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# OPTIMIZATION APPROACHES FOR CLIMATE-INDUCED DISPLACEMENT: A MULTI-MODEL FRAMEWORK FOR LONG-TERM PLANNING

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OPTIMIZATION APPROACHES FOR CLIMATE-INDUCED DISPLACEMENT: A MULTI-MODEL FRAMEWORK FOR LONG-TERM PLANNING

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# Abstract

Climate change is reshaping global patterns of human mobility as environmental degradation, prolonged droughts, sea-level rise, and other slow-onset changes gradually push communities to leave their homes. Unlike sudden disasters, these changes build over time, often leading to severe and sometimes irreversible declines in the long-term habitability of these regions.

As climate-related displacement increases in scale and frequency, there is a growing need for long-term relocation planning that can address its complex and evolving impacts. This dissertation addresses the long-term climate-induced relocation challenge through three optimization models, each designed to capture a distinct and critical dimension of planned migration. Together, these models offer a comprehensive framework for designing relocation strategies that are proactive, equitable, and responsive to practical constraints and real-world complexities.

The first model introduces a temporal network-based approach to resettlement planning that considers evolving demands, fluctuating capacities, and the importance of long-term integration. By decomposing the relocation timeline into distinct intervals, this model constructs a series of time-layered networks that capture the dynamic evolution of relocation systems. Each temporal layer involves solving a minimum-cost flow problem based on cultural distance, aiming to enhance cultural integration over time. The model provides decision-makers with tools to delay or advance flows based on changing conditions, enabling more adaptive and socially responsive resettlement strategies.

The second study proposes a multi-commodity relocation framework that categorizes displaced populations by their vulnerability levels. Each vulnerability group is treated as a distinct commodity within an optimization structure that simultaneously considers individuals preferences and capacity constraint. The model supports fairness and adaptability by accounting for changes in host country capacities over time, considering individual relocation preferences in planning decisions, and ensuring continued access for the most vulnerable populations.

Finally, the third model presents a digital twin inspired framework for long-term relocation planning under evolving conditions driven by climate stress. It simulates changes in population distribution and destination capacity, updating decisions over time. It enhances adaptability by embedding forecasting in the planning process, enabling more effective responses to future uncertainty.

Together, these models contribute to the growing body of climate adaptation research by offering scalable, optimization-based frameworks that address both logistical and social dimensions of planned relocation. Computational experiments conducted across multiple scenarios demonstrate the models' capacity to balance competing objectives such as maximizing integration, ensuring equitable treatment of vulnerable populations, and optimizing resource use over multiple time periods. These results underscore the importance of data-driven, long-term strategies for mitigating the human impacts of climate change and suggest new directions for future research in humanitarian logistics and other areas of operations research.

# Chapter 1

# Introduction

## 1.1 Problem Definition and Motivation

The increasing impact of climate change has made climate-induced displacement a growing global challenge. Across the world, communities are being forced to move as rising sea levels threaten coastal areas, extreme weather events disrupt lives, and environmental conditions continue to deteriorate. In 2022, millions of people were displaced worldwide due to floods, wildfires, and storms [1]. Beyond these immediate climate events, long-lasting droughts and fluctuating rainfall patterns disrupted agriculture, resulting in crop losses and forcing vulnerable communities to seek new livelihoods. As climate change intensifies, displacement is expected to increase, highlighting the urgent need for adaptation and resettlement strategies.

Recent evidence increasingly supports the connection between climate change and human mobility. The World Bank's Groundswell report projects that without effective climate action, up to 216 million people in six regions could be forced to migrate internally by 2050 [2]. In Southeast Asia, rising sea levels could cause 37 million people to relocate by 2040 according to recent estimates [3]. This is not just a future concern, as the effects of climate change on relocation are already visible today. For example, in 2023, cyclones in Madagascar displaced more than 80,000 people, while wildfires forced thousands to evacuate communities in Hawaii [4, 5]. Small island nations in the Pacific face an existential threat due to rising sea levels. One of these islands, the Republic of Kiribati, is at risk of becoming uninhabitable in the coming decades as sea levels continue to rise. To prepare for this, Kiribati has adopted a *migration with dignity* policy, which includes purchasing land in Fiji as a potential relocation site for its population [6].

The urgency of addressing climate-induced migration is underscored by growing evidence that extreme weather events are increasing in frequency and reshaping global migration patterns [7]. Although existing studies emphasize the importance of planned relocation strategies [8], few provide optimization-based approaches to support long-term decision-making. Most efforts remain focused on short-term responses, often overlooking the complexity of sustained adaptation needs [9, 10, 11]. Moreover, current models rarely incorporate population-level differences in vulnerability, which can significantly affect the equity and effectiveness of resettlement outcomes.

Planning for climate-induced relocation involves complex and interdependent challenges, ranging from immediate logistics to long-term sustainability. Effective strategies must account for the dynamic nature of displacement, shaped by environmental, economic, social, and security factors. These challenges are further compounded by the need to allocate limited resources efficiently, invest in resilient infrastructure, and ensure the continuity of essential services. Long-term uncertainty surrounding climate change adds another layer of difficulty, calling for adaptive solutions that balance humanitarian response with long-term planning under uncertainty.

In response to the growing challenges of climate-induced displacement, and motivated by the need for long-term planning, this dissertation develops three optimization-based models to support strategic relocation under climate stress. The goal is to provide decision-makers with a quantitative approach that can enable proactive, fair, and sustainable resettlement strategies. Rather than addressing relocation as a short-term intervention, the dissertation emphasizes sustained planning over time, accounting for changing population needs, evolving capacities, and uncertainty. Across all three models, the aim is to bridge the gap between humanitarian response and long-term planning, offering a structured approach to manage complex relocation decisions under intensifying climate pressures.

## 1.2 Structure of the Dissertation

This dissertation comprises six chapters, each focusing on a different aspect of the research. Chapter 1 presents the research problem, describes the motivation, and defines the main objectives of the dissertation. Chapter 2 reviews the existing literature on climate-induced migration, resettlement planning, and related optimization models and identifies key gaps that motivate the modeling approaches developed in this study. Chapter 3 presents a temporal multilayer network-based model for long-term relocation planning that models how relocation needs and system capacities evolve over time. Chapter 4 presents a multi-commodity model that addresses equitable allocation and explicitly models queuing to reflect limited processing capacity. Chapter 5 presents a digital twin-inspired framework that integrates forecasting into relocation planning to enhance adaptability under uncertainty. Finally, Chapter 6 concludes the dissertation by summarizing key findings, discussing limitations, and proposing directions for future research.

# Chapter 2

# Literature Review

## 2.1 Displacement Studies: Overview

In recent years, Operations Research techniques have increasingly been applied to various displacement problems. While these models have helped improve short-term response efforts, their application to climate-induced displacement, particularly in the context of long-term planning, remains limited. Given the inherently interdisciplinary nature of planned relocation, integrating logistical, social, and policy dimensions is essential for developing actionable and equitable strategies.

This chapter reviews the existing literature on displacement planning, with a particular focus on resettlement models and the analytical frameworks that support long-term relocation decisions under climate-induced displacement.

Although research on climate-induced displacement remains relatively recent, it has gained growing attention in recent years. However, long-term, multi-period relocation planning remains underexplored, particularly from an operations research perspective. To provide a foundation for the models developed in this dissertation, this chapter reviews related areas that share logistical and structural features, including , such as disaster response, large-scale population movements, and long-term relocation planning. These related areas help clarify the challenges involved in organizing and managing displacement. By examining how similar problems are addressed in these fields, we can identify limitations in current methods. These insights help clarify the need for the modeling approaches discussed in the following chapters.

Humanitarian operations models within displacement studies typically fall into four broad categories: camp location and service planning, route analysis, flow estimation, and resettlement planning. These categories are summarized in Figure 2.1, which illustrates the structure of existing displacement modeling approaches and highlights the resettlement planning branch most relevant to this dissertation. Among these categories, resettlement, particularly in the context of long-term climate-induced displacement, is the primary focus of this dissertation. Within the resettlement literature, further distinctions can be made between preference-based models, which incorporate displaced population or host community priorities, and outcome-based models, which aim to optimize system-level objectives such as efficiency, equity, or integration outcomes.

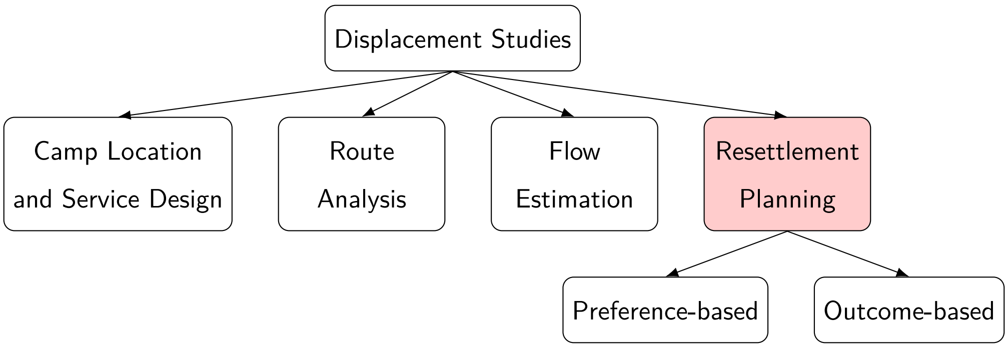



Figure 2.1: Categorization of migration studies.

In camp planning and service design, some studies focus solely on facility location, while others integrate location decisions with administrative and operational planning. Several works combine camp placement with mobile service operations, often modeled through location-routing frameworks [12, 13]. Route analysis frequently employs agent-based modeling to simulate decision-making under uncertainty. For instance, Czaika et al. [14] emphasize that displaced individuals often rely on limited information and tend to follow routes taken by earlier movers. Bijak et al. [15] implement an event-based simulation where agents make routing decisions through interactions with others during their journeys. Flow estimation remains a core area in both traditional and climate-related displacement research. One major challenge is the scarcity of reliable displacement data, especially when examining links between environmental stressors and mobility patterns [16]. Regression analysis remains widely used to explore correlations between climate indicators and population movements [17], while machine learning approaches for forecasting displacement flows have gained increasing attention in recent years [18, 19]. While these three areas form a substantial part of displacement studies, this dissertation focuses on a fourth category: resettlement planning, which addresses the long-term relocation of displaced populations. The remainder of this literature review is dedicated to examining existing approaches in this area.

## 2.2 Climate-Induced Displacement and Relocation Models

In displacement studies, resettlement planning addresses the complex challenges involved in the long-term relocation of displaced populations. Climate-induced displacement introduces additional layers of complexity, as environmental changes such as sea-level rise, drought, and extreme weather events often lead to gradual, large-scale population movements. These situations require carefully planned relocation strategies that account for evolving risks, changing host capacities, integration challenges, and fairness considerations. Various modeling approaches have been developed to support decision-making in this context, integrating methods from operations research, simulation, and data-driven forecasting. This section reviews existing contributions to climate-induced displacement modeling, with a particular focus on analytical frameworks that inform long-term relocation planning.

A wide range of modeling techniques has been applied to study population displacement, including gravity models, agent-based simulations, and network-based approaches. Recent reviews, such as Askland et al. [20], have evaluated the diverse theoretical and empirical methods used to examine migration dynamics under environmental pressures. These studies emphasize the importance of interdisciplinary frameworks that integrate social science perspectives with quantitative modeling to address the complexity of climate-induced relocation better. To provide context for the models developed in this dissertation, the following discussion reviews the modeling approaches used in climate-related displacement and their contributions to resettlement planning.

Behavioral approaches to climate-induced displacement emphasize how personal preferences, perceptions, and social context influence decisions about relocation. Individuals often consider a range of factors, such as economic opportunities, cultural connections, and environmental risks, based on their own experiences and circumstances [21, 22]. In climate migration modeling, these approaches are often classified as either preference-based, which focuses on individual decision-making processes, or outcome-based, which examines aggregate relocation outcomes at the system level. Behavioral models align with preference-based frameworks because they capture how displaced populations evaluate and prioritize the various factors that shape their relocation choices.

Agent-based models (ABM) build on individual decision-making frameworks by simulating how personal choices aggregate into larger-scale displacement dynamics. These models are often applied to displacement contexts to capture how individuals respond to environmental stress, accounting for variation in behavior and local conditions. Nourali et al. [23] propose a stochastic agent-based model (ABM) to examine household relocation in response to coastal flooding, incorporating differences in risk perception, income, and housing access. Similarly, Entwisle et al. [24] develop an ABM based on empirical data from rural Thailand to study how migration, land use, and demographic behavior interact under different climate scenarios. While these models are helpful in examining how displacement might evolve, they are less suited for planning efforts that require clear guidance on where people should be relocated and how many individuals can be accommodated in different destinations.

Recent studies have increasingly applied machine learning methods to analyze and predict migration patterns linked to climate stress. These approaches focus on identifying complex relationships between environmental variables and human mobility, often using large datasets and non-linear models. Tarraga et al. [25] apply Gaussian processes to identify the most influential environmental drivers of displacement, such as floods and storms, offering a probabilistic understanding of migration triggers. Similarly, Aoga et al. [26] use tree-based algorithms to explore how weather conditions influence migration intentions in agriculture-dependent regions. Expanding the use of tree-based methods, Best et al. [27] utilize random forests to analyze household survey data, highlighting critical predictors of migration in Bangladesh. Building on this, Best et al. [28] apply random forest modeling to social datasets from southwestern Bangladesh, further demonstrating how machine learning techniques can help identify key social and environmental factors influencing migration.Complementing these data-driven approaches, several recent studies have applied multi-criteria decision-making approaches to support structured resettlement evaluations [29, 30].

Together, the models discussed above provide essential insights into the dynamics of climate-induced migration. These models help identify behavioral patterns, spatial relationships, and environmental factors associated with displacement. However, they are primarily descriptive. Although they improve understanding of migration dynamics and influencing factors, these models offer little direct guidance for planners who must make decisions about the allocation of displaced populations. In contrast, optimization-based models are explicitly designed to support decision-making by identifying efficient and equitable relocation strategies that account for policy goals, capacity limits, and fairness objectives. Optimization-based models provide structured approaches for determining how to allocate displaced populations while addressing constraints related to capacity, fairness, security, and policy goals. Unlike descriptive models that explain how migration might occur, optimization models are designed to identify efficient and equitable relocation strategies. Table 2.1 reviews examples of optimization-based models, describing their approaches, goals, and implementation contexts.

Zahir et al. [31] introduced a multi-objective optimization framework designed to assist decision-makers in balancing preferences, safety considerations, and costs within a single-period relocation planning context. Andersson et al. [32] developed a matching model that aims to assign displaced populations to destination locations in a way that balances fairness and capacity constraints. Golz and Procaccia [33] applied submodular optimization to address competition effects by capturing how marginal benefits decline as more individuals are assigned to the same destination assigned to the same destination. Ahani et al. [34] developed an assignment model designed to improve short-term placement decisions by optimizing employment opportunities for displaced populations. In a subsequent study, Ahani et al. [35] introduced a two-stage stochastic programming model that incorporates practical considerations such as family connections, batch arrivals, and arrival uncertainties. Both models emphasize integration outcomes and are classified as outcome-based approaches to relocation planning. Bansak et al. [36] proposed a dynamic assignment model that adjusts to fluctuations in destination capacities. The model focuses on optimizing employment outcomes, offering a flexible framework to support outcome-based relocation decisions.

Table 2.1: Comparison of optimization-based resettlement models.

| Study | Methodology | Objective Focus | Resettlement Level | Planning Horizon |
|---|---|---|---|---|
| Zahir et al. [31] | Multi-objective optimization | Preference-based | Group-level | Single-period |
| Andersson et al. [32] | Matching | Equity-based | Individual-level | Single-period |
| Golz & Procaccia [33] | Submodular optimization | Equity-based | Individual-level | Single-period |
| Ahani et al. [34] | Assignment | Outcome-based | Group-level | Single-period |
| Ahani et al. [35] | Two-stage stochastic programming | Outcome-based | Group-level | Single-period |
| Cilali et al. [37] | Multi-objective optimization | Outcome-based | Individual-level | Long-term |
| Bansak et al.[36] | Dynamic assignment optimization | Outcome-based | Individual-level | Single-period |
| Cilali et al. [38] | Two-stage stochastic programming | Outcome-based | Individual-level | Long-term |
| Emre et al. [39] | Multi-layer temporal network optimization | Outcome-based | Individual-level | Long-term |

These models address different aspects of resettlement planning by proposing optimization approaches that consider various constraints and objectives. However, most of them focus on short-term relocation decisions. In contrast, climate-induced displacement presents long-term challenges, including changing capacities, evolving policies, and changing needs over time. In response to these challenges, recent studies have focused on developing models that address these complexities and optimize long-term outcomes for displaced populations. Cilali et al. [37] introduced a multi-objective facility location model that emphasizes cultural compatibility and travel costs in placement decisions, aiming to improve integration outcomes over the long term. Then, Cilali et al. [38] proposed a two-stage stochastic optimization model for long-term, climate-driven relocation planning. Finally, Emre et al. [39] introduced a multi-layer temporal network optimization model that captures evolving pressures at origin countries and capacity constraints at destinations.

# Chapter 3

# Temporal Multilayer Network-Based Optimization for Long-Term Resettlement Planning

## Preface

The content presented in this chapter is adapted from my previously published work:

Emre, D., Barker, K., González, A. D., Cilali, B., Radhakrishnan, S., & Noyori-Corbett, C. (2025). *Optimizing climate-induced migration: A temporal multi-layer network approach. International Journal of Disaster Risk Reduction*, 117, 105172. `https://doi.org/10.1016/j.ijdrr.2024.105172`

Editorial adjustments were made to align with the dissertation format and maintain narrative continuity. The core methodology, model formulation, and results remain consistent with the published version.

## 3.1 Introduction

Resettlement planning has historically focused on immediate, short-term solutions, often with limited attention to the longer-term challenges that arise as conditions evolve. Many existing models are built on static frameworks that do not fully capture how individual needs and capacities shift over time. As climate change intensifies and conditions continue to evolve, there is a growing need for planning approaches that can accommodate these changes and support decision-making across multiple time horizons.

Addressing these long-term challenges requires planning models capable of adapting to future resource demands and shifting relocation needs. In response, a model is introduced that considers fluctuating demands and capacities in resettlement planning. Inspired by the concept of temporal networks, proposed method constructs a time-dependent network divided into various temporal layers. Each layer serves as a static depiction of the network at specific intervals, capturing the system's evolution and reflecting the shifting resettlement needs.

A minimum-cost flow problem is solved for each temporal layer, with results applied across periods. In addition to addressing the logistical aspects of relocation, the model incorporates integration success as a key indicator for evaluating the quality of resettlement outcomes. The approach is implemented through a mixed-integer linear programming model (MILP) and evaluated across a range of planning scenarios. The model offers a comprehensive framework for resettlement planning that balances immediate needs with long-term integration outcomes. The results demonstrate how the model captures dynamic adjustments in supplies and capacities over time, allowing for strategic delays and modifications in relocation flows to improve overall outcomes.

## 3.2 Temporal Multilayer Network Modeling Framework

This section presents the temporal multilayer network model developed for resettlement planning. The framework captures the evolving nature of resettlement needs over time and jointly considers logistical operations and integration outcomes in an optimization model.

### 3.2.1 Temporal Network Structure

The temporal multilayer network is designed to consider the evolution of resettlement decisions over a planning horizon divided into multiple discrete time periods. Each period forms a separate temporal layer, reflecting changes in both the availability of individuals awaiting relocation and the capacities of host locations as conditions change over time.

The network includes two primary types of nodes: origins, which represent locations where individuals are initially located and awaiting resettlement, and destinations, which represent host locations available to receive individuals. In each time period, individuals may either remain at their origin if they have not yet been assigned or be permanently relocated to one of the available host locations. Once individuals are assigned to a destination, they remain permanently at that location for the remainder of the planning horizon, reflecting the irreversible nature of resettlement decisions.

Each temporal layer provides a static representation of the network at a given point in time, where the set of origins, destinations, and feasible relocation pathways are fixed for that period. Within each temporal layer, connections between origins and destinations represent the possible relocation flows that can occur during that period. The model allows for partial relocation, meaning that a portion of the available population at any origin may be relocated in a given period while others remain for potential relocation in future periods.

In addition to these within-period relocation flows, the model incorporates inter-layer connections that capture how system conditions evolve from one period to the next. These inter-layer links do not represent physical movement but instead reflect the carryover of unrelocated individuals at origins and unused capacities at destinations. As decisions are made in each period, the available supply of individuals awaiting relocation and the available capacity at host locations are updated and carried forward to inform decisions in subsequent periods. This structure enables the model to represent both the temporal progression of relocation decisions and the dynamic adjustment of system conditions across the planning horizon.

### 3.2.2 Parameters and Decision Variables

The temporal multilayer network model is formulated based on a set of parameters and decision variables that represent the evolution of relocation decisions across multiple time periods. Origin locations represent areas exposed to environmental pressures leading to population displacement, while host locations serve as potential destinations for resettlement. The parameters characterize system capacities, relocation costs, environmental feasibility constraints, and integration-related factors, while the decision variables define the allocation of relocation flows and the evolution of supply availability and host capacities across the planning horizon. A full summary of the model parameters is provided in Table 4.1, and the decision variables are listed in Table 3.2.

The model is formulated over two primary sets: $N_o$, representing the set of origin locations subject to environmental displacement pressures, and $N_h$, representing the set of host locations available for resettlement.

Table 3.1: Model Parameters

| | |
|---|---|
| $s_{it}$ | Supply at origin node $i \in N_o$ in time period $t$ |
| $cap_{jt}$ | Capacity at host node $j \in N_h$ in time period $t$ |
| $c_{ijt}$ | Transfer cost between origin node $i \in N_o$ and host node $j \in N_h$ in time period $t$ |
| $o_{jt}$ | Opening cost for host node $j \in N_h$ in time period $t$ |
| $m_{jt}$ | Maintenance cost for host node $j \in N_h$ in time period $t$ |
| $p_{it}$ | Penalty cost for remaining unmet supply at origin node $i \in N_o$ in time period $t$ |
| $k_{ijt}$ | Cultural distance between origin node $i \in N_o$ and host node $j \in N_h$ in time period $t$ |
| $G_i$ | Climate resilience score for node $i$, where $i \in N_o \cup N_h$ |

Table 3.2: Model Decision Variables

| | |
|---|---|
| $x_{ijt}$ | Flow from origin $i \in N_o$ to host $j \in N_h$ at time $t \in T$ |
| $y_{it}$ | Remaining supply at origin $i \in N_o$ at time $t \in T$ |
| $z_{jt}$ | Remaining capacity at host $j \in N_h$ at time $t \in T$ |
| $r_{jt}$ | Binary variable equal to 1 if the facility at host $j \in N_h$ is operational at time $t$, 0 otherwise |
| $q_{jt}$ | Binary variable equal to 1 if the facility at host $j \in N_h$ is built at time $t$, 0 otherwise |
| $\delta_{ij}$ | Binary parameter equal to 1 if relocation from $i \in N_o$ to $j \in N_h$ is feasible based on environmental conditions ($G_j > G_i$), and 0 otherwise |

The cost-related parameters include transportation costs, as well as opening and maintenance costs associated with facilities at host locations. The travel cost parameter $c_{ijt}$ represents the cost of relocating individuals from origin $i$ to host location $j$ during period $t$. The opening cost parameter $o_{jt}$ reflects the initial investment required to establish a facility at a host location, including construction, equipment procurement, and other one-time start-up expenses. The maintenance cost $m_{jt}$ reflects the recurring expenses required to operate and sustain active facilities at each host location throughout the planning horizon. These cost elements are integral to capturing the long-term resource commitments associated with resettlement operations. The model also includes a penalty cost $p_{it}$ for individuals who remain unrelocated within the specified time frame, reflecting the operational consequences of unmet relocation needs. This cost incentivizes the model to prioritize the relocation of as many individuals as possible to minimize instances of unfulfilled relocation needs.

The supply parameter $s_{it}$ represents the number of individuals located at each origin who are available for relocation during time period $t$, reflecting the population in need of resettlement. On the other hand, the parameter, $cap_{jt}$, denotes the maximum number of individuals that host location $j$ can accommodate during period $t$. This parameter reflects the available resources of host locations to support incoming populations. The parameter of cultural distance, $k_{ij}$, measures the difference in cultural attributes between the origin and the host locations. We are incorporating Hofstede's cultural dimensions into our optimization model for the long-term sustainability of resettlement efforts. Hofstede's cultural dimensions framework identifies key aspects of cultural differences across societies, such as power distance, individualism vs. collectivism, and uncertainty avoidance [40]. These dimensions provide a quantitative basis for comparing cultural attributes between locations, enabling the optimization model to incorporate cultural compatibility as a factor in long-term resettlement planning. By prioritizing cultural integration, the model helps ensure that migration, particularly that forced by climate change, results in positive outcomes for both migrants and host communities.

Since the model focuses on climate-induced migration, it aims to relocate individuals to safer and more sustainable environments. The ND-GAIN score, represented by the parameter $G_i$, plays a critical role in this process. The ND-GAIN Index, developed by the Notre Dame Global Adaptation Initiative, evaluates each location's vulnerability and readiness to adapt to climate change. Vulnerability is assessed across six dimensions: food, water, health, ecosystem services, human habitat, and infrastructure, incorporating factors related to exposure, sensitivity, and adaptive capacity. Readiness is measured through economic, governance, and social indicators. These components are combined into a single composite score, providing an integrated assessment of each location's ability to cope with climate risks. By intergating ND-GAIN scores into the model, relocation decisions prioritize destinations that are less vulnerable to climate impacts and better prepared to support long-term stability and resilience for resettled populations.

The flow variable, $x_{ijt}$, represents the number of individuals moving from an origin location $i \in N_o$ to a host location $j \in N_h$ during time period $t \in T$. The variable $y_{it}$ denotes the remaining supply at the origin location $i \in N_o$ at the end of time period $t$, reflecting the number of individuals who have not relocated in the given time period. Similarly, $z_{jt}$ represents the remaining capacity at the host location $j \in N_h$ at the end of time period $t$, indicating the unused capacity of the host after accounting for incoming individuals. The binary variable, $q_{jt}$, denotes whether a new facility is built at the location $j$ during the period $t$. It is set to 1 if a new facility is established at the location $j$ at time $t$ and to 0 if no new facility is built. This binary variable directly reflects the development of new infrastructure to support relocation efforts. The binary variable $r_{jt}$, indicates whether a host location $j$ is operational in the period $t$. It is set to 1 if a host location $j$ is operational and to 0 if the location is not operational.

### 3.2.3 Model Formulation

To optimize the dynamic relocation process associated with climate-induced relocation, a bi-objective mixed-integer linear programming model is formulated. The model integrates both discrete and continuous decision variables across multiple time periods, enabling relocation and operational decisions to adjust as resource availability, capacities, and system needs evolve. By capturing both logistical and operational components within a temporal multilayer network structure, the formulation reflects the complex trade-offs inherent in long-term resettlement planning. The complete mathematical formulation of the temporal multilayer network model (TMNM) is presented below.

$$\min \quad \sum_{t=1}^{T} \sum_{i \in N_o} \sum_{j \in N_h} c_{ijt} \cdot x_{ijt} + \sum_{t=1}^{T} \sum_{i \in N_o} p_{it} \cdot y_{it} + \sum_{t=1}^{T} \sum_{j \in N_h} (o_{jt} \cdot q_{jt} + m_{jt} \cdot r_{jt}) \tag{1}$$

$$\min \quad \sum_{t=1}^{T} \sum_{i \in N_o} \sum_{j \in N_h} k_{ijt} \cdot x_{ijt} \tag{2}$$

Subject to:

$$\sum_{j \in N_h} x_{ij1} + y_{i1} = s_{i1} \qquad \forall i \in N_o \tag{3}$$

$$\sum_{j \in N_h} x_{ijt} + y_{it} = s_{it} + y_{i,t-1} \qquad \forall i \in N_o,\ \forall t \in \{2, \ldots, T\} \tag{4}$$

$$\sum_{i \in N_o} x_{ij1} + z_{j1} = cap_{j1} \qquad \forall j \in N_h \tag{5}$$

$$\sum_{i \in N_o} x_{ijt} + z_{jt} = cap_{jt} + z_{j,t-1} \qquad \forall j \in N_h,\ \forall t \in \{2, \ldots, T\} \tag{6}$$

$$x_{ijt} \leq M(G_j - G_i) \cdot \delta_{ij} \qquad \forall i \in N_o,\ \forall j \in N_h,\ \forall t \in T \tag{7}$$

$$\delta_{ij} = \begin{cases} 1 & \text{if } G_j > G_i, \\ 0 & \text{otherwise} \end{cases}$$

$$\sum_{i \in N_o} x_{ijt} \leq r_{jt} \cdot d_{jt} \qquad \forall j \in N_h,\ \forall t \tag{8}$$

$$r_{jt} \leq \sum_{t'=1}^{t} q_{jt'} \qquad \forall j \in N_h,\ \forall t \tag{9}$$

$$x_{ijt},\ y_{it},\ z_{jt} \geq 0 \qquad \forall i \in N_o,\ \forall j \in N_h,\ \forall t \in T \tag{10}$$

$$r_{jt},\ q_{jt},\ \delta_{ij} \in \{0, 1\} \qquad \forall i \in N_o,\ \forall j \in N_h,\ \forall t \in T \tag{11}$$

The first objective function (1) aims to minimize the total relocation costs across the planning horizon. This includes transportation costs between the origin and host locations, penalty costs for unmet relocation demands at origin locations, and the initial establishment and ongoing operational costs of host facilities. The objective determines an efficient allocation of relocation flows that balances these cost components over time. The second objective function (2) aims to minimize the cultural distance between the origin and host locations, which helps promote smoother integration by prioritizing relocation flows with lower cultural distances.

Constraint (3) establishes the supply balance at each origin location for the initial time period. It requires that the sum of individuals relocated from an origin and those who remain unassigned equals the initial supply available at that origin. Constraint (4) generalizes this balance for all subsequent periods by ensuring that the total number of individuals relocated and those remaining at the origin equals the current period's available supply, which includes both newly available individuals and the carryover from the previous period. Constraints (5) and (6) govern the capacity balance at each host location over the planning horizon. Constraint (5) ensures that, in the initial period, the total number of individuals relocated to a host location combined with its remaining capacity equals the facility's initial available capacity. Constraint (6) extends this balance to subsequent periods by accounting for dynamic adjustments. Specifically, it requires that, for each period, the sum of individuals relocated to a host and the remaining unused capacity matches the available capacity at the beginning of that period, which incorporates both newly assigned capacity and any unused capacity carried forward from previous periods. These constraints balance the distribution of individuals across host locations, aligning with their respective capacities and demands.

Constraint 7 ensures that relocation is only permitted to hosts with higher ND-GAIN scores, reflecting better environmental and sustainability conditions, since it limits migration flows $x_{ijt}$ to zero in cases where $G_j$ is less than $G_i$. To implement this condition effectively, we selected $M$ as the summation of the maximum total flows across all periods. This choice provides an upper bound, reflecting the scale of relocation in the system and ensuring the constraint operates consistently within realistic flow levels. Constraint 8 ensures that no incoming flow will occur when the host location is not operational during a given period. This is determined by the host location's status (operational or non-operational). Constraint 9 ensures that the operational status of a host location in any given period depends on its establishment in that or a preceding period, ensuring a sequential foundation for migration dynamics.

TMNM's operational mechanism and the network's structural design are depicted in Figure 1. There are two types of link: intra-layer and interlayer. Intralayer links represent the relocation between nodes, where individuals move through time and location. The interlayers represent the number of individuals who move only through time. The interlayer links contain the unmet demand at the origin location and the remaining demands at the host location. They carry them over to the next period and adjust the capacities for the following year. In Figure 1, the nodes labeled $N_1$ and $N_2$ represent the supply nodes, while $N_3$ and $N_4$ represent the demand nodes within our migration network model. This depiction captures the temporal dynamics of the system, where individuals who are not relocated in an earlier period remain in the available supply pool for subsequent periods. Thus, the model accounts for the temporal progression of supply and demand dynamics inherent to long-term resettlement planning.

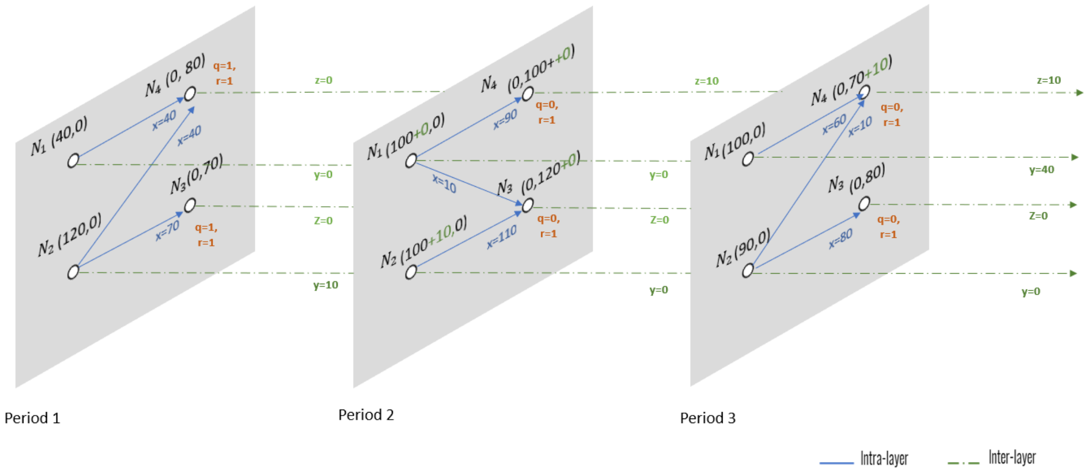



Figure 3.1: Illustration of layers representing temporal snapshots.

Intra-layer links, represented as solid lines, capture the relocation flows occurring within a single period, indicating how individuals are assigned from supply nodes ($N_1$ or $N_2$) to host nodes ($N_3$ or $N_4$). This structure captures the relocation decisions and resource allocations within each discrete time frame.. In contrast, inter-layer links, depicted as dashed lines, represent the carryover of unassigned supply and unused capacity between consecutive periods. For instance, individuals who are not allocated in one period contribute to the available supply in the following period, while unutilized capacity is rolled forward to adjust the receiving capacities in subsequent periods. The numerical values presented in the figure are for illustrative purposes only, providing a conceptual demonstration of how supply, demand, and relocation flows evolve over successive periods. This example clarifies the model's representation of dynamic adjustments between available supply and host capacities over time. Each period reflects one year, though alternative temporal resolutions can be applied depending on scenario design.

## 3.3 Case Study Design and Data Description

One of the main strengths of the proposed modeling framework is its capacity to address the complex problem of climate-driven resettlement, which involves a large number of individuals from multiple regions over a long-term planning horizon. To ensure that the model provides a realistic representation of the problem, it is essential to utilize data and parameters that capture the inherent complexity and variation present in actual displacement contexts. In particular, one of the defining features of such large-scale resettlement planning is its inherently spatiotemporal complexity, where evolving climate risks, population vulnerabilities, and varying degrees of willingness to move over time shape relocation decisions.

For the implementation of the model, a synthesized dataset developed by [38] is used. This dataset offers projections of future relocation needs across a four-period planning horizon, capturing the anticipated impacts of climate change on livelihoods, vulnerability levels, demographic trends, and individual propensities to migrate. The dataset provides estimated relocation supply quantities at the national level for 29 origin countries, spanning the years 2030 to 2050. These countries, illustrated in Figure 3.2, have been selected based on their acute exposure to climate hazards combined with relatively low adaptive capacity, reflecting a particularly high vulnerability to climate-induced displacement risks [41]. Several key factors contribute to the estimation of supply levels for each origin country: future population projections, the anticipated share of the population likely to experience significant impacts from climate-related hazards, and the degree of willingness among affected individuals to consider relocation as a potential adaptation strategy.

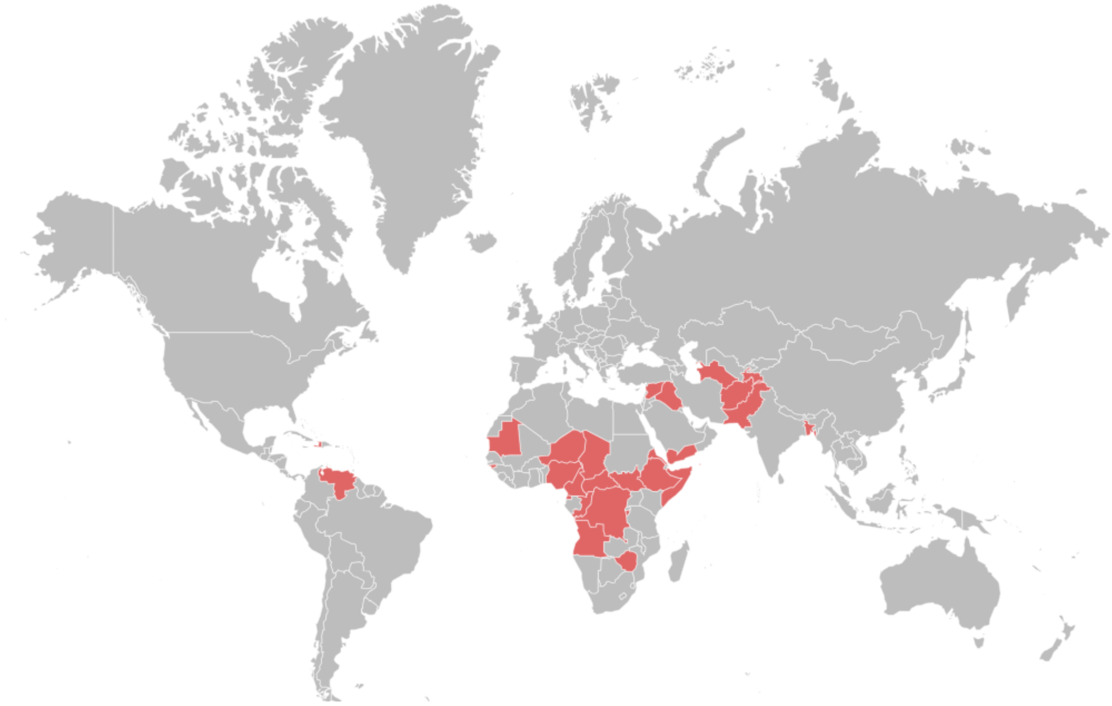


Figure 3.2: The 29 origin countries considered especially vulnerable to climate change, from [38].

Once the origin locations and associated supply levels are established, the next step involves selecting appropriate host locations. Five host locations were selected based on multiple factors relevant to their ability to support long-term resettlement. The identification of host locations is based on a set of substantive criteria reflecting their suitability to absorb climate-induced migration. These included the country's economic capacity, its resilience to environmental stressors, the demonstrated ability to integrate displaced populations in the past, and the presence of robust administrative and social support systems to manage future flows. To preserve the neutrality of the analysis and avoid potential political implications, the host countries are not explicitly identified.

Host capacities are established by projecting the total relocation demand across multiple periods and allocating these opportunities proportionally to the population sizes of the respective host countries. This proportional allocation serves as a proxy for each host's potential absorption capacity, providing a baseline that reflects differences in demographic scale while abstracting from explicit political, economic, or policy constraints. It does not account for political willingness or policy impacts on-demand allocation, which are discussed subsequently as part of future work. We utilized Hofstede's six cultural dimensions [42] to calculate cultural distances, with a focus on cultural compatibility in migration paths. ND-GAIN scores are used to assess the vulnerability and readiness of host countries to address climate change, which in turn influences the allocation of migration flows.

Cost-related parameters include transportation, opening, and maintenance costs for facilities in various host locations. Transportation costs between countries are derived from real geographical distances and scaled from 1 to 100. To account for temporal variations in transportation costs due to factors such as inflation, we introduced a time-dependent component, allowing $c_{ijt}$ to reflect changes over different periods.

The estimation of opening and maintenance costs for host facilities incorporates differences in economic conditions across countries by utilizing gross domestic product (GDP) data adjusted by purchasing power parity (PPP). This adjustment takes into account variations in both economic productivity and the relative cost of living, which collectively influence the resources required to establish and sustain resettlement infrastructure. To calibrate opening costs in a manner that reduces potential distortions caused by extreme economic disparities among host countries, the GDP (PPP) values are scaled using a square-root transformation. This transformation dampens the effect of large GDP differentials while preserving the relative differences between countries in a controlled and interpretable manner [43, 44]. Similarly, base maintenance costs are scaled by each country's level of economic development to reflect the recurring financial obligations associated with operating host facilities over the planning horizon.

## 3.4 Model Implementation

### 3.4.1 Overview

The implementation of the proposed model provides a structured framework for analyzing long-term climate-induced relocation flows under a range of resettlement conditions. The model generates relocation outcomes by simultaneously considering multiple interacting factors, including economic conditions, cultural compatibility, geographic distance, operational costs, and host country capacities. These factors are embedded in a multi-period optimization framework for relocation planning, allowing for temporal variation in both supply and capacity.

The implementation supports long-term strategic planning by capturing the dynamic interactions between relocation supply, destination capacity, and integration priorities. The resulting allocation patterns provide a foundation for scenario-based analysis, enabling stakeholders to explore how different policy or environmental conditions affect relocation outcomes over time.

The model was implemented in Python and solved using Gurobi Optimizer, which supports efficient computation for large-scale optimization problems involving mixed-integer decision variables across multiple time periods.

### 3.4.2 Scenario Design and Evaluation Framework

To systematically evaluate the model's performance under varying planning conditions, a series of computational scenarios are designed. These scenarios enable the exploration of how changes in key parameters such as host location capacities, transfer cost weights, and cultural distance preferences influence relocation outcomes over a multi-period planning horizon.

This scenario-based approach supports both baseline evaluation and sensitivity analysis, offering insights into how economic, cultural, and logistical considerations interact to influence long-term relocation patterns. By adjusting assumptions related to policy priorities, capacity constraints, and environmental thresholds, the model facilitates a structured assessment of planning trade-offs and potential policy impacts.

The following subsections present scenario-specific results, including the evolution of destination preferences over time, the effects of cost and cultural tradeoffs, and the distribution of flows under capacity and environmental constraints. Together, these analyses provide a comprehensive understanding of the model's behavior across different strategic contexts in climate-induced resettlement planning.

### 3.4.3 Baseline Scenario

The results of the illustrative example, where host country capacities are set in proportion to national population sizes and the objective function assigns equal weights to transfer cost and cultural distance, are provided in Appendix Table A.1 The model output reveals noticeable shifts in destination preferences over time, driven by the dynamic interaction among host capacity constraints, transfer costs, fixed costs, and cultural distance. Together, these factors influence how attractive each destination becomes throughout the planning horizon, shaping the evolving flow patterns observed in the allocation results.

To interpret the model outcomes, it is important to examine how allocation patterns evolve over time across different origin-destination pairs. In the initial years, Host 1 received the highest volume of migrants from a range of origin countries, indicating its relative attractiveness as a destination. This pattern likely reflects favorable attributes such as high intake capacity and flexibility in accommodating large numbers of individuals. As the planning horizon progresses, several temporal trends emerge in the interactions between origin and host countries. For instance, countries like Angola and Burundi exhibit steady increases in flows to Host 1 across multiple periods, suggesting either a growing need for relocation or continued compatibility with this destination.

By contrast, some flows remain relatively stable over time. Bangladesh's consistent allocation to Host 1 reflects a sustained migration pattern with minimal variation throughout the planning horizon. However, in later years, several countries show sharp increases in movement following earlier periods of limited or no engagement. A notable example is the sudden shift in flows from Bangladesh to Host 4. These late reallocations appear to represent strategic adjustments in response to unmet needs, penalty costs, or efforts to fully utilize remaining capacity at previously underutilized destinations.

Overall, the results demonstrate a diverse pattern of flows. Relocation is not dominated by a single origin or a unidirectional movement toward any single host. Instead, movements originate from countries across different regions, reflecting the global and multifaceted nature of climate-induced displacement. This diversity underscores the range of drivers influencing migration decisions, including economic opportunity, environmental exposure, and cultural proximity.

In addition to observing allocation patterns under baseline assumptions, we also explore how adjusting the objective weights in the relocation model affects outcomes. Organizations can manage their budgetary constraints and allocate resources more efficiently by prioritizing and minimizing total costs. Increasing the cost weight in the objective function ensures that the relocation process remains cost-effective and financially sustainable in the long run. Conversely, prioritizing the reduction of the cultural distance underscores the importance of fostering integration and collaboration among relocated individuals and host communities. This emphasis on cultural alignment is significant for facilitating smoother transitions and integration. By carefully considering these factors and adjusting the weights accordingly within the relocation model, organizations can effectively tailor their strategies to achieve their desired outcomes.

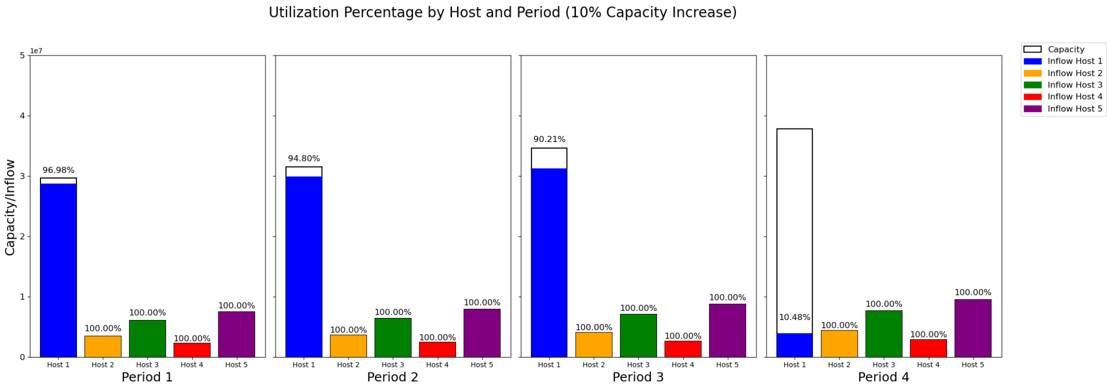
### 3.4.4 Capacity Analysis

Capacity adjustments at host locations are analyzed through two distinct cases: increases and decreases. The first case examines how expanded capacity influences the attractiveness and utilization of host destinations. The second focuses on reductions in host capacity and the resulting effects on origin-destination flow patterns. Together, these cases provide insight into how variations in capacity parameters shape both local utilization dynamics and broader migration system behavior. Analyzing both directions of change helps reveal the system's responsiveness and the trade-offs involved in resettlement planning.

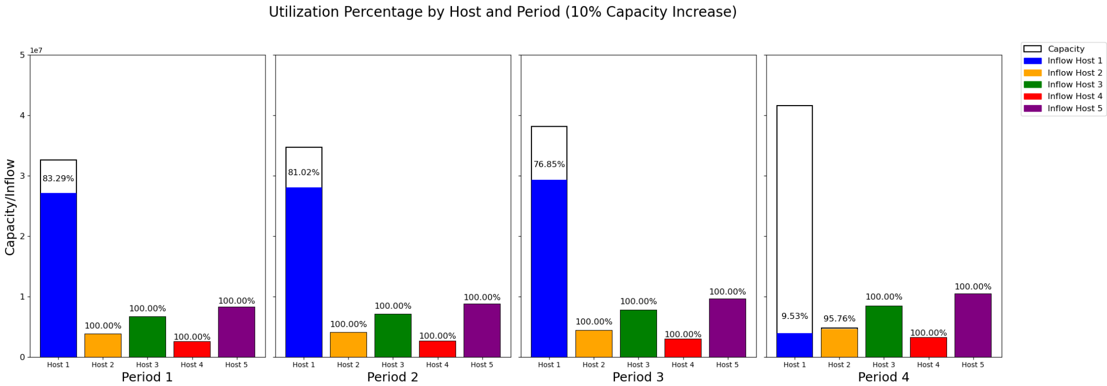
**Case 1: Increase in Host Location Capacity**

The relationship between host location capacities and their utilization percentages is examined to understand how variations in capacity influence utilization rates at destination sites. The utilization of capacities across the host locations is illustrated in Figure 3(a), where capacities are proportional to host populations. Host 1, possessing the highest capacity, does not achieve the 100% utilization observed in other host locations. These utilization rates raise essential questions about the factors that contribute to the under-utilization of capacity at certain host locations despite their capability to accommodate larger populations. Therefore, there is a need for a deeper analysis of how capacity adjustments might influence utilization patterns, which would serve as a foundation for strategies for optimizing resource allocation and enhancing the efficiency of host location operations.

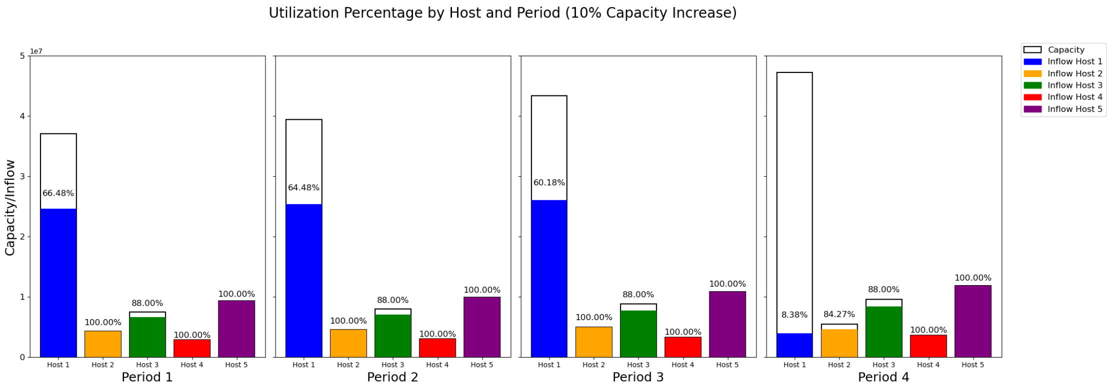
A sensitivity analysis is conducted to examine the impact of increased capacity on the utilization rates of various host locations. The utilization of the host locations after increasing it by 10% and 25% is illustrated in Figures 3(b) and 3(c), respectively. As we expand the host location capacities, we observe that the utilization percentages of Host 1 decrease. This decrease underscores the relation between capacity and utilization rates and may not always lead to proportional increases in utilization. Thus, while Host 1 initially benefited from its capacity to attract a significant share of utilization, expanding capacities at other host locations, aligned with travel cost considerations and cultural proximity, has diversified the landscape of host preferences. As shown in Figure 3(c), Host 5 emerges as a more prominent player in the network by maintaining a 100% utilization ratio under expanded capacities. This stability is related to Host 5's geographical advantage; being closer to the supply origins diminishes logistic expenses and reveals a distinctive pattern where it consistently maintains high utilization levels despite capacity increments. Host 4 also achieves full utilization despite receiving flows from only a few countries, a situation that is closely tied to its continental location. It implies that its strategic position plays a crucial role in attracting and efficiently managing these flows, highlighting the importance of geographical advantages in the dynamics of utilization rates.




(a) Original capacity




(b) 10% capacity increase




(c) 25% capacity increase

Figure 3.3: Total flows by host location under different capacities.

The insights from these results offer an understanding of optimizing resource allocation and refining relocation strategies. Stakeholders can make more informed decisions by identifying how changes in capacity, coupled with factors like travel costs and cultural distances, influence utilization rates. The model highlights the significance of considering the attributes of competing locations in relocation and resource distribution planning. These insights provide stakeholders with a foundation to develop strategies that ensure the optimal and effective use of host location capacities.

**Case 2: Decrease in Host Location Capacity**

As in the previous analysis of capacity increases, here we analyze the relocation flows under various scenarios of host capacity adjustments: the original capacity, a 10% decrease, and a 25% decrease. When we decrease the capacities of host locations, we observe shifts in migration flow patterns from origin countries. Among these, we identify distinct categories of behavior. Category 1 includes countries like Mauritania, Cameroon, and Afghanistan, whose relocation flows remain unchanged despite reductions in host capacities. This consistent behavior can be interpreted as indicative of inelastic demand for specific routes. Specifically, these flows are directed towards Host 1, which is culturally closer than other potential hosts and maintains a larger capacity. Therefore, it is essential to note that this perceived inelasticity might also relate to the sufficient capacity at larger host countries like Host 1. Overall, in this category, the system prioritizes destinations where cultural distances are minimized and adequate capacity is available.

Category 2 describes relocation flows that adapt to changes in host capacities. This category highlights how migration patterns shift to different countries based on available capacities. Such changes show flows' flexibility and response to changing conditions. The adaptability of the flows over the years, adjusting to fluctuations in host capacities and diversifying destinations, can be seen in Figure 5. Over the years, Yemen's relocation flows exhibit adaptability in response to fluctuating host capacities. In the original scenario, Yemen's primary focus on Host 5 indicates a strong preference and logistics decisions associated with this destination. However, as host capacities decreased by 10%, Yemen exhibited a strategic shift, redistributing flows to Host 1 and Host 3. This shift shows the model's ability to adapt quickly, avoiding overloading a single host and spreading the risk. The 25% reduction in host capacities demonstrates that significant flows redirected to Host 3, which was less prominent before, indicate an effort to diversify and reduce dependency on any single host. There are no flows in Year 4, with people staying in Yemen, indicating that capacity constraints became too restrictive.

Category 3 includes countries that cease sending relocation flows entirely when host capacities are reduced. Iraq and Angola, which have the maximum cultural distance to the given hosts in the data, fall into this category. They have outflows under original and 10% reduced capacities but cease flows entirely under 25% reduction. From the model's perspective, Category 3 highlights the importance of identifying and understanding capacity thresholds and cultural and logistic distances in relocation planning. The cessation of flows from Iraq and Angola under restrictive capacity demonstrates the model's ability to identify critical capacity thresholds beyond which original relocation plans become infeasible. The model prioritizes culturally closer locations in such extreme capacity situations. By increasing penalty costs for non-relocation and defining urgent categories for each origin, decision-makers can leverage the model's adaptability to ensure fair and equitable relocation, addressing the urgent needs of each origin.

Category 4 includes countries that do not send relocation flows in specific years but dispatch

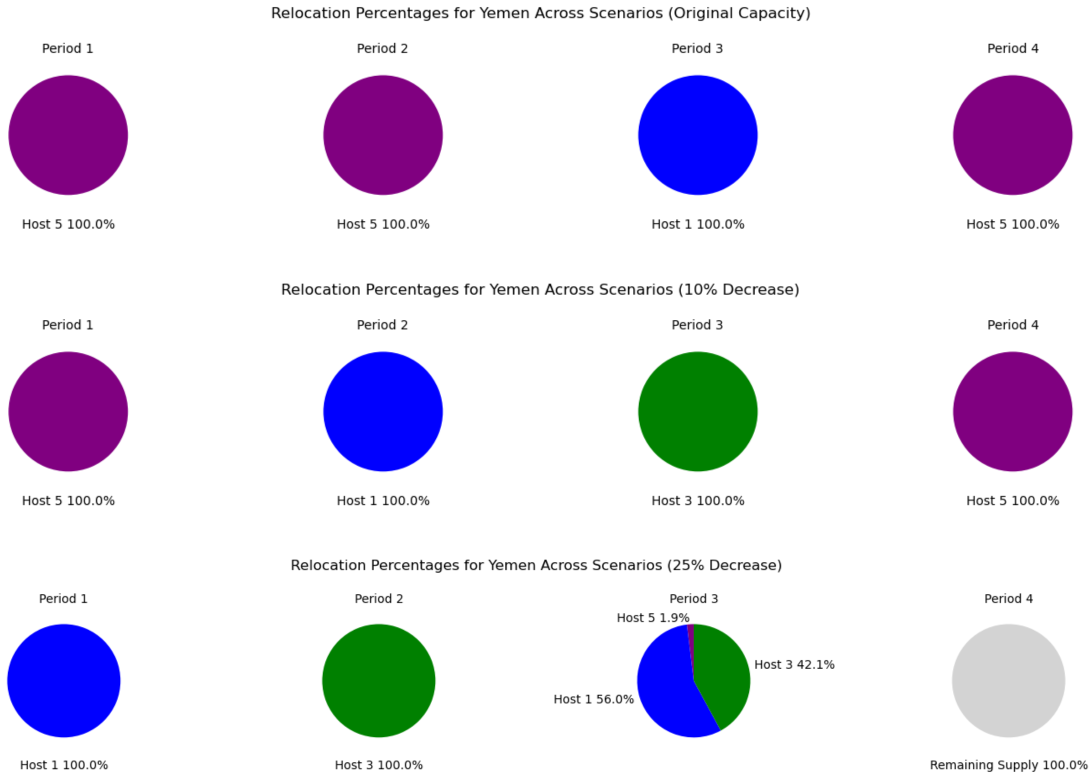



Figure 3.4: Relocation flows for Yemen under different capacities.

significant flows in subsequent years. This pattern is seen in countries like Eritrea and Tajikistan, and it shows the model's capacity to delay relocation flows to optimize conditions and resources. Figure 5 illustrates the relocation percentages for Eritrea, and no relocation occurred in Period 2, resulting in 100% of the supply remaining. This remaining supply is added to Period 3's capacity, leading to a total relocation percentage of 193.3% to Host 3. This high percentage indicates that the entire supply from Period 2 and Period 3 was dispatched in Period 3, reflecting the model's strategy of carrying over and accumulating resources for more favorable conditions.

By delaying flows, the model accumulates necessary supplies, ensuring that when relocation does occur, it is well-supported. However, this strategy might also introduce risks. Long delays can expose people to extended risk periods in origin locations and create coordination challenges when large volumes need to be relocated. Therefore, monitoring conditions in origin locations is essential to mitigate these risks, as planning resources carefully and protecting vulnerable populations during the delay. This strategic approach could show the model's ability to balance immediate needs with long-term sustainability, ensuring effective relocations even when resources are limited.

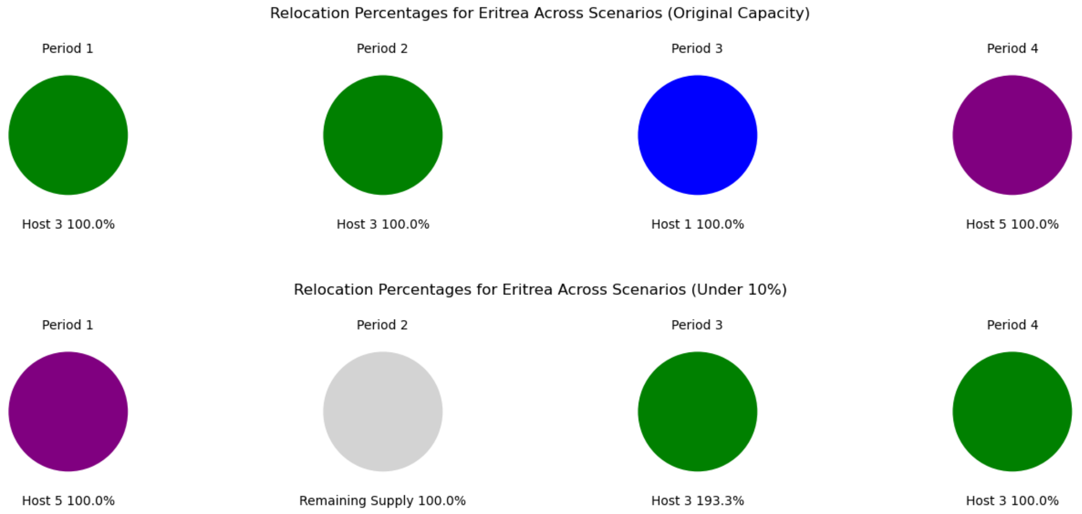


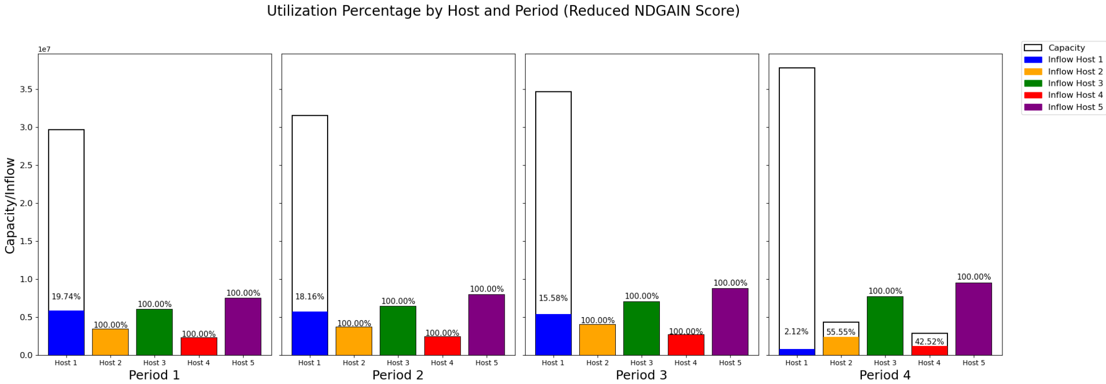

Figure 3.5: Relocation flows for Eritrea under different capacities.

### 3.4.5 ND-GAIN Index Threshold Scenario

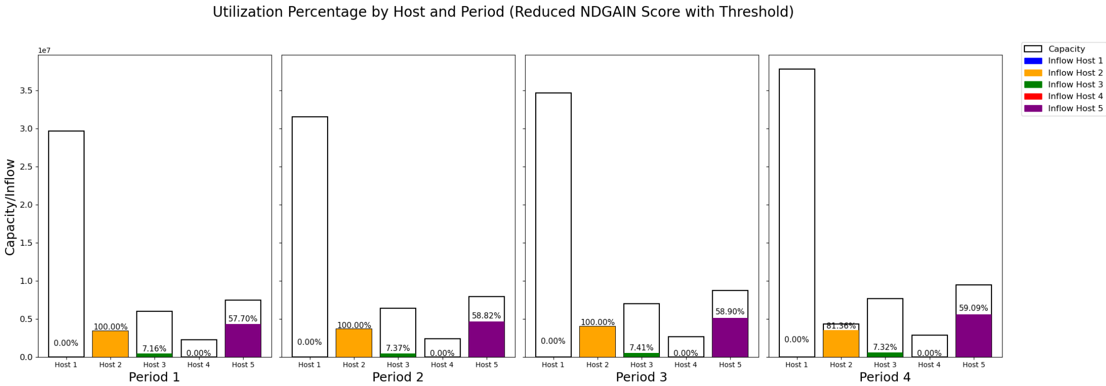
In the base scenario, the relocation from one location to another is allowed if the destination's ND-GAIN score is higher than that of the origin. Under the scenario introduced in this section, the destination is selected because the host location's ND-GAIN score exceeds the origin's by a predefined percentage. This threshold represents the desire of individuals to improve living conditions and future security substantially, acknowledging that the motivation for relocation is often driven by the quest for a qualitatively better life rather than a marginal improvement. In addition, some countries have historically been recipients of migration despite their vulnerability to climate change and other challenges. Under the base model without an ND-GAIN threshold, individuals from more vulnerable regions could choose a vulnerable location as a destination if it offers a slightly better ND-GAIN score. In this case, increasing population pressure and the demand for scarce resources could exacerbate the challenges the host location faces.

We observe that the ND-GAIN score for host locations was, on average, over 30% higher than that of the origin countries. To explore the impact of implementing a threshold on flow patterns, we reduced the ND-GAIN scores of all host locations by 40%. Figure 4(a) illustrates the inflow amounts and capacity utilizations when ND-GAIN scores are reduced by 40% for each location under the base scenario. After this reduction, we observe a decrease in the utilization of Hosts 1 and 2 when compared to the initial ND-GAIN case 3(a). Following the addition of a 25% threshold, which permits relocation only if the destination location's ND-GAIN score is 25% higher than that of the origin, we observe changes in flows and utilization. Applying this threshold reduces inflows or, in some instances, stops them entirely. Figure 4 illustrates that Hosts 1 and 4 receive no flows, as their ND-GAIN indices fall below the threshold.

This modification shows the significant role that the ND-GAIN index threshold plays in the




(a) Reduced ND-GAIN score




(b) Reduced ND-GAIN score with 25% threshold

Figure 3.6: Total flows to host locations using the ND-GAIN index threshold score.

relocation decision-making process. It illustrates that adjusting the threshold not only influences the attractiveness of host locations but also fundamentally alters the distribution of flows among them. This adjustment to the ND-GAIN index threshold scenario further refines the relocation decision-making process, highlighting how thresholds can influence flow patterns and the attractiveness of host locations.

This scenario can offer valuable insights for preference-based relocation algorithms, where individuals have specific preferences and thresholds in their decision-making process. By incorporating environmental and economic standards and ND-GAIN scores as part of these preferences, such algorithms can simulate realistic choices that individuals consider during the relocation process. This approach allows for exploring how varying levels of environmental readiness and vulnerability impact individual preferences and migration patterns.

## 3.5 Concluding Remarks

### 3.5.1 Key Contributions

Climate change is expected to drive substantial and sustained displacement in the coming decades. Sea-level rise, intensifying natural disasters, and declines in agricultural productivity will increasingly disrupt the habitability of vulnerable regions. In response, proactive and long-term resettlement planning has become an essential component of climate adaptation. Resettlement, when strategically planned, can offer a durable solution by ensuring the safety, stability, and integration of displaced populations. This dissertation contributes to that effort by developing quantitative tools that support the design of equitable and sustainable relocation strategies.

Motivated by these challenges, the proposed approach introduces a structured modeling framework for long-term relocation planning under climate stress. At the core of this framework is a temporal multilayer network model, which represents each planning period as a distinct layer. This structure allows the model to capture changes in population supply, destination capacity, and relocation flows over time. It supports multi-period decision-making by incorporating cost efficiency, cultural compatibility, and host-country readiness and vulnerability.

A distinctive contribution of the model is its explicit consideration of cultural distance. By moving beyond purely economic or geographic optimization, the model integrates social dimensions of resettlement. This holistic approach aims to foster social cohesion and improve the long-term success of integration. Simulation results demonstrate how changes in transfer costs, cultural distance, and host attractiveness shape allocation patterns. For instance, when capacities expand, demand shifts toward cost-efficient or culturally proximate destinations, revealing elastic dynamics that depend on both policy and location-specific attributes.

The model also serves as a decision-support tool for policymakers, offering the ability to test alternative policy configurations and simulate future scenarios. For example, by incorporating the ND-GAIN index, the framework links relocation decisions to host countries' readiness and vulnerability. This integration encourages a shift toward more climate-resilient migration policies and offers guidance on how to distribute flows equitably and efficiently. Threshold-based decision rules can prevent overburdening fragile destinations and enhance the overall sustainability of the relocation system.

Finally, the model's methodological innovation lies in the temporal multilayer structure of the model. This design enables the relocation system to adapt over time, carrying forward supply, adjusting to shifting capacities, and identifying bottlenecks or capacity thresholds as they emerge. This flexibility distinguishes the proposed framework from traditional models that assume static flows or one-time relocation decisions. By capturing the evolving nature of climate displacement, the model offers a practical and forward-looking planning tool for long-term resettlement strategies.

### 3.5.2 Limitations

While the temporal model provides a structured framework for analyzing long-term relocation under climate stress, several limitations remain. First, the model assumes a deterministic setting and does not explicitly account for uncertainty in climate impacts, policy shifts, or population behavior. In real-world planning, such uncertainty can significantly alter outcomes. Incorporating stochastic parameters or robust planning methods could improve reliability.

Moreover, the model focuses on aggregate population flows and does not capture important social dynamics such as family reunification, which often influence relocation decisions and affect social cohesion in host locations. In addition, the proposed approach does not differentiate between populations based on specific needs or urgency levels. This limits its ability to reflect more granular planning priorities and respond to emergency-driven relocation scenarios.

Finally, the model does not include formal fairness mechanisms to ensure equitable outcomes across regions or population groups. Embedding such considerations through constraints or evaluation metrics would strengthen its applicability to real-world relocation planning.

### 3.5.3 Future Directions

Several extensions of this research can further enhance the relevance and applicability of the relocation framework. First, incorporating a multi-commodity structure would allow the model to represent diverse population groups with varying needs. Treating these groups as distinct commodities would support more granular planning and facilitate the design of customized allocation strategies, better aligning relocation plans with real-world demographic heterogeneity.

Another promising direction involves accounting for family reunification, a factor that significantly influences migration decisions and affects both the timing and destination of relocation. Integrating policies that promote family unity could improve the model's realism and support outcomes that are socially cohesive.

The model's current structure assumes fully connected temporal layers, where each destination is accessible from all origins in each time period. Introducing topological constraints within layers could reflect real-world limitations in migration corridors and policy restrictions, offering a more refined representation of the network structure. Similarly, embedding urgency levels at origin locations, such as those identified by UNHCR or other humanitarian agencies, would allow the model to prioritize relocations based on vulnerability or crisis severity. This addition would introduce a humanitarian dimension to planning, aligning outcomes with ethical and needs-based principles.

Finally, beyond logistical modeling, future work should more directly engage with the social integration dimension of resettlement. Programs such as language training, vocational support, and community engagement are critical to long-term success. Cultural compatibility, partially captured in this study using Hofstede's dimensions, could be expanded to reflect evolving integration policies and host society receptiveness. Incorporating these factors into the model would strengthen its relevance for decision-makers, bridging the gap between quantitative planning and the lived realities of displaced populations.

# Chapter 4

# A Multi-Commodity Optimization Model for Climate-Induced Relocation Decisions

## 4.1 Introduction

This chapter introduces a multi-commodity optimization model that offers a new approach to climate-induced relocation problems, complementing the temporal planning framework discussed previously. As highlighted in the previous chapter, displaced populations face varying levels of vulnerability, urgency, and integration needs. These differences are not captured when treating individuals as a homogeneous group (e.g., UNHCR 2022). The multi-commodity framework shifts attention to these variations and to the operational complexities that arise in realistic migration systems.

By enabling the separate representation of different groups within the population, this model provides a more detailed and realistic understanding of migration flows and priorities. Distinguishing among populations based on their specific needs and risk profiles allows for a granular view of how relocation can be planned and managed more equitably and effectively. This approach supports a more responsive and socially responsible framework for long-term resettlement under climate stress.

In addition to capturing variation across population groups, the model incorporates queue dynamics and waiting times to reflect the delays that often arise in real-world migration processes. These delays may result from administrative procedures, limited processing capacity, or logistical constraints. By explicitly modeling waiting periods and introducing penalties for excessive delays, the framework allows for a more realistic and policy-relevant analysis. The model supports the evaluation of not only where and when individuals are relocated, but also whether delays in the process are distributed fairly across groups and destinations.

Fairness is a key component of this approach, addressing both the fair treatment of different migrant groups and the balanced sharing of responsibility among host countries. This approach acknowledges that planning must prioritize not only efficiency but also fairness and ethical outcomes. These features make the multi-commodity model a practical tool for long-term migration planning, capturing important complexities.

## 4.2 Proposed Approach

A multi-period, multi-commodity flow optimization model for long-term planning for climate-induced migration. The model supports relocation decisions that balance individual preferences, fairness across groups and locations, and resource constraints such as destination capacity. Origin countries refer to areas experiencing high climate vulnerability, while destination countries denote locations with the capacity to receive and resettle displaced populations. The model tracks vulnerable populations across origin-destination pairs over several periods, accounting for supply limitations, destination capacities, queue evolution, and equity metrics. Each commodity in the model represents a group defined by vulnerability level, allowing differentiated treatment in flow allocation and fairness evaluation.

We formulate the relocation planning problem as a linear optimization model. The objective is to determine optimal flows for vulnerable populations affected by climate impacts, balancing individual preferences, fairness targets, capacity limitations, and budget constraints over time. The model includes key features such as dynamic supply and capacity rollover, evolving preference scores based on prior relocation patterns, and queue tracking to reflect potential delays at destination sites. Fairness is addressed across two dimensions: burden sharing among destination countries and equitable treatment of different vulnerability groups. The remainder of this section introduces the model's components, including sets, parameters, decision variables, objectives, and constraints.

The model is built on several assumptions that structure how individuals move through the system. Individuals who are not assigned to any destination in a given period remain at their origin and are reconsidered in subsequent periods. Once assigned to a destination, individuals enter a queue at the destination if the available capacity is insufficient to accommodate relocation within the given period. This structure reflects the assumption that, in the context of climate-induced displacement, individuals who have already been assigned to a destination location are expected to wait at the destination rather than remain in vulnerable origin areas while their relocation is processed. The queueing mechanism also captures system delays and models real-world limitations in processing and infrastructure. The model does not explicitly track families, but operates at an aggregate level based on group-specific flows and incorporates family reunification indirectly through preference adjustments based on prior flows, capturing the influence of diaspora dynamics and social ties in shaping destination preferences.

### 4.2.1 Parameters and Decision Variables

The model is defined over four main sets. Let $I$ denote the set of origin locations, $J$ the set of destination locations, $V$ the set of vulnerability groups, and $T$ the set of time periods. These sets

Table 4.1: Parameters in the proposed model.

| | |
|---|---|
| $S_{ivt}$ | Supply for group $v$ from origin $i$ at time $t$ |
| $C_{jt}$ | Capacity of destination $j$ at time $t$ |
| $\gamma_{jt}$ | Rollover rate for unused capacity at $j$ from $t$ to $t$+1 |
| $B_t$ | Budget at time $t$ |
| $\delta_\tau$ | Budget rollover rate from previous time $\tau$ |
| $c_{ijv}$ | Relocation cost for group $v$ from origin $i$ to destination $j$ |
| $p_{ijv}^{\text{init}}$ | Initial preference score for group $v$ from origin $i$ to destination $j$ |
| $\rho$ | Reunification boost factor |
| $N$ | Normalization constant for preference update |
| $\omega_v$ | Weight for waiting time for group $v$ |
| $G_t$ | Destination fairness threshold at time $t$ |
| $R_t$ | Vulnerability fairness threshold at time $t$ |
| $\tau_v$ | Target processing rate for group $v$ |

establish the structure of the relocation planning problem. The combination of origin, destination, group, and time defines a possible relocation flow. The time dimension allows for multi-period planning, and the inclusion of vulnerability groups enables the model to differentiate among population segments based on their exposure to climate-related risks.

The parameters can be found in Table 4.1. The parameter $S_{ivt}$ denotes the number of individuals available for relocation from origin location $i$, belonging to vulnerability group $v$, in period $t$. Destination location capacity is represented by $C_{jt}$, which defines the maximum number of individuals that destination $j$ can accept in period $t$. The model includes a rollover mechanism, where a fraction of unused capacity at time $t$ may be carried over to the next period. This is captured by the parameter $\gamma_{jt}$, the capacity rollover rate at destination $j$ from period $t$ to $t$+1. The value of $\gamma_{jt}$ can reflect different destination location strategies, ranging from full retention to partial or no rollover depending on administrative constraints and policies.

The parameter $c_{ijv}$ represents the normalized relocation cost of moving an individual from origin location $i$ to destination location $j$, for vulnerability group $v$, based on geographic distance and other considerations. These values reflect the relative difficulty of relocation and provide a standardized basis for comparing flows across origin–destination pairs. The total normalized cost of all flows in each period $t$ is limited by a budget parameter $B_t$, which defines the upper bound on the total relocation burden that can be supported in period $t$, accounting for logistical limitations or policy-defined thresholds. To support multi-period planning, the model also includes a budget rollover mechanism: a fraction of unused budget from earlier periods $\tau < t$, controlled by the rollover rate $\delta_\tau$, can be carried forward into period $t$. This structure enables the model to represent a range of planning scenarios, including fixed-period allocations and dynamic multi-period strategies.

To include individual preferences related to destination characteristics, such as cultural proximity and existing diaspora networks, we use parameters that represent initial preferences and allow them to evolve over time based on relocation patterns. The parameter $p_{ijv}^{\text{init}}$ represents the initial preference score for individuals in vulnerability group $v$ relocating from origin $i$ to destination $j$. These values are fixed at the start of the planning horizon and act as the baseline input for preference-based assignments. To reflect evolving relocation dynamics, the model updates preference scores over time based on cumulative past flows. The reunification boost factor $\rho$ increases preferences for destinations that have received more individuals from the same origin and group. The normalization constant $N$ controls the magnitude of this effect and helps maintain consistent influence of preference updates across time.

To support fairness and time-sensitive relocation, the model uses several additional parameters. Waiting time sensitivity is captured by $\omega_v$, which penalizes delays experienced by individuals in vulnerability group $v$. Higher values of $\omega_v$ indicate greater urgency in relocating these groups. The parameter $\tau_v$ represents the target processing rate for group $v$, defining equitable treatment in terms of the proportion of the group successfully relocated over time. Fairness is further addressed through two threshold parameters: $G_t$, which limits deviations in destination utilization during period $t$ to promote burden-sharing among destinations, and $R_t$, which sets a bound in period $t$ on the disparity between the actual and target relocation rates across vulnerability groups.

The decision variables used in the model are listed in Table 4.2. These variables determine how individuals are assigned and relocated over time, how delays are tracked, and how fairness and capacity dynamics are monitored. The variable $a_{ijvt}$ represents the number of individuals from origin $i$, in vulnerability group $v$, assigned to destination $j$ in period $t$, regardless of whether they are officially processed for relocation within that period. The variable $x_{ijvt}$ denotes the number of individuals from origin $i$ in vulnerability group $v$ who are relocated to destination $j$ in period $t$, subject to the available capacity at the destination. If the number of assigned individuals exceeds the destination's capacity, the excess is captured by the queue variable $q_{ijvt}$, which reflects pending relocations at the destination. In contrast, individuals who are not assigned at all in a given period remain at their origin and are tracked by the carry-over variable $y_{ivt}$, which allows them to be reconsidered in future periods.

In addition to assignment and relocation decisions, the model includes variables that track unused capacity, update preferences over time, and support fairness across both destination countries and vulnerability groups. The variable $z_{jt}$ represents unused capacity at destination $j$ in period $t$, which is rolled over into future periods based on policy. The preference score $p_{ijvt}$ is updated dynamically relative to its initial value, $p_{ijv}^{\text{init}}$, to reflect changes in individual preferences, influenced by past relocation flows and the presence of diaspora communities. To enforce fairness across destination locations, the variable $g_{jt}$ measures the deviation of destination $j$'s utilization from the average in period $t$. Similarly, $r_{vt}$ captures the deviation between the actual relocation rate and the target processing rate for vulnerability group $v$. The slack variables $s_t^h$ and $s_t^v$ provide flexibility in meeting fairness constraints by softening the thresholds on destination utilization and vulnerability level relocation equity, respectively. Using these parameters and decision variables.

Table 4.2: Decision variables in the proposed model.

| | |
|---|---|
| $a_{ijvt}$ | Number of individuals in group $v$ assigned from $i$ to $j$ at time $t$ |
| $x_{ijvt}$ | Number of individuals in group $v$ relocated from $i$ to $j$ at time $t$ |
| $y_{ivt}$ | Unassigned individuals in group $v$ from $i$ carried to time $t$ |
| $q_{ijvt}$ | Queue length for group $v$ from $i$ to $j$ at time $t$ |
| $z_{jt}$ | Unused capacity at $j$ at time $t$ |
| $p_{ijvt}$ | Updated preference score for group $v$ from $i$ to $j$ at time $t$ |
| $g_{jt}$ | Deviation from average load at $j$ at time $t$ |
| $r_{vt}$ | Deviation from target processing rate for group $v$ at time $t$ |
| $s_t^h$ | Slack for destination fairness constraint at time $t$ |
| $s_t^v$ | Slack for vulnerability fairness constraint at time $t$ |

### 4.2.2 Model Formulation

This chapter introduces a multi-commodity flow model formulated as a MILP to represent the dynamic relocation process associated with climate-induced migration. The model tracks the movement of different population groups, defined by vulnerability levels, across a temporal multilayer network of origin and host countries. It integrates both discrete and continuous decision variables across multiple time periods, enabling relocation plans to adjust in response to changes in capacities, resource availability, and other factors. By modeling relocation as a network flow problem with multiple commodities, the formulation captures fairness-related trade-offs in long-term resettlement planning. The complete mathematical formulation of the multi-commodity temporal network model (MTNM) is presented below.

$$\max \quad \sum_{i\in I}\sum_{j\in J}\sum_{v\in V}\sum_{t\in T} p_{ijvt}a_{ijvt} \tag{1}$$

$$\min \quad \sum_{i\in I}\sum_{j\in J}\sum_{v\in V}\sum_{t\in T} \omega_v \frac{q_{ijvt}}{C_{jt}} + \alpha_1 \sum_{t\in T} s_t^h + \alpha_2 \sum_{t\in T} s_t^v \tag{2}$$

$$\sum_{j\in J} a_{ijv1} + y_{iv1} = S_{iv1}, \quad \forall i \in I,\, v \in V \tag{3}$$

$$\sum_{j\in J} a_{ijvt} + y_{ivt} = S_{ivt} + y_{iv,t-1}, \quad \forall i \in I,\, v \in V,\, t \in T \setminus \{1\} \tag{4}$$

$$\sum_{i\in I}\sum_{v\in V} x_{ijv1} + z_{j1} \leq C_{j1}, \quad \forall j \in J \tag{5}$$

$$\sum_{i\in I}\sum_{v\in V} x_{ijvt} + z_{jt} \le C_{jt} + \gamma_{j,t-1} z_{j,t-1}, \quad \forall j \in J,\ t \in T\setminus\{1\} \tag{6}$$

$$q_{ijv1} = a_{ijv1} - x_{ijv1} \quad \forall i \in I,\ j \in J,\ v \in V \tag{7}$$

$$q_{ijvt} = q_{ijv(t-1)} + a_{ijvt} - x_{ijvt} \quad \forall i \in I,\ j \in J,\ v \in V,\ t \in T\setminus\{1\} \tag{8}$$

$$\sum_{i\in I}\sum_{j\in J}\sum_{v\in V} c_{ijv}\, x_{ijv1} \ \le\ B_1 \tag{9}$$

$$\sum_{i\in I}\sum_{j\in J}\sum_{v\in V} c_{ijv}\, x_{ijvt} \ \le\ B_t + \sum_{\tau=1}^{t-1} \delta_\tau \left( B_\tau - \sum_{i\in I}\sum_{j\in J}\sum_{v\in V} c_{ijv}\, x_{ijv\tau} \right), \quad \forall t \in T\setminus\{1\} \tag{10}$$

$$p_{ijvt} = p_{ijv}^{\mathrm{init}} + \rho \frac{\sum_{\tau<t} x_{ijv\tau}}{N} \quad \forall i \in I,\ j \in J,\ v \in V,\ t \in T \tag{11}$$

$$\phi_{jt} = \frac{\sum_{i\in I}\sum_{v\in V} x_{ijvt}}{C_{jt}} \quad \forall j \in J,\ t \in T \tag{12}$$

$$\bar{\phi}_t = \frac{1}{|J|}\sum_{j\in J} \phi_{jt} \quad \forall t \in T \tag{13}$$

$$g_{jt} \ge \phi_{jt} - \bar{\phi}_t \quad \forall j \in J,\ t \in T \tag{14}$$

$$g_{jt} \ge \bar{\phi}_t - \phi_{jt} \quad \forall j \in J,\ t \in T \tag{15}$$

$$\sum_{j\in J} g_{jt} \le G_t + s_t^h, \quad \forall t \in T \tag{16}$$

$$\ell_{vt} = \frac{\sum_{i\in I}\sum_{j\in J} x_{ijvt}}{\sum_{i\in I} S_{ivt}} \quad \forall v \in V,\ t \in T \tag{17}$$

$$r_{vt} \ge \ell_{vt} - \tau_v \quad \forall v \in V,\ t \in T \tag{18}$$

$$r_{vt} \ge \tau_v - \ell_{vt} \quad \forall v \in V,\ t \in T \tag{19}$$

$$\sum_{v \in V} r_{vt} \leq R_t + s_t^v, \quad \forall t \in T \tag{20}$$

$$a_{ijvt},\ x_{ijvt},\ y_{ivt},\ q_{ijvt},\ z_{jt} \in \mathbb{Z}^{\geq 0}, \quad g_{jt},\ r_{vt},\ s_t^h,\ s_t^v \geq 0, \quad \forall i, j, v, t \tag{21}$$

The model has a bi-objective structure to balance two key goals in the long-term relocation of individuals displaced by climate impacts: aligning relocations with individual preferences, and minimizing waiting times while promoting fair and efficient use of destination location capacities. These objectives balance individual preferences with timely, equitable, and sustainable system outcomes. The first objective function (1) seeks to maximize the cumulative satisfaction of individual preferences over the planning horizon. The preference score $p_{ijvt}$ captures the temporal desirability of each destination, which may depend on factors such as cultural proximity, historical ties, existing diaspora, and socio-economic opportunity. The objective ensures the solution reflects individual preferences and aims to support long-term integration. Furthermore, the dynamic structure of preferences, updated over time based on prior flows, captures evolving sentiment and network effects. For example, as more individuals from a particular origin settle in a destination, that location may become more attractive to future applicants from the same region, reinforcing diaspora-driven pathways. The second objective (2) focuses on reducing waiting times while also promoting fair burden sharing between destination countries and equitable treatment of different vulnerability groups. Minimizing accumulated waiting queues is the core of this objective, reflecting the importance of reducing delays in the relocation process. The term $\frac{q_{ijvt}}{C_{jt}}$ captures the relative size of the waiting population from origin $i$, with vulnerability level $v$, awaiting placement in destination country $j$ at time $t$, normalized by that destination's capacity. This normalization ensures that delays are evaluated in proportion to each country's ability to absorb individuals. The weighting factor $\omega_v$ increases the penalty for delays affecting more vulnerable groups, prioritizing timely relocation for individuals with higher needs. Beyond logistics, queue reduction also has security and humanitarian implications. Long delays can increase frustration, erode trust in formal relocation systems, and lead to irregular movements such as unauthorized crossings or exploitation by trafficking networks. Extended delays can also create challenges for coordination, integration, and overall stability, which makes timely relocation important from a humanitarian perspective. To ensure feasibility when fairness targets are difficult to meet, slack variables are included in the objective to allow controlled deviations from ideal burden sharing and vulnerability based allocations.

Constraint (3) initializes the supply balance for the first period, ensuring that the total number of individuals assigned for relocation plus those carried over matches the initial available supply. Constraint (4) extends this balance to subsequent periods and ensures that the total number of individuals approved for relocation in period $t$, along with those who are not yet approved and thus carried over as $y_{ivt}$, does not exceed the available supply. The right-hand side includes both the newly available population $S_{ivt}$ for the current period and any unassigned individuals $y_{iv\tau}$ carried over from previous periods. This constraint allows individuals to remain eligible across periods and ensures that total approvals do not exceed the cumulative available supply up to that point. This structure adds flexibility to multi-period planning and allows the model to consider individuals who were not approved in earlier periods for relocation in subsequent ones. Constraint (5) defines the capacity constraint for the first period, ensuring that the total number of individuals relocated to each destination plus unused capacity does not exceed the initial available capacity. Constraint (6) extends this capacity limit to subsequent periods and limits the number of individuals actually relocated to destination country $j$ in period $t$, along with any unused capacity $z_{jt}$, to the available capacity $C_{jt}$ plus a portion of unused capacity from earlier periods that can be rolled over. The rollover is determined by a policy parameter $\gamma_{j\tau} \in [0, 1]$, which specifies the fraction of unused capacity $z_{j\tau}$ from a previous period $\tau$ that can be added to the current period. This aligns with real-world operational planning, where destination countries may underutilize capacity in one year and carry forward a portion of it depending on institutional readiness or national policy. The rollover introduces temporal flexibility in capacity management and allows the model to simulate scenarios where destination locations adjust their commitments over time without being bound by strict annual fulfillment targets.

Constraint (7) defines the queue length in the initial period based on the difference between the approved inflows and the number of individuals relocated. Constraint (8) defines the evolution of queues over time for each combination of origin, destination, and vulnerability group. The queue length $q_{ijvt}$ at time $t$ depends on the number of individuals already in the queue in the previous period $q_{ijv(t-1)}$, the number newly approved for relocation to destination $j$ in the current period $a_{ijvt}$, and the number actually relocated $x_{ijvt}$. This constraint tracks pending relocations and maintains them across periods to capture time-dependent dynamics. It reflects the accumulation of pending relocations, which is essential for assessing waiting times and pressure on destination location capacities. By tracking how queues evolve over time, the model helps identify delays and supports more timely relocation decisions within capacity limits. It provides a foundation for policy design by revealing where and when backlogs occur, and by enabling scenario testing to evaluate how different strategies affect queue dynamics and equitable access.

Constraint (9) imposes a budget limit on relocation activities in the initial period. Constraint (10) places a budget constraint on total relocation activities in each period, while allowing partial rollover of unused funds from previous periods. This structure reflects financial constraints often present in real-world planning and supports more flexible, multi-period resource allocation. The right-hand side includes the current period's budget $B_t$ and a fraction of any unspent budget from prior periods, governed by the rollover factor $\delta_\tau \in [0, 1]$. This constraint reflects real-world financial practices by allowing unused resources to be partially carried forward, enabling the model to simulate scenarios in which decision-makers strategically delay or accelerate relocations based on available funds.

Constraint (11) updates preference scores dynamically based on relocation history. The preference score $p_{ijvt}$ combines the initial value $p_{ijv}^{\text{init}}$ with a time-dependent adjustment based on past relocation flows from origin $i$ to destination $j$ for vulnerability group $v$. The adjustment is scaled by the parameter $\rho$ and normalized by a factor $N$. This formulation captures factors that might impact the attractiveness of a destination location, including the presence of diaspora or the strength of bonds in social networks. It allows preferences to evolve as more individuals relocate to the same destination. It reflects realistic behavioral dynamics, where observed resettlement patterns influence future preferences and improve model responsiveness to temporal trends. In the long-term resettlement setting, preference scores are modeled as non-decreasing since accumulated diaspora networks are assumed to have a lasting and persistent influence on future relocation decisions. As communities grow and become established, they create social and institutional support structures that continue to attract additional individuals. The cumulative preference formulation reflects the development of diaspora networks and includes factors such as family reunification, where existing family members or social ties strengthen the appeal of destinations over time. While preferences may decline under short-term disruptions, the formulation focuses on gradual, planned relocation processes where diaspora effects build and strengthen over time.

Constraints (12) through (16) collectively promote fairness in how destination country capacities are used over time. This group of constraints aims to produce more balanced relocation outcomes by discouraging imbalance in how destination country capacities are utilized. Constraint (12) measures the utilization rate of each destination $j$ in each period $t$, denoted by $\phi_{jt}$, which represents the proportion of capacity used at each destination. Constraint (13) defines $\bar{\phi}_t$ as the average utilization across all destinations in that period. Constraints (14) and (15) introduce non-negative auxiliary decision variables $g_{jt}$ to capture the absolute deviation between each destination's utilization and the average utilization. These constraints handle both over- and under-utilization, representing the positive and negative deviations, and linearizing the absolute value of the difference. Constraint (16) imposes a soft upper bound on the total deviation across destinations, limiting the overall imbalance while allowing flexibility through a slack variable. While Constraint (16) controls overall imbalance by limiting total deviations across destinations, an alternative approach could impose individual upper bounds directly on each $g_{jt}$, ensuring per-destination fairness more strictly but potentially reducing flexibility under varying system conditions. Together, these constraints enable the model to incorporate equity in destination country contributions without enforcing fixed allocation rules.

Constraints (17) through (20) together ensure fairness across vulnerability groups over time. Constraint (17) computes the relocation rate for each vulnerability group $v$ in period $t$, denoted by $\ell_{vt}$, representing the proportion of individuals from group $v$ who are actually relocated relative to the total supply available for that group. Constraints (18) and (19) introduce non-negative auxiliary decision variables $r_{vt}$ to capture the absolute deviation between each group's relocation rate $\ell_{vt}$ and its target processing rate $\tau_v$. These two inequalities linearize the absolute value by separately representing positive and negative deviations. Constraint (20) places a soft limit on the total deviation across all groups, using a slack variable to allow flexibility. This helps the model promote more balanced outcomes across vulnerability levels, while the exact fairness criteria can be adjusted and explored through scenario analysis. An alternative approach could impose individual upper bounds directly on each $r_{vt}$, ensuring more strict fairness per group but potentially reducing flexibility under varying supply-demand conditions. Finally, constraint (21) provides the domain constraints for the decision variables.

The proposed model integrates individual preferences, capacity constraints, fairness considerations, and budget flexibility for long-term relocation planning. In the following section, we present an illustrative case study to demonstrate how the model operates in practice and examine the outcomes under different parameter settings and policy configurations.

## 4.3 Case Study Design and Data Description

To construct the case study, origin countries are selected based on their high vulnerability to climate change and limited capacity to adapt or mitigate its impacts due to economic constraints. The ND-GAIN index is used to guide this selection, as it ranks countries based on their exposure, sensitivity, and adaptive capacity to climate-related risks [45]. Developed by the Notre Dame Global Adaptation Initiative, the ND-GAIN index helps identify locations where both environmental stress and socioeconomic limitations are likely to drive significant long-term displacement.

To include different levels of climate vulnerability in the model, we classify the selected origin countries into three groups: high, medium, and low. This classification is based on each country's ND-GAIN score and the dominant type of climate-related hazard they face. The goal is to reflect not only environmental exposure but also the urgency and type of risks that may influence displacement pressures. Countries in the high vulnerability group are exposed to rapid-onset, high-intensity events such as sea-level rise or prolonged droughts. Medium vulnerability countries typically face recurring seasonal hazards like flooding or heatwaves. Those in the low vulnerability group experience slower-moving but persistent forms of environmental degradation. This grouping is supported by national-level climate risk profiles [46], which document exposure to hazards such as extreme heat, drought, food insecurity, and sea-level rise. This categorization allows the model to treat different levels of vulnerability separately and supports the evaluation of fairness across distinct risk profiles. Table 4.3 provides representative examples for each group and associated hazard types.

To estimate anticipated climate-related displacement from origin locations, it is assumed that approximately 10% of each country's population may be displaced due to climate impacts by 2050. This assumption is consistent with scenario-based projections from the World Bank [47] and supported by global assessments of displacement risk in highly exposed regions [46]. National population estimates for origin countries were obtained from the World Bank's most recent available data [48]. These base-year estimates were used to calculate the number of individuals potentially displaced, assuming 10% of each population. The resulting values were then distributed across four planning periods, gradually increasing over time to reflect escalating climate-related pressure.

Seven destination locations are selected to ensure a balance between model realism and com-

Table 4.3: Vulnerability levels based on the ND-GAIN index, including dominant climate-related hazards and origin countries [45, 46].

| Vulnerability level | Dominant climate hazards | Origin locations |
|---|---|---|
| High | Fast-onset and high-intensity events such as sea-level rise, prolonged droughts, and climate-related conflict stress | Chad, Central African Republic, Eritrea, Democratic Republic of the Congo, Sudan, Guinea-Bissau, Madagascar, Mali, Haiti |
| Medium | Recurring or seasonal events including floods, heatwaves, and agricultural disruption | Yemen, Afghanistan, Sierra Leone, Niger, Burundi, Bangladesh, Zimbabwe, Angola, Cameroon |
| Low | Long-term environmental decline and gradual habitability loss | Nigeria, Pakistan, Ethiopia, South Sudan, Venezuela, Iraq, Congo, Guinea, Somalia, Benin, Mozambique, Liberia |

putational tractability. These countries were chosen based on geographic diversity, economic strength, and historical involvement in refugee resettlement. Capacity estimates are derived from a combination of sources, including historical intake data from the UNHCR [49], policy trends from the OECD International Migration Outlook [50], and socioeconomic indicators such as GDP and population size from the World Bank [48]. These sources guide the selection of countries that represent both high-capacity regions and varied geographic settings. To avoid controversy, real names of destination countries are not used. Capacity allocations are set to increase gradually over time to reflect growing global recognition of climate migration and the need for international support.

Initial preference scores represent how individuals from different origin–vulnerability groups perceive potential destination locations. They are based on two main factors: geographic proximity, which reflects regional familiarity, and language proximity, which is an indicator for cultural integration. Geographic familiarity influences how accessible and feasible a destination appears, while language proximity reflects how linguistic similarity can support communication, access to services, and long-term integration. The combined initial preference score is defined in Eq. (18), where $\lambda \in [0, 1]$ is a weighting parameter balancing the influence of spatial versus cultural alignment.

$$p_{ijv}^{\text{init}} = \lambda \times \text{RegionScore}_{ij} + (1 - \lambda) \times \text{LangScore}_{ij} \tag{22}$$

$\text{RegionScore}_{ij}$ is generated from a predefined base range determined by the geographic relationship between origin $i$ and destination $j$, ensuring consistency with regional logic. $\text{LangScore}_{ij}$ is a categorical score assigned based on linguistic similarity between the two countries.

Language proximity scores are assigned based on the level of linguistic similarity between origin and destination. A score of 1.0 indicates a shared official or primary language, 0.8 reflects a historically linked or widely spoken language, and 0.4 indicates no significant overlap. Language is a well-established factor in migration research, influencing social cohesion, labor market outcomes, and access to services [51, 52]. Table 4.4 provides representative examples of language proximity scores and and their underlying explanation.

Table 4.4: Language proximity scores for several example origin and destination countries.

| Origin | Destination | Score | Explanation |
|---|---|---|---|
| Chad | 4 | 1.0 | Shared official language |
| Haiti | 5 | 0.8 | Historically linked and widely spoken |
| Bangladesh | 3 | 0.4 | No significant linguistic connection |

The cost parameter $c_{ijv}$ represents the relative difficulty of relocating individuals from origin $i$ to destination country $j$. It is calculated by first measuring the Haversine distance [53] between each origin–destination pair, measuring the shortest distance between two points on the Earth's surface, and then applying normalization to ensure comparability across all routes. To account for real-world operational challenges, each normalized distance is scaled by a scenario-based multiplier. This multiplier reflects factors such as infrastructure quality and geographic accessibility.

Origins facing greater challenges are assigned higher multipliers, whereas those with more easier coordination conditions receive lower values. This hybrid structure ensures that the relocation cost reflects both geographic and practical considerations. The budget value, $B_t$, is calculated by multiplying the estimated number of individuals expected to relocate from the origin countries by the average relocation cost.

The remaining parameters are used to tune the model across different fairness and operational trade-offs. These include vulnerability weights for queue penalties and fairness penalty weights for deviations. Additionally, fairness tolerance thresholds and the budget rollover rate introduce flexibility in how the model responds to constraints across periods. Since these parameters primarily tune model dynamics, we do not specify their values here.

## 4.4 Implementation and Results

The model's behavior is analyzed by examining the distribution of relocation flows across vulnerability levels, queue lengths over time, and how individual preferences evolve based on previous relocations. These analyses provide insight into how the model balances fairness, efficiency, and policy constraints across multiple time periods. The following subsections explore these components individually to better understand how the model performs across different dimensions. By looking at flows, queues, and preference shifts in turn, the analysis sheds light on the system's internal dynamics and how different constraints shape the results.The model is implemented in Python using Gurobi.

#### Relocation Flows and Vulnerability

Figure 4.1 shows relocation flows by the destination, time period, and vulnerability level, along with percentages indicating the share of each vulnerability group's total supply relocated. The graphs demonstrate that the model strongly prioritizes high-vulnerability populations, typically accounting for 60–95% of relocations across most destinations and periods. The allocation for medium- and low-vulnerability groups varies significantly by destination and time, reflecting dynamic and flexible utilization of resources based on available capacities and demand fluctuations. Large-capacity destinations such as destination 5 accommodate significant numbers from all vulnerability groups, resulting in more balanced distributions, especially evident during 2030–2035 and 2040–2045 periods. Figure 4.1 highlights the model's ability to manage relocation priorities, reflecting vulnerability-driven fairness objectives and efficient use of destination resources.

#### Queue Analysis

To better understand bottlenecks and unmet demand in the system, we visualize the 10 largest queue accumulations. As shown in Figure 4.2, most long queues are associated with low-vulnerability groups, particularly those assigned to high-demand destinations. Although these individuals are officially allocated, relocation is delayed due to limited priority in the model. This reflects how the model balances urgency and fairness through the waiting time penalty weights ($\omega_v$) and group-level processing targets ($\tau_v$). The absence of high-vulnerability groups among the largest queues suggests that the model prioritizes their timely relocation, while lower-priority groups tend to accumulate in queues at more desirable locations. These patterns align with the model's objective of promoting fair and efficient outcomes across both origin groups and destinations. The accumulation of queues reflects structural dynamics in the model, particularly related to supply, capacity limits, and preferences. When the number of individuals eligible for relocation from an origin exceeds the available capacity in a given period, the unmet portion is retained in the system, contributing to queue formation. This is further compounded when many origins share similar preferences, placing a disproportionate demand on a few destination countries. Even when capacity is available elsewhere, strong preference alignment can lead to congestion at specific destinations. The queueing effect also builds across time when previous backlogs are not fully cleared. Altogether, queues reflect the combined impact of limited capacity, preference clustering, and accumulation.

### Preference Changes

Figure 4.3 illustrates the evolution of preference scores over time for selected origin–destination pairs. These scores are updated dynamically in the model based on cumulative relocation flows, where each successful relocation strengthens future preference through a reinforcement mechanism. The preference trends show different patterns over time, driven by flow volumes, initial scores, and destination availability. Nigeria's preference for destination 4 grows steadily due to relatively modest but consistent relocations, which gradually reinforce the destination's attractiveness over multiple periods. This pattern reflects a typical positive feedback loop where steady integration supports ongoing preference gains. In contrast, Chad's fluctuating pattern results from non-monotonic flow behavior, shaped by temporary constraints or queue dynamics that limit movement despite high prioritization. These two cases highlight how preference shifts are shaped not only by initial alignment but also by evolving relocation outcomes and systemic constraints within the model.

### Fairness

Fairness in burden sharing is an essential principle in resettlement planning. It aims to distribute relocation loads proportionally to each destination's total capacity. Table 4.5 shows the fairness gap by comparing each destination's ideal share, which represents the percentage of total flows they would receive if allocation were strictly proportional to capacity, with their actual share in the model results. Some locations, such as destinations 1 and 2, receive slightly less than their fair share. Others, including destinations 4 and 7, receive more than expected. These differences occur because the model balances fairness with other objectives, such as minimizing cultural distance, prioritizing preferences, and reducing queues. For example, destination 4 exceeds its ideal share, driven by strong preference alignment. In contrast, destination 2 receives less than its expected share, suggesting underutilized capacity. Overall, the table highlights how dynamic factors interact with equity goals in shaping relocation outcomes.

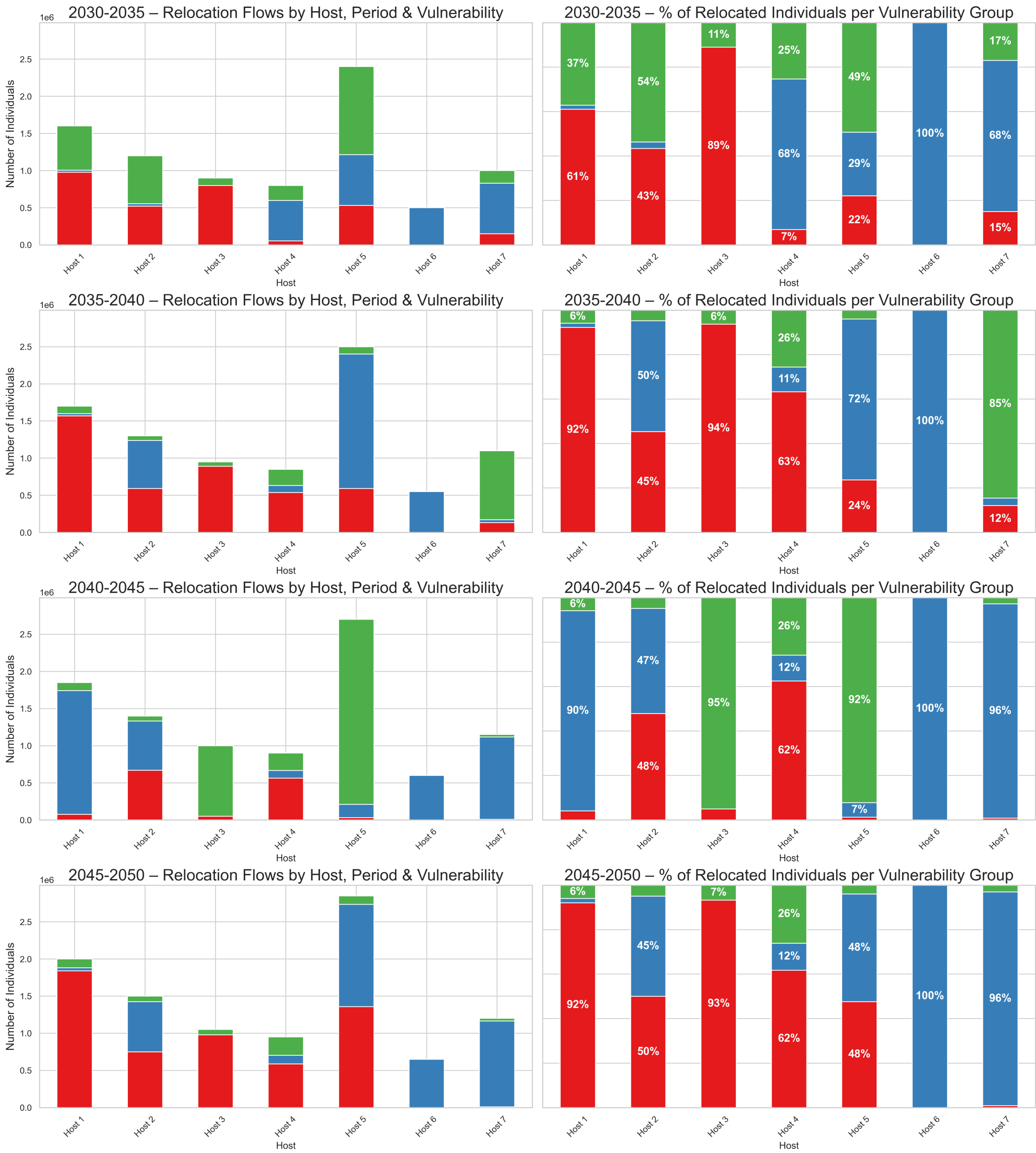



Figure 4.1: Relocation flows and vulnerability distribution by destination across time periods.

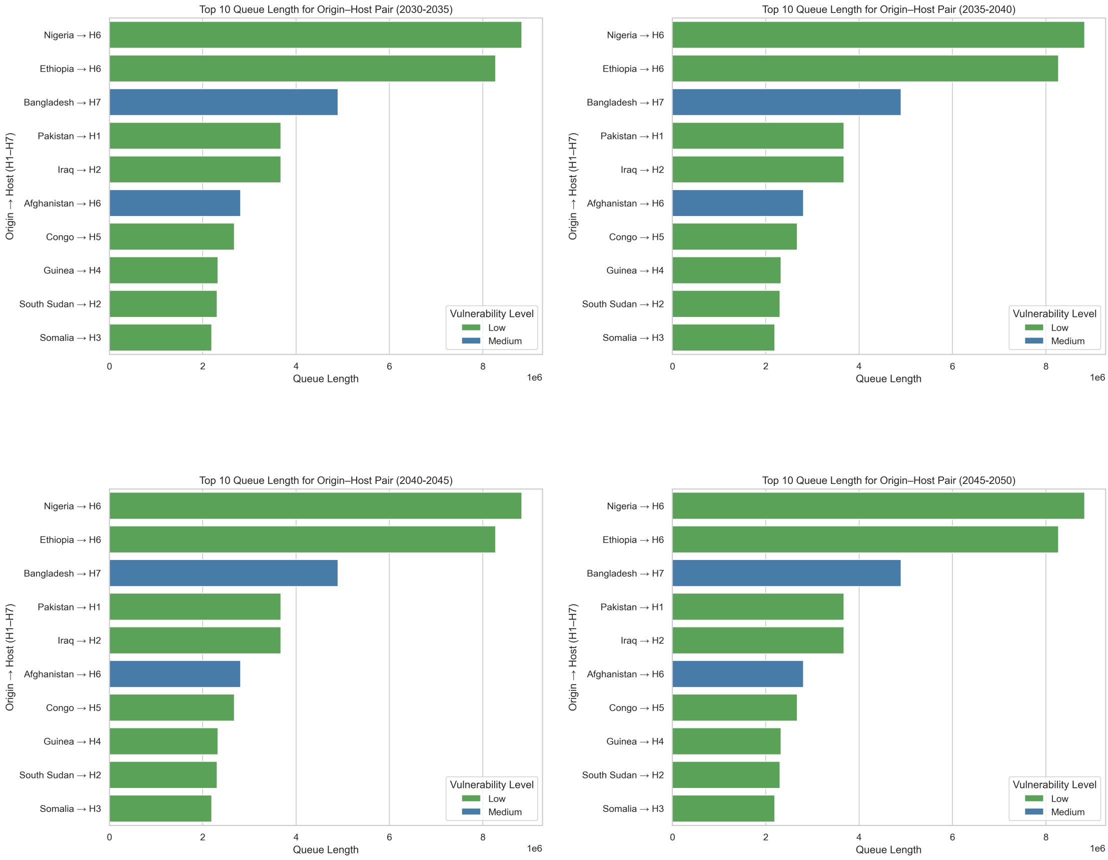



Figure 4.2: Top 10 queue accumulations per period, by origin, destination (H1–H7), and vulnerability group.

Table 4.5: Fairness gap across destination locations, all periods combined.

| Destination | Ideal share (%) | Actual share (%) | Gap (%) |
|---|---|---|---|
| 1 | 26.56 | 26.17 | -0.39 |
| 2 | 18.17 | 17.11 | -1.06 |
| 3 | 13.73 | 15.29 | +1.56 |
| 4 | 11.31 | 13.93 | +2.62 |
| 5 | 10.16 | 11.30 | +1.14 |
| 6 | 8.89 | 9.99 | +1.10 |
| 7 | 5.85 | 7.63 | +1.78 |

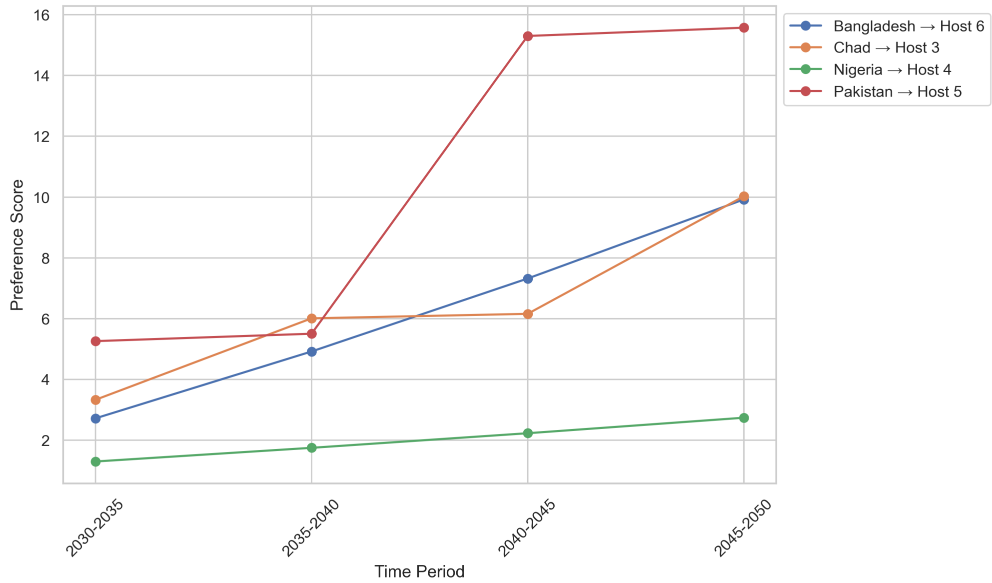



Figure 4.3: Preference score evolution over time for selected origin–destination pairs.

### Disruptions Scenarios

To evaluate the robustness of the resettlement model under uncertainty, we introduce a scenario tree that simulates disruptions in destination country availability across different periods. These disruptions are designed to reflect real-world uncertainties such as abrupt policy shifts, geopolitical instability, natural disasters, or global pandemics (e.g., COVID-19). The scenario structure consists of three severity levels. Scenario 1 represents a mild case, such as a policy change affecting one destination action. Scenario 2 introduces moderate disruptions, with one country disrupted in each time period. Scenario 3 represents a severe shock with simultaneous shutdowns of multiple destination countries. Table 4.6 summarizes the disruptions considered across scenarios. To ensure consistency between disruption severity and model impact, disrupted destinations were selected based on their baseline relocation volume in the initial model run. Destinations with lower intake were affected in the mild scenario, while high-volume destinations were progressively included in the moderate and severe scenarios. This nested design supports a clear escalation of disruption severity while allowing for comparison across scenario runs.

Table 4.6: Disrupted destination locations across time periods and scenarios.

| Time period | Scenario 1 (mild) | Scenario 2 (moderate) | Scenario 3 (severe) |
|---|---|---|---|
| 2030–2035 | Destination 1 | Destinations 1, 2 | Destinations 1, 2, 4 |
| 2035–2040 | Destination 6 | Destinations 6, 3 | Destinations 6, 3, 7 |
| 2040–2045 | Destination 2 | Destinations 2, 4 | Destinations 2, 4, 5 |
| 2045–2050 | Destination 7 | Destinations 7, 3 | Destinations 7, 3, 5 |

In the mild scenario, each destination is unavailable for one of the four periods. Because only one location is down at a time, the model reallocates its displaced arrivals among the remaining six. The most vulnerable groups still receive priority placement, and small shifts occur among medium- and low-vulnerability levels. Under the moderate scenario, two destinations are out of service at once. The model first reallocates high-vulnerability placements to any under-used locations, then fills the rest of the capacity with medium- and low-vulnerability. Even when two destinations are offline, the model preserves its minimum placement targets for the most vulnerable. In the severe scenario, different combinations of two and three destinations are unavailable in each of the four periods, creating substantial gaps in capacity. The remaining destinations absorb the majority of displaced flows according to their available capacity and vulnerability-weighted preference scores. High-vulnerability placement targets remain inviolate, and medium- and low-vulnerability groups are reassigned to destinations with available space, resulting in a more geographically diverse distribution than in the baseline.

## 4.5 Concluding Remarks

### 4.5.1 Key Contributions

This study develops a multi-period, multi-commodity optimization model for long-term climate-induced resettlement. The model accounts for varying vulnerability levels among displaced populations, changing destination preferences, and fairness considerations to support equitable and effective relocation decisions. By treating migration as a dynamic allocation problem, it captures how relocation flows evolve over time in response to supply, capacity, and preference feedback. It also reflects real-world constraints such as limited destination availability, queue buildup, and uncertain disruptions to destination countries.

The model offers several contributions to the resettlement planning literature. It allows preference scores to adapt over time based on cumulative relocation patterns, reflecting how migrant networks and destination attractiveness can evolve. It includes fairness mechanisms that promote equitable distribution across destinations and protect highly vulnerable groups. The disruption scenarios further enable evaluation of policy robustness under destination inaccessibility or instability.

This framework provides a practical foundation for long-term policy analysis in climate displacement contexts. Future extensions could explore spatial analysis of relocation flows, incorporate more detailed integration outcomes, or refine preference formation using historical migration data. Further, the emphasis on individuals could be considered a limitation of this model, whereas accounting for family structures may be a useful future consideration.

### 4.5.2 Limitations

Despite the advances introduced by the multi-commodity model, there are limitations. More comprehensive consideration of uncertainty is needed; incorporating stochastic or robust optimization methods could enhance model resilience in future work. Additionally, the fairness constraints implemented focus primarily on proportional equity; exploring alternative fairness concepts could provide deeper insights into equitable relocation outcomes.

### 4.5.3 Future Directions

Future extensions could explore spatial analysis of relocation flows, incorporate more detailed integration outcomes, or refine preference formation using historical migration data. Further, the emphasis on individuals could be considered a limitation of this model, whereas accounting for family structures may be a useful future consideration. Lastly, significant uncertainty surrounds how environmental changes will influence migration patterns. To improve the model's applicability, future work can explicitly address this uncertainty.

# Chapter 5

# Digital Twin–Inspired Framework for Adaptive Relocation Planning

## Preface

#### Terminology and Scope

This chapter presents a framework for adaptive, feedback-driven migration planning that draws on core principles of digital twin methodology. A digital twin is generally understood as a virtual representation of a physical system that is continuously updated with real-world data, enabling dynamic monitoring, forecasting, and decision-making. In this work, the term refers to a set of specific features integrated into the planning process: continuous tracking of key system variables, dynamic updating of model inputs based on recent outcomes, and a feedback loop that iteratively adjusts relocation plans over multiple time periods. These components allow the model to evolve alongside the system it supports, embodying the essence of digital twin functionality. However, the framework does not constitute a full digital twin in the strictest sense. It does not provide a high-level simulation of the entire process and does not incorporate live data from all sources. Instead, it serves as a planning-layer digital twin that captures the core dynamics of supply, capacity, and policy change at the system level. Expanding this framework toward a more comprehensive digital twin with detailed modeling, real-time data integration, and broader system representation remains an important direction for future work.

## 5.1 Introduction and Motivation

Long-term relocation planning for climate-displaced populations is a complex task shaped by uncertainty and changing conditions. Previous chapters introduced models that improved relocation planning by addressing multiple objectives and operational constraints. However, these models have deterministic characteristics. As mentioned in earlier discussions on limitations and future work, there is a need for approaches that are more dynamic and adaptive, capable of handling uncertainty, adjusting to evolving circumstances, and utilizing real-time feedback. Effective planning depends on the flexible allocation of limited resources across diverse host locations and over extended periods. Shifting policy priorities, fluctuating capacities, and unpredictable migration patterns further complicate this landscape. While the models proposed in earlier chapters offer valuable insights and introduce novel modeling approaches in this field, they do not fully address the inherently dynamic nature of the problem and the uncertainties associated with long-term climate-induced displacement.

To address these challenges, this chapter is inspired by dynamic resource allocation methods developed in other fields, most notably cloud computing and data center management. In these domains, sophisticated models have been developed to tackle dynamic allocation problems under uncertainty. A particularly relevant example is Virtual Machine (VM) migration, where digital workloads are dynamically reassigned to physical servers in order to optimize system performance, balance resource utilization, and minimize operational costs. VM migration models are notable for their ability to operate under strict resource constraints, account for relocation costs, and maintain service-level targets despite shifting demands and changing infrastructure conditions.

Although VM migration was initially developed for computational systems, its logic shares structural similarities with relocation planning. In both contexts, entities must be allocated across a network of limited-capacity destinations to optimize multiple objectives, minimize disruptions, and adapt to external changes. Both involve uncertain future demand, dynamic resource availability, and the need for equitable distribution across receiving nodes.

This similarity presents an opportunity to adapt modeling frameworks and concepts from VM migration to relocation. VM migration models offer several advantages that directly address the limitations identified in previous approaches to resettlement planning. They are inherently designed for dynamic environments, integrate forecasting into allocation decisions, and provide robust optimization formulations that can accommodate complex trade-offs and evolving system states. By leveraging these features, it is possible to construct a resettlement planning framework that incorporates time-series forecasting, evolving policy constraints, and adaptive resource allocation across multiple periods.

While this framework is inspired by digital twin concepts, it functions as a computational replica of the relocation system that monitors, simulates, and updates the system's state over time. Embedding these ideas into resettlement planning enables explicit modeling of uncertainty and feedback, supporting iterative decision-making that responds to new data, emerging risks, and policy changes. This dynamic feedback loop allows the system to learn from implemented outcomes and adjust future plans accordingly, enhancing adaptability and resilience in complex, long-term displacement scenarios.

By combining insights from VM migration and digital twin methodologies, this work develops an adaptive relocation model that responds to the limitations of static and reactive approaches. The resulting framework is designed to enhance the resilience, flexibility, and policy relevance of migration planning, particularly in the context of growing climate-related risks. The next section provides a detailed conceptual adaptation, connecting these computational approaches to the specific challenges of resource allocation in climate-driven migration.

Building on these insights, we develop a stochastic optimization model that captures the core dynamic and uncertain features of the relocation problem. This approach enables adaptive and feedback-driven planning envisioned in digital twin methodologies.

## 5.2 Conceptual Adaptation

Resource allocation problems arise in many domains where limited capacities must be distributed among competing demands. Although the contexts differ, the underlying optimization structures share common features that allow methodological insights to be transferred between disciplines. This section establishes a detailed mapping between VM migration, a problem in computational resource management, and relocation planning, a significant challenge in humanitarian logistics.

At a basic level, both VM migration and relocation can be viewed as processes of assigning units to destinations within a constrained network:

- In VM migration, virtual machines, which represent digital workloads, are assigned to physical servers in a data center.
- In resettlement, displaced individuals are assigned to host locations.

Despite differences in domain, both systems share several structural features that create opportunities for methodological adaptation. Table 5.1 summarizes these parallels between VM migration and resettlement planning.

Table 5.1: Similarities between VM Migration and Relocation Allocation

| **VM Migration** | **Resettlement Planning** |
|---|---|
| Virtual Machines | Displaced Individuals or Households |
| Physical Servers | Host Locations |
| CPU, Memory, Network Capacity | Location Capacities |
| Migration Cost | Relocation Cost |
| Service-Level Agreements | Policy Agreements |
| Real-Time Monitoring | Real-Time Monitoring of Flows |
| Forecasting Demand | Forecasting Relocation Trends |
| Load Balancing Algorithms | Fair Distribution |
| Infrastructure Failures | Environmental and Policy Shocks |

Resource capacity constraints are fundamental in both domains. In VM systems, each server has limited resources, and the allocation of virtual machines must respect these limits at all times. Similarly, host countries face capacity limits in housing, healthcare, employment, and education. Explicit modeling of these constraints is essential to ensure feasible and efficient allocations. Relocation incurs costs in both settings. In VM migration, these may result from increased network traffic and temporary service interruptions. In resettlement planning, relocation costs can include travel expenses, administrative processing, and disruptions caused by policy changes.

Both systems operate within environments that evolve over time, requiring dynamic reallocation and policy adjustments. In VM migration, user demands change over time, and there are unexpected server failures or shifting energy optimization needs. Similarly, resettlement planning must adapt to new displacement events, evolving policy frameworks, or changes in the capacities of host locations. Optimization models that include dynamic, multi-period structures to accommodate changing conditions and support insightful decision-making over extended planning horizons.

Forecasting plays a central role in both. VM systems utilize workload prediction models to anticipate future resource demands and proactively schedule migrations. Likewise, resettlement planning relies on forecasts of future displacement flows. Embedding forecasting mechanisms within the optimization framework enables more proactive resource allocation decisions. Finally, fairness considerations are critical in both settings. In VM migration, fairness involves balancing server workloads to prevent over utilization and ensure stable system performance. In resettlement planning, fairness encompasses equitable distribution of displaced populations across host countries, consideration of long-term integration outcomes, and alignment with ethical and policy commitments.

This conceptual alignment between VM migration and relocation planning provides a foundation for adapting existing optimization methods to address long-term displacement challenges. The similarities identified here suggest that computational resource allocation frameworks, originally developed for dynamic environments in cloud computing, can offer valuable modeling strategies to guide relocation decisions under evolving humanitarian conditions.

## 5.3 Model and Adaptive Feedback Loop

This section introduces a stochastic optimization model designed to highlight the adaptive nature of the digital twin-inspired feedback loop. In contrast to the more comprehensive deterministic models discussed in earlier chapters, this formulation intentionally leaves out factors such as cultural distance, socio-economic adaptation, and additional fairness constraints. The intention is not to address all complexities of resettlement planning, but to demonstrate how the system can adjust dynamically to uncertainty and changing conditions within an iterative decision-making framework.

In Chapter 4, the relocation model has a mostly deterministic structure, with decision variables $x_{ijvt}$, $y_{ivt}$, and $z_{jt}$ defined for each origin $i$, host $j$, vulnerability group $v$, and time period $t$. In that framework, all input parameters and decisions are treated as known in advance, and no scenario index is included. In this chapter, the formulation is extended to address uncertainty in key inputs, particularly the number of arrivals to be relocated at each origin and in each period. This is accomplished by introducing a scenario index $\omega$ and corresponding scenario probabilities $p_\omega$.

The extended model distinguishes between two sets of decisions. The first stage involves committing the level of capacity $w_{jt}$ at each host $j$ in each period $t$. These commitments are made before the actual realization of uncertainty, and therefore must remain fixed across all scenarios. After a scenario $\omega$ is realized, the model then determines the operational variables $x_{ijvt\omega}$, $y_{ivt\omega}$, and $z_{jt\omega}$ for each scenario. The extended model is expressed as follows:

$$\min_{cap} \left[ \sum_{j \in J} \sum_{t \in T} c_{jt}(cap_{jt}) \; + \sum_{\omega \in \Omega} p_\omega \, Q(cap, \omega) \right] \tag{5.1}$$

where, for each scenario $\omega$,

$$Q(cap, \omega) = \min_{x,y,z} \left\{ \sum_{i\in I} \sum_{j\in J} \sum_{v\in V} \sum_{t\in T} c_{ijt} \, x_{ijvt\omega} \right\} \tag{5.2}$$

subject to:

$$\sum_{j\in J} x_{ijv1\omega} + y_{iv1\omega} = S_{iv1\omega} \qquad \forall i \in I,\, v \in V,\, \omega \in \Omega \tag{5.3}$$

$$\sum_{j\in J} x_{ijvt\omega} + y_{ivt\omega} = S_{ivt\omega} + y_{iv,t-1,\omega} \qquad \forall i \in I,\, v \in V,\, t > 1,\, \omega \in \Omega \tag{5.4}$$

$$\sum_{i\in I} \sum_{v\in V} x_{ijv1\omega} + z_{j1\omega} = \mathrm{cap}_{j1} \qquad \forall j \in J,\, \omega \in \Omega \tag{5.5}$$

$$\sum_{i\in I} \sum_{v\in V} x_{ijvt\omega} + z_{jt\omega} = w_{jt} + \gamma_{j,t-1} z_{j,t-1,\omega} \qquad \forall j \in J,\, t > 1,\, \omega \in \Omega \tag{5.6}$$

$$0 \leq \mathrm{cap}_{jt} \leq C_{jt} \qquad \forall j \in J,\, t \in T \tag{5.7}$$

$$x_{ijvt\omega} \geq 0, \;\; y_{ivt\omega} \geq 0, \;\; z_{jt\omega} \geq 0 \qquad \forall i \in I,\, j \in J,\, v \in V,\, t \in T,\, \omega \in \Omega \tag{5.8}$$

The model presented above is a two-stage stochastic optimization approach designed to capture the uncertainty and evolving conditions that are central to long-term relocation planning. Unlike earlier deterministic models, this formulation introduces scenario-based uncertainty through the scenario index $\omega$ and associated probabilities $p_\omega$. Each scenario in $\Omega$ represents a possible trajectory of future arrivals and resource conditions, such as shifts in displacement patterns or changes in available capacity.

Decisions in this model are split into two groups. The first-stage variables, $\mathrm{cap}_{jt}$, represent the allocated capacity at each host location $j$ for each period $t$. These decisions must be made before knowing which scenario will occur, so they remain fixed for all scenarios. This structure reflects practical planning requirements, where capacity allocations need to be set in advance.

Once the actual scenario $\omega$ is realized, the second-stage variables,$x_{ijvt\omega}$, $y_{ivt\omega}$, and $z_{jt\omega}$, describe the operational decisions that adapt to the observed situation. The variables $x_{ijvt\omega}$ represent the amount of supply moved from each origin $i$ and group $v$ to each host $j$ in every period $t$ for scenario $\omega$. The variables $y_{ivt\omega}$ record any backlog or waiting list at the origins, capturing supply that remains to be relocated in future periods. The $z_{jt\omega}$ variables track unused capacity at each host, which may carry over to the next period depending on the rollover factor $\gamma_{j,t-1}$.

The objective function seeks to minimize the total expected cost, which combines any costs from the initial capacity commitments with the expected operational costs of relocation across all scenarios. Scenario probabilities $p_\omega$ are used to weight each scenario in the calculation of expected costs, ensuring that the solution is robust on average.

### 5.3.1 Proposed Framework

The proposed approach, illustrated in Figure 5.1, is based on a multi-step framework with feedback mechanisms, inspired by digital twin concepts to support long-term planning for climate-induced migration. This framework integrates data from multiple domains, applies forecasting techniques to project displacement patterns, and employs optimization methods to shape relocation decisions. As conditions evolve, the system continuously updates its parameters based on observed outcomes, allowing for adaptive and responsive planning.

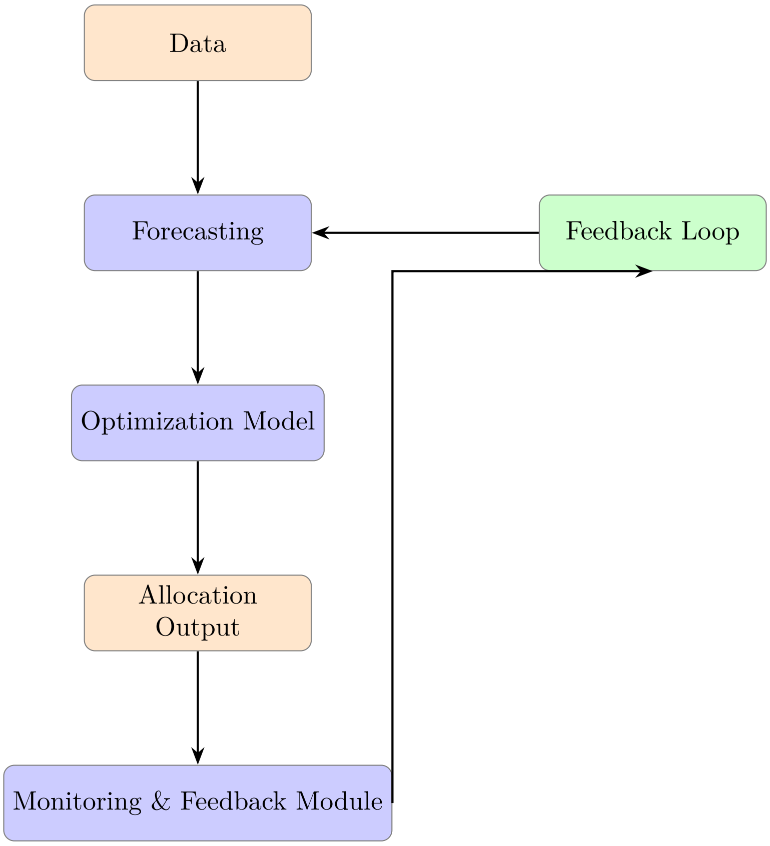



Figure 5.1: Overview of the digital twin-inspired framework for climate-induced relocation planning.

Figure 5.1 illustrates how the framework operates as a closed-loop system. The process begins with data collection and forecasting to estimate future displacement and capacity needs. These forecasts are used in the optimization stage to determine allocations for each planning period. After implementation, the monitoring module gathers data on actual arrivals, capacity use, backlogs, and any unexpected events. This updated information is then fed back into the forecasting module to improve future projections and keep each planning cycle aligned with the most recent system conditions.

The core of this feedback framework is the proposed stochastic model that supports decision-making under uncertainty. At the start of each planning cycle, the forecasting module generates multiple plausible displacement scenarios, forming the scenario set $\Omega$ with associated probabilities $p_\omega$. These scenarios capture a range of possible events, such as sudden supply surges, temporary host closures, or capacity reductions. Using this input, the stochastic model selects proactive capacity levels $\text{cap}_{jt}$ for each host and period before the actual scenario is known. For each scenario $\omega \in \Omega$, the model then determines the relocation flows $x_{ijvt\omega}$, backlog levels $y_{ivt\omega}$, and unused capacities $z_{jt\omega}$. This process produces a robust allocation plan that hedges against multiple possible futures within that cycle

Once the plan is implemented, the monitoring module tracks the actual outcomes and compares them with the projected scenarios. Any differences, such as higher arrivals or lower capacity than expected, are recorded and used to update future forecasts. Scenario probabilities and parameters are adjusted for the next cycle, so the model stays current. The stochastic optimization is then solved again using the revised data, creating an iterative process that gradually improves the planning approach over time.

This rolling-horizon approach links proactive planning with adaptive execution. Capacity decisions are made in advance to ensure preparedness, while operational decisions remain flexible to the specific conditions that materialize in each scenario. By embedding the stochastic optimization model within the feedback loop, the planning process combines foresight with adaptability. Scenario-based decisions account for uncertainty in each cycle, while the feedback loop improves accuracy and responsiveness as new information emerges. Over multiple cycles, this integration creates a dynamic planning system that can respond more effectively to shifting migration patterns, evolving risks, and policy changes than static methods.

### 5.3.2 Scenario-Based Design and Hybrid Integration

While traditional digital twin and virtual machine frameworks focus primarily on real-time monitoring, forecasting, and adaptive decision-making, this work extends the planning-layer digital twin concept by combining stochastic scenario modeling with stress testing under disruptive conditions. Long-term climate-induced migration systems face both *modeled uncertainty* such as fluctuating supply and capacity, and *unforeseen shocks* such as sudden host closures or compound crises. To address these challenges, a hybrid approach is used. Some events are explicitly represented within the stochastic scenario set $\Omega$, while others are introduced as external stress tests to evaluate how well the feedback loop performs beyond the planned uncertainty.

In long-term relocation planning, gradual environmental pressures lead to relatively predictable migration flows, but sudden shocks can disrupt even the most carefully designed plans. Examples include unexpected policy shifts, pandemic-related restrictions, and natural disasters that temporarily reduce host capacity.

Scenario-based stress testing complements stochastic modeling by going beyond the predefined probabilities $p_\omega$ used in the optimization model. The stochastic model anticipates a range of likely outcomes, selecting capacity levels $\text{cap}_{jt}$ and planning relocations $x_{ijvt\omega}$ that hedge against multiple futures. However, it cannot include every possible disruption without making the scenario set $\Omega$ unmanageably large. Stress testing fills this gap by introducing additional shocks after the model produces its allocation plan, revealing how the feedback loop reacts to extreme or compounding conditions that were not explicitly considered during optimization.

This hybrid approach therefore serves two purposes. First, the stochastic model directly integrates realistic uncertainty, accounting for probable disruptions like supply surges or moderate capacity reductions. Second, stress testing evaluates the resilience of the adaptive feedback loop when exposed to rare or highly disruptive events outside the modeled scenario set.

In the hybrid framework, disruptions play two distinct roles:

- **Probabilistic scenarios within Ω:** Some events are explicitly included into the optimization model. For example, a sudden supply surge at an origin or a partial reduction in host capacity can be represented as low-probability scenarios. These events contribute to the expected cost calculation, influencing the proactive selection of capacity levels $\text{cap}_{jt}$ to prepare for their possible occurrence.
- **External stress tests:** Other events are applied after the stochastic model produces an allocation plan, serving as extreme shocks that test the robustness of the feedback loop. For example, sequential disruptions like a pandemic followed by a route embargo are not explicitly modeled but are introduced during the monitoring phase to evaluate how the system adjusts in subsequent cycles.

By separating these two roles, the framework remains computationally tractable while still being evaluated under realistic and unforeseen conditions. Disruptions included in Ω directly shape the optimization outcome, whereas external stress tests validate how well the feedback loop recovers from unexpected events.

### 5.3.3 Design of Disruptions

The stress-test scenarios are designed to capture operationally significant shocks frequently observed in real-world migration systems. Disruptions affect different dimensions of the system, including origin supply, host capacity, relocation routes, and cost parameters. They range from relatively mild fluctuations to extreme events that force the system to temporarily suspend operations.

The types of disruptions used in stress testing include sudden increases in displacement supply, temporary host country closures, reductions in intake capacity, migration restrictions due to health crises, blocked transit routes, and abrupt cost escalations in specific regions. These disruptions are implemented at different points during the planning horizon to evaluate both immediate impacts and delayed recovery through the feedback loop.

Table 5.2 summarizes these disruption types, their typical causes, and the associated operational consequences. Some of these are included directly as scenarios in Ω, while others are introduced externally after optimization as stress tests.

Table 5.2: Disruption Types Used in Scenario Modeling and Stress Testing

| **Disruption Type** | **Examples and Impact** |
|---|---|
| Sudden Supply Surge | A drought triggers a sharp increase in displaced populations, creating unexpected backlog pressures. |
| Host Location Closure | A host country temporarily stops accepting individuals due to policy or political shifts. |
| Capacity Reduction | A host reduces intake because of infrastructure strain or long-term climate pressures. |
| Epidemic Event | A disease outbreak triggers a temporary ban on relocation and cross-border movement. |
| Route Embargo | Severe weather damages transport routes, temporarily halting relocation operations. |
| Regional Cost Spike | A storm or disaster sharply increases relocation costs in affected areas. |
| Facility Reopening | A host location resumes accepting individuals after a period of closure. |
| Compound Disruptions | Sequential events, such as a host closure followed by a surge in supply, amplifying system strain. |

### 5.3.4 Integration with the Feedback Loop

The implementation of disruptions is integrated directly with the feedback-driven relocation model developed earlier. At the start of each planning cycle, the forecasting module updates the scenario set $\Omega$, assigning probabilities $p_\omega$ to expected variations in supply and capacity. The stochastic model then selects proactive capacity levels $\text{cap}_{jt}$ and determines relocation flows $x_{ijvt\omega}$, backlogs $y_{ivt\omega}$, and unused capacities $z_{jt\omega}$ for each scenario. This produces a robust plan for the upcoming cycle that hedges against modeled uncertainty.

After implementation, stress tests introduce additional disruptions beyond those captured in $\Omega$. For example, a previously stable host might unexpectedly close due to a political decision, or a new epidemic could halt relocation flows. These external shocks are applied to the realized state of the system, after which the monitoring module records the actual arrivals, backlogs, and utilization levels. The updated data feed back into the forecasting module, which revises future scenarios and probabilities. In the next cycle, the stochastic model is re-solved with the revised inputs, allowing the system to gradually recover from disruptions.

This hybrid design makes it easier to assess how well the digital twin approach can adapt to real challenges. By including both realistic uncertainty in the scenarios and extra stress tests after optimization, the model shows how the feedback loop handles both expected and unexpected events. This approach gives a clearer picture of how the system adapts over time and ensures the framework works under a variety of conditions.

## 5.4 Realized Outcomes in the Feedback Loop

Although the model accounts for multiple possible futures through the scenario set $\Omega$, actual outcomes often differ from planned allocations. Unexpected disruptions, delays, or policy changes can still cause deviations from the anticipated flows. To reflect this, the digital twin framework includes a simulation layer that slightly perturbs the planned relocation decisions and produces *realized outcomes* for each cycle. This step serves two purposes: it tests how robust the stochastic plan is under implementation uncertainty and provides updated, realistic data to improve forecasts for the next planning cycle.

The feedback loop operates as follows. At the beginning of each cycle, the forecasting module generates multiple scenarios $\Omega$ with associated probabilities $p_\omega$, reflecting possible displacement surges, capacity reductions, or policy-related disruptions. The two-stage stochastic model is then solved for this cycle. It selects proactive capacity levels $\text{cap}_{jt}$ for each host and period and computes scenario-specific flows $x_{ijvt\omega}$, backlogs $y_{ivt\omega}$, and unused capacity $z_{jt\omega}$. This yields a robust allocation plan that hedges against the modeled uncertainties.

Once the plan is implemented, the simulation layer introduces additional random disturbances $\xi_t$ to mimic real-world deviations. The planned flows $x_{ijvt}$ are perturbed to produce realized flows $\hat{x}_{ijvt}$:

$$\hat{x}_{ijvt} = x_{ijvt} + \varepsilon_{ijvt}, \qquad \varepsilon_{ijvt} \sim N\big(0,\, 0.05 \cdot \max(1, x_{ijvt})\big), \tag{5.9}$$

where $\varepsilon_{ijvt}$ is normally distributed noise with a variance proportional to the planned flow. This ensures that larger relocations are associated with greater potential deviations, while fluctuations for smaller flows remain limited.

The realized outcomes, including actual arrivals, remaining backlogs at origins, and capacity utilization at hosts, are recorded as the updated system state. These observations are compared with the modeled scenarios to assess how well the stochastic plan performs under both expected and unexpected variations. The updated state information is then fed back into the data and forecasting modules, where it is used to adjust the scenario probabilities $p_\omega$ and other model parameters for the next cycle.

In this way, the stochastic model provides decisions for each planning cycle, while the simulation layer keeps the digital twin aligned with actual implementation outcomes. Together, they form a hybrid approach to managing uncertainty, combining planning for modeled scenarios with adjustments based on observed deviations.

The hybrid feedback loop combining the stochastic model and simulation layer is summarized in Algorithm 1. It integrates scenario-based optimization with stochastic realization of outcomes, ensuring that each cycle reflects both planned uncertainty and real-world noise.

**Algorithm 1** Hybrid Feedback Loop with Stochastic Optimization and Realized Simulation

**Input:** Initial state $S_0$, model parameters, scenario set $\Omega$ with probabilities $p_\omega$
**for** $t \in T$ **do**
  **Forecasting:** Update scenarios $\Omega_t$ and probabilities $p_{\omega,t}$ based on current data
  **Optimization:** Solve two-stage stochastic model for cycle $t$ to obtain:
    Proactive capacity $\text{cap}_{jt}$ and scenario-specific allocations $x_{ijvt\omega}$, $y_{ivt\omega}$, $z_{jt\omega}$
  **Implementation:** Use planned allocation $x_{ijvt}$ for deployment
  **Simulation:** Generate realized flows $\hat{x}_{ijvt} = x_{ijvt} + \varepsilon_{ijvt}$ with $\varepsilon_{ijvt} \sim N(0, 0.05 \cdot \max(1, x_{ijvt}))$
  **Update System State:** Compute new backlogs $y_{ivt}$ and unused capacity $z_{jt}$ using $\hat{x}_{ijvt}$
  **Feedback:** Record realized outcomes and feed them into the next forecasting step
**end for**

This hybrid loop allows the digital twin to account for modeled uncertainty while also testing how well its decisions hold up under unexpected shocks. By repeatedly re-optimizing and updating, the system stays flexible and gradually improves its ability to respond to both expected and unforeseen changes in climate-driven migration patterns.

### 5.4.1 Preliminary Evaluation

To evaluate the benefit of adaptive, feedback-driven planning, we compare the proposed feedback loop to a static baseline. Table 5.3 summarizes the initial simulation outcomes.

Table 5.3: Performance comparison: feedback-driven vs static baseline (initial results).

| Approach | Total Relocated | Total Backlog |
|---|---|---|
| Feedback-loop | **516,750** | **303,479** |
| Static No-Feedback | 493,205 | 327,024 |

The adaptive feedback approach increases successful relocations by nearly 5% compared to the static plan. Total backlog is also reduced, suggesting that continuous adjustment to new information enables better use of available capacity over time. These initial results, based on illustrative test data, support the value of integrating a feedback loop for improved migration outcomes under uncertainty.

These findings are preliminary, but indicate that adaptive, feedback-driven planning can deliver tangible benefits compared to traditional static approaches. Further work will explore the impact of more complex disruptions and expanded system features.

## 5.5 Concluding Remarks

### 5.5.1 Contributions

This chapter advances relocation planning under uncertainty by introducing an adaptive, feedback-driven framework for climate-related migration that applies key digital twin principles. Unlike static models, the proposed approach continuously learns from new data and updates decisions through a closed-loop feedback cycle. This enables more robust and flexible planning as conditions change. Another contribution is the methodological transfer of ideas from virtual machine migration in cloud computing to humanitarian relocation, adapting advanced resource allocation strategies to the challenges of migration. By bridging these domains, the framework offers a dynamic optimization paradigm that supports more resilient and responsive migration planning. This approach helps policymakers explore scenarios and allocate capacity more effectively in uncertain environments, demonstrating clear benefits for humanitarian decision-making.

### 5.5.2 Limitations

While the proposed model incorporates logic to handle uncertainty and supports adaptive planning through a feedback loop, it has major limitations First, it is a planning-layer digital twin rather than a complete digital twin of the entire migration system. The model focuses on overall system-level dynamics such as supply, host capacity, and basic policy changes, and relies on periodic rather than continuous updates. In a full digital twin, the virtual model would be tightly linked with the real system and receive live data from operational sources. In contrast, this implementation updates at set planning intervals and mirrors only a portion of real-world variables. As a result, it cannot fully represent or anticipate every aspect of the actual relocation process.

Second, because the framework depends on forecasted data for displacement and capacity, its results are sensitive to prediction errors. In situations with limited or unpredictable data, the model may misjudge future conditions and produce less effective plans. While the scenario approach tries to buffer against some uncertainty, it is constrained by the assumed scenario probabilities and ranges. Unmodeled events outside the scenario set, for example, compounding crises or policy shifts, can still catch the system off guard. A limited set of stress tests is included to evaluate such cases, but not every real-world contingency can be anticipated or simulated.

### 5.5.3 Future Research

A key direction for future research is to develop a full digital twin system for relocation planning. This will require working more with real-time data, connecting monitoring tools, and building interactive platforms to support policy simulation and decision-making. Expanding the framework to include additional system components, such as detailed facility logistics, would allow the digital twin to better represent actual relocation processes. Further work could also explore more robust approaches for handling uncertainty, generating realistic scenarios, and automating adaptive policy responses. These steps would help move the current planning-layer model toward a comprehensive digital twin that supports both strategic and operational decisions in migration management.

# Chapter 6

# Concluding Remarks

Climate-induced displacement poses one of the most complex humanitarian and policy challenges of our time. The increasing frequency and intensity of climate hazards require proactive, flexible, and equitable relocation planning strategies. This dissertation addresses these needs by developing and analyzing three optimization models, each designed to tackle different aspects of the relocation problem under climate stress.

The first model introduces a temporal multilayer network framework that captures dynamic relocation flows over multiple planning periods. It incorporates evolving supply and capacity considerations, cost factors, and cultural distance metrics, providing a structured approach for long-term, adaptive planning. This model highlights the importance of balancing logistical efficiency with social integration across time.

The second model adopts a multi-commodity perspective, distinguishing populations by vulnerability levels to reflect heterogeneous needs and priorities. By integrating queue dynamics and fairness constraints, this framework advances the representation of real-world constraints and ethical considerations, enabling more nuanced and just relocation outcomes.

The third model introduces a digital twin-inspired approach that enables planners to simulate and adjust relocation decisions dynamically as environmental and policy conditions evolve. This supports more responsive policy-making under uncertainty and changing climate impacts.

Together, these models help clarify how uncertainty, fairness, and challenges in climate relocation. They emphasize the importance of integrating social, economic, and environmental factors into realistic and equitable resettlement plans. Moreover, although the models were developed with long-term horizons, their design is adaptable. By adjusting the length of planning periods, for example, treating each period as a month instead of a year, the same frameworks can guide short-term relocation efforts. Notably, while most disaster-related displacement is short-term, slow-onset climate impacts, such as sea-level rise, lead to more permanent migration. The flexibility of our models allows them to support both immediate, short-term displacements, such as evacuations following extreme events, and strategic, long-term displacements. This adaptability enhances their practicality across different time scales, ensuring that decision-makers can use these tools for both urgent crises and multi-decade climate adaptation planning.

The first two models have deterministic characteristics, offering structured long-term planning under fixed assumptions. The third model begins to address uncertainty through a more dynamic, adaptive, digital twin-inspired approach, but further enhancements are needed. Future work could strengthen this concept by integrating stochastic methods, scenario simulations, and real-time data streams, enabling continuous updates that better reflect unpredictable climate impacts and shifting policy conditions. Such advancements would make the models more robust, responsive, and aligned with the evolving nature of relocation challenges.

Ultimately, this research highlights the value of quantitative models as decision-support tools that can assist policymakers and practitioners in developing effective, equitable, and resilient relocation strategies. Addressing the complex challenges of climate-induced migration will require ongoing interdisciplinary collaboration and continued methodological advancements.

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# Appendices

Table A.1: Optimal flows from origin countries to host locations (2030–2050).

| Origin location | Host location | [2030–2035) | [2035–2040) | [2040–2045) | [2045–2050) |
|---|---|---|---|---|---|
| Afghanistan | Host 1 | 1350000 | 1430000 | 1550000 | 0 |
| Afghanistan | Host 2 | 0 | 0 | 0 | 1660000 |
| Angola | Host 1 | 1390000 | 1570000 | 1800000 | 0 |
| Bangladesh | Host 3 | 1450000 | 1360919 | 1100478 | 0 |
| Bangladesh | Host 4 | 0 | 0 | 0 | 2284320 |
| Bangladesh | Host 1 | 3000000 | 3000000 | 3000000 | 0 |
| Bangladesh | Host 2 | 0 | 119081 | 479522 | 0 |
| Burundi | Host 1 | 490000 | 540000 | 610000 | 0 |
| Cameroon | Host 1 | 1060000 | 1150000 | 1280000 | 0 |
| Central African Republic | Host 1 | 180000 | 200000 | 220000 | 0 |
| Chad | Host 1 | 480000 | 540000 | 600000 | 0 |
| Chad | Host 5 | 0 | 0 | 0 | 670000 |
| Congo | Host 1 | 3300000 | 3300000 | 3300000 | 0 |
| Congo | Host 3 | 420000 | 840000 | 1390000 | 0 |
| Eritrea | Host 5 | 130000 | 140000 | 150000 | 170000 |
| Equatorial Guinea | Host 1 | 60000 | 60000 | 70000 | 0 |
| Ethiopia | Host 1 | 3000000 | 2375073 | 2021838 | 0 |
| Ethiopia | Host 3 | 0 | 0 | 688162 | 3230000 |
| Ethiopia | Host 5 | 2120000 | 3104927 | 3300000 | 3300000 |
| Guinea | Host 1 | 800000 | 860000 | 970000 | 1070000 |
| Guinea-Bissau | Host 1 | 80000 | 80000 | 90000 | 100000 |
| Haiti | Host 1 | 1050000 | 1010000 | 1060000 | 1100000 |
| Iraq | Host 1 | 1753419 | 0 | 0 | 0 |
| Iraq | Host 3 | 0 | 980092 | 637886 | 0 |
| Iraq | Host 5 | 156581 | 1049908 | 1582114 | 0 |
| Mauritania | Host 1 | 200000 | 210000 | 240000 | 260000 |
| Niger | Host 3 | 0 | 0 | 0 | 1380000 |
| Niger | Host 1 | 870000 | 1010000 | 1190000 | 0 |
| Nigeria | Host 1 | 2900000 | 2900000 | 2900000 | 0 |
| Nigeria | Host 2 | 3403934 | 3500000 | 3500000 | 0 |
| Nigeria | Host 3 | 3200000 | 3200000 | 3200000 | 2479577 |
| Nigeria | Host 4 | 2239430 | 2380974 | 2618107 | 0 |
| Nigeria | Host 5 | 3200000 | 3200000 | 3200000 | 0 |
| Pakistan | Host 1 | 2410000 | 2570000 | 2750000 | 0 |
| Pakistan | Host 2 | 0 | 0 | 0 | 2678566 |
| Pakistan | Host 5 | 0 | 0 | 0 | 231434 |
| Republic of Congo | Host 1 | 180000 | 200000 | 220000 | 0 |
| Somalia | Host 5 | 360000 | 410000 | 460000 | 84908 |
| South Sudan | Host 3 | 0 | 0 | 0 | 560000 |
| South Sudan | Host 1 | 430000 | 470000 | 520000 | 0 |
| Sudan | Host 1 | 1710000 | 1850000 | 2050000 | 0 |
| Sudan | Host 5 | 0 | 0 | 0 | 2240000 |
| Syria | Host 3 | 931673 | 0 | 0 | 0 |
| Syria | Host 1 | 0 | 1560000 | 1650000 | 0 |
| Syria | Host 5 | 608327 | 0 | 0 | 1730000 |
| Tajikistan | Host 1 | 150000 | 160000 | 180000 | 0 |
| Turkmenistan | Host 1 | 80000 | 80000 | 90000 | 0 |
| Venezuela | Host 1 | 1370000 | 1360000 | 1400000 | 1430000 |
| Yemen | Host 1 | 0 | 910000 | 980000 | 0 |
| Yemen | Host 5 | 860000 | 0 | 0 | 1050000 |
| Zimbabwe | Host 1 | 460000 | 490000 | 530000 | 0 |
| Zimbabwe | Host 4 | 0 | 0 | 0 | 570000 |