UNIVERSITY OF OKLAHOMA

GRADUATE COLLEGE

PLANNING FOR CLIMATE CHANGE-INDUCED DISPLACEMENT: SOCIAL INTEGRATION, UNCERTAINTY, DECENTRALIZATION, ADAPTABILITY, AND FAIRNESS

A DISSERTATION

SUBMITTED TO THE GRADUATE FACULTY

in partial fulfillment of the requirements for the

Degree of

DOCTOR OF PHILOSOPHY

By

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Norman, Oklahoma

2024

PLANNING FOR CLIMATE CHANGE-INDUCED DISPLACEMENT: SOCIAL INTEGRATION, UNCERTAINTY, DECENTRALIZATION, ADAPTABILITY, AND FAIRNESS

A DISSERTATION APPROVED FOR THE

SCHOOL OF INDUSTRIAL AND SYSTEMS ENGINEERING

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Acknowledgments

PhD has been a journey, a long and challenging one at that. It is finally PhinisheD; thanks to all the people who supported and cherished me during this time. That is why I would like to start with a heartfelt shout-out to each and every single one of you! However, I have to name some names…

First and foremost, my advisor, **Dr. Kash Barker**… Greetings! My deepest gratitude goes to you since your trust in me started this journey and, most of the time, kept me going. Thank you for your invaluable advice on all things research and beyond. I am incredibly fortunate to have had you as my mentor and academic role model.

My co-advisor, **Dr. Andrés González**… I am grateful for your expertise and guidance. Thank you for meeting my tears with laughter and helping me when things felt overwhelming.

To my esteemed committee members, **Dr. Talayeh Razzaghi**, **Dr. Sridhar Radhakrishnan**, and **Dr. Eric Heinze**… Thank you for being part of my PhD journey. It was a pleasure and an honor to achieve my PhD milestones under your guidance.

The director and pillar of OU ISE, **Dr. Shivakumar Raman**… Your belief in my potential has inspired me to strive for excellence, and I am truly grateful for your encouragement.

And my dearest family, Cilali et al. - my mom, **Nese**, my dad, **Ali**, and my sister, **Bengu**… Mom and Dad, I owe everything to you. Your unconditional love and support got me through my darkest times. Sis, I cannot wait to celebrate our achievements together as Dr. Cilali and Dr. Cilali! Sharing this moment with you makes it all the more meaningful.

Finally, my beloved friends, **Derya**, **Hakan**, and **Burcu**… Thank you for always being "here" for me, even from oceans away.

Table of Contents

List of Tables

List of Figures

Abstract

The looming climate crisis is a significant driver of the displacement of communities. The adverse effects of slow-onset climate change are anticipated to strike people worldwide, causing displacements in significant quantities. These displacements will lead to large-scale movements from high-risk and less resilient areas to safer or more resilient ones, creating a relocation problem: where people should go and when. This is a problem with distinctive characteristics that has received limited attention in the field of operations research. The complexities of the problem, including the need for long-term planning, uncertainties about the future, the involvement of multiple stakeholders, diverse populations, and different locations experiencing varying levels of climate change impacts, call for unique ways. It requires taking up approaches that can assist in developing urgently needed high-level relocation plans to manage climate change-induced movements in a timely manner and with a long-term outlook while using the resources effectively and protecting the peace, well-being, and dignity of displaced people and receiving communities.

This dissertation presents a comprehensive proposition for high-level and long-term relocation planning amidst the escalating climate crisis, contributing to the field of humanitarian operations research for societal good. It comprises three studies designed to assist decision-makers in preparing for future actions at the strategic level, even those that may unfold years from now. Each study addresses a challenge associated with optimizing high-level relocation planning in response to climate change-induced forced displacement: future uncertainties, decentralized systems, and ensuring fairness.

The first study proposes a two-stage stochastic programming model that optimizes relocation decisions under demand uncertainty with a focus on societal integration outcomes based on diversity indicators. The second study introduces a consensus-driven decentralized optimization framework that balances global utilitarian goals with local interests inherent to relocation planning utilizing a combination of altruistic and self-centered models, negotiations, and a bi-level

optimization model that considers culture-based social integration, irregular movements, the associated costs of social conflicts, and fairness among different origins. The third and final study investigates the fairness of destination selection and flow assignment decisions within the context of the high-level relocation problem, providing a comparative analysis of multiple fairness metrics from the perspectives of various stakeholders and considering different principles.

Chapter 1: Introduction

1.1 Background and Motivation

Humanity has long been on the move for various reasons, such as pursuing better economic conditions, seeking protection against conflicts or human rights violations, escaping from adverse effects of environmental factors, or simply aspiring to a better life [1]. Whatever the reasons may be, large and irregular movements of refugees and migrants are a global issue on the rise. As of the end of 2021, there are 89.3 million forcibly displaced people worldwide [2]. Moreover, since 2020, we have seen displacement due to increased vulnerabilities brought on by the amplifying effects of the COVID-19 crisis and climate change [3].

A problem today turning into a much more significant problem tomorrow; climate change is one of the crucial drivers for forced displacement. The adverse effects of global climate change are already detectable and will continue with an intensified severity [4]. While there are different forecasts about its level and expected outcomes, we know the climate is already changing, and people suffer from its short- and long-term effects even today. With the combined effects of the direct impacts varying from extreme temperatures to accelerated sea-level rise and the conflicts caused by those impacts, regions worldwide are becoming uninhabitable, and people will be forced to leave their homes if they have not already. For example, widespread drought has already caused migration due to lost livelihoods in Guatemala and civil unrest in Syria [5]. At the same time, in coastal regions, the rise in sea level is expected to displace millions [6].

By 2050, between 25 million and 1 billion climate refugees are expected to be on the move [7]. A significant movement that is more than likely to upset the regional balances is inevitable at this point, and "the only way to mitigate the most destabilizing aspects of mass migration is to prepare for it, and preparation demands a sharper imagining of where people are likely to go, and when"

[8]. There is a need to devise a plan to address the relocation of individuals who have been displaced as a result of climate change. This motivates us to pay more attention to climate-driven displacement problem before it is too late to act upon it.

This problem should be handled at different levels, starting with high-level decisions regarding which destinations to choose and how many people to send there. So, this dissertation can be seen as a foundational work that will provide host communities with the information and facilitate early preparations -such as infrastructure and service planning- at these destinations, ensuring timely actions without delays.

However, we are not only interested in learning about future relocation movements, but we also want to plan for and establish a level of control over those flows so that the threat of chaotic and irregular movements can be turned into an opportunity both for the origin and host communities by means of orderly relocation. For this reason, we prefer to optimize those flows rather than trying to forecast or simulate them. As a result, we address the climate change displacement problem with an operations research perspective and focus on relocation planning.

To effectively handle relocation planning, we must first understand the characteristics of the forced displacement caused by climate change. Forced displacement due to climate change will occur over a period of decades, which requires the consideration of (i) the movement of large masses of people, (ii) a long-term planning horizon, (iii) uncertainties related to future parameters, (iv) socio-economic impacts of movements, (v) various stakeholders that would be involved in the decision-making process, and (vi) regional and global relationships and policies, among others.

These characteristics require us to work on the challenges they cause and the issues they arise. As a result, this dissertation aims to address social integration, uncertainty, decentralization, adaptability, and fairness in relocation planning for climate change-induced forced displacement.

1.2 A Note on Terminology

Before delving into the related models and analysis in the literature, it would be pertinent to clarify the dispute about how to address the people who are in need of relocation due to adverse climate change impacts. Even for displacement due to more traditional reasons, the distinction between the terms “refugee” and “migrant” is not so clear [9], [10]. The traditional definition of refugees, as stated in the 1951 Refugee Convention [17], is that refugees are people who cross international borders based on a fear of being persecuted due to conflicts. This differs from migrants, which generally refer to a more self-imposed movement for various reasons. As such, classifying individuals on the move due to the effects of climate change may not be so straightforward, as they are not being prosecuted (directly). Still, it could be argued that their movement is also not self-imposed. Such individuals displaced by the adverse effects of climate change have been referred to as “climate refugees” [12] and “environmental migrants” [13] in a broader sense by some organizations. However, as no globally accepted term is defined under international law, we will try to avoid using specific words such as refugees or migrants and instead use more comprehensive terms such as climate-driven displacement and displaced people.

1.3 Structure Of the Dissertation

This dissertation consists of six chapters. Chapter 1 introduces the origins of the problem and explains the motivation behind the studies included in the dissertation. Chapter 2 presents literature from various disciplines related to forced displacement and large movements of people. Chapter 3 proposes a stochastic model to deal with the uncertainty of the future relocation demand. Chapter 4 proposes a consensus-driven framework to handle the decentralized nature of the authorities involved in the global relocation efforts. Chapter 5 investigates and compares various measures and approaches that can be used to incorporate fairness into the relocation models. Chapter 6 summarizes and compares the studies included in the dissertation.

Chapter 2: Literature Review

This dissertation focuses on high-level relocation planning for climate change-induced forced displacement.

Various studies regarding human mobility exist in different disciplines; however, none of them reflect the same goals or the problem characteristics in which we are interested. In general, studies regarding human mobility due to environmental factors focus on analyzing or predicting those movements, not on optimizing those movements. In the operations research literature, the application of optimization to relocation planning studies focuses exclusively on conflict-based displacement involving shorter-term planning horizons and lower-level uncertainty. Because of the many differences in the nature of these two displacement problems, existing literature on conflict-based forced displacement, even though relevant to a degree and very important, cannot be regarded as previous examples of climate-change-induced forced displacement. Since, to the best of our knowledge, there is no prior work on long-term relocation planning for climate-change-induced displacement, we look at moderately related studies with intersecting characteristics in the literature review.

Modeling studies of human migration policies have a long history. However, in this dissertation, we are interested in a relatively more recent group of studies related to modeling human migration driven by environmental factors, specifically climate change. These studies generally analyze and/or try to predict uncontrolled and large movements of people. For human migration, including climate-driven migration, Nagurney and Daniele [14] propose a network modeling approach to general human migration and analyze the effect of regulations on international migration. Smith et al. [15] focus on the synergies between multiple factors and spatial interaction affecting human migration driven by the environment, proposing an agent-based model based on the cognitive decision-making process.

Some studies narrow the focus to a specific climate change impact or region. Robinson et al. [16] model US migration patterns due to sea-level rise with an artificial neural network model, examining how future migration projections deviate from the regular migration patterns under potential future sea-level rise scenarios. They note the extension of climate change impacts beyond the affected areas. Davis et al. [17] and De Lellis et al. [18] also focus on the effect of sea-level rise, but they try to model future human migration under climate change in Bangladesh. Best et al. [19] use machine learning, particularly random forest methods, to identify significant predictors of migration from household survey data in southwestern Bangladesh. Cai et al. [20] analyze the relationship between temperature and international outmigration due to the adverse effects of agriculture.

Walelign et al. [21] approach the problem from a different perspective by considering the resettlement capacity provided by host locations. They propose an empirical methodology based on the hierarchical aggregation of the resettlement capacity indicators for climate-induced displacements, emphasizing the importance of spatial variations and population density.

Studies related to the planning of conflict-driven (forced) displacement deal with the relocation of the displaced people to asylum or resettlement locations. Two groups are naturally formed within these studies concerning how they design the relocation problem. The first group of studies related to conflict-driven displacement approach relocation as an assignment optimization problem. They focus on improving integration outcomes, specifically the likelihood of employment resulting from the assignments [22], [23]. These studies seek the optimal resettlement assignments based on the resulting employment success where the machine learning techniques are used to predict employment likelihoods. In a recent study, Ahani et al. [24] reframe their deterministic perspective and propose a two-stage stochastic model to deal with the uncertainty in the number of future arrivals of conflict-based refugees within a fiscal year while still trying to improve employment outcomes. Bansak and Paulson [25] also address the dynamic refugee resettlement based on employment outcomes when there is an uncertainty in the number of future arrivals. However, they focus on the issues of minimum discord and balanced allocation design over time. Different from the previous two studies, Cilali et al. [26] focus on improving the integration outcomes with respect to cultural distances. They adapt the capacitated facility location problem in the resettlement context and employ a multicriteria approach to improve various resettlement considerations synchronously. The second group of conflict-driven displacement studies approaches relocation as a matching problem. The most distinguishing characteristic of these studies is that they consider the preferences of the involved parties [27]–[30]. Among the matching studies, the application of dynamic matching [27] and usage of tradable immigration quotas [31] are worth special attention since they address essential requirements of the relocation problem.

This dissertation is built upon the lessons learned from the previous displacement studies and especially the requirements of the long-term planning associated with gradual displacement from origin locations (where the living conditions severely deteriorated due to climate change) to destinations (where there are available capacity and resources to accommodate incoming people due to climate change). While other studies focus on predicting future movements or planning for the current displacement, this dissertation contributes to the literature by addressing the scarcely mentioned issue of planning for future displacements and considering related uncertainties, decision-making structures, and fairness issues. As a result, it addresses the stochastic and dynamic nature of the problem over the planning horizon. Moreover, different from the previous studies, it measures the success of local integration directly considering social and cultural measures.

Chapter 3: Addressing Uncertainty

3.1 Overview

To deal with the uncertainty in the relocation demand, we propose a two-stage multi-period stochastic model representing a centralized system wherein a single entity makes relocation decisions while considering inputs from local stakeholders (e.g., budget inputs from national governments or capacity inputs from regional governments). The proposed mathematical formulation for this problem accounts for the long-term planning horizon, the uncertainty of future relocation demand, the dynamics of managing capacity, the locational dependencies, the social impacts of the movements, the restrictions on budgets, and the effect of participation enforcement at the host locations.

3.2 Proposed Approach

To reflect the dynamics of the climate-driven displacement problem, we incorporate long-term planning horizons and associated future uncertainties. However, in the current resettlement/migration literature in operations research, no studies consider actions beyond the immediate time period and related uncertainties. As such, we adopt stochastic programming that is widely used for problems with temporal planning horizons under uncertainty. Common examples of multi-period stochastic models include problems such as financial planning, capacity expansion, and distribution planning [32]. We aim to use a two-stage multi-period stochastic programming over a long planning horizon for the relocation planning problem.

The stages and structures of stochastic models are defined by the uncertainty involved. In the long-term displacement problem, the primary source of uncertainty is related to the future relocation demand of the origin locations. For this work, we assume that the uncertainty related to future relocation demand can be represented by three different demand scenarios: low, medium, and high. Each scenario includes a series of demands for each origin location over the planning horizon. Thus, we assume that all locations would concurrently have low, medium, or high demand, the reasoning for which is that while it is very likely to observe regional differences based on regional characteristics and reactions, the overall climate change severity will be the same for all countries at a given time. We also assume that the aforementioned uncertainty would be realized only once and separate the model into two stages. The first stage includes the decisions that would remain the same regardless of the revealed uncertainty (here-and-now decisions). The second stage contains decisions reflecting the realized uncertain scenario (recourse actions). While some of these decisions would be made only once and remain the same throughout the entire planning horizon, others would be repeated every time period. The proposed model determines the location opening and capacity decisions once for the first stage, and relocation flows at each time period for the second stage. The overview of the resulting two-stage multi-period stochastic model is depicted in Figure 1.

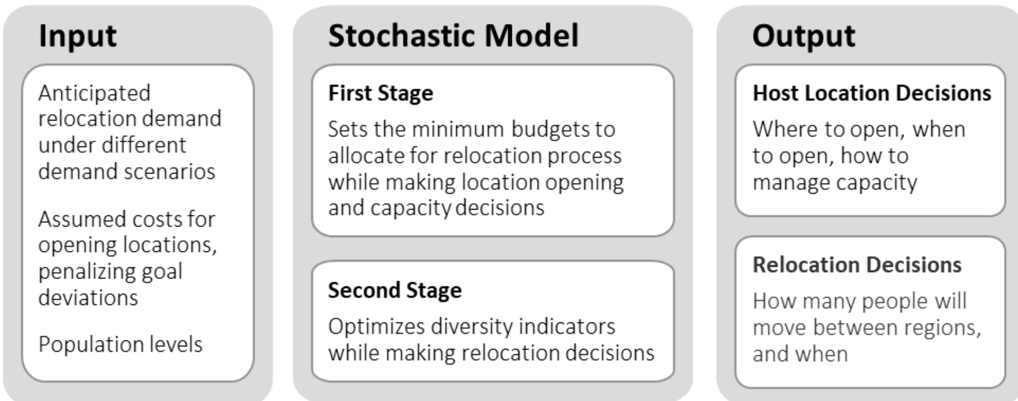


Figure 1. Model Overview.

Further assumptions of the model are the following.

- Model inputs such as budgets, availabilities, and capacities are assumed to be collected from various resources and decentralized regional authorities. However, assignment and location opening decisions are made by a central decision-maker and implemented as they are. We assume a central decision-maker who tries their best to represent the needs of local communities because we aim to devise a preliminary plan that will exhibit the common needs and provide the grounds for international agreements and advance preparations. Naturally, the relocation of large groups of people will require input and decisions regarding such agreements and preparations, as discussed in the future work.
- The capacity of a host location is measured with respect to the number of people that can be placed there.
- The capacity of a host location can be expanded if this location is open to service. Also, the maximum expansion is restricted by an upper bound. However, we do not consider a capacity reduction. We assume that the capacity would be expanded whenever required to

satisfy a need, and that need would not disappear since we also take that there will not be secondary movements of the relocated people.

- In a given period, people can be assigned to a host location only if this host location has been opened and has spare capacity.
- The diversity level of the host locations represents the success of local integration, hence the success of the relocation plan. The diversity level is measured with respect to two indicators. The first indicator is fractionalization, which is a proxy index based on the number of different groups within a population. Since it implies a potential for growth, we aim to maximize it. The second indicator is polarization, which is a proxy index based on the relative sizes and distances of different groups within a population. We aim to minimize it since it implies a potential for social unrest and conflict. [33]–[35]
- The diversity indicators calculated for a host location account for the proportions of the populations already settled from various origin countries but are only measured relative to the origin countries considered in this analysis.
- The population ratios used in the calculation of diversity indicators are updated based on the incoming flows assigned by the model in each period and assumed to be unaffected by other population changes (e.g., changes in birth rates and other secondary movements).
- We define geographical divisions within which host locations are located. Each host location belongs to a single higher division of geographical granularity. For example, if host locations are defined in the model at the city level, the higher division associated with a host location may be a state or country. Or if host locations are defined at the country level, the higher division may be a corresponding country group (e.g., the European Union). We define "higher divisions" because, while relocation capacities and assignments are managed at the host location level, the total budgets for location opening and goal deviation are handled at the higher division level. Since the proposed model allows for the adjustment of granularity, host locations, and their corresponding higher divisions can be defined at a convenient level as long as the higher divisions are mutually exclusive and collectively exhaustive regions.

3.2.1 Notation

Table 1, Table 2, and Table 3 present the sets, parameters, and decision variables of the model, respectively.

Table 1. Sets and indices.

I	Set of origin locations, indexed by i
J	Set of host locations, indexed by j
L	Set of higher divisions of host locations, indexed by l
J^l	Subset of host locations belonging to the same higher division such that $J = J^1 \cup \dots \cup J^{\lvert L \rvert}$, indexed by l
K	Set of all locations $K = I \cup J$, indexed by k
T	Set of periods such that $T = \{1, \dots, n\}$ where n is the number of periods, indexed by t
Ω	Set of scenarios, indexed by ω

Table 2. Parameters.

${UB_l}^o$	Highest amount of total budget that local authorities are willing or allowed to allocate to open host locations that belong to the same higher division J^l such that $J = J^1 \cup \dots \cup J^{\lvert L \rvert}$
${UB_l}^p$	Maximum budget that local authorities are willing or allowed to allocate for the penalty of not satisfying the promised relocation levels of host locations that belong to the same higher division J^l such that $J = J^1 \cup \dots \cup J^{\lvert L \rvert}$
UB^{φ}	Maximum capacity change at any host location in one period
c_j^o	Cost of setting up and opening host location $j \in J$ to relocation for the first time
c^p	Unit cost of deviating from the relocation goals by one individual; not relocating one individual
Φ_{j0}	Initial relocation capacity of the host location $j \in J$ at period zero
V_{kj}	Number of people from $k \in K$ in host location $j \in J$ at period zero
p^{ω}	Probability of scenario $\omega \in \Omega$

ξ_{jt}^{ω}	Binary value representing the availability of host location $j \in J$ at period $t \in T$ under scenario $\omega \in \Omega$
d_{it}^{ω}	Cumulative relocation demand forecasted for origin location $i \in I$ by the end of period $t \in T$ under scenario $\omega \in \Omega$
q_{lt}^{ω}	Relocation goal of host locations that belong to the same higher division J^l set for period $t \in T$ under scenario $\omega \in \Omega$ such that $J = J^1 \cup \ldots \cup J^{\|L\|}$
M	Big M

Table 3. Decision variables.

b_l^o	Budget to be allocated to open host locations that belong to the same higher division J^l such that $J = J^1 \cup \ldots \cup J^{\|L\|}$
b_l^p	Budget to be allocated for the penalty of not satisfying the promised relocation levels of host locations that belong to the same higher division J^l such that $J = J^1 \cup \ldots \cup J^{\|L\|}$
y_{jt}	Binary variable equal to 1 if host location $j \in J$ is opened at period $t \in T$, 0 otherwise
z_{jt}	Binary variable equal to 1 if host location $j \in J$ is open at period $t \in T$, 0 otherwise
$\Delta\varphi_{jt}$	Capacity expansion for the upcoming period of the host location $j \in J$ at period $t \in T \setminus \{\|T\|\}$
φ_{jt}	Total relocation capacity of the host location $j \in J$ at the beginning of period $t \in T$
x_{ijt}^{ω}	Number of individuals assigned / relocation flow from origin location $i \in I$ to host location $j \in J$ at period $t \in T$ in scenario $\omega \in \Omega$
v_{kjt}^{ω}	Number of individuals from $k \in K$ in host location $j \in J$ at the end of period $t \in T$ in scenario $\omega \in \Omega$
s_{kj}^{ω}	Ratio of the number of individuals from each location in the host location $j \in J$ to the total population of the host location $j \in J$ at the end of the planning horizon in scenario $\omega \in \Omega$
α_j^{ω}	Level of fractionalization of host location $j \in J$ at the end of the planning horizon in scenario $\omega \in \Omega$
β_j^{ω}	Level of polarization of host location $j \in J$ at the end of the planning horizon in scenario $\omega \in \Omega$

$\overline{\alpha}^{\omega}$	Average fractionalization of all host locations in scenario $\omega \in \Omega$
$\overline{\beta}^{\omega}$	Average polarization of all host locations in scenario $\omega \in \Omega$
r_{lt}^{ω}	Total deviation from the promised relocation goals of host locations that belong to the same higher division J^l at period $t \in T$ such that $J = J^1 \cup \dots \cup J^{\vert L\vert}$
$\bar{r}_{lt}^{\omega}$	Projection of the goal deviation onto the penalty budget constraint for each higher division J^l at period $t \in T$ such that $J = J^1 \cup \dots \cup J^{\vert L\vert}$ that is equal to r_{lt}^{ω} if r_{lt}^{ω} is positive, 0 otherwise
δ_{lt}^{ω}	Indicator variable to assign $\bar{r}_{lt}^{\omega}$ value subject to a conditional rule

3.2.2 Mathematical Formulation

The proposed two-stage multi-period model can be formulated as below. The objective functions in Eqs. (1) and (2) define and combine the objectives for the two stages of the model. Constraints (3) through (9) define the constraints of the first stage, while constraints (10) through (27) define the constraints of the second stage. Finally, constraints (28) through (31) define the nature of the decision variables.

The objective of the model, formulated in Eq. (1), is to concurrently optimize the objective functions of the two stages on the same scale: the first stage objective of minimizing budget allocations for all divisions on average with the second stage objective of optimizing the expected level of diversity over two indicators under different demand scenarios, defined subsequently in Eq. (2).

$$\text{Min} \quad \frac{\sum_{l\in L}\frac{b_l^o}{UB_l^o}}{|L|} + \frac{\sum_{l\in L}\frac{b_l^p}{UB_l^p}}{|L|} + E_{\Omega}\left[Q\left(b_l^o, b_l^p, y_{jt}, z_{jt}, \varphi_{jt}, \Delta\varphi_{jt}\right)\right] \tag{1}$$

$$E_{\Omega}\left[Q\left(b_l^o, b_l^p, y_{jt}, z_{jt}, \varphi_{jt}, \Delta\varphi_{jt}\right)\right] = min \sum_{w\in\Omega} p^{\omega}\left(\overline{\beta}^{\omega} - \overline{\alpha}^{\omega}\right) \tag{2}$$

In the first stage, our goal is to set the budgets to allocate, decide which locations to open, and manage their capacities for the relocation decisions of the following stage.

Constraints (3) and (4) are related to budget restrictions. They ensure that the allocated budgets are no more than what the local authorities are willing to pay for the setup and penalty purposes. Even though the model mimics a central decision-maker who considers the overall good, these inequalities give local authorities of host locations a low level of authority.

$$b_l^o \leq UB_l{}^o \qquad \forall\, l \in L \tag{3}$$

$$b_l^p \leq UB_l{}^p \qquad \forall\, l \in L \tag{4}$$

Constraints (5) and (6) are related to location opening decisions. Constraint (5) ensures that the allocated setup budget is enough to cover the cost of opening host locations within each higher division, where early openings are penalized with a higher weight. Constraint (6) ensures that once a host location is opened, its status will remain open for the rest of the planning horizon. Since the open status is controlled by a binary variable, constraint (6) simultaneously ensures that a host location can be opened at most once during the planning horizon.

$$\sum_{t \in T} \sum_{j \in J^l} c_j^o \times y_{jt} \times \frac{|T| + 1 - t}{|T|} \leq b_l^o \qquad \forall\, l \in L \tag{5}$$

$$z_{jt} = \sum_{m=1}^{t} y_{jm} \qquad \forall\, j \in J, t \in T \tag{6}$$

Constraints (7) through (9) are related to capacity management. Constraint (7) initializes the capacities for the first period. Constraint (8) is a capacity balance constraint stating that the current total capacity is the sum of the total capacity and the capacity expansion from the previous period. Constraint (9) states that capacity expansion per location per period cannot exceed the allowed upper bound and that a host location should be opened prior to fulfillment of the capacity expansion.

$$\varphi_{j1} = \Phi_{j0} \qquad \forall\, j \in J \tag{7}$$

$$\varphi_{jt} = \varphi_{j(t-1)} + \Delta\varphi_{j(t-1)} \qquad \forall\, j \in J, t \in T\backslash\{1\} \tag{8}$$

$$\Delta\varphi_{j(t-1)} \leq z_{j(t-1)} \times UB^{\varphi} \qquad \forall\, j \in J, t \in T\backslash\{1\} \tag{9}$$

In the second stage, we aim to optimize diversity in the host locations while making relocation decisions.

Constraint (10) ensures that the allocated penalty budget is enough to cover the cost of deviating from promised relocation goals for each higher division of host locations.

$$\sum_{t \in T} c^p \times \bar{r}_{lt}^{\omega} \leq b_l^p \qquad \forall\, l \in L,\ \omega \in \Omega \tag{10}$$

Constraints (11) through (18) help us to define diversity indicators for each demand scenario. Constraint (11) initializes the population levels for the first period, where population levels represent the number of individuals from specific origins in each host location. At the beginning of the planning horizon, population levels are equal to the number of individuals from particular origins from all locations. Then, population levels are updated concerning the incoming flows suggested by the model for subsequent periods. Thus, constraints (11) through (13) update the population level of an origin in a specific host location for each period, while constraint (14) calculates the ratio of a particular origin with respect to the entire population *at the end of the planning horizon*. Constraints (15) and (16) calculate the diversity indicators at the end of the planning horizon – fractionalization adapted from [34] and polarization adapted from [35], respectively. Constraints (17) and (18) take averages of the diversity indicators for all locations. To simplify the model, we focus on diversity optimization not during the planning horizon but at the end of it.

$$v_{ij1}^{\omega} = V_{ij} + x_{ij1}^{\omega} \qquad \forall\, i \in I, j \in J, \omega \in \Omega \tag{11}$$

$$v_{ijt}^{\omega} = v_{ij(t-1)}^{\omega} + x_{ijt}^{\omega} \qquad \forall\, i \in I, j \in J, t \in T\backslash\{1\}, \omega \in \Omega \tag{12}$$

$$v_{ijt}^{\omega} = V_{ij} \qquad \forall\, i \in J, j \in J, t \in T, \omega \in \Omega \qquad (13)$$

$$s_{kj}^{\omega} = \frac{v_{kj|T|}^{\omega}}{\sum_{k \in K} v_{kj|T|}^{\omega}} \qquad \forall\, k \in K,\ j \in J, \omega \in \Omega \qquad (14)$$

$$\alpha_j^{\omega} = 1 - \sum_{k \in K} {s_{kj}^{\omega}}^2 \qquad \forall\, j \in J, \omega \in \Omega \qquad (15)$$

$$\beta_j^{\omega} = 1 - \sum_{k \in K} \left(\frac{0.5 - s_{kj}^{\omega}}{0.5} \right)^2 \times s_{kj}^{\omega} \qquad \forall\, j \in J, \omega \in \Omega \qquad (16)$$

$$\overline{\alpha}^{\omega} = \frac{\sum_{j \in J} \alpha_j^{\omega}}{|J|} \qquad \forall\, \omega \in \Omega \qquad (17)$$

$$\overline{\beta}^{\omega} = \frac{\sum_{j \in J} \beta_j^{\omega}}{|J|} \qquad \forall\, \omega \in \Omega \qquad (18)$$

Constraints (19) and (20) are related to flow balance. Constraint (19) ensures that if a host location is open to relocation and available during that period, its cumulative inflow up until then cannot exceed its current total capacity. Constraint (20) manages the relationship between the outflow and the demand of origin locations, ensuring that the cumulative outflow of an origin location at a specific period cannot exceed its relocation need, where relocation need is represented as the cumulative forecasted demand.

$$\sum_{m=1}^{t} \sum_{i \in I} x_{ijm}^{\omega} \le \xi_{jt}^{\omega} \times z_{jt} \times \varphi_{jt} \qquad \forall\, j \in J, t \in T, \omega \in \Omega \qquad (19)$$

$$\sum_{m=1}^{t} \sum_{j \in J} x_{ijm}^{\omega} \le d_{it}^{\omega} \qquad \forall\, i \in I, t \in T, \omega \in \Omega \qquad (20)$$

Constraints (21) through (27) are related to goal deviation. Constraint (21) calculates the amount of deviation from the promised relocation goal for each higher division of host locations for each period. Constraint (21) allows both positive and negative deviations where a positive deviation represents the amount of unmet relocation goal for that period, and a negative deviation represents the excess level of relocation for that period to compensate for the previously unmet goals. While negative deviations are acceptable, allowing them to affect the objective by including them in the penalty cost constraint might be misleading. Thus, we allow negative deviations in constraint (21) but include only the positive deviations in the penalty cost constraint in constraint (10). Constraints (22) through (27) help us to reflect only the positive deviations to the penalty cost constraint and, hence, the objective.

$$q_{lt}^{\omega} = \sum_{j \in J^l} \sum_{i \in I} x_{ijt}^{\omega} + r_{lt}^{\omega} \qquad \forall\, l \in L, t \in T, \omega \in \Omega \tag{21}$$

$$-M \times (1 - \delta_{lt}^{\omega}) \leq r_{lt}^{\omega} \qquad \forall\, l \in L, t \in T, \omega \in \Omega \tag{22}$$

$$r_{lt}^{\omega} \leq M \times \delta_{lt}^{\omega} \qquad \forall\, l \in L, t \in T, \omega \in \Omega \tag{23}$$

$$r_{lt}^{\omega} - M \times (1 - \delta_{lt}^{\omega}) \leq \bar{r}_{lt}^{\omega} \qquad \forall\, l \in L, t \in T, \omega \in \Omega \tag{24}$$

$$\bar{r}_{lt}^{\omega} \leq r_{lt}^{\omega} + M \times (1 - \delta_{lt}^{\omega}) \qquad \forall\, l \in L, t \in T, \omega \in \Omega \tag{25}$$

$$-M \times \delta_{lt}^{\omega} \leq \bar{r}_{lt}^{\omega} \qquad \forall\, l \in L, t \in T, \omega \in \Omega \tag{26}$$

$$\bar{r}_{lt}^{\omega} \leq M \times \delta_{lt}^{\omega} \qquad \forall\, l \in L, t \in T, \omega \in \Omega \tag{27}$$

Finally, constraints (28) through (31) define the nature of the decision variables. Eq. (28) states that decision variables regarding budgets and diversity indicators are continuous and non-negative. Eq. (29) states that decision variables regarding relocation flows, population levels, capacities, and positive goal deviation are integer and non-negative since they are measured as the number of individuals. Eq. (30) states that decision variables regarding goal deviation are integers. Finally, Eq. (31) states that decision variables regarding the opening of locations and indicator variables are binary.

$$b_l^o, b_l^p, s_{kj}^{\omega}, \alpha_{jt}^{\omega}, \beta_{jt}^{\omega}, \overline{\alpha}^{\omega}, \overline{\beta}^{\omega} \in \mathbb{R}_{\geq 0} \tag{28}$$

$$x_{ijt}^{\omega}, v_{kjt}^{\omega}, \varphi_{jt}, \Delta\varphi_{jt}, \bar{r}_{lt}^{\omega} \in \mathbb{Z}_{\geq 0} \tag{29}$$

$$r_{lt}^{\omega} \in \mathbb{Z} \tag{30}$$

$$y_{jt}, z_{jt}, \delta_{lt}^{\omega} \in \mathbb{Z}_2 \tag{31}$$

3.3 Solution Approach

3.3.1 Reformulations

Since the proposed model is a mixed-integer non-linear model which is non-convex in nature, it is computationally hard to solve. Moreover, the proposed model with its original formulation may not be appropriate to solve with every commercial solver. We implement the model using Python programming language and the Gurobi optimization solver. To do so, we implemented the following reformulations presented in Eqs. (37) through (45). Additional decision variables used in the reformulations are provided in Table 4.

Table 4. Additional decision variables for reformulation.

Δ_j^{ω}	Converter variable to reformulate the definition of s_{kj}^{ω}
ψ_{kj}^{ω}	Converter variable to reformulate the definition of $\overline{\beta}^{\omega}$

We replace constraint (14) with constraints (32) and (33) so that we could turn the non-linear constraint into a form manageable by Gurobi. Since the division of decision variables is not supported by Gurobi, we introduce a new decision variable to represent the summation of population levels in the divisor of constraint (14). Rather than dividing the specific population level by the summation to calculate the ratio, we multiply the ratio with the summation to calculate the particular population level.

$$\Delta_j^{\omega} = \sum_{k \in K} v_{kj|T|}^{\omega} \qquad \forall\, j \in J, \omega \in \Omega \tag{32}$$

$$s_{kj}^{\omega} * \Delta_j^{\omega} = v_{kj|T|}^{\omega} \qquad \forall\, k \in K,\ j \in J, \omega \in \Omega \tag{33}$$

We replace constraints (15) and (17) with constraint (34) so that we eliminate intermediate steps and combine the calculations made separately in the original formulation: the calculation of the fractionalization level for each host location and the calculation of the average fractionalization level for all host locations. Ultimately, we obtain one average fractionalization level for each demand scenario. As such, we decrease the number of decision variables by eliminating the random variableα_j^ω for the fractionalization level of each host location and reduce the number of constraints by completing the required calculations in a single step.

$$\overline{\alpha}^\omega = \frac{\sum_{j\in J}(1-\sum_{i\in K} s_{ij}^{\omega^2})}{|J|} \qquad \forall\ \omega \in \Omega \tag{34}$$

Then, we repeat the same process to obtain an average polarization level under each demand scenario. However, we apply an additional step to transform the non-linear polarization calculation into a form manageable by Gurobi. Since the multiplication of more than two variables is not supported by Gurobi, we introduce a new decision variable to store the multiplication of two decision variables and then multiply it by the third variable term. As a result, we replace constraints (16) and (18) with constraints (35) and (36).

$$\psi_{kj}^\omega = \left(\frac{0.5 - s_{kj}^\omega}{0.5}\right)^2 \qquad \forall\ k \in K,\ j \in J, \omega \in \Omega \tag{35}$$

$$\overline{\beta}^\omega = \frac{\sum_{j\in J}(1 - \sum_{k\in K} \psi_{kj}^\omega \times s_{kj}^\omega)}{|J|} \qquad \forall\ \omega \in \Omega \tag{36}$$

In the original formulation, we use binary variable y_{jt} to represent the exact time period when a host location is opened to relocation, and we use the binary variable z_{jt} to represent whether the host location is open at a given time period. The variable y_{jt} , representing the opening decision, gets the value of 1 only at the time period in which the act of opening occurs. Meanwhile, the variable z_{jt}, representing the openness status, takes the value of 1 for all the time periods starting with the period in which the act of opening occurs. The variable z_{jt} at a given time period can be rewritten as the summation of the variables y_{jt} up until that period. To reduce the number of redundant variables and constraints in the model, we remove the variable representing the openness status of the host locations, z_{jt}, and directly insert the corresponding formulation using the variable representing the opening decision, y_{jt}. We remove constraint (6) and update constraints (9) and (19) accordingly. By doing so, we eliminate the random variable z_{jt}. We add constraint (37) to ensure each host location can be opened only once. While we replace constraint (9) directly with the equivalent reformulation presented in constraint (38), we apply an additional step to reformulate constraint (19) to linearize it at the same time. We use the Big M method to eliminate the non-linear multiplication of two decision variables. As a result, we replace constraint (19) with constraints (39) and (40).

$$\sum_{t\in T} y_{jt} \leq 1 \qquad \forall\, j \in J \tag{37}$$

$$\Delta\varphi_{j(t-1)} \leq \sum_{m=1}^{t-1} y_{jm} \times UB^{\varphi} \qquad \forall\, j \in J, t \in T\backslash\{1\} \tag{38}$$

$$\sum_{m=1}^{t}\sum_{i\in I} x_{ijm}^{\omega} \leq \xi_{jt}^{\omega} \times \sum_{m=1}^{t} y_{jm} \times M \qquad \forall\, j \in J, t \in T, \omega \in \Omega \tag{39}$$

$$\sum_{m=1}^{t}\sum_{i\in I} x_{ijm}^{\omega} \leq \varphi_{jt} \qquad \forall\, j \in J, t \in T, \omega \in \Omega \tag{40}$$

Also, we replace constraint (28) with constraint (41), replace constraints (29) and (30) with constraints (42) and (43), replace constraint (31) with constraint (44), and add constraint (45) to reflect the changes in the decision variables and to relax the integer decision variables into a continuous form. We apply the linear programming relaxation based on the assumption that the discrepancy between the mixed-integer version and the relaxed version would be overcomed by the large number of parameters, inherent uncertainties, and the high-level nature of the output plan.

$$b_l^o, b_l^p, s_{kj}^{\omega}, \overline{\alpha}^{\omega}, \overline{\beta}^{\omega} \in \mathbb{R}_{\geq 0} \tag{41}$$

$$x_{ijt}^{\omega}, v_{kjt}^{\omega}, \Delta\varphi_{jt}, \varphi_{jt}, \bar{r}_{lt}^{\omega} \in \mathbb{R}_{\geq 0} \tag{42}$$

$$r_{lt}^{\omega} \in \mathbb{R} \tag{43}$$

$$y_{jt}, \delta_{lt}^{\omega} \in \mathbb{Z}_2 \tag{44}$$

$$\Delta_j^{\omega}, \psi_{kj}^{\omega} \in \mathbb{R}_{\geq 0} \tag{45}$$

3.3.2 Piecewise Linear Approximation

Piecewise linear approximation is a common technique to handle nonlinearity in optimization models [36]. It can be used to reformulate the original non-linear formulation with the help of additional binary and continuous variables and constraints. The basic idea behind piecewise linearization is to replace the continuous non-linear function with multiple linear segments defined between breakpoints over corresponding subintervals. As such, these linear segments trace the trajectory of the non-linear function as closely as possible depending on the selected breakpoints.

Since the random variables representing population level, fractionalization indicator, and polarization indicator remain non-linear even after the initial reformulations, we apply piecewise linear approximations to linearize the calculations of the random variables $v_{ij|T|}^{\omega}$, $\overline{\alpha}^{\omega}$, and $\overline{\beta}^{\omega}$.

Additional parameters and decision variables used during the piecewise linearization can be found in Table 5 and Table 6, respectively.

Table 5. Additional parameters for linearization.

$P_{nj}^{v}\left(a_{snj}^{v}, a_{\Delta \mathrm{nj}}^{v}, b_{nj}^{v}\right)$	nth breakpoint used for the linearization of $v_{ij\|T\|}^{\omega}$ such that $n = 1, \ldots, n^{v}$, where n^{v} breakpoints are selected, and $j \in J$
$P_{n}^{\alpha}(a_{n}^{\alpha}, b_{n}^{\alpha})$	nth breakpoint used for the linearization of $\overline{\alpha}^{\omega}$ such that $n = 1, \ldots, n^{\alpha}$, where n^{α} breakpoints are selected
$P_{n}^{\beta}\left(a_{n}^{\beta}, b_{n}^{\beta}\right)$	nth breakpoint used for the linearization of $\overline{\beta}^{\omega}$ such that $n = 1, \ldots, n^{\beta}$, where n^{β} breakpoints are selected

Table 6. Additional decision variables for linearization.

$\bar{\bar{v}}_{kj}^{\omega}$	Linear approximation of the non-linear term which is replaced in the function of $v_{kj\|T\|}^{\omega}$ such that $k \in K,\ j \in J,\ \omega \in \Omega$
$\bar{\bar{\alpha}}_{kj}^{\omega}$	Linear approximation of the non-linear term which is replaced in the function of $\overline{\alpha}^{\omega}$such that $k \in K,\ j \in J,\ \omega \in \Omega$
$\bar{\bar{\beta}}_{kj}^{\omega}$	Linear approximation of the non-linear term which is replaced in the function of $\overline{\beta}^{\omega}$ such that $k \in K,\ j \in J,\ \omega \in \Omega$
$\lambda_{nkj}^{v\omega}$	Non-negative decision variable representing the weight of each breakpoint $P_n^v(a_{sn}^v, a_{\Delta\mathrm{n}}^v, b_n^v)$ such that $n = 1, \ldots, n^v$where $n^v = 4$ breakpoints are selected and $k \in K,\ j \in J,\ \omega \in \Omega$
$\lambda_{nkj}^{\alpha\omega}$	Non-negative decision variable representing the weight of each breakpoint $P_n^{\alpha}(a_n^{\alpha}, b_n^{\alpha})$ such that $n = 1, \ldots, n^{\alpha}$where $n^{\alpha} = 4$ breakpoints are selected and $k \in K$, $j \in J,\ \omega \in \Omega$
$\lambda_{nkj}^{\beta\omega}$	Non-negative decision variable representing the weight of each breakpoint $P_n^{\beta}\left(a_n^{\beta}, b_n^{\beta}\right)$ such that $n = 1, \ldots, n^{\beta}$where $n^{\beta} = 4$ breakpoints are selected and $k \in K$, $j \in J,\ \omega \in \Omega$
$\delta_{mkj}^{v\omega}$	Indicator decision variable representing which linear region is selected during the linearization of $v_{ij\|T\|}^{\omega}$ such that $m = 1, \ldots, m^v$where $m^v = 2$ triangles are created using n^v breakpoints and $k \in K,\ j \in J,\ \omega \in \Omega$
$\delta_{mkj}^{\alpha\omega}$	Indicator decision variable representing which linear segment is selected during the linearization of $\overline{\alpha}^{\omega}$ such that $m = 1, \ldots, n^{\alpha} - 1$ when $n^{\alpha} - 1$ line segments are created where n^{α} breakpoints are selected and $k \in K,\ j \in J,\ \omega \in \Omega$
$\delta_{mkj}^{\beta\omega}$	Indicator decision variable representing which linear segment is selected during the linearization of $\overline{\beta}^{\omega}$ such that $m = 1, \ldots, n^{\beta} - 1$ when $n^{\beta} - 1$ line segments are created where n^{β} breakpoints are selected and $k \in K,\ j \in J,\ \omega \in \Omega$

The linearization constraints that replace the previous function used in the calculations of representing population level, fractionalization indicator, and polarization indicator are structured as follows.

First, we linearize the calculation of the population level. Since the population level is calculated with a two-dimensional function, we use triangulation, motivated by the finite element method, and apply the piecewise linearization by using the resulting triangular mesh rather than linear line segments. For this linearization, we select four corner breakpoints that create two triangles. Finally, we replace Eq. (33) with Eqs. (46) through (55).

$$v_{kj|T|}^{\omega} = \bar{\bar{v}}_{kj}^{\omega} \qquad \forall\, k \in K,\ j \in J, \omega \in \Omega \tag{46}$$

$$\bar{\bar{v}}_{kj}^{\omega} = \sum_{n=1}^{n^{v}} b_{nj}^{v} \lambda_{nkj}^{v\omega} \qquad \forall\, k \in K,\ j \in J, \omega \in \Omega \tag{47}$$

$$s_{kj}^{\omega} = \sum_{n=1}^{n^{v}} a_{snj}^{v} \lambda_{nkj}^{v\omega} \qquad \forall\, k \in K,\ j \in J, \omega \in \Omega \tag{48}$$

$$\mathit{\Delta}_{j}^{\omega} = \sum_{n=1}^{n^{v}} a_{\Delta \mathrm{nj}}^{v} \lambda_{nkj}^{v\omega} \qquad \forall\, k \in K,\ j \in J, \omega \in \Omega \tag{49}$$

$$\sum_{n=1}^{n^{v}} \lambda_{nkj}^{v\omega} = 1 \qquad \forall\, k \in K,\ j \in J, \omega \in \Omega \tag{50}$$

$$\delta_{1kj}^{v\omega} + \delta_{2kj}^{v\omega} \geq \lambda_{1kj}^{v\omega} \qquad \forall\, k \in K,\ j \in J, \omega \in \Omega \tag{51}$$

$$\delta_{1kj}^{v\omega} \geq \lambda_{2kj}^{v\omega} \qquad \forall\, k \in K,\ j \in J, \omega \in \Omega \tag{52}$$

$$\delta_{1kj}^{v\omega} + \delta_{2kj}^{v\omega} \geq \lambda_{3kj}^{v\omega} \qquad \forall\, k \in K,\ j \in J, \omega \in \Omega \tag{53}$$

$$\delta_{2kj}^{v\omega} \geq \lambda_{4kj}^{v\omega} \qquad \forall\, k \in K,\ j \in J, \omega \in \Omega \tag{54}$$

$$\sum_{m=1}^{m^{v}} \delta_{mkj}^{v\omega} = 1 \qquad \forall\, k \in K,\ j \in J, \omega \in \Omega \tag{55}$$

Secondly, we linearize the calculation of the fractionalization and polarization indicators. Based on the behavior of the non-linear terms, we select four breakpoints that create three linear line segments.

We replace Eq. (34) with Eqs. (56) through (63) to linearize the calculation of the fractionalization indicator.

$$\overline{\alpha}^{\omega} = \frac{\sum_{j\in J}(1-\sum_{k\in K}\bar{\bar{\alpha}}_{kj}^{\omega})}{|J|} \qquad \forall\, \omega \in \Omega \tag{56}$$

$$\bar{\bar{\alpha}}_{kj}^{\omega} = \sum_{n=1}^{n^{\alpha}} b_n^{\alpha} * \lambda_{nkj}^{\alpha\omega} \qquad \forall\, k \in K,\ j \in J, \omega \in \Omega \tag{57}$$

$$s_{kj}^{\omega} = \sum_{n=1}^{n^{\alpha}} a_n^{\alpha} * \lambda_{nkj}^{\alpha\omega} \qquad \forall\, k \in K,\ j \in J, \omega \in \Omega \tag{58}$$

$$\sum_{n=1}^{n^{\alpha}} \lambda_{nkj}^{\alpha\omega} = 1 \qquad \forall\, k \in K,\ j \in J, \omega \in \Omega \tag{59}$$

$$\delta_{1kj}^{\alpha\omega} \geq \lambda_{1kj}^{\alpha\omega} \qquad \forall\, k \in K,\ j \in J, \omega \in \Omega \tag{60}$$

$$\delta_{(n-1)kj}^{\alpha\omega} + \delta_{nkj}^{\alpha\omega} \geq \lambda_{nkj}^{\alpha\omega} \qquad \forall\, n \in \{2, \dots, (n^{\alpha}-1)\},\ k \in K,\ j \in J, \omega \in \Omega \tag{61}$$

$$\delta_{(n^{\alpha}-1)kj}^{\alpha\omega} \geq \lambda_{n^{\alpha}kj}^{\alpha\omega} \qquad \forall\, k \in K,\ j \in J, \omega \in \Omega \tag{62}$$

$$\sum_{m=1}^{n^{\alpha}-1} \delta_{mkj}^{\alpha\omega} = 1 \qquad \forall\, k \in K,\ j \in J, \omega \in \Omega \tag{63}$$

We replace Eqs. (35) and (36) with Eqs. (64) through (71) to linearize the calculation of the polarization indicator.

$$\overline{\beta}^{\omega} = \frac{\sum_{j\in J}(1-\sum_{k\in K}\bar{\bar{\beta}}_{kj}^{\omega})}{|J|} \qquad \forall\, \omega \in \Omega \tag{64}$$

$$\bar{\bar{\beta}}_{kj}^{\omega} = \sum_{n=1}^{n^{\beta}} b_n^{\beta} \lambda_{nkj}^{\beta\omega} \qquad \forall\, k \in K,\ j \in J, \omega \in \Omega \tag{65}$$

$$s_{kj}^{\omega} = \sum_{n=1}^{n^{\beta}} a_n^{\beta} \lambda_{nkj}^{\beta\omega} \qquad \forall\, k \in K,\ j \in J, \omega \in \Omega \tag{66}$$

$$\sum_{n=1}^{n^{\beta}} \lambda_{nkj}^{\beta\omega} = 1 \qquad \forall\, k \in K,\ j \in J, \omega \in \Omega \tag{67}$$

$$\delta_{1kj}^{\beta\omega} \geq \lambda_{1kj}^{\beta\omega} \qquad \forall\, k \in K,\ j \in J, \omega \in \Omega \tag{68}$$

$$\delta_{(n-1)kj}^{\beta\omega} + \delta_{nkj}^{\beta\omega} \geq \lambda_{nkj}^{\beta\omega} \qquad \forall\, n \in \{2, \dots, (n^{\beta}-1)\}, \tag{69}$$

$$k \in K,\ j \in J, \omega \in \Omega$$

$$\delta^{\beta\omega}_{(n^{\beta}-1)kj} \geq \lambda^{\beta\omega}_{n^{\beta}kj} \qquad \forall\ k \in K,\ j \in J, \omega \in \Omega \qquad (70)$$

$$\sum_{m=1}^{n^{\beta}-1} \delta^{\beta\omega}_{mkj} = 1 \qquad \forall\ k \in K,\ j \in J, \omega \in \Omega \qquad (71)$$

3.4 Illustrative Example

While creating the illustrative example, we make substantial assumptions to parametrize the model, given our interest in building the example with a forward-looking perspective.

The uncertainty in demand is the most significant characteristic of the long-term climate change displacement and, hence, of the stochastic model proposed in this study. Therefore, we concentrate our efforts on selecting the most relevant origin locations and reflecting their future relocation demands as realistically as possible in the illustrative example. Only after that do we generate other problem parameters in accordance with the demand.

For a relocation demand to emerge in an origin location due to climate change, some conditions should be observed: (i) the region in question is under at least one climate change impact at a level significant enough that the habitability or the livelihood within the region deteriorates over time, (ii) local solutions based on adaptation or mitigation strategies fall short of getting through the adverse effects of climate change, (iii) the residents of the region are willing to move, and (iv) the residents of the region have the means for relocation. This study uses proxy indicators to consider the effects of the first three conditions on relocation demand. Regarding the fourth condition, we assume the necessary funds will be provided by the central authorities charged with the relocation process.

We start creating the illustrative example by selecting the origin locations that we will consider in the example, focusing on countries that are under significant risk but incapable of responding to the adverse effects of climate change. To this end, we select 29 countries listed as hotspots in the Ecological Threat Report 2021 due to their exposure to high ecological threats and low resilience [37]. We expect only a portion of the future population in each hotspot country to require relocation. To calculate those portions, we use future population projections [38] of the corresponding countries together with the proxy ratio of 55%, the proportion of the global population that will be affected by moderate or severe climate hazards under a 2.0°C warming scenario [39] (assuming that such a ratio is maintained uniformly across all 29 origin countries). Then, we believe that only a portion of those affected will be willing to move, creating a relocation demand. We adapt Potential Net Migration Index scores [40] as a proxy measure of the mobility appetite of the people who live in the selected hotspot countries. Finally, we multiply the estimated demands with an adjustment factor of 15%. The aim is to ensure that the total relocation demand falls within the range of the most pessimistic and optimistic global forecasts and is approximated to be around 200 million, as commonly cited [7]. By doing so, we show that the illustrative example represents the capability of our model to solve the real-life problem at the global level. The estimated relocation demands of 29 hotspot countries are provided in Table 7. Assuming that the calculated relocation demands correspond to the medium demand scenario, we generate three different demand scenarios, assuming that the low and high demand scenarios are 50% and 150% of the medium demand scenario, respectively. Due to the modular structure of the data generation process, it is possible to update these scenarios using different relationships among scenarios as more information becomes available for our use.

Table 7. Estimated relocation demands for the medium (nominal) scenario.

Origin	**[2030-2035)**	**[2035-2040)**	**[2040-2045)**	**[2045-2050)**
Afghanistan	1,350,000	1,430,000	1,550,000	1,660,000
Angola	1,390,000	1,570,000	1,800,000	2,060,000
Bangladesh	4,450,000	4,480,000	4,580,000	4,640,000
Burundi	490,000	540,000	610,000	680,000
Cameroon	1,060,000	1,150,000	1,280,000	1,410,000

Central African Republic	180,000	200,000	220,000	240,000
Chad	480,000	540,000	600,000	670,000
Congo	3,720,000	4,140,000	4,690,000	5,270,000
Equatorial Guinea	60,000	60,000	70,000	80,000
Eritrea	130,000	140,000	150,000	170,000
Ethiopia	5,120,000	5,480,000	6,010,000	6,530,000
Guinea	800,000	860,000	970,000	1,070,000
Guinea-Bissau	80,000	80,000	90,000	100,000
Haiti	1,050,000	1,010,000	1,060,000	1,100,000
Iraq	1,910,000	2,030,000	2,220,000	2,410,000
Mauritania	200,000	210,000	240,000	260,000
Niger	870,000	1,010,000	1,190,000	1,380,000
Nigeria	15,840,000	16,820,000	18,810,000	20,840,000
Pakistan	2,410,000	2,570,000	2,750,000	2,910,000
Republic of Congo	180,000	200,000	220,000	250,000
Somalia	360,000	410,000	460,000	520,000
South Sudan	430,000	470,000	520,000	560,000
Sudan	1,710,000	1,850,000	2,050,000	2,240,000
Syria	1,540,000	1,560,000	1,650,000	1,730,000
Tajikistan	150,000	160,000	180,000	190,000
Turkmenistan	80,000	80,000	90,000	90,000
Venezuela	1,370,000	1,360,000	1,400,000	1,430,000
Yemen	860,000	910,000	980,000	1,050,000
Zimbabwe	460,000	490,000	530,000	570,000
Total	**48,730,000**	**51,810,000**	**56,970,000**	**62,110,000**

While we use 29 actual countries considered at risk for climate impacts to generate the set of origin locations, we intentionally avoid any possible controversy with identifying particular host locations. As such, we assume that five representative host locations exist to satisfy the relocation demand. For each host location, we generate a random initial capacity and a location opening budget proportional to its initial capacity (i.e., one-unit initial capacity generates one unit cost of opening). We also assume that these locations belong to two higher divisions such that the host locations within the same higher division share a location opening budget, a relocation goal, and a goal deviation budget. Then, we generate the relocation goals for two divisions such that each period's total relocation goal is equal to that period's total relocation demand under each demand scenario. We define the unit goal deviation cost as four (i.e., one unit goal deviation generates four units of penalty cost of deviation). Finally, we assign upper bounds for opening budgets, goal deviation budgets, and capacity expansion allowance to prevent the model from assigning unrealistically high values to decision variables regarding budgets and capacity expansion.

3.5 Analysis and Results

In this section, we present and compare the model decisions and their effects on the system with and without focusing on the social impacts. For each analysis, first, we consider the results of the model when diversity is optimized based on fractionalization (positive effect on society) and polarization (negative effect on society) dimensions. Then, we consider the results of the model without any consideration of social impacts and compare them to the previous results with diversity optimization.

The two-stage stochastic model that we propose is solved as a multi-objective model optimized with a weighted sum approach. To convert these objectives with different units into a comparable form, we scale them between zero and one. Then, we give them equal weights to contribute to the main objective at equal levels. Note that the effect of different budgets also depends on the corresponding unit costs used within the model constraints, and we incentivize opening locations, hence, relocating more people by assigning a higher unit cost to penalty. In Figure 2, we see the multiple model objective values resulting from the two optimization approaches we adopt: (a) with diversity optimization and (b) without diversity optimization. In this figure, we see the position of each objective value on a scale where lighter colors represent the theoretically ideal values that we want to approximate. We can observe some trade-offs that could be made among these objectives.

Our main model with diversity optimization is willing to spend more on opening locations, hence relocating more people rather than paying the penalty of not satisfying relocation goals. It is also willing to sacrifice the polarization level for a better fractionalization level. When we compare it to the model without diversity optimization results in Figure 2(b), we see an 18.0% improvement in the fractionalization level in exchange for a 23.9% deterioration in the polarization level. These results suggest that our diversity optimization model is successful at promoting the positive dimension of diversity but not as successful at managing the negative side effects that may be caused by the negative dimension of diversity. So, both in our optimization model and in the preparations of host locations, we need to focus on polarization minimization and bridging between different groups.

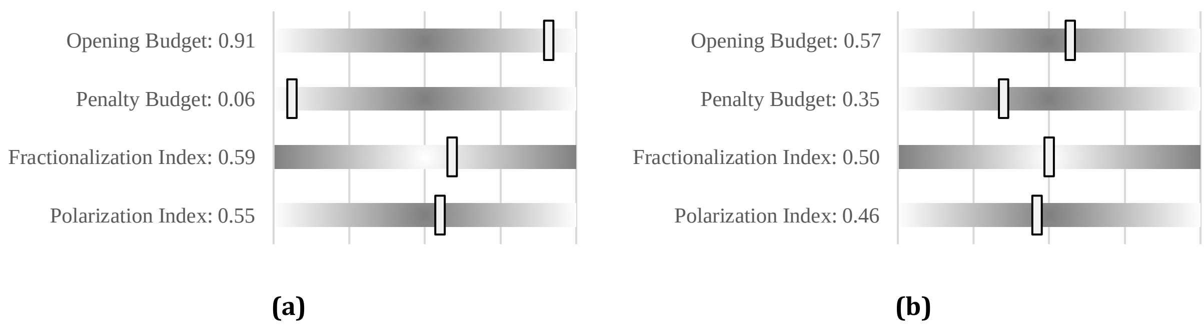


Figure 2. Objective Values.

(a) with and (b) without the two diversity objectives.

Two important sets of decisions come from the two stages of our proposed stochastic model. In the first stage, we determine, from the perspective of a central decision-maker, which host locations to open when and how to manage their capacities. In Table 8 and Table 9, we see when the initial capacity of a host location is opened to relocation first and how it changed thereafter. We can observe that focusing on diversity optimization urges the model to open a variety of locations. In contrast, the model prefers to open fewer host locations without a focus on diversity.

Table 8. Total open capacity of host locations over time with diversity optimization.

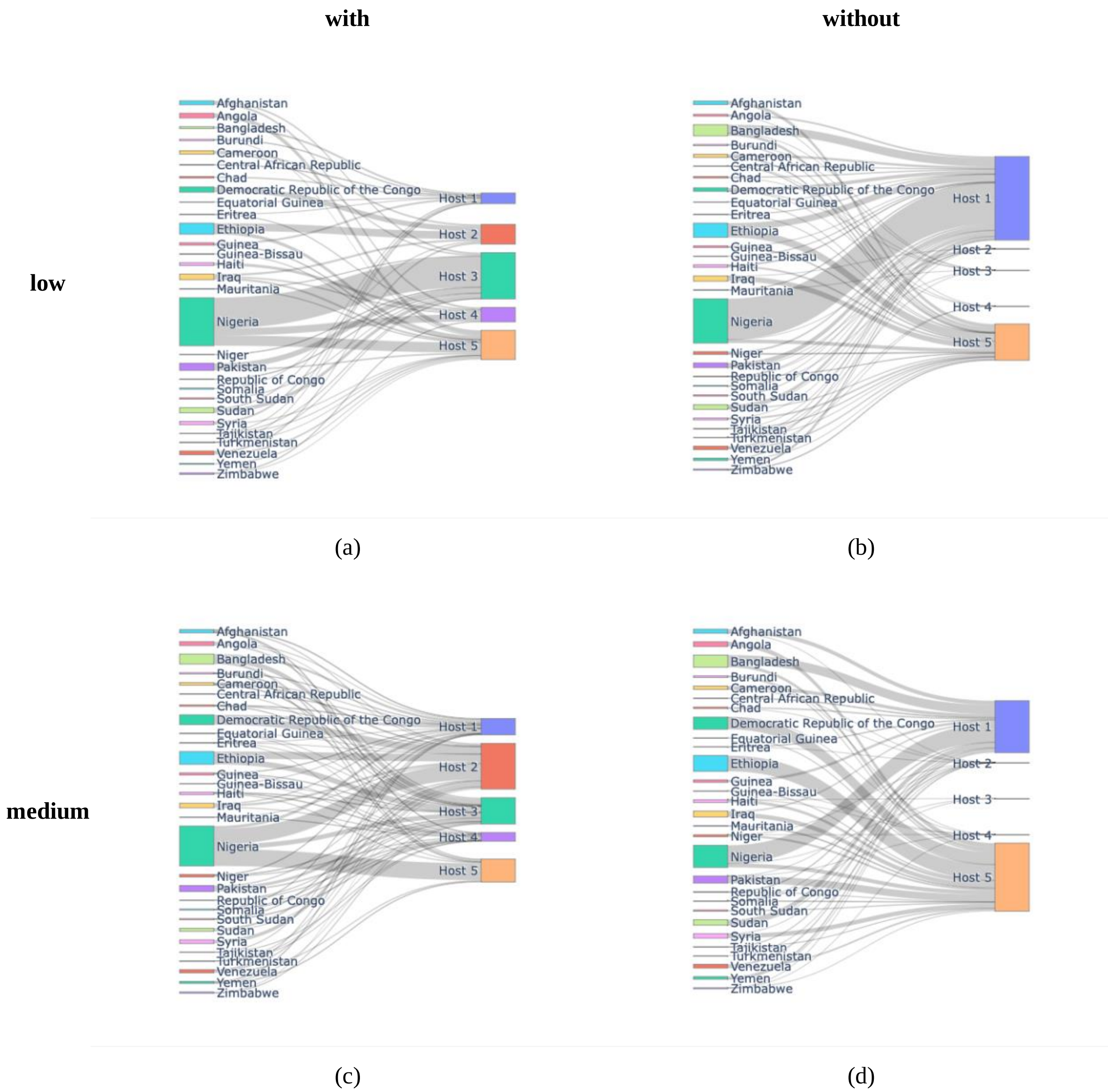
	$t = 1$	$t = 2$	$t = 3$	$t = 4$
Host 1	26,600,000	26,600,000	26,600,000	29,690,000
Host 2	28,900,000	55,098,000	74,839,630	126,668,630

Host 3	38,950,000	38,950,000	49,454,000	56,789,000
Host 4	-	-	51,640,000	51,640,000
Host 5	78,900,000	178,900,000	278,900,000	378,900,000
Total	173,350,000	299,548,000	481,433,630	643,687,630

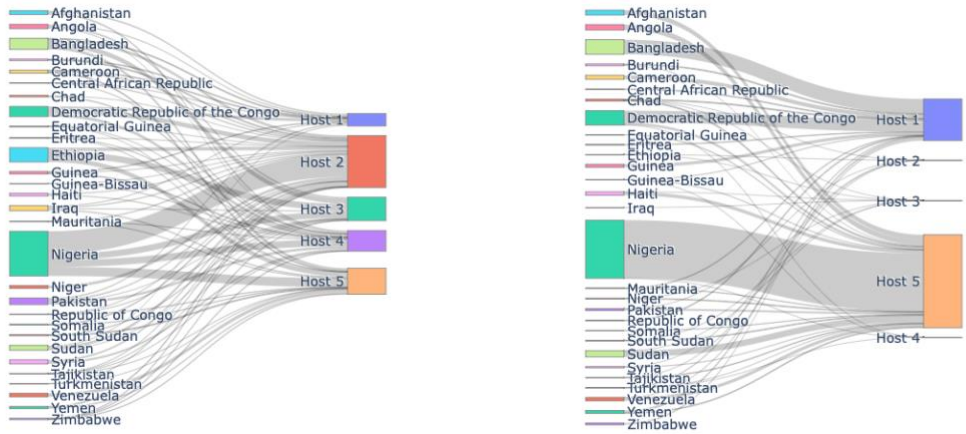
Table 9. Total open capacity of host locations over time without diversity optimization.

	$t = 1$	$t = 2$	$t = 3$	$t = 4$
Host 1	-	26,600,000	43,512,000	77,787,000
Host 2	-	-	-	-
Host 3	-	-	-	-
Host 4	-	-	-	-
Host 5	78,900,000	78,900,000	78,900,000	173,103,000
Total	78,900,000	105,500,000	122,412,000	250,890,000

In the second stage, again from the perspective of a central decision-maker, we determine how many people to relocate from each origin location to each host location in each period. In Figure 3, Sankey charts capture the cumulative flows from origin locations to host locations under different demand scenarios with a focus on diversity optimization (on the left side) and without a focus on diversity optimization (on the right side). When comparing cases with and without diversity optimization, we see that the inclusion of the diversity measure increases the number of host locations open to relocation, and the pattern of the movements becomes less concentrated and more spread out across multiple destinations. When we compare the diagrams for the same optimization approach under different demand scenarios, it is notable that the utilization ratio of each host location with respect to the other locations changes. This is also suggested in Figure 4, where cumulative inflows into each host location are demonstrated with bar charts with and without including diversity objectives under low- and high-demand scenarios. In these charts, the percentages on the bars show the percentage inflow of the corresponding host location with respect to total inflow. While an increase in the utilization percentage of each location is expected when comparing the low-demand scenario to the high-demand scenario, we also observe that the importance or preferability of the host locations changes as well. For example, while optimizing diversity, Host 2 becomes the location with the highest inflow among all open host locations under the high-demand scenario, whereas it is not favored under the low-demand scenario.



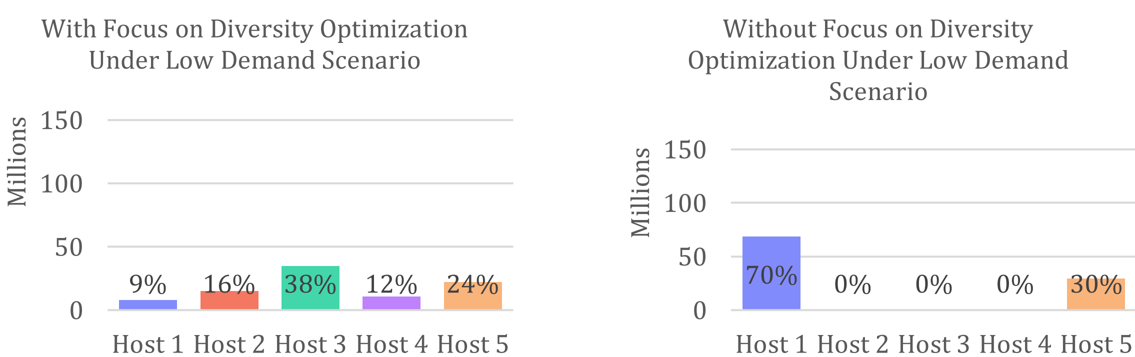
high



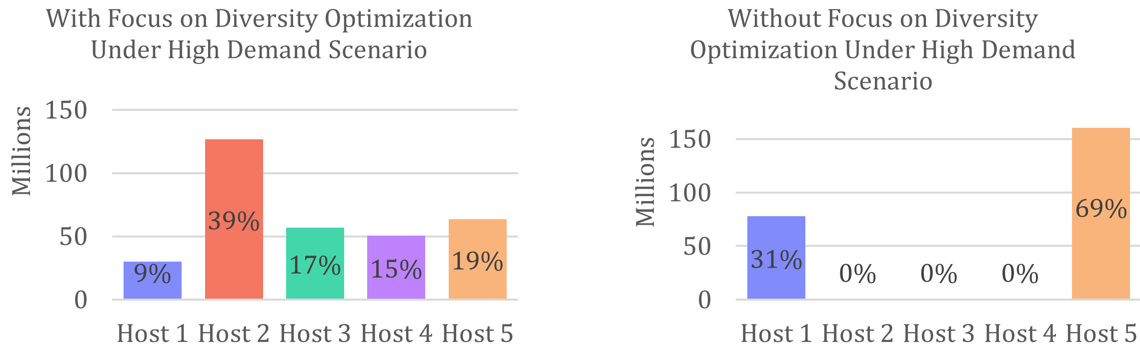
(e) (f)

Figure 3. Cumulative Flows.

from origins to hosts under different demand scenarios (low/medium/high) and inclusion of the diversity objective (with/without): (a) low/with, (b) low/without, (c) medium/with, (d) medium/without, (e) high/with, and (f) high/without.



(a) (b)

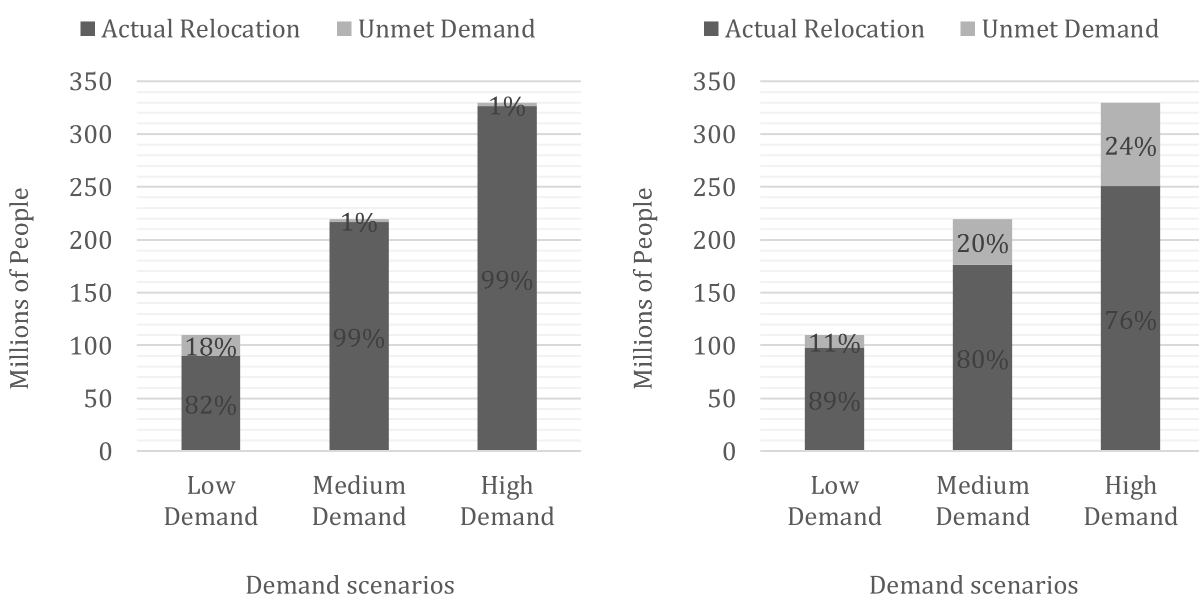


(c) (d)

Figure 4. Total Inflows.

into host locations under different demand scenarios (low/high) and inclusion of the diversity objective (with/without): (a) low/with, (b) low/without, (c) high/with, and (d) high/without.

Finally, Figure 5 shows higher percentages of satisfied relocation demands for the higher-demand scenarios when the diversity is optimized, supporting our initial analysis stating that the model, when focused on diversity optimization, is good at promoting diversity and relocating more people.



(a) (b)

Figure 5. Relocation Demands versus Actual Relocations.

under different demand scenarios (low/medium/high) and inclusion of the diversity objective (with/without): (a) with, (b) without.

3.6 Concluding Remarks

The model presented in this chapter is our first step in handling the long-term climate change-induced forced displacement problem. We approach the problem from the perspective of a central decision-maker who also attends to regional interests. We aim to expose the scope of this problem and prepare the grounds for a high-level agreement among the interested parties so that all stakeholders can take in the situation, come to terms, and start preparations.

To this end, we propose a two-stage stochastic program under demand uncertainty. Our model takes different relocation demand scenarios and potential future host locations as inputs to provide a high-level relocation plan that regards the societal impacts of the movements with respect to diversity indicators. While making relocation decisions ensuring the optimization of the diversity indicators and hence social impacts in the second stage, it comes up with a plan for opening host locations and the required capacity expansions in the first stage. The output of the first stage is a valuable asset for international stakeholders and potential hosts to take forward-looking actions.

Results of the proposed model compared to a version of it without optimization of diversity indicators show that considering diversity, indeed, makes a big difference in relocation flows, ergo, the location opening and capacity expansion decisions. The analysis also reveals that the model performs better at promoting diversity's positive dimension than preventing the negative one.

3.6.1 Research Contributions

In addition to the new operations research perspective on the climate-driven displacement problem, another contribution of this work is the introduction of diversity indicators to measure the success of local integration. The level of local integration is an important outcome to be considered while determining the optimal relocation plan. It could be measured in various ways. While other relocation planning studies (detailed subsequently in the literature review section) are motivated by employment outcomes, we use diversity indicators to measure local integration level and, hence, the success of the relocation plan. We take our inspiration from socio-economic studies where the diversity indicators are used in the empirical analysis of past human movements. Rodríguez-Pose and Berlepsch [33] generalize diversity studies into two opposing groups: (i) one that focuses on the number of different populations and advocates the positive effect of diversity on population growth, and (ii) another that focuses on the relative sizes of different populations and advocates the destabilizing effect of diversity. Among the possible diversity perspectives mentioned in [33], we adopt in our optimization model a fractionalization measure [34] to promote diversity at host locations and a polarization measure [35] to prevent potential conflicts between diverse groups.

3.6.2 Limitations and Improvement Areas

While we can list the above-mentioned trade-off between different dimensions of diversity as one of the first limitations of the model, the most important limitation would probably be future uncertainty. Against the high-level uncertainty of future events and parameters, our assumptions regarding demand scenarios or potential host locations might be too naïve to reflect reality. That is why one of the immediate future works should be to grasp uncertainty better. This includes analyzing different demand patterns, creating more realistic scenarios based on various climate change forecasts, and considering the availability of the existing host locations or the possibility of new host locations in the future. Then, we may also update the model structure to consider multiple stages instead of two. Every time an uncertainty is observed, it changes the stage structure of the stochastic model. Currently, we assume that demand uncertainty would be observed only once. Thus, we use a two-stage model. However, the impact of climate change, and hence, the model parameters, such as the behavior of the relocation demand, may fluctuate over time. We can capture this change by increasing the number of stages. For example, we can assume the uncertainty regarding relocation demand could be observed at the beginning of every time period. This would result in a scenario tree and a multi-stage stochastic model. Furthermore, we can generate more effective estimates for capacity and cost parameters by considering future uncertainty and the system dynamics.

Moreover, a more analytical approach can improve model assumptions and the parameters. For example, the capacity expansion upper bound of each host location at each time period could be defined based on the characteristics of that location. Or, more sophisticatedly, relocation goals, which are currently assigned as parameters with respect to the initial relocation capacities and total demand, could be incorporated into the model as another decision.

A major limitation of the model is the centralized nature of information and decision-making, wherein a lone decision-maker plans the relocation of individuals in all origin and host locations. While it serves well for the purpose of this study, a decentralized structure should be incorporated for future work. We partially address this issue in the following chapter on decentralization.

Another limitation of the model is that it assumes a primarily static environment where the only movements between locations are the ones we suggest, and there are no other changes in the populations. However, in reality, the displaced people might have irregular and secondary movements. We may observe mobility between locations for another interdependent or entirely different reason. We should anticipate and assess the effects of all types of movements on the system and the resulting decisions they require. Similarly, even though we can only suggest and cannot dictate policies or movements, we should study, parametrize, and incorporate the effects and consequences of those policies and movements.

Finally, one of the most critical limitations, hence an important topic of future work, is that the proposed model provides high-level plans for long-term preparations. However, in the future, we will come to a point where operational decisions are required for the prioritization and assignments of specific individuals. So, we should work on not only long-term plans to help decision-makers and authorities prepare in advance but also short-term plans to help with the assignment process.

Chapter 4: Addressing Decentralization

4.1 Overview

This chapter introduces the Consensus-Driven Decentralized Optimization Framework (CDDOF) to use in decision-making settings where multiple local authorities negotiate with the central authority to make decisions for a global cause. In the context of the climate change displacement problem, the goal of the framework is to assist decision-makers with high-level relocation planning by finding common ground for both central and local authorities while building an integrated and fair environment. The aforementioned high-level decisions include flow assignments from origin locations to host locations, location selection decisions, and capacity management decisions. CDDOF utilizes a step-by-step approach to reach these decisions. The step-by-step approach is designed to mimic the give-and-take negotiations that are expected to occur in real life. It's important to note that these decisions may not always align with the best interests of the entire system or the preferred choices of a specific local authority.

4.2 Proposed Approach

CDDOF has four main components employed in the four phases of the framework: Altruistic (System-Optimal) Global Model (AGM), Self-Centered (Self-Optimal) Global Model (SGM), Negotiation Model (NM), and Consensus Model (CM). The overview and the connection of the components and the phases are depicted in Figure 6.

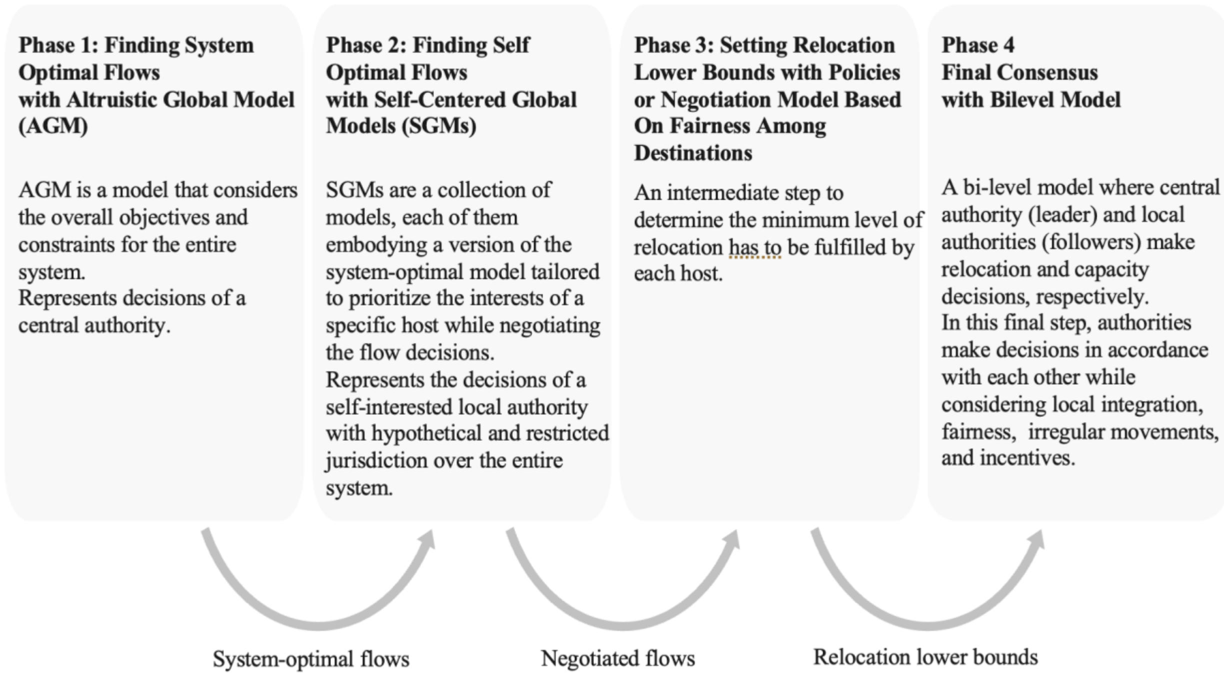


Figure 6. CDDOF Overview.

4.2.1 Phases of The Framework

While the final phase is where the hierarchical decision-making process with interactions is implemented to reach the final consensus, the initial phases represent the back-and-forth negotiations between the central and the local authorities, adding a practical but optional layer to the framework. The framework emphasizes flexibility, especially in these initial phases. In the first phase, users can incorporate any model or methodology of their choice. The following phases, especially the second one, can be adapted accordingly, allowing the different phases of the framework to align seamlessly. This modular approach facilitates customized applications while preserving the integrity of the overall process. That is why we present guidelines for the initial phases and focus on the detailed implementation of the final phase. The explanations of the phases are given below.

Phase 1: Finding System Optimal Flows

In this phase, we use the Altruistic Global Model (AGM) to approach the relocation problem from a centralized perspective. The AGM's decisions represent those of a central authority. This model helps make relocation decisions for both central and local authorities while considering the overall objectives and constraints of the entire system.

Among the AGM's outputs, we pass the flow assignments (system-optimal flows) made for each of the local authorities to the next phase as a benchmark.

Phase 2: Finding Self-Optimal Flows

In this phase, we approach the relocation problem with a decentralized perspective using the Self-Centered Global Models (SGMs). SGMs are a collection of models, each embodying a version of the AGM tailored to prioritize the interests of a specific host while negotiating the flow decisions. They help observe the behavior of the local authorities while considering the overall objectives and constraints for the entire system with a bias towards self-interests. The decisions made by each SGM represent those of a particular self-interested local authority with hypothetical and restricted jurisdiction over the entire system. The jurisdiction of the local authority over the entire system is defined as hypothetical because we would like to see how each local authority would handle the problem if they had power over other authorities, but when it comes to implementing those decisions, we consider only the self-decisions of each local authority. The jurisdiction of the local authority over the entire system is defined as restricted because, even when the local authorities are the decision-makers, they are still bounded by the system-optimal flows determined by the central authority. If they adjust the system-optimal flows to benefit their interests, they have to pay a penalty for deviating from the optimal system. In other words, they have to trade benefits to have power or a biased impact on the system.

Through SGMs, we observe what level of contribution each local authority can promise if the others contribute a certain amount. We use the self-flow assignments (negotiated flows) made for each local authority as a benchmark for the next phase.

Phase 3: Setting Relocation Lower Bounds

In this phase, we determine the minimum number of relocated people who have to be accommodated at each destination based on the negotiated flows from the previous phase. As a result of each SGM, each local authority promises to fulfill a certain level of relocation, given that others also contribute a certain amount. However, in reality, local authorities do not need to meet the expectations of the others. This results in a conflict between the promised relocation level and multiple expected relocation levels set by the others. As a result, local authorities cannot be held accountable for their promises. Yet, they still represent how much a local authority has the potential to contribute. So, these promises can be used to determine the minimum level of relocation for each destination to be used in the final phase. This process can be based on pre-determined policies (e.g., relocation lower bound should be 50% of the negotiated self-assignments) or a more sophisticated approach (e.g., an additional model that will adjust relocation lower bound to ensure fairness among all local authorities).

We pass the relocation lower bound for each local authority to the final phase as a parameter to ensure that relocation is enforced fairly and reasonably.

Phase 4: Final Consensus

In this phase, we approach the problem from the perspective of both central and local authorities using a final consensus model, set as a bi-level model to represent the hierarchical relationship between the central authority (leader/owner of the upper level) and local authorities (followers/owners of the lower level) where they make decisions in accordance with each other while considering local integration, fairness, irregular movements, and incentives. The final consensus model utilizes the lower bounds determined by the initial phases as inputs to ensure minimum level of relocation.

The sets, parameters, variables and the formulation of the upper and lower levels of the bi-level model are presented below.

Table 10. Sets and indices.

I	Set of origin locations, indexed by i
J	Set of destinations, indexed by j
T	Set of periods indexed by t

Table 11. Parameters.

w_{ij}^t	Weight of one unit of relocation flow from origin $i \in I$ to destination $j \in J$ at period $t \in T$
d_i^t	Relocation demand forecasted to arise for origin $i \in I$ at period $t \in T$
d_{ij}^{CD}	Cultural distance based on partition between origin $i \in I$ and destination $j \in J$
d_{ij}^{TD}	Travel distance based on ease of transportation between origin $i \in I$ and destination $j \in J$
p_i	Probability of a remaining individual attempting irregular emigration from origin $i \in I$
L_j	Minimum relocation demand that has to be satisfied by destination $j \in J$
c_j^e	Unit cost of capacity expansion for destination $j \in J$
c_j^p	Unit cost of social conflict per irregular immigrant in destination country $j \in J$
α	Policy-determined lower bound percentage tying financial support to the cost of expanding capacity
β	Policy-determined upper bound percentage tying financial support to the cost of expanding capacity

Table 12. Decision variables.

x_{ij}^t	Relocation flow assigned from origin $i \in I$ to destination $j \in J$ at period $t \in \mathrm{T}$

s_i^t	Unmet relocation demand at origin $i \in I$ at period $t \in$ T
g_{ij}^t	Probability of an irregular migration from origin $i \in I$ to destination $j \in J$ at period $t \in T\backslash\{1\}$
em_i^t	Total number of irregular emigrants leaving origin $i \in I$ at period $t \in T\backslash\{1\}$
m_{ij}^t	Number of irregular migrants leaving origin $i \in I$ for destination $j \in J$ at period $t \in T\backslash\{1\}$
im_j^t	Total number of irregular immigrants arriving destination $j \in J$ at period $t \in T\backslash\{1\}$
Π_j	Financial support provided to destination $j \in J$ by the central authority
U_{max}^t	Highest value of proportional unmet demands among all origins
U_{min}^t	Lowest value of proportional unmet demands among all origins
cap_j^t	Relocation capacity of the destination $j \in J$ at period $t \in$ T
$\text{cap}\Delta_j^t$	Relocation capacity expansion of the destination $j \in J$ at period $t \in T\backslash\{1\}$
def_j^t	Magnitude of the capacity deficit of the destination $j \in J$ when the total inflow (relocation and irregular immigration) is more than the total capacity at period $t \in$ T

The upper level of the bi-level problem has four main objectives explained as follows in the order of appearance. First objective function presented in (72) maximizes the relocation assignments factoring in weights based on bilateral agreements, origin, and destination characteristics. This objective is the most important one since the main purpose of the model is to relocate displaced people. Second objective function presented in (73) minimizes the cultural distances between relocated and receiving communities based on cultural partition dissimilarities, ensuring social integration at the destinations. This is an important objective because social or local integration is the most direct way to measure the success of a relocation plan. Third objective function presented in (74) minimizes the total funds to be distributed by the central authority among destinations. This is a critical objective since we want to incentivize local authorities to accommodate relocation by providing financial support while the funds allocated for humanitarian efforts are very limited. Fourth objective function presented in (75) minimizes the maximum difference among the proportional unmet demands of origin locations, ensuring the fairness among origins. This objective is important in order to help origin locations fairly without favoring the origins with higher demands.

Max $\sum_{t\in T}\sum_{j\in J}\sum_{i\in I} w_{ij}^t \times x_{ij}^t$ (72)

Min $\sum_{t\in T}\sum_{j\in J}\sum_{i\in I} d_{ij}^{CD} \times x_{ij}^t$ (73)

Min $\sum_{j\in J} \Pi_j$ (74)

Min $\sum_{t\in T} U_{max}^t - U_{min}^t$ (75)

The upper level has four main groups of constraints regarding demand management, irregular migration, inflow restrictions, and fairness calculations.

First group of upper-level constraints presented in (76) and (77) manages the demand by ensuring a balance between planned and irregular outflows, unmet demands, and emerging demand in the first and following periods, respectively.

$$\sum_{j\in J} x_{ij}^1 + s_i^1 = d_i^1 \qquad \forall\, i \in I \tag{76}$$

$$\sum_{j\in J} x_{ij}^t + s_i^t + \mathrm{em}_{it} = s_i^{t-1} + d_i^t \qquad \forall\, i \in I, t \in T\backslash\{1\} \tag{77}$$

The second group of upper-level constraints presented in from (78) to (81) accounts for the unanticipated movements, that is, the movements of people who will relocate by themselves when they are left behind waiting for relocation due to limited capacities. We refer to these unanticipated movements as irregular migration. It should be noted that, in this content, *irregular* migration describes the movements that occur outside of planned relocation efforts and not *illegal* migration.

The first step in incorporating irregular movements is to foresee how many people would emigrate from their countries of origin. To calculate this, we use judgment calls inspired by their application in decentralized interdependent network design problems. Talebiyan and Duenas-Osorio [41] use judgment calls to model how decision-makers anticipate the restoration efforts of others by assigning an assumption-based restoration probability to each node and using it as the success probability while conducting the Bernoulli trial, resulting in a binary outcome, whether the node is either repaired or not. In our study, we assume that each individual left behind has an emigration probability unique to and shared by the citizens of the same origin country. For a single individual, this probability can be used as the success probability in a Bernoulli trial to anticipate whether that individual will emigrate. However, rather than an individual's behavior, we are interested in predicting how many of the remaining individuals would emigrate by themselves, that is, the total number of emigration outcomes among all of the individual Bernoulli trials. This aggregate outcome, the total number of emigrations from an origin country at a period, em_{it}, can be represented by a random variable $X \sim \mathrm{Binomial}(s_i^{t-1}, p_i)$. The expected value of this variable can then be calculated as the product of the number of trials (total unmet demand from the previous period, s_i^{t-1}) and the probability of success of each Bernoulli trial (probability of emigration, p_i), hence the equation (78). Using judgment calls provides a structured way to estimate irregular emigrations, grounding our predictions in a probabilistic framework.

While this process helps us estimate the number of irregular emigrants leaving their origins, there remains a need to predict their distribution among destinations. We adapt and use the idea behind the Gravity Model of Migration [42] to estimate the irregular migration flows between origins and destinations. The Gravity Model of Migration is derived from Newton's Law of Universal Gravitation. While Newton's Law of Universal Gravitation calculates the gravitational force between two masses proportional to the magnitudes of their masses and inversely proportional to the distance between their centers, The Gravity Model of Migration calculates the number of people who will migrate between two locations proportional to the sizes of the corresponding populations and inversely proportional to the distance between locations. We adapt this model, as presented in equations (79) and (80), to address key shortcomings and better represent the determinants of unanticipated movements in our system. We calculate the total irregular migration between an origin and a destination, m_{ij}^{t}, proportional to the total number of emigrants from the corresponding origin, em_{it}, and the relocation capacity of the corresponding destination, cap_j^t, and inversely proportional to the travel distance between them, d_{ij}^{TD}. Instead of relying on physical distances, which are less representative in a globalized world with modern technology, we use distances that reflect travel difficulties between origins and destinations. To ensure that total emigration equals total migration and immigration across the system, we introduce g_{ij}^{t}, the probability of irregular migration between the corresponding origin and destination pair, instead of directly using the capacity-to-travel difficulty of the destination. This probability is calculated in equation (79) as the ratio of the relocation capacity-to-travel difficulty of a destination to the sum of these ratios for all destinations. This ensures the probabilities are normalized across all destinations. Then, equation (80) calculates the total irregular migration between the origin and destination pair as the product of this probability and the total number of emigrants from the corresponding origin. Finally, equation (81) calculates the total number of immigrants into a destination as the sum of corresponding migration flows from all origins.

$$\mathrm{em}_{it} = s_i^{t-1} * p_i \qquad \forall\, i \in I, t \in T\backslash\{1\} \tag{78}$$

$$g_{ij}^{t} = \frac{\frac{cap_j^t}{dist_{ij}^{PI}}}{\sum_{j' \in J} \frac{cap_{j'}^t}{dist_{ij'}^{PI}}} \qquad \forall\, i \in I, j \in J, t \in T\backslash\{1\} \tag{79}$$

$$\mathrm{m}_{ij}^{t} = g_{ij}^{t} * \mathrm{em}_{it} \qquad \forall\, i \in I, j \in J, t \in T\backslash\{1\} \tag{80}$$

$$\mathrm{im}_j^t = \sum_{i \in I} \mathrm{m}_{ij}^{t} \qquad \forall\, j \in J, t \in T\backslash\{1\} \tag{81}$$

The third group of upper-level constraints restricts the maximum and minimum level of inflow a destination can receive. Equation (82) ensures that the total relocation flows planned to be assigned to a destination cannot exceed its capacity. On the other hand, equation (83) ensures that the total relocation flows planned to be assigned to a destination must satisfy at least a minimum level.

$$\sum_{i \in I} x_{ij}^{t} \leq \mathrm{cap}_j^t \qquad \forall\, j \in J, t \in T \tag{82}$$

$$\sum_{t \in T} \sum_{i \in I} x_{ij}^{t} \geq L_j \qquad \forall\, j \in J \tag{83}$$

The fourth group of upper-level constraints, represented by equations (84) and (85), helps ensure fairness among origin locations. These constraints define the maximum and minimum values of the normalized unmet demand across all origins, respectively. By establishing these bounds, the differences in unmet demand can be leveled, contributing to the fairness objective.

$$U_{max}^t \geq s_i^t / d_i^t \qquad \forall\, i \in I, t \in T \tag{84}$$

$$U_{min}^t \leq s_i^t / d_i^t \qquad \forall\, i \in I, t \in T \tag{85}$$

The following and final group of upper-level constraints define the nature of the upper-level decision variables.

$$x_{ij}^t, s_i^t, g_{ij}^t, \mathrm{em}_i^t, \mathrm{m}_{ij}^t, \mathrm{im}_j^t, \Pi_j, U_{max}^t, U_{min}^t \geq 0 \tag{86}$$

The lower level of the bi-level problem has two main objectives explained as follows in the order of appearance. The first objective presented in (87) minimizes the cost of capacity expansion. On the other hand, the second objective presented in (88) minimizes the weighted cost of social conflict. The cost of social conflict is calculated as the product of the unit cost of social conflict and the total number of irregular immigrants. The weights are calculated based on capacity deficits such that if the inflow of irregular movements takes up more capacity than the availability, it will be charged more under the assumption that capacity scarcity will cause a cascading effect on conflicts. These two objectives create a very strong trade-off at the lower level since the local authorities have to choose between spending their funds on capacity expansion to sustain social balance and peace or on paying for the cost of social conflict when insufficient capacity limits planned relocation and causes more irregular movements.

$$\text{Min} \quad \sum_{\mathrm{t} \in \mathrm{T}} \sum_{\mathrm{j} \in \mathrm{J}} \mathrm{c}_{\mathrm{j}}^{\mathrm{e}} \times \mathrm{cap}\Delta_{\mathrm{j}}^{\mathrm{t}} - \sum_{\mathrm{j} \in \mathrm{J}} \Pi_j \tag{87}$$

$$\text{Min} \quad \sum_{t \in T} \sum_{j \in J} c_j^p \times im_j^t \times \left(1 + \frac{def_j^t}{\sum_{t \in T} \sum_{i \in I} d_{it}^t}\right) \tag{88}$$

The lower level has three main constraints regarding capacity management, financial support policy, and the calculation of capacity deficit due to irregular immigration.

The first group of lower-level constraints presented in (89) and (90) manages the capacity by ensuring a balance between the capacity level, planned or unanticipated inflows, and the required capacity expansion in the first and following periods, respectively.

$$\mathrm{cap}_j^1 = \mathrm{cap}\Delta_j^1 \qquad \forall\, j \in J \tag{89}$$

$$\mathrm{cap}_j^t = \mathrm{cap}_j^{t-1} - \left(\sum_{i \in I} x_{ij}^{t-1} + \mathrm{im}_j^{t-1}\right) + \mathrm{cap}\Delta_j^t \qquad \forall\, j \in J, t \in T\backslash\{1\} \tag{90}$$

The second group of lower-level constraints presented in (91) and (92) bind the minimum and maximum financial support each destination may get to their capacity expansion expenditures, respectively.

$$\alpha \times \sum_{t \in T} c_j^e \times \mathrm{cap}\Delta_j^t \le \Pi_j \qquad \forall\, j \in J \tag{91}$$

$$\beta \times \sum_{t \in T} c_j^e \times \mathrm{cap}\Delta_j^t \ge \Pi_j \qquad \forall\, j \in J \tag{92}$$

The third group of lower-level constraints presented in (93) and (94) helps calculate the capacity deficit at a destination when the total inflow of planned relocation and irregular immigration is more than the total capacity at a given period. These constraints work as activation functions such that the capacity deficit is equal to zero if there is sufficient capacity, but it is equal to the amount of shortage otherwise.

$$\mathrm{def}_j^t \ge -\left(\mathrm{cap}_j^t - \left(\sum_{i \in I} x_{ij}^{t-1} + \mathrm{im}_j^{t-1}\right)\right) \qquad \forall\, j \in J, t \in T \tag{93}$$

$$\mathrm{def}_j^t \ge 0 \qquad \forall\, j \in J, t \in T \tag{94}$$

The following and the final group of lower-level constraints define the nature of the lower-level decision variables.

$$\mathrm{cap}_j^t, \mathrm{cap}\Delta_j^t, \mathrm{def}_j^t \geq 0 \qquad \forall\, j \in J, t \in T \tag{95}$$

4.3 Solution Approach

To solve the bi-level problem with multiple objectives on different units and with nonlinearities, we reformulate non-linear constraints in a form that can be solved by common optimization solvers, combine the upper level objectives with weighted sum method after scaling each of them between zero and one, and finally, reformulate and incorporate the lower level using Karush–Kuhn–Tucker conditions.

To solve the bi-level optimization problem with multiple objectives of which each expressed in different units and with nonlinearities, we take the following steps.

Reformulation of nonlinear constraints

Nonlinear constraints are rewritten into forms compatible with common optimization solvers, ensuring computational tractability.

Combination of multiple objectives

The upper-level objectives are combined using the weighted sum method. Before aggregation, each objective is scaled between zero and one to account for differing units and ensure comparability.

Incorporating lower level

The lower-level problem is incorporated into the upper-level formulation by reformulating it using the Karush–Kuhn–Tucker (KKT) conditions, which transform the lower-level problem into a set of constraints. KKT reformulation of the lower level is presented below.

Primal Feasibility

$$\mathrm{cap}_j^1 - \mathrm{cap}\Delta_j^1 = 0 \qquad \forall\, j \in J \tag{96}$$

$$\mathrm{cap}_j^t - \mathrm{cap}_j^{t-1} + \sum_{i \in I} x_{ij}^{t-1} + \mathrm{im}_j^{t-1} - \mathrm{cap}\Delta_j^t = 0 \qquad \forall\, j \in J, t \in T \backslash \{1\} \tag{97}$$

$$\alpha \times \sum_{t \in T} c_j^e \times \mathrm{cap}\Delta_j^t - \Pi_j \leq 0 \qquad \forall\, j \in J \tag{98}$$

$$\Pi_j - \beta \times \sum_{t \in T} c_j^e \times \mathrm{cap}\Delta_j^t \leq 0 \qquad \forall\, j \in J \tag{99}$$

$$-\mathrm{def}_j^t - \left(\mathrm{cap}_j^t - \sum_{i \in I} x_{ij}^t - \mathrm{im}_j^t \right) \leq 0 \qquad \forall\, j \in J, t \in T \tag{100}$$

$$-\mathrm{def}_j^t \leq 0 \qquad \forall\, j \in J, t \in T \tag{101}$$

$$-\mathrm{cap}_j^t \leq 0 \qquad \forall\, j \in J, t \in T \tag{102}$$

$$-\mathrm{cap}\Delta_j^t \leq 0 \qquad \forall\, j \in J, t \in T \tag{103}$$

Lagrangean Function

$\boldsymbol{\theta} = \{x_{ij}^t, s_i^t, \mathrm{em}_i^t, \mathrm{m}_{ij}^t, \mathrm{im}_j^t, \Pi_j, U_{max}^t, U_{min}^t, \mathrm{cap}_j^t, \mathrm{cap}\Delta_j^t, \mathrm{def}_j^t\}$

$$
\begin{aligned}
\mathcal{L}(\boldsymbol{\theta}) = {} & \sum_{\mathrm{t}\in\mathrm{T}}\sum_{\mathrm{j}\in\mathrm{J}} \mathrm{c}_{\mathrm{j}}^{\mathrm{e}} \times \mathrm{cap}\Delta_{\mathrm{j}}^{\mathrm{t}} - \sum_{\mathrm{j}\in\mathrm{J}} \Pi_j + \sum_{t\in T}\sum_{j\in J} c_j^p \times \mathrm{im}_j^t \times \left(1 + \frac{\mathrm{def}_j^t}{\sum_{t\in T}\sum_{i\in I} d_{it}^t}\right) \\
& + \sum_{j\in J} \lambda_j^1 \times \left(\mathrm{cap}_j^1 - \mathrm{cap}\Delta_j^1\right) \\
& + \sum_{t\in T\{1\}}\sum_{j\in J} \lambda_j^t \times \left(\mathrm{cap}_j^t - \mathrm{cap}_j^{t-1} + \sum_{i\in I} x_{ij}^{t-1} + \mathrm{im}_j^t - \mathrm{cap}\Delta_j^t\right) \\
& + \sum_{j\in J} \kappa_j \times \left(\alpha \times \sum_{t\in T} c_j^e \times \mathrm{cap}\Delta_j^t - \Pi_j\right) + \sum_{j\in J} \mu_j \times \left(\Pi_j - \beta \times \sum_{t\in T} c_j^e \times \mathrm{cap}\Delta_j^t\right) \\
& + \sum_{t\in T}\sum_{j\in J} \gamma_j^t \times \left(-\mathrm{def}_j^t - \left(\mathrm{cap}_j^t - \sum_{i\in I} x_{ij}^t - \mathrm{im}_j^t\right)\right) + \sum_{t\in T}\sum_{j\in J} \delta_j^t \times \left(-\mathrm{def}_j^t\right) \\
& + \sum_{\mathrm{t}\in\mathrm{T}}\sum_{\mathrm{j}\in\mathrm{J}} \nu_{\mathrm{j}}^t \times \left(-\mathrm{cap}_j^t\right) + \sum_{\mathrm{t}\in\mathrm{T}}\sum_{\mathrm{j}\in\mathrm{J}} \omega_{\mathrm{j}}^t \times \left(-\mathrm{cap}\Delta_j^t\right)
\end{aligned}
$$

Stationary Conditions

$$
\nabla_{\mathrm{cap}_j^t}\mathcal{L}(\boldsymbol{\theta}) = 0
$$

$$
\begin{aligned}
& \sum_{j\in J} \lambda_j^1 + \sum_{t\in T\{1\}}\sum_{j\in J} \lambda_j^t + \sum_{\mathrm{t}\in\mathrm{T}}\sum_{\mathrm{j}\in\mathrm{J}} -\gamma_j^t \\
& \qquad + \sum_{\mathrm{t}\in\mathrm{T}}\sum_{\mathrm{j}\in\mathrm{J}} -\nu_j^t = 0
\end{aligned} \tag{104}
$$

$$
\nabla_{\mathrm{cap}\Delta_j^t}\mathcal{L}(\boldsymbol{\theta}) = 0
$$

$$
\begin{aligned}
& \sum_{\mathrm{t}\in\mathrm{T}}\sum_{\mathrm{j}\in\mathrm{J}} \mathrm{c}_{\mathrm{j}}^{\mathrm{e}} + \sum_{j\in J} -\lambda_j^1 + \sum_{t\in T\setminus\{1\}}\sum_{j\in J} -\lambda_j^t \\
& \qquad + \sum_{j\in J} \kappa_j \times \left(\alpha \times \sum_{t\in T} c_j^e\right) \\
& \qquad + \sum_{j\in J} \mu_j \times \left(-\beta \times \sum_{t\in T} c_j^e\right) \\
& \qquad + \sum_{\mathrm{t}\in\mathrm{T}}\sum_{\mathrm{j}\in\mathrm{J}} -\omega_{\mathrm{j}}^t = 0
\end{aligned} \tag{105}
$$

$$
\nabla_{\mathrm{def}_j^t}\mathcal{L}(\boldsymbol{\theta}) = 0
$$

$$\sum_{t\in T}\sum_{j\in J} c_j^p \times \mathrm{im}_j^t \times \left(\frac{1}{\sum_{t\in T}\sum_{i\in I} d_{it}^t}\right) + \sum_{t\in T}\sum_{j\in J} -\gamma_j^t + \sum_{t\in T}\sum_{j\in J} -\delta_j^t \tag{106}$$

Dual Feasibility

$$\kappa_j \geq 0 \qquad \forall\, j \in J \tag{107}$$

$$\mu_j \geq 0 \qquad \forall\, j \in J \tag{108}$$

$$\gamma_j^t \geq 0 \qquad \forall\, j \in J, t \in T \tag{109}$$

$$\delta_j^t \geq 0 \qquad \forall\, j \in J, t \in T \tag{110}$$

$$\mathrm{v}_\mathrm{j}^t \geq 0 \qquad \forall\, j \in J, t \in T \tag{111}$$

$$\omega_\mathrm{j}^t \geq 0 \qquad \forall\, j \in J, t \in T \tag{112}$$

Complementary Slackness

$$\kappa_j \times \left(\alpha \times \sum_{t\in T} c_j^e \times \mathrm{cap}\Delta_j^t - \Pi_j\right) = 0 \qquad \forall\, j \in J \tag{113}$$

$$\mu_j \times \left(\Pi_j - \beta \times \sum_{t\in T} c_j^e \times \mathrm{cap}\Delta_j^t\right) = 0 \qquad \forall\, j \in J \tag{114}$$

$$\gamma_j^t \times \left(-\mathrm{def}_j^t - \left(\mathrm{cap}_j^t - \sum_{i\in I} x_{ij}^t - \mathrm{im}_j^t\right)\right) = 0 \qquad \forall\, j \in J, t \in T \tag{115}$$

$$\delta_j^t \times \left(-\mathrm{def}_j^t\right) = 0 \qquad \forall\, j \in J, t \in T \tag{116}$$

$$\mathrm{v}_\mathrm{j}^t \times \left(-\mathrm{cap}_j^t\right) = 0 \qquad \forall\, j \in J, t \in T \tag{117}$$

$$\omega_\mathrm{j}^t \times \left(-\mathrm{cap}\Delta_j^t\right) = 0 \qquad \forall\, j \in J, t \in T \tag{118}$$

4.4 Illustrative Example

Either because climate change is rarely recorded as the main driver of human mobility, or extended and significant forced displacement due to the adverse and slow-onset climate change impacts is unprecedented, or future uncertainties do not allow a clear understanding; we lack the immediate data that can be used in the relocation planning for the yet-to-come long-term displacements. To demonstrate the workings and capabilities of the model, we generate data for each of the parameters introduced and explained in the previous section, making grounded assumptions and using proxy measures. The part-by-part process of creating the illustrative example is as follows.

Relocation demand

We prepare the relocation demand data based on the raw data used for the Climate Mobility Dashboard created by IOM's Global Data Institute (GDI) [43]. Before moving forward with the details of our process, we should state our assumptions despite the nature and purpose of the data. We will use a version of the dashboard data to represent the relocation demand at the country level. However, this dashboard was created originally to visualize the projections of exposure to various climate change hazards under various warming and socio-economic scenarios at aggregated levels. So, we should note that exposure does not necessarily lead to relocation, it may be handled using one of the other mitigation and adaptation strategies. Also, the data is more appropriate to use at low granularity.

Under the assumption that, when a location is affected by multiple hazards, the highest exposure value among the hazards represents the total exposure (encompassing smaller values), we focus on the heatwave data. This is justified by heat waves being the dominant hazard in this dataset. Using this data, we calculate the number of vulnerable people exposed to high warming (RCP 6.0) and regional rivalry (SSP3) scenarios at the country level for the next seven decades.

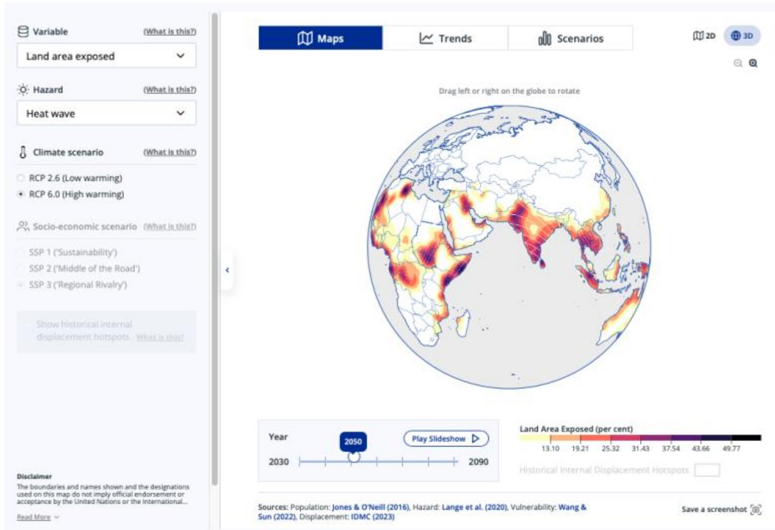


Figure 7. Climate Mobility Impacts Dashboard.

Origin countries

Among the 64 countries we had relocation demand data for heatwave hazard, we selected the top 10 countries with the highest number of vulnerable people exposed. These countries are Colombia, the Democratic Republic of Congo, India, Iraq, Kenya, Mozambique, Myanmar, Pakistan, Somalia, and South Sudan.

Destination countries

We selected four destination countries considering factors like climate risk, readiness, openness to migration, and being in a different region than the others. However, in order not to cause speculation, we will not name these countries in our analysis.

Unit cost of social conflict

We assume that a percentage, representing the economic value of conflict, of the annual GDP of a destination country [44] divided by its total population [45] can be used as a proxy measure for the unit cost of social conflict per person per year in that country. We selected this percentage as 13.5%, which is stated as the percentage of global GDP equivalent to the impact of violence on the global economy in the Global Peace Index 2024 report by the Institute for Economics & Peace [46]. Since the social cost of conflict would be in effect during the entire period, we adjusted it as the unit cost of social conflict per person per period.

Unit cost of capacity expansion

We assume that a percentage, representing the capacity building spending, of the annual GDP of a destination country [44] divided by its total population [45] can be used as a proxy measure for the unit cost of capacity expansion per person per year in that country. We select a different percentage for each destination country from the OECD Social Expenditure Database (SOCX) [47], presenting social spending in units of in percentages of GDP based on policy areas such as old age, survivorship, disability-related benefits, health, family, active labor market policies, unemployment, and housing.

Probability of emigration

We assume that the historical trends can represent the probability of emigration. We calculate the emigration rate of each origin by dividing the average number of annual emigrations by its population. We get the data for historical emigration amounts from the International Migrant Stock 2020 dataset by the United Nations Department of Economic and Social Affairs, Population Division [48]. Then, we adjust these rates using the Potential Net Migration Index by Gallup in order to combine historical trends with recent changes in migration perceptions.

Cultural partition distances

In order to improve social/local integration in destination countries, we minimize the social distance between the origin and destination pairs while making relocation assignments. We assume that similarities or differences between their fractionalization levels based on various dimensions can represent the cohesion or partition between countries. In order to calculate an average cultural partition score for each origin-destination pair, we compare the fractionalization levels of each pair for each dimension and assign a partition value based on the amount of difference and whether the levels are high-high, high-low, or low-low. For the calculations, we use the ethnic, linguistic, and religious fractionalization indices [34].

Irregular migration distances

In order to calculate the irregular migration from an origin to a destination, we need a distance representing the travel difficulty to use in our adaptation of the Gravity Model of Migration. We assume that similarities or differences between their global mobility levels can represent the travel ease or difficulty between countries. In order to calculate the distance, we compare their Henley Passport Power Index rankings (based on the Economic Mobility Scores measured in % of global GDP) [49] along with bilateral entry visa requirements and assign a distance value such that the distance is higher if the difference between the rankings is high and if the citizens of the origin country need an entry visa to enter the destination country.

Weight of relocation

The relocation weights are defined for each origin and destination pair, representing the local features and bilateral relationships of the countries. These weights can be calculated based on the climate change risk and emergency of relocation at the origin country, the welfare of the destination country, and the historical or political tendency to move between the origin and destination countries over the planning horizon. For this example, they are defined as one for all pairs.

Relocation lower bounds

Relocation lower bounds can be determined as the outcome of the initial three phases of the CDDOF or assigned based on a policy. For this example, they are defined as zero for all destination countries.

Funding policy percentages

Funding policy percentages set the minimum and maximum amount of financial support a destination country may receive as a function of how much money it spends for building capacity for relocation purposes. These percentages can be assigned to different levels for different destination countries based on intentional policies. For this example, they are defined as 10% and 90% for all destination countries.

4.5 Analysis and Results

In this section, we present and compare the model decisions and their effects on the system.

Figure 8 presents all model objectives scaled between zero and one, with lighter tones representing better values for each objective. It allows us to easily assess which goals are achieved more effectively. Given the significant trade-offs between objectives, the performance of the model is reflected in having all objective values closer to the optimal ends of their respective scales.

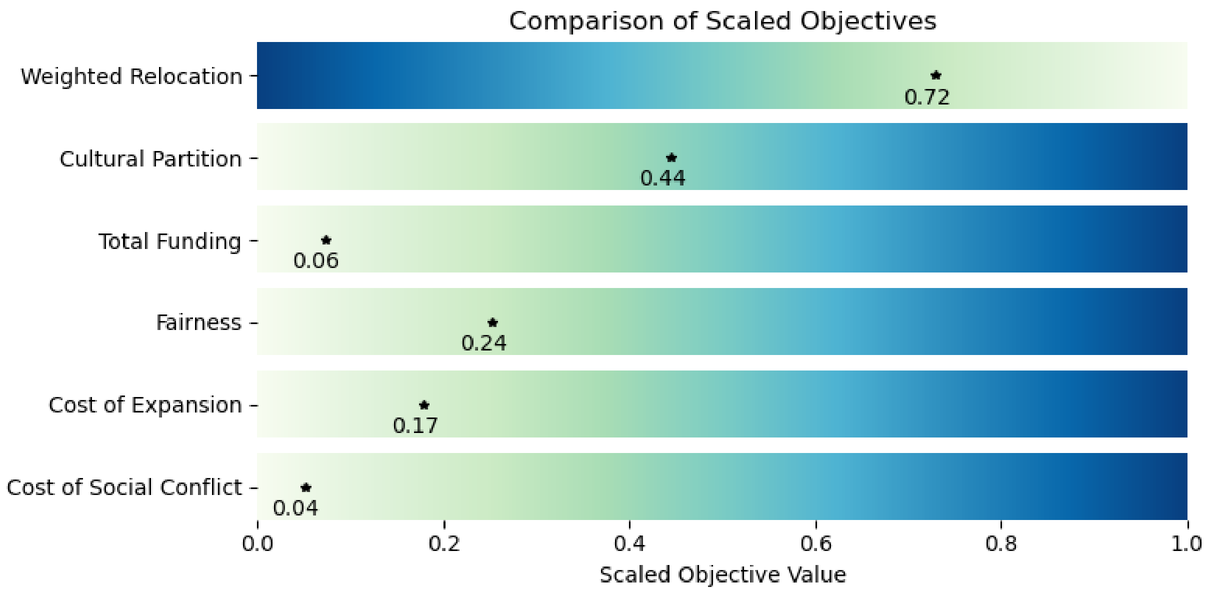


Figure 8. Comparison of Scaled Objectives.

Figure 9 and Figure 10 are Sankey charts demonstrating planned relocation and irregular migration flows from origins to destinations, respectively. They show how the distribution of the flows between origin and destination pairs varies for planned relocation and irregular migration cases. While the flows are more clustered and intentional in planned relocation cases, there is no observable distribution trend for irregular migration flows.

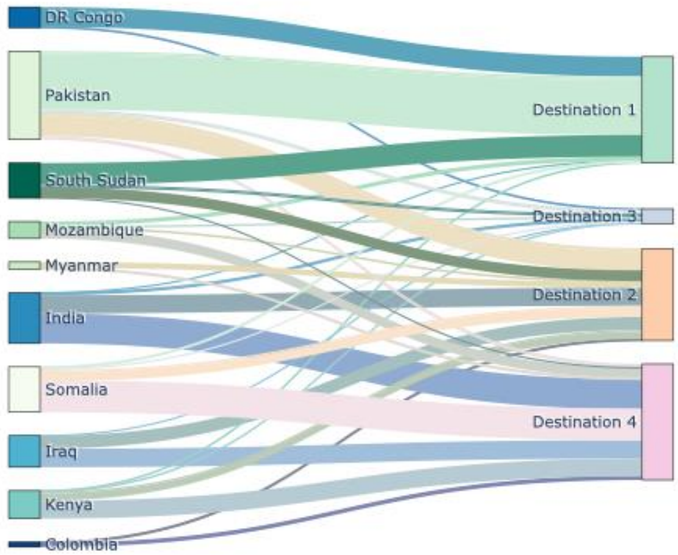


Figure 9. Planned Relocation Flows.

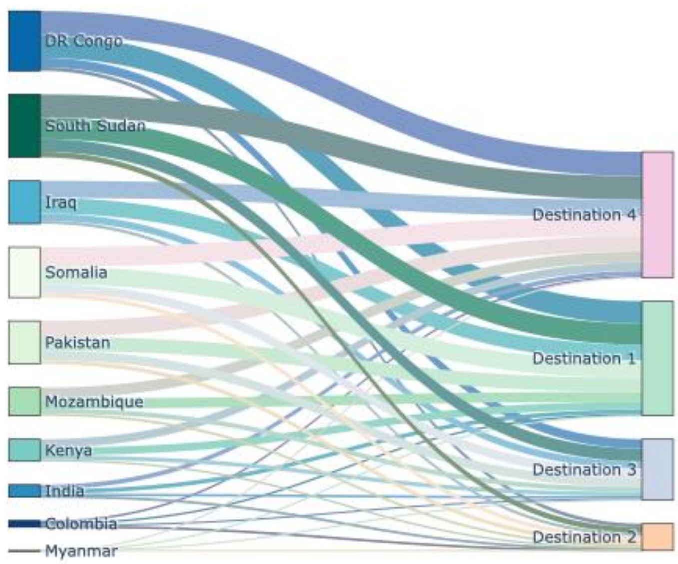


Figure 10. Irregular Migration Flows.

Figure 11 and Figure 12 are bubble charts in which the bubble colors show the pairwise unit cultural partition distances between origin and destination countries while the bubble sizes are proportional to the flows between those pairs for planned relocation and irregular migration, respectively. Figure 11 shows that countries with lower cultural partition scores, meaning the countries similar in the distribution of ethnic, linguistic, and religious groups, are assigned to higher flows between them. This proves that the relocation plan produced by the model prioritizes local integration at the destination countries while meeting other requirements. However, we do not observe a similar pattern in Figure 12 due to defining the determinants of irregular migrations as expected availabilities and travel ease. We see that the cultural aspects are entirely ignored when there is no intentional design.

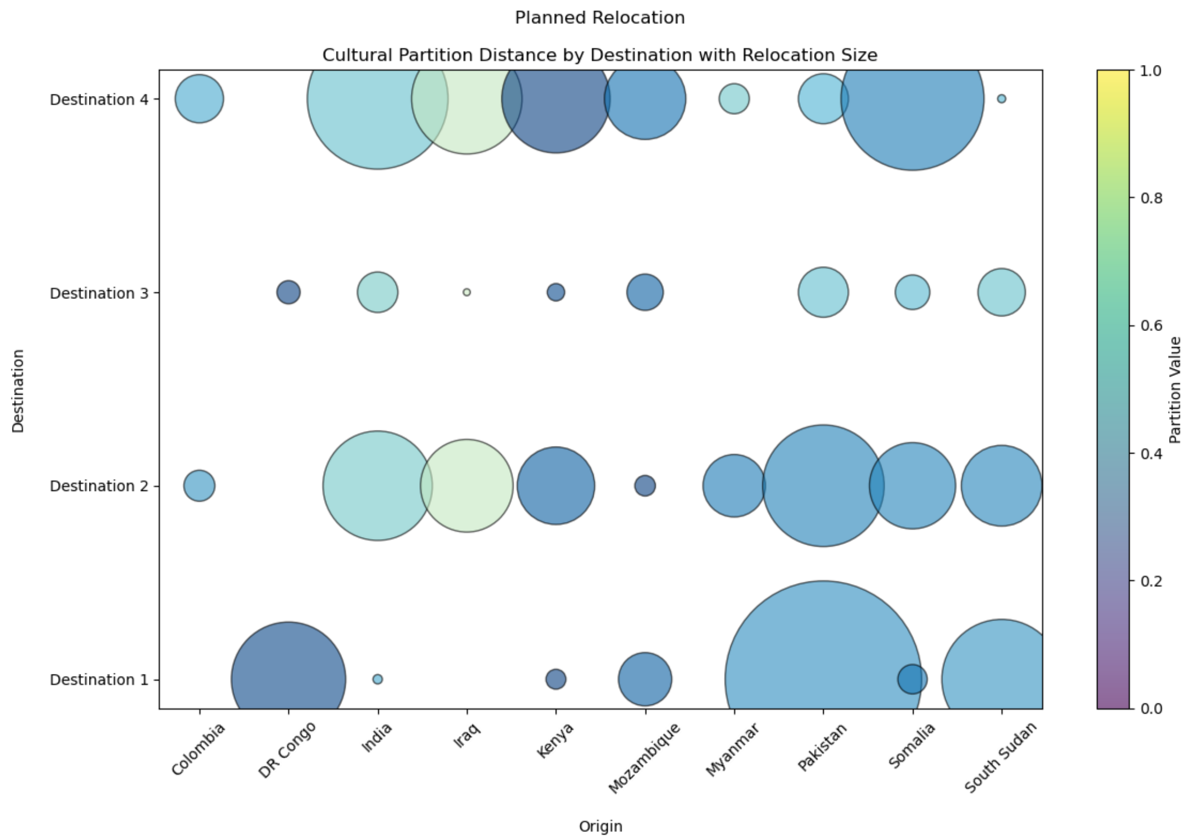


Figure 11. Cultural Partition Effect on Planned Relocation.

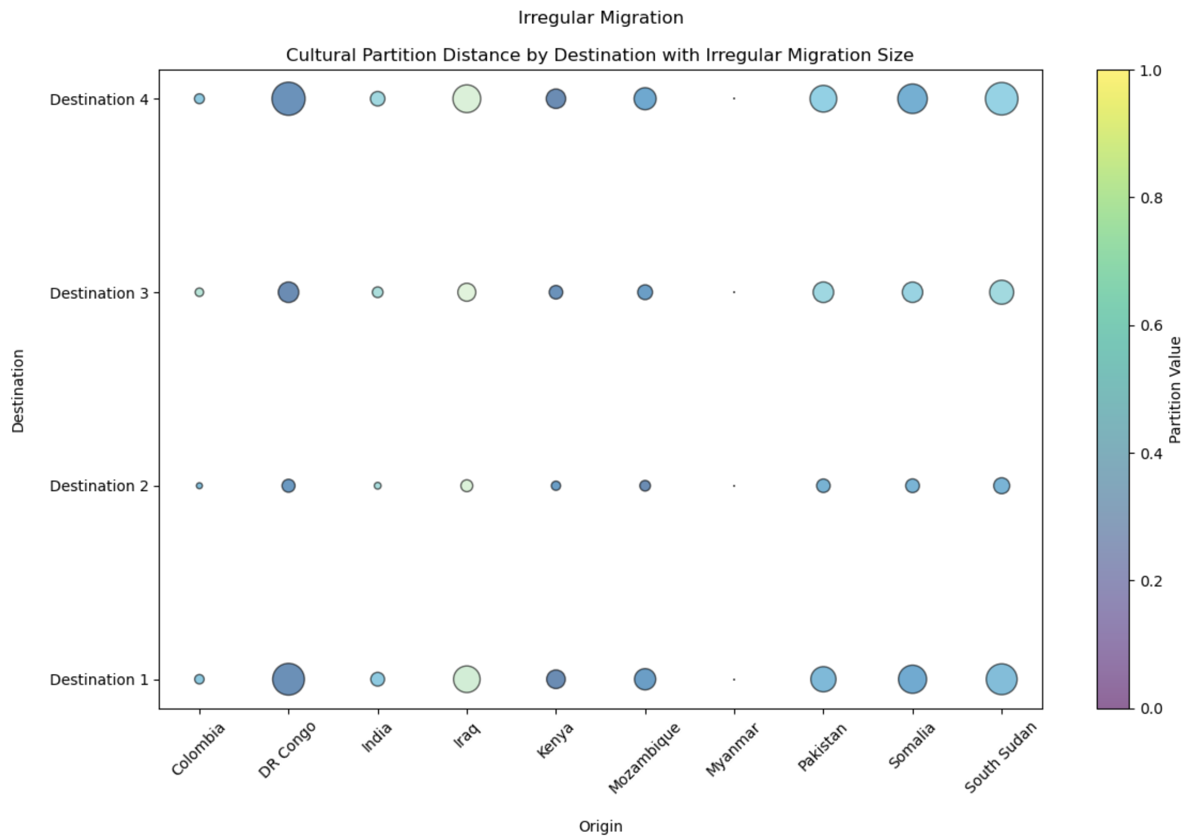


Figure 12. Cultural Partition Effect on Irregular Migration.

Figure 13 demonstrates the total relocation, irregular emigration, and unmet demand of each origin with respect to its total demand. We can see that the ratio of unmet demand is low and proportional to the total demand of the corresponding origin, proving the effectiveness of the fairness measure based on the minimization of the maximum difference between relative unmet demands of origin countries.

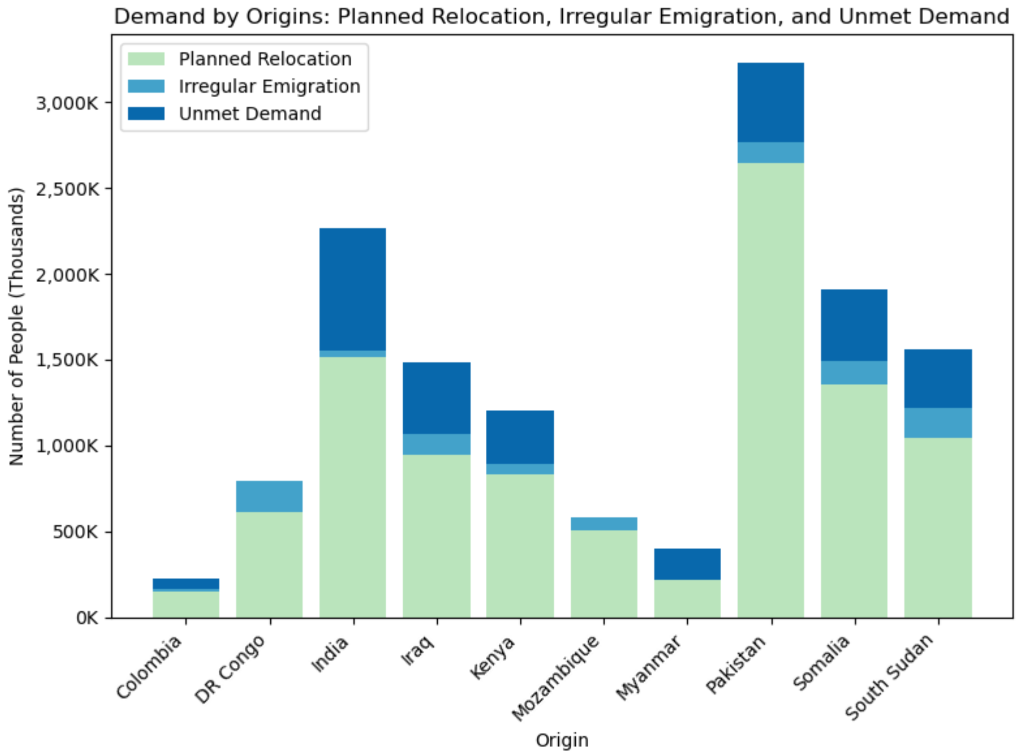


Figure 13. Comparison of Relocation, Irregular Migration, and Unmet Demand in Origins.

4.6 Concluding Remarks

The model presented in this chapter is a continuum of our efforts to handling the long-term climate change-induced forced displacement problem. We approach the problem by considering the perspectives of an altruistic central authority, self-centered local authorities, and the dynamics between them. Once again, we aim to explore the scope of the relocation problem and prepare the ground for a high-level agreement among the interested parties so that all stakeholders can accept the situation, come to terms, and start preparations.

To this end, we propose a consensus-driven decentralized optimization framework. This framework consists of modular phases related to the optimization of the system from different perspectives and alignment between them. The modular structure of the framework allows decision-makers to customize the framework according to their expectations and needs. The suggested initial phases bring real-life negotiation dynamics into the picture. On the other hand, the main and final phase of the framework puts a novel approach to model the decentralized decision hierarchy using a bi-level model. In this bi-level model, the central authority makes relocation and funding decisions, while local authorities are responsible for making capacity expansion plans accordingly. Their decisions are coordinated to ensure alignment between the central and local authorities. These decisions account for multiple critical factors, including local integration, fairness, irregular movements, and incentives, aiming for a balanced and effective relocation process.

The analysis of the planned relocation efforts and the effect of irregular migration on the system shows the effectiveness of the model in dealing with multiple objectives and unanticipated movements. We observe how the planned relocation flows are governed by social considerations while irregular movements are random in the sense of societal concerns. This highlights the importance of taking preventative actions against irregular movements. The analysis also reveals that the model performs well at promoting fairness within the scope of the way it is defined.

4.6.1 Research Contributions

This study brings another operations research perspective to the climate-driven displacement problem. It offers a novel approach to modeling the dynamic interplay between central and local authorities, planned and unanticipated movements, the costs of preventing and resolving social conflicts, and societal characteristics.

The proposed framework provides actionable insights for decision-makers to proactively plan for upcoming movements under various decentralization and cooperation scenarios. Its modular structure integrates diverse perspectives in a customizable way, enabling decision-makers to effectively explore the impacts of their strategic and modeling choices.

Unlike existing models for relocation planning, which often overlook the complexities of multiple authorities and irregular movements, the bi-level model we propose uniquely integrates judgment calls and gravity models to predict irregular migration, providing a probabilistic yet tractable approach to model unanticipated migration dynamics.

4.6.2 Limitations and Improvement Areas

The framework's ability to reflect a decentralized decision-making structure is limited to mimicking one scenario of back-and-forth negotiations in the initial phases and one way of modeling a hierarchical decision-making structure in the final phase. Future improvements to the framework could focus on incorporating more diverse strategies and enhancing the dynamics between decision-making authorities, as it would provide a deeper understanding of their interactions.

Another limitation is that the current dynamics of the decentral authorities are mostly based on the interplay between the central authority versus local authorities. While the second phase briefly touches upon the conditional behaviors of local authorities with respect to the expected participation of others, this topic is not explored in depth. Expanding this aspect to examine how local authorities react to and influence each other's decisions could offer valuable insights.

Finally, a major limitation of the bi-level model is its assumption of a static action-reaction scheme, where the central authority makes decisions for the entire planning horizon, followed by the local authorities reacting over the same horizon. A potential improvement would involve introducing iterative action-reaction schemes, where decisions are made and adjusted dynamically within each period, better capturing more dynamic decision-making processes over time.

Chapter 5: Addressing Fairness

5.1 Overview

The study presented in this chapter explores and compares fairness metrics from multiple perspectives within the context of climate change-induced relocation planning for forced displacements. It builds on the previous chapter, which addressed decentralization, by conducting an additional analysis of the bi-level model outcomes using various factors and fairness metrics. As a result, this chapter constitutes the early stages of a broader fairness study, focusing on identifying critical factors that influence the definition of fairness and exploring a range of relevant metrics.

5.2 Proposed Approach

5.2.1 Definition of Fairness and Perspectives on Fairness in Relocation Planning

We begin by identifying the key factors necessary for defining fairness in the context of relocation planning. These factors can be organized within a three-dimensional framework, as illustrated in Figure 14, which serves as a guide for exploring the key aspects of fairness in relocation problems.

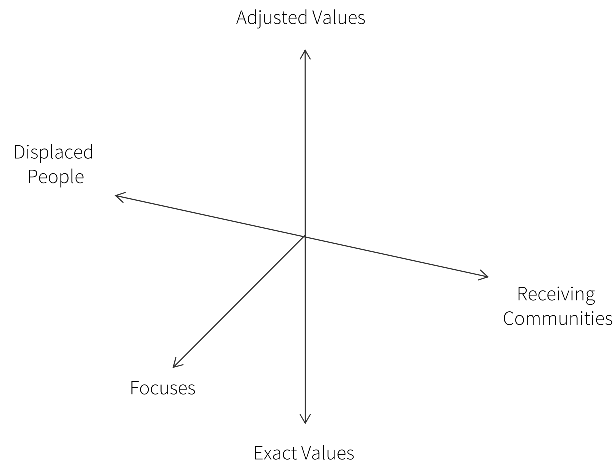


Figure 14. Factors Determining the Definition of Fairness.

The first dimension considers the perspective from which fairness is evaluated, who will be affected by the decisions and who will benefit from the fairness inclusion. In the relocation problem, two primary parties are significantly affected by the decisions: displaced people and receiving communities.

Then, depending on the chosen perspective, the second dimension considers the evaluation criteria based on various factors such as unmet demands (fairness in terms of satisfying the needs of displaced populations), relocation levels (equitable distribution of relocation efforts across origin or destination locations), distribution of funds (ensuring balanced allocation of resources among local authorities).

Finally, the third dimension involves deciding whether to use exact or adjusted values to account for relative and proportional differences. For instance, adjusting values could normalize them based on factors such as population sizes or existing capacities, offering a more nuanced view of fairness.

This structured framework enables the exploration of diverse fairness definitions and metrics, providing a basis for analyzing their implications in the context of the relocation problem. Based on this framework, we identify eight perspectives to be employed in our analysis:

- Unmet demand by origins
- Demand-adjusted unmet demand by origins
- Relocation by origins
- Demand-adjusted relocation by origins
- Relocation by destinations
- Population-adjusted relocation by destinations
- Funding received by destinations
- Expenditure-adjusted funding by destinations

5.2.2 Fairness Measures

To evaluate fairness in the context of climate change-induced relocation planning, we employ three widely used easy-to-comprehend fairness measures: the Gini Index, Entropy, and the Robin Hood Index. Each measure offers a unique perspective on fairness, enabling a comprehensive assessment of inequality and equity across various dimensions of the relocation process.

Gini Index

The Gini Index is a measure of inequality in the distribution. It is mathematically defined as:

$$G = \frac{\sum_{i=1}^{n} \sum_{j=1}^{n} \left| x_i - x_j \right|}{2n \sum_{i=1}^{n} x_i}$$

where n is the number of elements and x_i is the value of the ith element [50]. Defined on a scale from 0 to 1, a value of 0 represents perfect equality (where each receives an equal share), and a value of 1 represents perfect equality (where each receives an equal share).

Entropy

Entropy measures the evenness of a distribution, capturing how balanced or imbalanced a set of values is. It is mathematically defined as:

$$E = -\sum_{i=1}^{n} p_i \, log(p_i)$$

where n is the number of elements and p_i is the proportion of the ith element [51]. Defined on a scale starting from 0, higher values represent a more equal distribution. Entropy's ability to capture balance and diversity makes it a valuable metric for fairness analysis in relocation planning.

Robin Hood Index

The Robin Hood Index quantifies the proportion of the total value that would need to be redistributed to achieve perfect equality. It is mathematically defined as:

$$R = \frac{1}{2} \frac{\sum_{i=1}^{n} |x_i - \bar{x}|}{\sum_{i=1}^{n} x_i}$$

where n is the number of elements, x_i is the value of the ith element, and $\bar{x}$ is the mean value [52]. Defined on a scale from 0 to 1, a value of 0 represents perfect equality. The interpretability of the Robin Hood Index makes it a valuable metric for fairness analysis in relocation planning.

5.3 Solution Approach

We utilize the outcomes of the bilevel optimization model described in Phase 4: Final Consensus in order to calculate fairness levels using the aforementioned three measures with respect to the eight perspectives we have selected to employ.

5.4 Illustrative Example

We continue to use the illustrative example described in Illustrative Example.

5.5 Analysis and Results

We evaluate the fairness of the bi-level model proposed for climate change-induced relocation planning across the eight selected perspectives using three fairness measures.

Figure 15 demonstrates the comparison of perspectives across the three fairness measures: Gini Index, Entropy, and Robin Hood Index. It provides an evaluation of the eight selected perspectives, where lighter colors indicate better fairness values, while darker colors represent worse outcomes. We can observe a high degree of variation in fairness values across different perspectives, even within the same fairness measure. This emphasizes the sensitivity of fairness outcomes to the perspective adopted, highlighting the importance of explicitly defining the fairness criteria used in relocation planning.

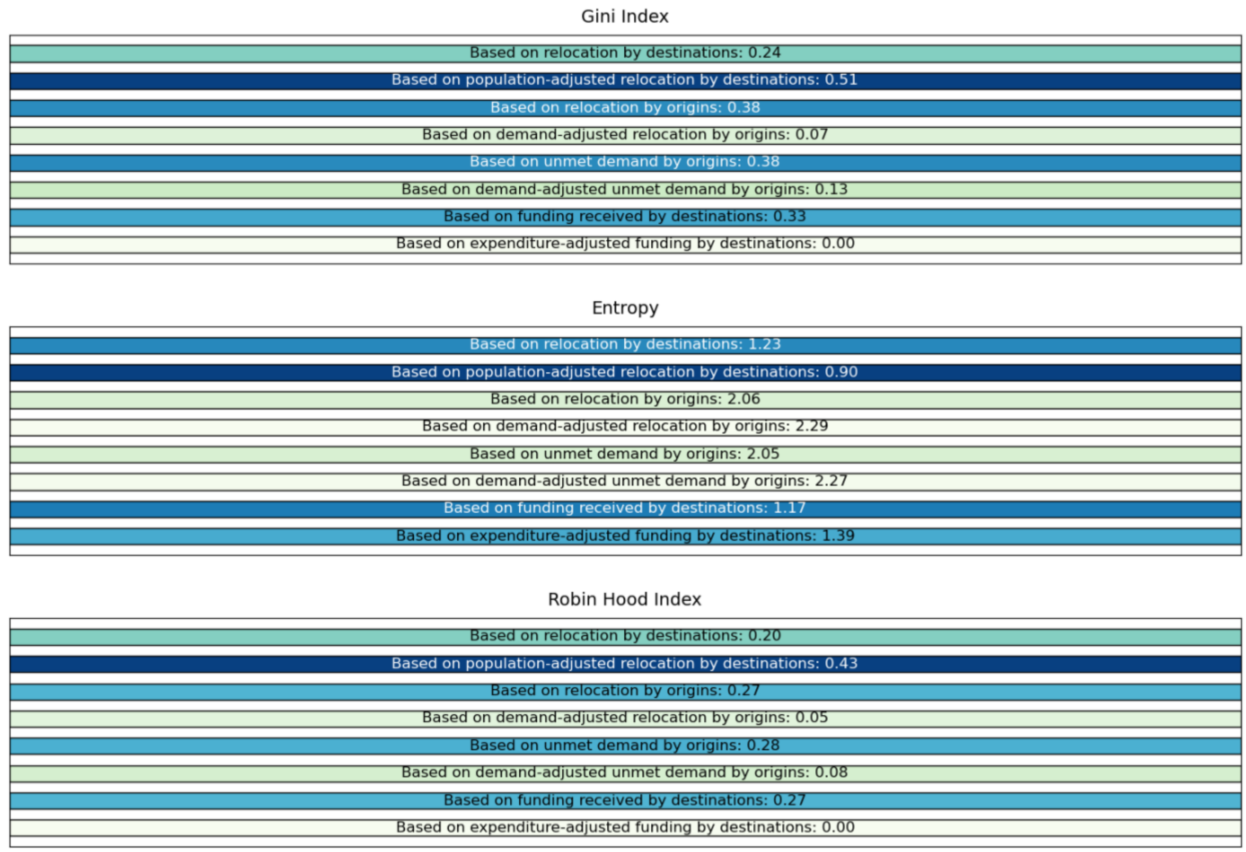


Figure 15. Comparison of Perspectives by Fairness Measures.

Figure 16 demonstrates the comparison of fairness measures across the eight perspectives. We can observe a variation in the performance of different fairness measures, even when evaluated from the same perspective. This emphasizes the sensitivity of fairness outcomes to the chosen metric, highlighting the critical role of selecting an appropriate fairness measure in relocation planning.

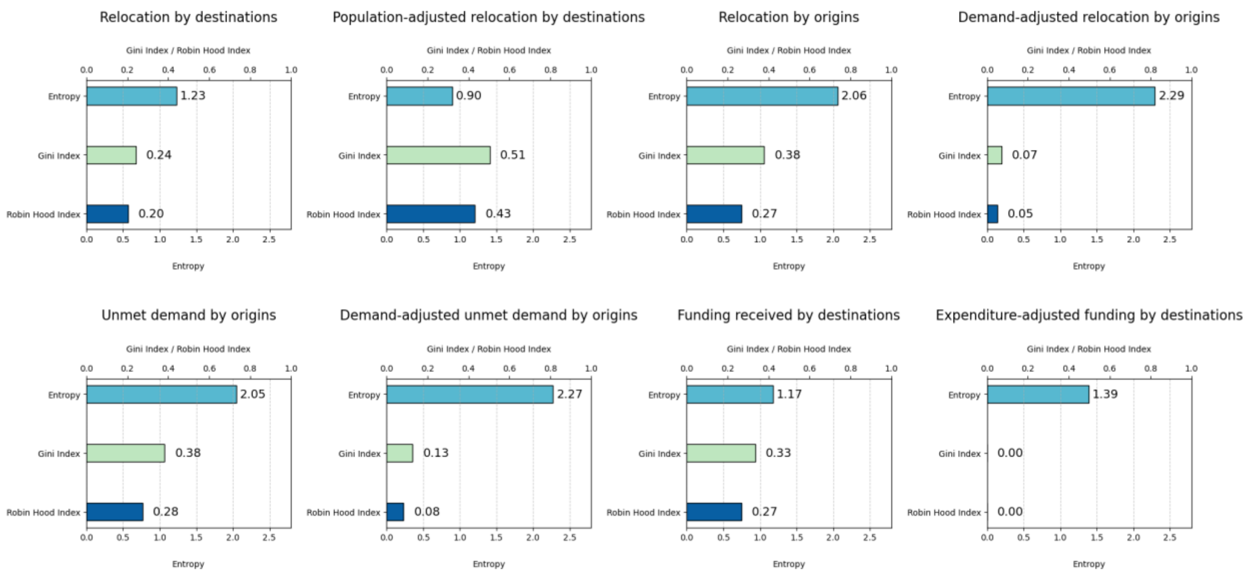


Figure 16. Comparison of Fairness Measures by Perspectives.

5.6 Concluding Remarks

Our analysis proves that different perspectives and fairness measures can result in highly varied levels of fairness, indicating their substantial influence on the final decisions and their broader implications if incorporated into optimization models. These findings emphasize the importance of explicitly defining fairness in policy-oriented optimization frameworks, as the choice of fairness perspective and metric can significantly shape relocation outcomes.

5.6.1 Research Contributions

This study contributes to the growing body of research on fairness by including a relocation planning application. Similarly, it contributes to relocation planning research by incorporating problem-specific usages and comparisons of fairness measures. As an initial version, this study shows the promise of methodically contributing to relocation planning research by strategically incorporating and analyzing various fairness measures optimization models.

This study contributes to the growing body of fairness research by integrating it into a relocation planning application. Similarly, it advances relocation planning research by incorporating problem-specific applications and comparative analyses of fairness measures. As an initial endeavor, this study demonstrates the potential of making a methodological contribution to relocation planning research by strategically incorporating and analyzing various fairness measures within optimization models.

5.6.2 Limitations and Improvement Areas

This study lays the groundwork for incorporating fairness into climate change-induced relocation planning. Due to the limitations of the scope, there remain multiple areas of improvement to be addressed in future studies.

The current analysis is limited to three fairness measures. Future research could expand the scope by exploring additional measures, particularly those tailored to specific relocation contexts or emphasizing other aspects of equity.

While this study evaluates fairness metrics post-optimization, a key next step involves embedding these metrics directly into the optimization process. Running the model separately for each fairness measure and comparing the outcomes would provide a deeper understanding of their impact on decision-making.

Finally, to address trade-offs between conflicting fairness measures, future research could explore the Pareto frontier by optimizing the model with multiple fairness measures simultaneously. This would enable decision-makers to visualize the trade-offs and effectively select solutions that balance competing objectives.

Chapter 6: Concluding Remarks

Even though the exact magnitude of the climate crisis is uncertain, studies indicate that we are on the brink of a significant crisis. While we acknowledge the importance of preliminary actions and support them, it may already be too late to prevent the severe impacts of the impending crisis [53] and many regions worldwide are likely to become uninhabitable soon [6]. Consequently, a mass movement of people is likely to be triggered. Reflecting on our recent experiences with forcibly displaced individuals, primarily due to conflicts and on relatively smaller scales, we must recognize the gravity of the challenges that lie ahead. We need to prepare for a mass movement that is uncertain in scale, timing, and direction. However, this mass movement could also present an opportunity for promoting inclusive growth and sustainable development. If we take the initiative to plan and prepare proactively, we can seize this opportunity and effectively address the challenge. This highlights the importance of timely planning in response to climate change-induced forced displacement and calls for attention to the complex problem of relocation planning.

The climate change-induced relocation problem is characterized by long planning horizons, significant future uncertainties, and the involvement of multiple stakeholders. Effective relocation planning requires careful coordination and decision-making across different stages, including risk assessment, strategic planning, capacity building, individual assignments, ongoing monitoring, and adaptive governance. Addressing these interconnected stages holistically is essential for ensuring a proactive and sustainable approach to managing climate-driven displacement. Among all the relocation planning efforts, high-level planning demands immediate attention, as it is a prerequisite for actual movements. It must be conducted well in advance to provide decision-makers and local authorities adequate time to take action and prepare. Therefore, this dissertation focuses on high-level planning for climate change-induced forced displacement, which includes determining where and when groups of people should go given the relocation demands, origins, and potential destinations.

Within this dissertation, we focus on three major challenges regarding relocation planning: uncertainty, decentralization, and fairness. This work embarks on a comprehensive exploration of high-level relocation planning, tackling its inherent complexities and challenges. Recognizing the urgent need for proactive measures in light of the looming climate crisis, the dissertation integrates theoretical models with practical decision-making frameworks to address the challenges of uncertainty, decentralization, and fairness as well as the critical issues of social integration and adaptability.

Chapter 1 introduces the origins of the problem, emphasizes the urgency of addressing climate-driven displacement, and outlines the motivation behind the studies included in this dissertation.

Chapter 2 consolidates research on forced displacement and large-scale movements of people, drawing on existing literature from various disciplines to establish a solid foundation for the subsequent methodological contributions.

Chapter 3 focuses on a stochastic model designed to address the uncertainty surrounding future relocation demand. By incorporating uncertain factors and decision dynamics, this chapter provides a systematic method for estimating demand across different scenarios and applying this information in optimization models, thereby offering a reliable basis for long-term planning.

Chapter 4 examines the decentralized nature of global relocation efforts, introducing a consensus-driven framework to manage the interactions between central and local authorities. This framework leverages bi-level optimization to balance competing priorities and ensure that decisions align across different hierarchical levels. Furthermore, it covers critical aspects such as unanticipated movements and social conflicts. It presents a solid approach to creating an appropriate illustrative example by combining socioeconomic factors and subject matter expertise.

Chapter 5 analyzes the concept of fairness by exploring and comparing various fairness measures and perspectives within the context of relocation planning. It demonstrates how sensitive results are to both the perspective adopted and the measure selected, laying the groundwork for systematically integrating fairness into future research.

Each chapter contributes to a holistic understanding of the relocation problem, offering frameworks and methodologies tailored to its unique challenges. By combining theoretical insights with practical applications, this dissertation provides actionable strategies for policymakers and practitioners, paving the way for more effective and equitable relocation planning. It emphasizes the importance of proactive decision-making and demonstrates the potential to transform what may seem like a daunting challenge into an opportunity.

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