur no deployment costs. For hotels and shelters, only operational costs apply. Hotels incur \$100 per household per night, while shelters cost \$10 per household per night. Given the phase durations (approximately 2 months for phase 1, 6 months for phase 2, and 10 months for phase 3), the cumulative operational costs are calculated accordingly. Table 3.3 summarizes operational costs.

Table 3.3 Operational costs by housing type (\$)

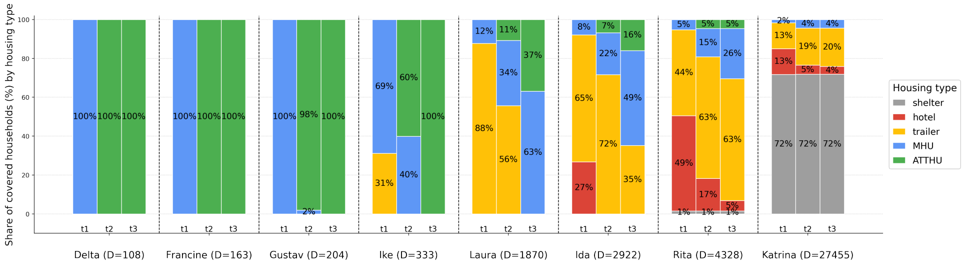
$k \in k^s \cup k^h$	$c_{k1}^{(\text{opr})}$	$c_{k2}^{(\text{opr})}$	$c_{k3}^{(\text{opr})}$
Hotel	6,000	18,000	30,000
Shelter	600	1,800	3,000

3.4.2 Case Results and Analysis

To evaluate the model's behavior under different risk profiles, we fix the pre-disaster budget at $b_0 = \$50M$ and the post-disaster budget at $b_1 = \$200M$. We then solve two planning problems: (i) Without Katrina, a scenario set comprising seven equiprobable historical events (Delta, Francine, Gustav, Ike, Laura, Ida, and Rita); and (ii) With Katrina, an expanded eight-scenarios portfolio that includes Katrina. These two allow us to examine how incorporating rare, extreme events reshapes optimal pre-disaster stockpiling strategies and post-disaster resource allocation decisions. We refer to the results of this analysis as the base case results.



(a) Without Katrina



(b) With Katrina

Fig. 3.6: Composition of covered households by housing type within each scenario and phase

Figure 3.6 illustrates the share of covered households by housing type for each scenario and phase under both planning approaches. In the immediate aftermath (phase 1), only pre-positioned stockpile units and operational lodging options (hotels and shelters) are available and contracted capacities cannot be activated. As recovery progresses into phase 2, the model activates supplier contracts, enabling procurement of additional mobile housing units. This phase represents the most significant shift in housing composition, as households transition from emergency accommodations to more stable temporary housing options. We set the transition burdens to $\phi_{\uparrow} = 0.05$ and downgrade burden $\phi_{\downarrow} = 2$. We checked the full journey of all covered households and found no downgrades in either plan. The housing allocation varies systematically with disaster magnitude. For small-scale events (Delta, Francine, Gustav, Ike), the generous post-disaster budget relative to demand enables the model to splurge on premium housing options that maximize per-household utility. In contrast, larger disasters (Laura, Ida, Rita) force a shift toward cost-effective coverage. Here, the model allocates budget to trailers and MHUs rather than ATTHUs, recognizing that covering more households with adequate housing generates greater total utility than providing luxury accommodations to a smaller subset. This reflects the trade-off between quality and coverage that emerges when budget becomes binding. The introduction of Hurricane Katrina into the scenario set changes system performance. Here, the budget $b_1 = \$200M$ is not enough to serve everyone. The plan covers about 52% of Katrina's demand (14,271 of 27,455 households). In this extreme case, the focus is on serving more survivors, often with shelters and trailers, rather than placing a smaller number in premium units.

Table 3.4 Pre-disaster stockpiles

Test	Trailer	MHU	ATTHU
No Katrina	885	632	4
With Katrina	1,911	229	0

Table 3.4 reports the optimal pre-disaster inventory composition under each planning approach. The inclusion of Katrina drives a shift toward cheaper coverage-oriented stockpiling (more trailers, less MHUs). For policymakers, this finding suggests a critical policy implication: if the planning objective emphasizes robustness to rare but catastrophic events, pre-disaster investments should favor large inventories of cost-effective units, while relying on procurement contracts (rather than stockpiles) for higher-specification units like MHUs and ATTHUs. Conversely, if planning targets range—moderate events that occur more frequently, maintaining a diversified stockpile with more MHUs and some ATTHUs maximizes average per-household utility across likely scenarios.

Table 3.5 presents the breakdown of post-disaster expenditures across four cost categories, along with total scenario costs and the percentage of the post-disaster budget utilized. The spending composition reveals a clear pattern: as disaster magnitude increases, the proportion of budget devoted to operational costs increases. In smaller-scale scenarios like Delta and Francine, the majority of spending flows to procurement and deployment of mobile housing units, reflecting a strategy focused on establishing stable, autonomous housing. For large-scale scenarios such as Rita and Katrina, the model allocates substantial budget shares to maintaining households in shelters and hotels across multiple phases. Spot market purchases happen only in scenarios where both (1) contracted supplier capacity is exhausted and (2) sufficient budget remains to warrant premium pricing for incremental units. Laura exemplifies this scenario, a large event that depletes contracted capacity

Table 3.5 Post-disaster spending by category (in $ millions)

Scenario	Procurement	Spot market	Deployment	Operational	Total	% of b_1
No Katrina						
Delta	11.44	0.00	5.32	0.00	16.76	8.40
Francine	17.49	0.00	8.07	0.00	25.56	12.80
Gustav	22.00	0.00	10.12	0.00	32.12	16.10
Ike	34.90	0.00	16.57	0.00	51.47	25.70
Laura	90.00	51.67	56.24	2.09	200.00	100.00
Ida	131.52	0.00	60.08	8.40	200.00	100.00
Rita	108.90	0.00	52.59	38.51	200.00	100.00
With Katrina						
Delta	11.88	0.00	5.40	0.00	17.28	8.60
Francine	17.93	0.00	8.15	0.00	26.08	13.00
Gustav	22.40	0.00	10.20	0.00	32.60	16.30
Ike	35.30	0.00	15.61	0.00	50.91	25.50
Laura	123.02	16.27	60.71	0.00	200.00	100.00
Ida	131.83	0.00	63.49	4.69	200.00	100.00
Rita	111.41	0.00	55.51	33.08	200.00	100.00
Katrina	62.78	0.00	40.63	96.59	200.00	100.00

but remains within feasible coverage range, justifying spot purchases to accommodate additional households in higher-quality units.

Table 3.6 reports the average utility per covered household across all phases for each scenario. The results confirm an intuitive pattern: with a fixed post-disaster budget, average per-household utility decreases with disaster magnitude. And Table 3.7 reports how much utility is obtained in each phase for each scenario, revealing that phase 2 drives the majority of total utility across nearly all scenarios. This temporal concentration occurs because phase 2 marks the first opportunity to activate supplier contracts and deploy mobile housing units that deliver substantially higher utility than the limited phase 1 options (stockpiles, hotels, shelters). Notably, despite higher procurement prices in phase 2 relative to phase 3, the model frequently opts to settle households earlier because the extended occupancy duration (spanning both phases 2 and 3) generates greater cumulative utility than delaying deployment to capture lower phase 3 prices. This finding highlights a critical cost-versus-stability trade-off: accepting premium procurement costs earlier in the recovery yields superior overall outcomes by providing households with stable, higher-quality accommodations for longer durations.

Table 3.6 Average utility across phases per covered household

Scenario	No Katrina	With Katrina
Delta	9.15	9.13
Francine	9.04	9.02
Gustav	9.05	9.03
Ike	8.69	8.48
Laura	7.21	6.87
Ida	6.08	5.97
Rita	4.76	4.70
Katrina	—	2.04

Table 3.7 Phase utilities by scenario

No Katrina							
	Delta	Francine	Gustav	Ike	Laura	Ida	Rita
Phase 1	852.8	1268.4	1588.4	2555.2	11,524.0	15,528.4	19,611.8
Phase 2	1056.2	1575.6	1975.6	2942.2	12,894.9	18,084.6	20,910.1
Phase 3	1056.2	1575.6	1975.6	3184.1	16,001.0	19,646.7	20,544.6

With Katrina								
	Delta	Francine	Gustav	Ike	Laura	Ida	Rita	Katrina
Phase 1	844.9	1260.5	1580.5	2353.3	11,156.9	15,918.0	20,496.6	37,555.2
Phase 2	1056.2	1575.6	1968.0	2934.6	11,757.7	16,883.7	21,319.9	28,716.9
Phase 3	1056.2	1575.6	1975.6	3184.1	15,627.6	19,531.8	20,047.3	21,280.5

3.4.3 Trade-off Analysis of Preparedness vs. Response Budgets

A fundamental question in disaster management policy concerns the optimal allocation of limited resources between pre-disaster preparedness and post-disaster response. To assess the value of preparedness investment, we conduct a sensitivity analysis that explores the budget allocation frontier while holding total available funding constant at \$250M. Starting from our base case allocation ($b_0 =$ \$50M preparedness, $b_1 =$ \$200M response), we incrementally shift resources toward preparedness in \$10M increments, testing budget combinations ranging from ($b_0 =$ \$10M, $b_1 =$ \$240M) to ($b_0 =$ \$110M, $b_1 =$ \$140M). For each budget pair (b_0, b_1), we re-solve the optimization model under both planning approaches, without Katrina and with Katrina, and record the resulting total expected utility (the first term of the objective function, summed across all scenarios and phases). Figure 3.7 presents the budget allocation frontier for both planning approaches along with marginal utility gains for each additional \$10M. The results reveal a pattern: across both planning approaches, shifting resources from response to preparedness consistently increases total expected utility. However, the marginal benefit of each additional \$10M shifted to preparedness exhibits diminishing returns. The slope of both curves, representing the marginal utility per million dollar of preparedness investment, declines monotonically as b_0 increases.

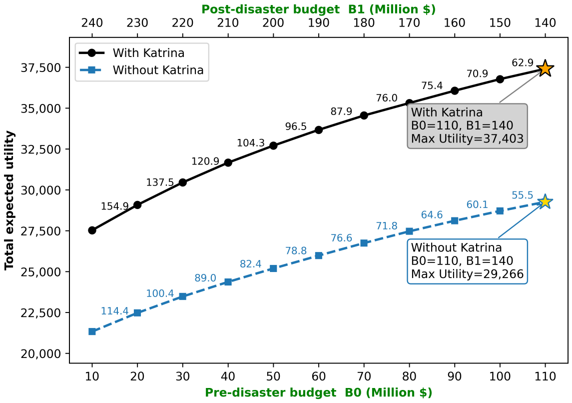


Fig. 3.7: Budget trade-off analysis

While we did not test allocations beyond the point of ($b_0 = \$110$M, $b_1 = \$140$M), the diminishing marginal returns pattern suggests that further shifts toward preparedness would eventually yield decreasing benefits, as response capacity becomes insufficient to address scenario-specific needs (i.e, operational expenses for hotels and ongoing deployment costs for mobile units). Note that in all of these combinations, we observed the same coverage rates achieved in the base case for each scenario (i.e., 100% coverage for small to moderate events and approximately 52% coverage for Katrina).

3.4.4 Need-Based Post-Disaster Budgeting

The base case analysis assumes a fixed post-disaster budget of $b_1 = \$200M$, allocated uniformly regardless of scenario. This reflects the common budgetary reality that emergency management agencies operate under predetermined appropriations established before disasters occur. However, this fixed-budget constraint imposes a mismatch: small disasters receive more resources per affected household than needed, while catastrophic events face severe resource scarcity relative to demand. An alternative policy paradigm scales post-disaster funding to actual need, providing resources commensurate with disaster magnitude. This subsection explores this question: if post-disaster resources can be flexibly scaled to match disaster size (for example, through federal supplemental appropriations or state emergency reserve funds), how does this flexibility reshape optimal preparedness strategies and household outcomes? To address this, we maintain the pre-disaster budget at $b_0 = \$50M$ but replace the fixed post-disaster budget constraint (equation 3.11) with a scenario-specific budget constraint (equation 3.23) that allocates $100K per qualified household in each scenario. Table 3.8 reports the resulting scenario-specific budgets, which range from $10.8M for Hurricane Delta (108 qualified households) to $2.75 billion for Hurricane Katrina (27,455 households).

$$\sum_{k\in K^m,t}\Big[\sum_{s\in S} c_{skt}^{(\text{unit})}\, Q_{sk\omega t} + c_k^{(\text{spot})}\, O_{k\omega t}\Big] + \sum_{k\in K^m,t,j} c_k^{(\text{dep})}\, V_{kj\omega t} + \sum_{k\in (K^s\cup K^h),i,t,j} c_{kt}^{(\text{opr})}\, Z_{ikj\omega t} \le b_1\omega, \quad \forall\omega \tag{3.23}$$

Table 3.8 Calibrated post-disaster budget

	Delta	Francine	Gustav	Ike	Laura	Ida	Rita	Katrina
$b_1\omega$	$10.8M	$16.3M	$20.4M	$33.3M	$187M	$292.2M	$432.8M	$2.8B

Figure 3.8 presents the share of covered households by housing type and Table 3.9 reports the optimal pre-disaster stockpile. Comparing this to the base case stockpile under "with Katrina" planning (Table 3.4) reveals a strategic re-balancing: (i) Trailer inventory decreases by 21% (from 1,911 to 1,502 units); (ii) MHU inventory increases by 12% (from 229 to 257 units); and (iii) ATTHU inventory appears (75 units, up from 0). Total expected utility increases to 43,245 (a 32% improvement compared to 32,707 in the base case) and we cover 100% of demand in all scenarios.

Table 3.9 Pre-disaster stockpiles with calibrated budget

Test	Trailer	MHU	ATTHU
With Katrina	1,502	257	75

This shift toward higher-specification mobile housing reflects a fundamental change in the model's strategic planning. Under fixed budgets, pre-disaster stockpiling must hedge

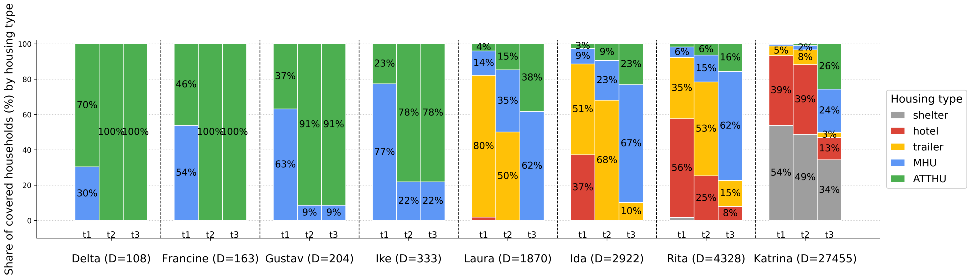


Fig. 3.8: Share of covered households by housing type under calibrated post-disaster budget

against resource scarcity in large scenarios, prioritizing low-cost trailers to maximize coverage. With calibrated b_1 budgets, the preparedness strategy can emphasize quality of phase 1 placements rather than quantity, stockpiling more MHUs and ATTHUs that deliver higher per-household utility when deployed immediately.

Examining Figure 3.8, one might expect substantially greater coverage with MHUs and ATTHUs in phases 2 and 3, given that \$100K per household fairly covers the total procurement and deployment costs for these premium units (\$80K-\$140K). However, the supplier capacity constraints are now the binding limitation on quality improvement. We observe limited spot market purchasing in phase 3; however, spot market prices (\$100K for MHUs, \$180K for ATTHUs) combined with deployment costs exceed the \$100K per-household budget allocation, making these purchases largely infeasible. This finding suggests that to meaningfully enhance coverage quality in catastrophic events, policymakers must invest in expanding and diversifying the supplier base, increasing aggregate procurement capacity through multi-vendor contracts and pre-qualified surge suppliers. The next subsection explicitly analyzes this supply-side intervention.

3.4.5 Expanding Supplier Base

To examine whether expanding supplier capacity can overcome the procurement limitations identified in the previous analysis, we modify the base case supplier structure by increasing the number of suppliers to three per housing type (rather than one), yielding nine total suppliers with identical agreement fee, per-unit pricing and capacity limits as the original single supplier (Tables 3.2 and 3.1). This configuration effectively triples the maximum procurable units of each housing type in each phase, at the cost of tripling upfront agreement fees from \$300K (3 suppliers) to \$900K (9 suppliers), paid from the pre-disaster budget b_0. Notably, the model chooses to contract with all nine suppliers despite the higher upfront cost, indicating that the value of relaxed capacity constraints justifies the investment. Under needs-based funding (\$100K per household) with this expanded supplier base, Figure 3.9 shows increased coverage with MHUs and ATTHUs in phases 2 and 3 across, with total expected utility rising to 47,081 (a 9% improvement over the single-supplier needs-based scenario (43,245) and a 44% gain relative to the base case (32,707)). Table 3.10 also shows a shift toward higher quality units in stockpiling.

Table 3.10 Pre-disaster stockpiles with calibrated budget & better base of suppliers

Test	Trailer	MHU	ATTHU
With Katrina	1,275	277	108

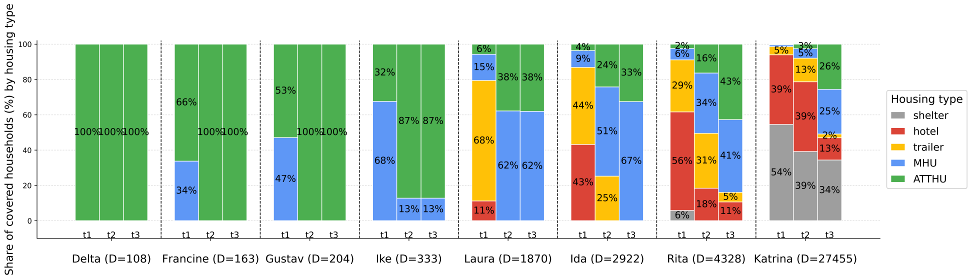


Fig. 3.9: Share of covered households by housing type when we have better base of suppliers

3.4.6 Impact of Expanded Hotel Participation

To examine whether expanded third-party lodging capacity can further improve disaster housing outcomes, we increase the available hotel inventory from the base case assumption of 20% of Louisiana's 98,877-room stock to 40%, effectively doubling accessible lodging capacity to approximately 40,000 rooms. We retain the needs-based post-disaster budget (\$100K per household) and nine-supplier configuration (three suppliers per housing type) established in the previous subsection, modifying only the hotel capacity constraint while maintaining the same scenario-based availability factors ρ_ω described in Section 3.4.1.1. The results reveal a strategic re-balancing toward stockpiling premium mobile housing units. As shown in Table 3.11, pre-disaster stockpiles shift from 1,275 trailers, 277 MHUs, and 108 ATTHUs to 692 trailers (-46%), 428 MHUs (+55%), and 153 ATTHUs (+42%).

Table 3.11 Pre-disaster stockpiles with calibrated budget & better base of suppliers & hotel capacity expansion

Test	Trailer	MHU	ATTHU
With Katrina	692	428	153

This reallocation drives total expected utility to 49,911, representing a 6% improvement over the nine-supplier baseline and a 53% gain relative to the original base case. Figure 3.10 illustrates the corresponding changes in household coverage composition by housing type across all phases under this expanded hotel capacity scenario.

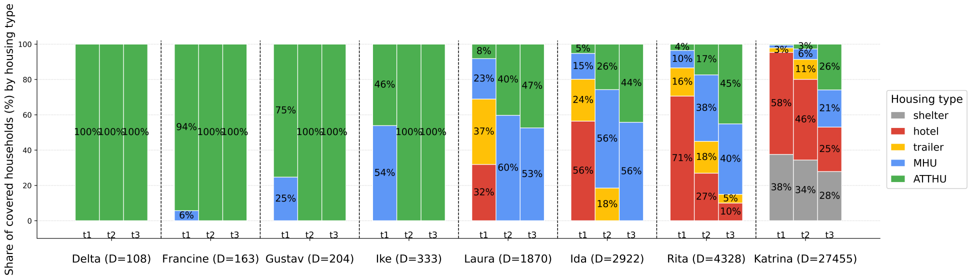


Fig. 3.10: Share of covered households by housing type when we have higher capacity of hotels statewide

The key observation here is: with sufficient hotel availability, the model systematically reduces expenditures on trailers, both in pre-disaster stockpiling and post-disaster procurement, reallocating these savings along two strategic pathways. First, freed pre-disaster funds shift toward stockpiling higher-quality MHUs and ATTHUs, enabling the model to accommodate households in more stable, autonomous housing during small and moderate disasters. Second, freed post-disaster budgets support increased hotel placements in catastrophic scenarios, allowing the model to avoid resorting to congregate shelters and maintain higher-quality emergency lodging even when mobile housing capacity is exhausted. From a disaster management policy perspective, this analysis demonstrates that strategic investments in expanding hotel industry partnerships can yield returns comparable to or exceeding direct investments in stockpiled housing inventory.

3.5 Conclusions

This research has addressed a critical gap in disaster housing literature by developing a comprehensive optimization framework that integrates survivor preferences with strategic resource planning across the entire post-disaster recovery period. Through the development and application of a two-stage stochastic programming model, this study provides state governments and emergency management agencies with a systematic approach to planning and deploying temporary housing resources that maximize the well-being of displaced households while navigating the inherent uncertainties of disaster occurrence and impact.

The framework makes important contributions to disaster housing theory and practice. The incorporation of household preferences into planning decisions represents a shift toward more survivor-centered disaster management that prioritizes not just the provision of shelter but the quality of life and recovery prospects of displaced households. By recognizing that survivor needs and preferences change over time, the model enables more nuanced decision-making that aligns housing solutions with the actual experiences and priorities of displaced households. The integration of pre-disaster and post-disaster procurement strategies within a unified optimization framework provides decision-makers with actionable insights into the trade-offs between preparedness investments and response capabilities. The model's ability to balance stockpiling strategies with supplier contracting options offers a more flexible and cost-effective approach to resource management than traditional methods that rely solely on post-disaster acquisition.

The application to Louisiana's hurricane response demonstrates the practical value of this framework in a state that faces recurring hurricane threats. From a policy perspective, this research offers several actionable recommendations for improving disaster housing practice. Specifically, we examine budget allocation trade-offs between pre-disaster and post-disaster phases, compare planning portfolios with and without extreme events like hurricane Katrina, evaluate the impact of expanding supplier capacity and third-party lodging availability, and assess the benefits of incorporating a needs-based post-disaster funding approach.

While this research advances our understanding of disaster housing planning, several areas warrant further investigation. Future research should explore the incorporation of social vulnerability indices and equity considerations explicitly into the optimization framework, ensuring that housing solutions address the needs of the most vulnerable populations. The development of more granular utility functions based on empirical household surveys and stated preference studies would enhance the model's ability to capture the heterogeneity of survivor preferences.

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General Conclusion

This thesis has advanced the field of disaster operations management by developing three interconnected optimization tools that address critical challenges in shelter network design, evacuation planning, and temporary housing management. Through systematic integration of risk assessment, behavioral modeling, and preference quantification, this research provides decision-makers with practical tools that enhance both the efficiency and attention to human needs in disaster response and recovery operations.

Collectively, the three chapters make substantial methodological contributions. Chapter 1 introduces the first risk-based optimization approach for shelter network design in the context of pedestrian-based evacuation in flood-prone areas, comprehensively assessing risks across all network components—population, shelters, and evacuation paths. Chapter 2 advances this foundation by proposing a novel bilevel optimization framework that explicitly models the hierarchical interactions between authorities and evacuees, capturing behavioral dynamics through a utility function grounded in the Fogg Behavior Model and enriched by interdisciplinary insights. Chapter 3 extends the temporal scope by developing a two-stage stochastic programming model for temporary housing capacity planning that integrates survivor preferences across multiple recovery phases while addressing uncertainty in disaster location and magnitude. Together, these chapters demonstrate how operations research can be enriched through interdisciplinary collaboration, integrating insights from behavioral science, economics, hydrology, and disaster management practice. The shift toward survivor-centered approaches that prioritize not just logistical efficiency but also quality of life and recovery prospects represents a fundamental advancement in humanitarian operations research.

The practical impact of this research is evidenced by successful collaborations with international organizations and government agencies. The partnership with the World Bank and the Government of Haiti enabled the development of well-defined, realistic problem formulations adequately parameterized using real data despite the scarcity of formal digital information in developing countries. The solutions have been validated by partners and extended to make recommendations for other regions of Haiti, with recognition as innovative tools applicable across different contexts. Similarly, the application to Louisiana's hurricane response demonstrates the tools' relevance for disaster-prone regions in developed countries, providing actionable policy recommendations on budget allocation, procurement strategies, and housing capacity planning.

This thesis opens rich avenues for future research. The demonstrated integration of behavioral theories into mathematical optimization frameworks invites exploration of other behavioral models, hazard types, and transportation modes. As a key research direction, accounting for decision uncertainty, a type of uncertainty unique to bilevel optimization, becomes crucial when authorities are not certain about evacuees' reaction or evacuees are not certain about the observed decision of authorities. In temporary housing planning, the development of more granular utility functions based on empirical household surveys and stated preference studies would enhance the model's ability to capture the heterogeneity of survivor preferences.

Ultimately, this thesis demonstrates that effective disaster sheltering and housing management requires moving beyond traditional approaches focused solely on logistical efficiency to embrace holistic frameworks that integrate risk, behavior, utility, and evolving preferences. The developed optimization tools facilitate the transfer of knowledge and recommendations to practitioners, inform managerial insights, and quantify the impact of policies across multiple dimensions of disaster management. As natural disasters continue to increase in frequency and intensity, such human-centered approaches become ever more essential for protecting vulnerable populations and building resilient communities capable of withstanding and recovering from future disasters.

Appendix A

Computing the percentage of uncovered people in the existing network

In order to compute the percentage of uncovered people in the existing network, we need to determine how many people are covered with the set of existing shelters denoted by J', $J' \cap J = \emptyset$. If there are no existing shelters ($J' = \emptyset$), then the percentage of uncovered people is 100%. Otherwise, we need to solve a mathematical model. In the following, we detail how to compute the percentage of uncovered people when $J' \neq \emptyset$.

When $J' \neq \emptyset$, we solve the following model to determine the percentage of uncovered people with the existing network:

Model 3

$$\text{Minimize} \quad \theta_1 \sum_{j \in J'} \sum_{i \in W_j(r)} -\tilde{r}_i^p p_i x_{ij} + \theta_2 \sum_{j \in J'} \tilde{r}_j^s q_j y_j + \theta_3 \sum_{j \in J'} \sum_{i \in W_j(r)} \tilde{r}_{ij}^e p_i x_{ij} \tag{A.1}$$

$$\text{s.t.} \sum_{i \in W_j(r)} p_i x_{ij} \leq q_j y_j, \quad j \in J' \tag{A.2}$$

$$\sum_{j \in V_i(r) \cap J'} x_{ij} \leq 1, \quad i \in I \tag{A.3}$$

$$x_{ij} \geq 0, i \in I, \quad j \in J' \tag{A.4}$$

$$y_j \in \{0, 1\}, \quad j \in J'. \tag{A.5}$$

This model is similar to Model 1 but has not budget constraints. In addition, for the set J', the normalized population risk is measured by assuming that the percentage of uncovered people is 100%.

In our set of experiments, we restrict ourselves to the weights $\theta_1 = \theta_2 = \theta_3 = 0.33$ when solving Model 2. Using the optimal solution of Model 2, the number of covered people in the existing network is computed as $\tilde{p}_i = \sum_{j \in J'} \sum_{i \in W_j(r)} p_i \tilde{x}_{ij}^{(2)}$, where $\tilde{x}_{ij}^{(2)}$ represents the values of the x-variables in the optimal solution of Model 2. Then, for each population point, we compute the percentage of uncovered people in the existing network as $(1 - \tilde{p}_i / p_i)$.

Normalization of the risk measures

In this section, we explain how the population risk, the shelter risk and the evacuation risk have been normalized. The data was normalized by using standard methods considering the interquartile range (IQR) and winsorizing for outlier values. Using the concept of IQR, and defining Q1 and Q3 as the first and third quartile, all values that are below Q1 - 1.5 IQR, and all values that are above Q3 + 1.5 IQR are considered as outliers, i.e., lower outliers and upper outliers. Winsorizing is then used by setting all values below Q1 - 1.5 IQR to Q1 - 1.5 IQR, and all values above Q3 + 1.5 IQR to Q3 + 1.5 IQR. Using the resulting data, it is then scaled to a [0, 1]-range. In the following, we provide the detailed notation to explain how each risk measure has been normalized.

The normalized population risk, $\tilde{r}_i^p, i \in I$, is computed as follows. As previously explained, all values in $\tilde{r}_i^p, i \in I$ are winsorized using 1.5 IQR, and the resulting risk is denoted by $\widehat{r_i^p}$. Then, the normalized value is obtained by dividing the resulting risk by its risk interval, that is,

$$\tilde{r}_i^p = \frac{\widehat{r_i^p} - \min_{i \in I} \widehat{r_i^p}}{\max_{i \in I} \widehat{r_i^p} - \min_{i \in I} \widehat{r_i^p}}, \forall i \in I. \tag{B.1}$$

The normalized shelter risk, $\tilde{r}_j^s, j \in J \cup J'$, is computed for 1) the normalized shelter risk for new potential shelters and 2) the normalized shelter risk for existing shelters. For the normalized shelter risk for new potential shelters, all values in $r_j^s, j \in J$ are winsorized using 1.5 IQR, and the resulting risk is denoted by $\widehat{r_j^s}$. Similarly, for the normalized shelter risk for existing shelters, all values in $r_j^s, j \in J'$ are winsorized using 1.5 IQR, and the resulting risk is denoted by $\widehat{r_j^s}$. Then, the normalized value is obtained by dividing the resulting risk by its risk interval, that is,

$$\tilde{r}^s_j = \frac{\widehat{r^s_j} - \min_{j \in J} \widehat{r^s_j}}{\max_{j \in J} \widehat{r^s_j} - \min_{j \in J} \widehat{r^s_j}}, \forall j \in J, \tag{B.2}$$

and

$$\tilde{r}^s_j = \frac{\widehat{r^s_j} - \min_{j \in J'} \widehat{r^s_j}}{\max_{j \in J'} \widehat{r^s_j} - \min_{j \in J'} \widehat{r^s_j}}, \forall j \in J'. \tag{B.3}$$

The normalized evacuation risk is computed for all pairs of population points i and shelters j within the maximal coverage radius r, that is, $\tilde{r}^e_{ij}, i \in I, j \in V_i(r)$. Similarly to the normalized shelter risk it is computed for 1) the evacuation towards new potential shelters and 2) the evacuation towards existing shelters. For the normalized evacuation risk towards new potential shelters, all values in $r^e_{ij}, i \in I, j \in V_i(r) \cap J$ are winsorized using 1.5 IQR, and the resulting risk is denoted by $\widehat{r^e_{ij}}$. Similarly, for the normalized evacuation risk towards existing shelters, all values in $r^e_{ij}, i \in I, j \in V_i(r) \cap J'$ are winsorized using 1.5 IQR, and the resulting risk is denoted by $\widehat{r^e_{ij}}$. Then, the normalized value is obtained by dividing the resulting risk by its risk interval, that is,

$$\tilde{r}^e_{ij} = \frac{\widehat{r^e_{ij}} - \min_{i \in I, j \in V_i(r) \cap J} \widehat{r^e_{ij}}}{\max_{i \in I, j \in V_i(r) \cap J} \widehat{r^e_{ij}} - \min_{i \in I, j \in V_i(r) \cap J} \widehat{r^e_{ij}}}, \forall i \in I, j \in V_i(r) \cap J, \tag{B.4}$$

and

$$\tilde{r}^e_{ij} = \frac{\widehat{r^e_{ij}} - \min_{i \in I, j \in V_i(r) \cap J'} \widehat{r^e_{ij}}}{\max_{i \in I, j \in V_i(r) \cap J'} \widehat{r^e_{ij}} - \min_{i \in I, j \in V_i(r) \cap J'} \widehat{r^e_{ij}}}, \forall i \in I, j \in V_i(r) \cap J'. \tag{B.5}$$

Building the *road layer*

In the following, we first describe the data extracted from OSM. Then, we explain how this data was connected with our shelter network (population points and shelters) to create the *road layer*.

First, from OSM, we extracted a network $\mathcal{G} = (\mathcal{N}, \mathcal{A})$, where $\mathcal{N}$ represents a set of single points in space (referred to as the set of nodes) and $\mathcal{A}$ represents the set of road segments (referred to as the set of arcs). Each node $n \in \mathcal{N}$ is associated with a latitude and a longitude. Each arc $(k, n) \in \mathcal{A}$ is associated with a source node $k \in \mathcal{N}$, a destination node $n \in \mathcal{N}$, and a distance $\tilde{d}_{kn}$ (in km). In the case of pedestrian-based evacuation, we assume that a road can be used in any direction. Therefore, if there exists two arcs between the same pair of nodes, that is $(k, n), (n, k) \in \mathcal{A}, k, n \in \mathcal{N}$, then we set the distance of arcs (k, n) and (n, k) as $(\tilde{d}_{kn} + \tilde{d}_{nk})/2$.

Second, we had to connect the *OSM data* with our set of population points I and shelters $J \cup J'$. Therefore, using the *population layer*, *existing shelter layer*, *potential new shelter layer*, and *OSM layer*, we created an additional layer referred to as the *road layer*. This *road layer* is represented by the network $\mathbf{G} = (\mathbf{N'}, \mathbf{A'})$. The set of increased nodes comprises the original set of nodes $\mathcal{N}$ as well as all the population and shelter vertices, that is, $\mathbf{N'} = \mathcal{N} \cup I \cup J \cup J'$. Because vertices V are not in the *OSM layer*, they had to be connected to the road network. Therefore, the set of increased arcs is defined as $\mathbf{A'} = \mathcal{A} \cup \{(i, n) : i \in I, n \in \mathcal{N}, d_{in} \leq r_1\} \cup \{(n, j) : n \in \mathcal{N}, j \in J \cup J', d_{nj} \leq r_2\}$ as the original set of arcs as well as arcs between the population points and nodes within a radius r_1, and arcs between nodes and shelters within a radius r_2. Note that the distances $d_{in}, i \in I, n \in \mathcal{N}$ and $d_{nj}, n \in \mathcal{N}, j \in J \cup J'$ are computed as an Euclidean distance. In addition, after discussions with the H-SDRMCRP team, the values of r_1 and r_2 were set to 3 and 0.25 km.

Determining the travel time from $i \in I$ to $j \in J \cup J'$

In this section, we explain how the travel time from $i \in I$ to $j \in J \cup J'$ has been estimated. First, we provide an estimate for the evacuation travel time of each arc in $\mathbf{A'}$. Second, because multiple paths can exist from $i \in I$ to $j \in J \cup J'$, a Dijkstra shortest-path algorithm is used to compute the shortest path (using the evacuation travel time) between each population point $i \in I$ and shelter $j \in J \cup J'$.

First, to determine the travel time of each arc $\mathbf{A}'$, we have to determine the evacuation speed which represents the walking speed according to the flood depth. Note that the evacuation speed is measured in kilometer per hour (km/h). Using the *Mean* values from Table 3 in Bernardini et al. [2020] (by converting the flood depth in meters and the walking speed in km/h), we conducted a linear regression to determine the evacuation speed. Figure 1 presents the converted *Mean* values from Table 3 (the speed in km/h according to the flood depth in meters) with our linear regression. This linear regression led us to compute the evacuation speed of each node of the increased network, i.e., $n \in \mathbf{N}'$, as:

$$\phi_k = \max\{0, -1.2446 f_k^d + 3.3861\} \tag{D.1}$$

where f_k^d is flood depth of node k in meters. For population points ($i \in I$), this value is set as f_i^d as defined in Section 1.5.2. For shelters ($j \in J \cup J'$), this value is set as f_j^d as defined in Section 1.5.3. For all other nodes ($n \in \mathcal{N}$), we defined a square buffer of 5m × 5m around each node $n \in \mathcal{N}$ and conducted zonal statistics by overlapping the *flood layer* with the *road layer*. We then obtained for each buffer around a node its average flood depth which was defined as $f_n^d, n \in \mathcal{N}$.

For each arc $(n, k) \in \mathbf{A}'$, if $\phi_n + \phi_k > 0$, its evacuation travel time is then computed as:

$$\frac{\tilde{d}_{nk}}{(\phi_n + \phi_k)/2}, \tag{D.2}$$

otherwise, if $\phi_n + \phi_k = 0$, then its evacuation time is 0.

Second, in graph $\mathbf{G} = (\mathbf{N}', \mathbf{A}')$, there might exist multiple paths between a given population point $i \in I$ and a given shelter $j \in J \cup J'$. Therefore, a Dijkstra shortest-path algorithm [Dijkstra, 1959] is used to determine the shortest evacuation travel time (as computed in Equation D.2) from each population point $i \in I$ to each shelter location j. This shortest evacuation travel time corresponds to $t_{ij}, (i, j) \in E$.

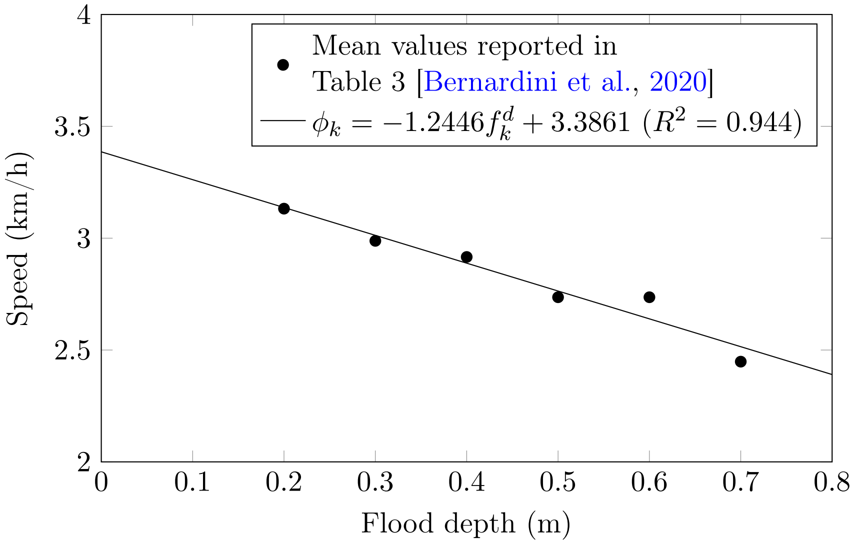

Fig. 1: Linear regression with the mean values reported in Table 3 of Bernardini et al. [2020]

Summary of the mathematical notation

Table 1 Summary of the mathematical notation

Sets	
I	Set of population points
J	Set of potential shelter locations
J'	Set of existing shelters
$V_i(r)$	Set of shelters located within a coverage radius of r from population point i
$W_j(r)$	Set of population points located within a coverage radius of r from shelter location j
Parameters	
p_i	Estimated sheltering demand in population point i
q_j	Capacity of shelter located at j
c_j	Cost of locating a shelter at j
$\tilde{r}_i^p$	Normalized population risk associated with people in population point i
$\tilde{r}_j^s$	Normalized shelter risk associated with locating a shelter at j
$\tilde{r}_{ij}^e$	Normalized evacuation risk associated with walking on edge (i, j)
B	Total budget to locate new shelters
Decision variables	
y_j	Binary variable equal to one if a new shelter is located at vertex j, and zero otherwise
x_{ij}	Proportion of population from i assigned to shelter j

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Appendix B

Single-level reformulation of the RBBO-SLEPP model using Karush-Kuhn-Tucker conditions of the lower-level problem

The bi-level optimization problem can be transformed into a single-level problem through a process known as single-level reformulation. This approach is widely used and is considered the most common approach for reformulating bi-level problems, especially when the lower-level problem is a convex and linear program, as in our case [Sinha et al., 2017].

The reformulation involves constructing Karush-Kuhn-Tucker (KKT) optimality conditions for the lower-level problem and incorporating these new conditions into the upper-level problem. This transformation is based on the principle that for linear optimization problems, KKT conditions, also referred to as complementary slackness conditions, are both necessary and sufficient for optimality [Calvete and Galé, 2020]. By replacing the lower-level optimization problem with its KKT conditions, we create an equivalent single-level problem that captures the essence of the original bi-level structure. The resulting single-level problem, while potentially more complex due to the added KKT conditions, allows for a more straightforward solution using standard optimization techniques.

To construct KKT optimality conditions of the lower-level problem, let λ_i and μ_j be the dual variable vectors for constraints 2.5 and 2.6, respectively. The dual formulation of the lower-level problem is:

$$\text{Minimize} \quad \sum_{i \in I} \lambda_i d_i + \sum_{j \in J} q_j y_j \mu_j \tag{A.1}$$

$$\text{s.t.} \quad \lambda_i + \mu_j \geq U_{ijt}, \quad i \in I, j \in J, t \in T \tag{A.2}$$

$$\lambda_i \geq 0, \quad i \in I \tag{A.3}$$

$$\mu_j \geq 0, \quad j \in J \tag{A.4}$$

Therefore, the dual feasibility condition is:

$$\lambda_i + \mu_j \geq U_{ijt}, \quad i \in I, j \in J, t \in T \tag{A.5}$$

And, the complementary slackness conditions are:

$$\lambda_i(d_i - \sum_{j \in J} \sum_{t \in T} x_{ijt}) = 0, \quad i \in I \tag{A.6}$$

$$\mu_j(q_j y_j - \sum_{i \in I} \sum_{t \in T} x_{ijt}) = 0, \quad j \in J \tag{A.7}$$

$$x_{ijt}(\lambda_i + \mu_j - U_{ijt}) = 0, \quad i \in I, j \in J, t \in T \tag{A.8}$$

Note that the complementary slackness conditions A.10, A.7, and A.8 are nonlinear. However, a constraint in the form $ab = 0$, where a, $b \geq 0$, can be linearized by replacing it with the two expressions $a \leq Mu$ and $b \leq M(1-u)$, where M is a sufficiently large number and u is a binary variable [Fortuny-Amat and McCarl, 1981]. Let us define such binary variables ζ_i, η_j, and ξ_{ijt} for the complementary slackness conditions. The linearization procedure creates two linear inequalities for each nonlinear constraint. After linearization of the constraints A.10, A.7, and A.8, the single-level reformulation of the bi-level optimization problem is:

$$\text{Minimize} \quad \sum_{j \in J} \sum_{i \in I} \sum_{t \in T} (\tilde{r}^e_{ijt} - \tilde{r}^p_i) x_{ijt} \tag{A.9}$$

$$\text{s.t.} \quad \sum_{j \in J} c_j y_j \leq B \tag{A.10}$$

$$\sum_{j \in J} \sum_{t \in T} x_{ijt} \leq d_i, \quad i \in I \tag{A.11}$$

$$\sum_{i \in I} \sum_{t \in T} x_{ijt} \leq q_j y_j, \quad j \in J \tag{A.12}$$

$$\lambda_i + \mu_j \geq U_{ijt}, \quad i \in I, j \in J, t \in T \tag{A.13}$$

$$\lambda_i \leq M\zeta_i, \quad i \in I \tag{A.14}$$

$$d_i - \sum_{j \in J} \sum_{t \in T} x_{ijt} \leq M(1 - \zeta_i), \quad i \in I \tag{A.15}$$

$$\mu_j \leq M\eta_j, \quad j \in J \tag{A.16}$$

$$q_j y_j - \sum_{i \in I} \sum_{t \in T} x_{ijt} \leq M(1 - \eta_j), \quad j \in J \tag{A.17}$$

$$x_{ijt} \leq M\xi_{ijt}, \quad i \in I, j \in J, t \in T \tag{A.18}$$

$$\lambda_i + \mu_j - U_{ijt} \leq M(1 - \xi_{ijt}), \quad i \in I, j \in J, t \in T \tag{A.19}$$

$$x_{ijt} \geq 0, \quad i \in I, j \in J, t \in T \tag{A.20}$$

$$\lambda_i \geq 0, \quad i \in I \tag{A.21}$$

$$\mu_j \geq 0, \quad j \in J \tag{A.22}$$

$$y_j \in \{0, 1\}, \quad j \in J \tag{A.23}$$

$$\zeta_i \in \{0, 1\}, \quad i \in I \tag{A.24}$$

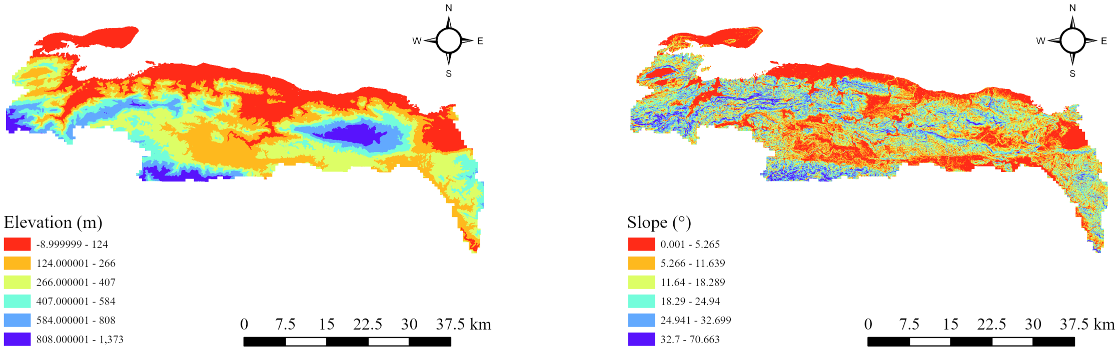
$$\eta_j \in \{0, 1\}, \quad j \in J \tag{A.25}$$

$$\xi_{ijt} \in \{0, 1\}, \quad i \in I, j \in J, t \in T \tag{A.26}$$

where M is a sufficiently large number.

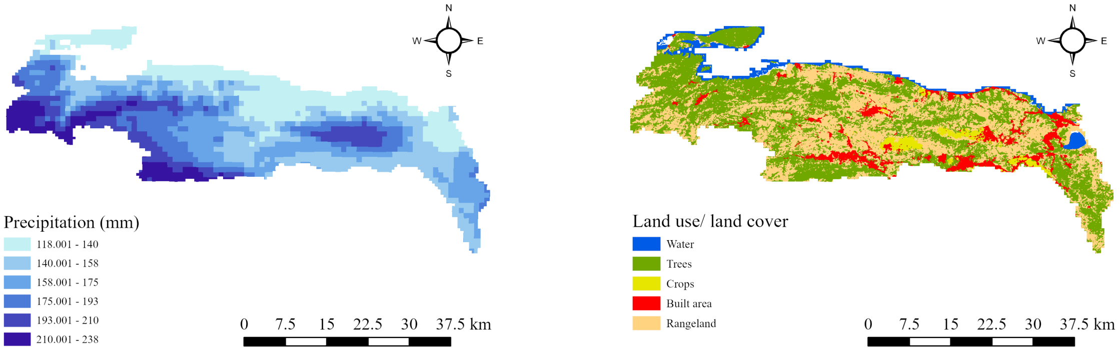
Building the Flood Evolution Index (FEI)

In developing countries like Haiti, access to advanced remote sensing technologies and comprehensive historical disaster data is often limited. This scarcity poses challenges in accurately tracking and predicting the behavior of disasters such as floods. To overcome this, we leverage Geographic Information System (GIS) tools to incorporate key influential factors that contribute to the evolution of floods. By integrating regional characteristics and available spatial datasets, we estimate flood behavior and create a relative index—the Flood Evolution Index (FEI)—to assess how floods may develop across different locations within the study area. Five critical factors were considered in constructing the FEI: elevation, slope, precipitation, land use/land cover, and flow accumulation (distance to streams). The selection of these factors is based on their relevance in influencing flood evolution [Shafapour et al., 2017, Malczewski, 2006, Kourgialas and Karatzas, 2011, Tehrany et al., 2014, 2015] and the availability of data for the region. ArcGIS Pro 3.3.0 was utilized for managing and processing all spatial data involved in developing the FEI.



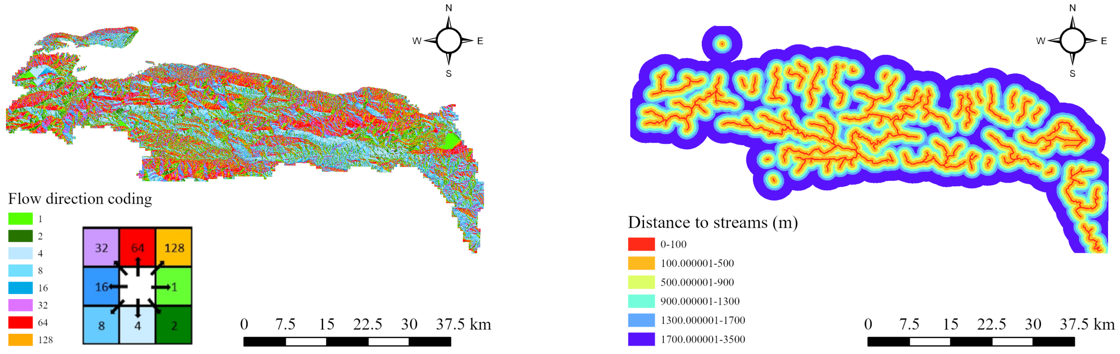
(a) Elevation map

(b) Slope map



(c) Precipitation map

(d) Land cover map



(e) Flow direction map

(f) Distance to streams map

Fig. 2: Overview of environmental maps used in the analysis.

Elevation This factor plays a significant role in flood evolution by influencing water accumulation and flow patterns. Areas with lower elevations are more prone to flooding because water naturally moves towards these zones due to gravity. In low-lying regions, water tends to accumulate and remain for extended periods, leading to quicker inundation and prolonged flood conditions. This accumulation accelerates the evolution of floods, making these areas particularly vulnerable [Shafapour et al., 2017]. To represent the elevation across the study area, we obtained a Digital Elevation Model (DEM) from the ASTER Global Digital Elevation Model (GDEM) with a 30-meter resolution, sourced from the Earth Explorer USGS data portal [U.S. Geological Survey (USGS), 2022]. The DEM provides a detailed representation of the bare earth's topographic surface, excluding vegetation and man-made structures (Figure 2a).

Slope This factor influences the speed and direction of water flow, thereby affecting how floods evolve in different terrains. Gentle or flat slopes, typically found in lower elevation areas, allow water to accumulate, facilitating rapid flood development. Conversely, steeper slopes encourage faster runoff, reducing the likelihood of water accumulation and slowing down flood evolution in those areas [Kourgialas and Karatzas, 2011]. Using the Slope tool of ArcGIS, we calculated the slope values in degrees from the processed DEM data (Figure 2b).

Precipitation The intensity and distribution of precipitation are fundamental factors in flood evolution. Higher precipitation levels contribute to greater water input into the system, accelerating flood development, especially in areas already prone due to topography and land cover [Kourgialas and Karatzas, 2011]. We extracted precipitation data from WorldClim [Worldclim, 2020], a database offering high-resolution global weather and climate information. Specifically, we utilized monthly precipitation data from 1970 to 2000 with 30 seconds (approximately 1 km^2) resolution. Haiti has a tropical marine climate with two distinct rainy seasons occurring from March to May and from August to October [Heimhuber et al., 2015]. By employing the Cell Statistics tool in ArcGIS, we calculated the average precipitation over six months for each cell, generating a spatial representation of precipitation intensity across the study area (Figure 2c).

Land use/land cover This factor affects the rate at which floods evolve by influencing surface runoff, infiltration, and water retention. Different land covers have varying capacities to absorb rainfall and slow down water movement. We derived a land use/land cover map from ESA Sentinel-2 imagery at 10-meter resolution [Observatory and Esri, 2022], classifying the Nippes department into five main classes (Figure 2d): (i) water: areas where water was predominantly present throughout the year; (ii) trees: any significant clustering of tall (approximately 15 feet or higher) dense vegetation, typically with a closed or dense canopy; (iii) crops: human planted/plotted cereals, grasses, and crops not at tree height; (iiii) rangeland: open areas covered in homogeneous grasses with little to no taller vegetation including wild cereals and grasses with no obvious human plotting; (iv) built area: human made structures, major road and rail networks, large homogeneous impervious surfaces including parking structures, office buildings and residential housing.

Distance to streams and channels The proximity to streams and the pattern of flow accumulation significantly influence how floods evolve in a region. Areas closer to rivers and streams are more likely to experience rapid flood onset due to the accumulation and overflow of water bodies during heavy rainfall events [Kourgialas and Karatzas, 2011]. Understanding the flow direction and accumulation helps in identifying pathways through which floodwaters may spread. To analyze this factor, we performed several steps using ArcGIS Pro: (i) filling sinks: we used the Fill tool to correct imperfections in the DEM, such as sinks or areas of artificially low elevation that could disrupt flow direction calculations; (ii) determining flow direction: the Flow Direction tool allowed us to establish the direction of steepest descent from each cell, essential for modeling how water moves across the surface (Figure 2e); (iii) calculating flow accumulation: with the flow directions established, we applied the Flow Accumulation tool to compute the accumulated flow into each downslope cell, effectively mapping the streamlines or natural drainage networks; (iv) calculating distance to streams: finally, using the Euclidean Distance tool, we calculated the distance of each cell from the nearest stream, producing a map that illustrates proximity of each cell to streamlines and channels (Figure 2f). Areas closer to streams are more susceptible to rapid flood evolution due to the higher likelihood of water accumulation and overflow.
After obtaining and processing the five layers, we standardized each layer using the Re-

classify tool in ArcGIS. Each factor was reclassified into five classes representing their contribution to flood evolution: 10=very high, 8=high, 6=moderate, 4=low, 2=very low. This reclassification made the layers unitless and suitable for overlay analysis. To combine the factors into a single index, we employed the Weighted Sum tool in ArcGIS. This tool overlays the reclassified rasters, multiplying each by an assigned weight and summing them to produce the final index. The weights were assigned based on the relative importance of each factor in influencing flood evolution [Kourgialas and Karatzas, 2011]: w(elevation)=0.34, w(slope)=0.165, w(precipitation)=0.13, w(land use/land cover)=0.235, w(distance to Streams)=0.13. The resulting FEI map (Figure 3) provides a spatial representation of the relative potential for flood evolution across different locations in the study area. Areas with higher FEI values are more likely to experience rapid flood development due to the combined effects of low elevation, gentle slopes, high precipitation, proximity to streams, and land cover types that promote runoff. Conversely, areas with lower FEI values are less susceptible to quick flood evolution.

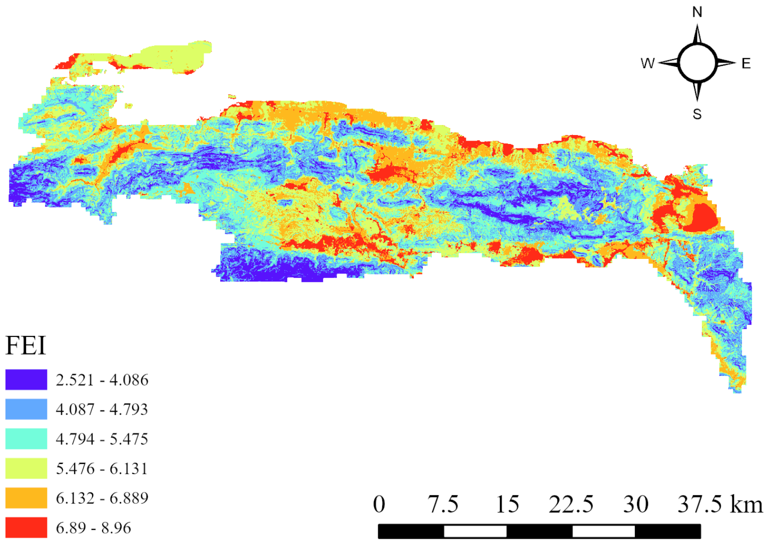


Fig. 3: Flood Evolution Index

Building the Urban Index (UI)

In this section, we detail the development of the UI for the Nippes department. This index quantifies the degree of urbanization within the study area, providing a relative measure that distinguishes between urban and rural grids based on population density and infrastructure availability. Rural regions, especially in developing countries, are commonly characterized by lower population densities and less developed infrastructure [Comín, 2020]. These attributes significantly influence accessibility and the provision of essential services, which are critical factors in road network analysis and planning. The process of building the UI involves several steps. First, the study area is divided into grids of 500 m × 500 m. For each grid i, the population density (d_i^p) is calculated as the number of people living within that grid, representing the population in need of shelter (p_i). To calculate the infrastructure density, we utilize real-road network data extracted from OpenStreetMap, which includes nodes and arcs representing the road network in Haiti. By overlaying the road network onto the population grid layer using the Intersection tool in the Geoprocessing toolbox of QGIS, we determine the road segments that pass through or intersect each grid. The infrastructure density (d_i^p) for each grid i is then calculated as the sum of the lengths of all road segments within the grid, serving as a proxy for road network density. Both population density and infrastructure density values are then normalized to ensure comparability and to mitigate the influence of outliers. We then formulate an index defined as:

$$UI_i = \tilde{d_i^p} \times \tilde{d_i^r} \tag{C.1}$$

Where the UI_i represent the Urban Index for grid i, $\tilde{d_i^p}$ is the normalized population density and $\tilde{d_i^r}$ is the normalized road network density in grid i. The resulting UI provides a relative measure of urbanity within the study area. Higher UI values indicate higher levels of urbanization—that is, higher population density and greater infrastructure availability—while lower values correspond to more rural characteristics.

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