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Integrating Uncertain Movements into Climate-Induced Refugee Resettlement Planning: A Scenario-Based Two-Stage Stochastic Approach

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Integrating Uncertain Movements into Climate-Induced Refugee Resettlement Planning: A Scenario-Based Two-Stage Stochastic Approach

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Abstract

To effectively plan for the large number of refugees that will require resettlement as climate conditions become increasingly critical around the world, decision-makers must be mindful of the current state of resettlement outcomes. We present a mathematical optimization model that can aid in understanding the effects of uncertain unplanned movements on resettlement planning decisions. Such decisions are optimized across two overall scenarios: (i) normal planning conditions and (ii) extreme events occurring as direct or indirect byproducts of climate change (e.g., civil unrest, violent conflict, natural disasters). Within those two scenarios, six nested scenarios represent the best-case, average, and worst-case resettlement success likelihoods. The results of this model indicate the number of resettlement failures a decision-maker should plan to realize, the extra capacity required at each host to accommodate the increased supply at each origin from failed resettlement, and insights into adjustments needing to be made to the planned parameters to recover from continuously low resettlement rates in each of the given planning conditions.

Contents

Chapter 1

Introduction

1.1 Climate crisis

A growing number of countries in several continents are facing the fervent effects of climate crisis, with the global warming likely to rise from 1.5°C to 3°C before 2100, causing the most detrimental effects to Asia, Africa, and Central and South America [1]. That is, these countries will face factors ranging from extreme food insecurity, intense flooding, increased surface temperature, coastal erosion, GDP degradation, and greater risks for diseases "where they were not previously present" [2][4][5]. As a result of these climate crises and other related issues, the United Nations High Commissioner for Refugees (UNHCR) reports that approximately 179,600, 776,500, and 1,609,200, individuals from the Americas, Asia and the Pacific, and Africa and the Middle East, respectively, will require resettlement in 2025 (2.9 million total, globally) [3]. Moreover, several predictive studies find that between 200 million and 1 billion people could be forced from their homes and required to migrate by 2050 due to climate change [6][7].

Not only are there immediate, physically damaging effects of climate change, but also profound effects on the social systems of affected countries. In a time of infrastructural damage, food and water scarcity, and economic degradation, people tend to compete for resources out of fear and uncertainty, which may "enhance the likelihood and intensity of violent conflict" [8]. For example, empirical research has found that longer, warmer periods of El Niño-Southern Oscillation under warming climate conditions have led to drier conditions in Southern South America and overwhelming flooding in Northern South America, and during these times, there were greater instances of labor strikes, violent conflict, and political strife [9][10]. There is overwhelming evidence that the effects of climate change are rapidly deteriorating crop economies, which many low-income countries rely on, and the likelihood of extreme events, such as disease, civil unrest, and violent conflict, is increasing [9][12][13].

To prepare for the necessary migration of refugees caused by climate-induced displacement, it's important to present a decision-making framework for efficiently resettling refugees. However, there are a multitude of moving parts associated with resettling a refugee from a given origin location to a host destination: individual agency, inter-country relationships, immigration policy, geography, cost of living, among others. A specific problem that is largely unanswered by the current literature is how resettlement planning is affected by accounting for the realistic, low proportion of actual resettlement versus the need. The UNHCR's Global Trends reports from 2011 to the present indicate that, on average, only 10.33 percent of the global resettlement need is met year over year; and, in extreme scenarios like those previously mentioned, as low as 2.33 percent [11]. We propose a two-stage stochastic mixed-integer linear program (MILP) that captures the immediate effects of failing to meet resettlement requirements and facilitates understanding of the long-term delay in satisfying the total resettlement need.

1.2 Literature review

Currently, the research landscape surrounding mathematical optimization in refugee resettlement planning includes locational decisions (host or facility locations), assignment decisions with either capacity or supply uncertainty, and decisions aiming to maximize societal integration. Cilali et al. proposed a multi-criteria mathematical optimization problem that optimized refugee resettlement locations, taking into account cultural distance, geographical distance, and other factors related to maximizing the chance of social integration [26]. Ahani et al. developed a software tool that makes efficient assignment decisions to increase the likelihood of economic and job market success for resettled refugees- one of the key factors in societal acceptance and integration [27]. Emre et al. provided a bi-objective, spatial-temporal approach for long-term resettlement planning horizons, accounting for future climate resilience, cultural compatibility, and dynamic changes in supplies and capacities [15]. In another application, Cilali et al. introduced a two-stage stochastic program for decision-making under demand uncertainties that stem from the fact that the total number of resettlement needs over the next 25 years is not fully known, creating several different plans for decision-makers in any such cases [14]. Collectively, mathematical optimization approaches to refugee resettlement planning have contributed a wide range of decision-making insights. As the issue at hand evolves, so too must the current literature reflect the growing complexity of refugee resettlement planning.

The refugee resettlement process is uncertain due to various factors: host country decisions, disruptions in resettlement channels, and the refugees themselves. Two-stage and multistage programs have been extensively utilized to address decision-making under uncertainty, owing to their capacity to formulate robust recourse plans that effectively account for a diverse array of potential outcomes. Ahmadi et al. extended a multi-depot location routing problem to a two-stage stochastic model that optimized disaster relief distribution centers under several earthquake magnitudes and disruption outcomes [28]. Rennemo et al. provided a three-stage stochastic program to make distribution facility location, supply allocation, and aid distribution and routing decisions under demand, vehicle availability, and infrastructural condition uncertainties in humanitarian logistics applications [29]. Several other humanitarian aid, logistics, and disaster response applications in stochastic programming can be found in [30][31][32]. Such a rich foundation of applications closely related to the refugee resettlement process presented in this paper provides crucial insight into modeling techniques that help strengthen our proposed approach. We utilize several uncertain scenarios that can occur as direct and indirect results of climate change's effects, and present several different reallocation strategies in response.

Chapter 2

Proposed Two-Stage Stochastic Mixed-Integer Linear Program

This modeling approach represents the migratory system as a network of origin, N_o, and host nodes, N_h, where each node represents a country, allowing us to zoom into the behavior of arrivals, unallocated refugees, failed resettlement, and unmet capacity. While the model contains the objectives for minimizing total costs (1a) related to the resettlement process and cultural distance (1b), the true motivation behind this model is to incorporate uncertainty into previous deterministic decision-making models. Specifically, we aim to assist the resettlement planning process with data-driven, probabilistic estimates of the proportion of planned resettlement that will be successful by the end of a given resettlement period. In doing so, we can better forecast a realistic planning horizon for which the previously mentioned 200 million to 1 billion refugees will be resettled.

In optimizing the model, the first stage optimizes refugee allocation from their origin to their assigned host location, minimizing the cost of facility construction and maintenance at the host locations, overall refugee transfer costs, costs related to unallocated refugees, and cultural distance. The second stage plans recourse actions across the six different scenarios after having realized the failed resettlement from the first stage. For our purposes, "successful resettlement" refers to a refugee's permanent resettlement to their assigned host country. "Failed resettlement" (unplanned) and "unallocated supply" (planned) indicate that a refugee did not resettle in their assigned host location and is instead still considered to be present at their origin, awaiting assignment.

To clarify, the first stage resettlement horizon is a period of 5 years, 2030-2035, where stage one allocations are executed. The second stage realizes the failed resettlement from 2030-2035, and makes scenario-dependent allocation and facility-related decisions for the period 2035-2040.

The parameters and decision variables are found below in Tables 2.1 and 2.2, in that order. Supply and capacity parameters, $s_i^{(1)}$ and $s_i^{(2)}$, along with $cap_j^{(1)}$ and $cap_j^{(2)}$, dictate the population of refugees at the origins requiring resettlement in each stage, and the maximum number of refugees that the host facilities can accommodate in each stage, respectively.

Parameters	**Description**
Stage 1 (2030–2035)	
$s_i^{(1)}$	Supply at origin node $i \in N_o$ in Stage 1
$cap_j^{(1)}$	Capacity at host node $j \in N_h$ in Stage 1
$c_{ij}^{(1)}$	Transfer cost from origin i to host $j \in N_h$ in Stage 1
$b_i^{(1)}$	Penalty cost for unallocated supply at origin $i \in N_o$ in Stage 1
$o_j^{(1)}$	Opening cost for host $j \in N_h$ in Stage 1
$m_j^{(1)}$	Maintenance cost for host $j \in N_h$ in Stage 1
$k_{ij}^{(1)}$	Cultural distance between origin $i \in N_o$ and $j \in N_h$ in Stage 1
Stage 2 (2035–2040)	
$s_i^{(2)}$	Supply at origin $i \in N_o$ in Stage 2
$cap_j^{(2)}$	Capacity at host node $j \in N_h$ in Stage 2
$c_{ij}^{(2)}$	Transfer cost from origin $i \in N_o$ to host $j \in N_h$ in Stage 2
$b_i^{(2)}$	Penalty cost for unallocated supply at origin $i \in N_o$ in Stage 2
$o_j^{(2)}$	Opening cost for host $j \in N_h$ in Stage 2
$m_j^{(2)}$	Maintenance cost for host $j \in N_h$ in Stage 2
$k_{ij}^{(2)}$	Cultural distance between origin $i \in N_o$ and $j \in N_h$ in Stage 2
p^s	Probability of scenario $s \in S$
α_{ij}^s	Fraction of Stage 1 flow from $i \in N_o$ to $j \in N_h$ that succeeds under scenario $s \in S$
Constant	
G_i	ND-GAIN climate resilience score of node $i \in N_o \cup N_h$
δ_{ij}	1 if $G_i > G_j$ for $i \in N_o$ and $j \in N_h$, 0 otherwise

Table 2.1: Stage 1 and Stage 2 parameters

Next, there are costs associated with the resettlement of refugees from their origin to a host: $c_{ij}^{(1)}$ and $c_{ij}^{(2)}$ are transportation costs; $b_i^{(1)}$ and $b_i^{(2)}$ are the penalty costs for not allocating available supply at an origin, which encourages the model to allocate all available supply; $o_j^{(1)}$ and $o_j^{(2)}$ represent the one-time capital required to construct and open the facilities that will host the incoming refugees; lastly, $m_j^{(1)}$ and $m_j^{(2)}$ are the costs to maintain the operational facilities to ensure refugee housing remains feasible.

The ND-GAIN Index, assigned the parameter G_i, was constructed by the University of Notre Dame's Global Adaptation Initiative. It serves as a tool to understand how vulnerable a country is to climate-induced issues and how ready a country is to adapt to those issues by assessing a country's "six life-supporting sectors" as well as their "economic readiness, governance readiness, and social readiness" [16]. As the number of origins with climate-induced refugees and hosts open to receiving them increases, we can utilize the ND-GAIN Index to ensure that the host countries are properly resilient to incoming climate-driven effects before resettling a large population of refugees. The UNHCR's goal by 2028 was for 50 countries to receive refugee submissions (before COVID-19), which exceeds the scope presented in this application, yet reinforces the need for the ND-GAIN's ability to decide the feasibility of flow between origin and host [17]. Moreover, the ND-GAIN Index may be used to assign priorities to refugees in countries that are on the brink of being completely uninhabitable.

The cultural distance parameter, k_{ij}, is the incorporation of Hofstede's 6 cultural dimensions into the model: individualism, power distance, masculinity, uncertainty avoidance, long-term orientation, and indulgence [18]. We incorporate this parameter to assist in a healthier and likely more successful resettlement process, as the model's second objective is to minimize cultural distance in the allocation process.

Parameters α_{ij}^s and p^s integrate the uncertain nature of the resettlement process into the model. For a given scenario, p^s represents its probability of occurrence. It allows the decision-maker to implement an informed belief about the likelihood of an extreme event, or lack thereof, into the model for the minimization of expected costs associated with the resettlement process. On the other hand, α_{ij}^s is the likelihood of a refugee successfully resettling in their planned host location.

The parameter α_{ij}^s considers several realistic factors that influence the likelihood of a refugee successfully resettling from their origin to their planned host. It includes historical resettlement statistics, as seen in Fig. 2.1, from the UNHCR, cost of living, geographical distance, and the Global Peace Index (GPI) of the origin and host countries [11][19][20]. This parameter helps reliably estimate the true number of refugees that will successfully resettle compared to the originally planned allocations. Using this parameter, the model gives crucial insight into how many extra refugees will require resettlement in the second stage versus what was planned, as well as the amount of capacity that will be unused. Furthermore, we can use expected resettlement outcomes to forecast how many years the resettlement process may take compared to the target year of 2050, as well as enhance the allocation planning process to include actual outcomes in addition to the cultural distance objective.

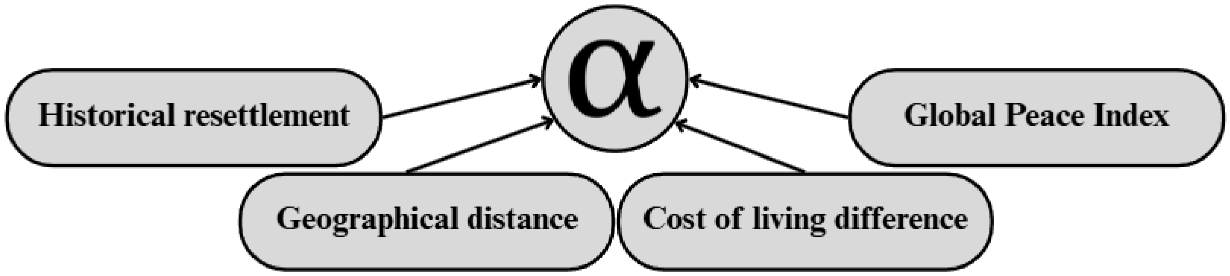

Figure 2.1: Visualization of the components of alpha

As for the decision variables, x_{ij} is the number of refugees allocated to resettle from origin $i \in N_o$ to host $j \in N_h$. Conversely, y_i is the variable representing the planned number of refugees *not* allocated to be resettled to a host in the given stage. Variable z_j is the planned amount of unmet capacity at a given host. Lastly, binary variables r_j and q_j are facility-related variables determining whether a facility is constructed in a given stage and whether the facility is operational during a given stage, respectively.

Decision Variables	**Description**
Stage 1 (2030–2035)	
$x_{ij}^{(1)}$	Flow from origin $i \in N_o$ to host $j \in N_h$ in Stage 1
$y_i^{(1)}$	Remaining supply at origin $i \in N_o$ in Stage 1
$z_j^{(1)}$	Remaining capacity at host $j \in N_h$ in Stage 1
$r_j^{(1)}$	Binary: 1 if host facility j is operational in Stage 1
$q_j^{(1)}$	Binary: 1 if host facility j is constructed in Stage 1
Stage 2 (2035–2040)	
$x_{ij}^{(2,s)}$	Flow from origin i to host j in Stage 2 under scenario $s \in S$
$y_i^{(2,s)}$	Remaining supply at origin i in Stage 2 and scenario $s \in S$
$z_j^{(2,s)}$	Remaining capacity at host j in Stage 2 and scenario $s \in S$
$r_j^{(2,s)}$	Binary: 1 if host facility j is operational in Stage 2 and scenario $s \in S$
$q_j^{(2,s)}$	Binary: 1 if host facility j is constructed in Stage 2 and scenario $s \in S$

Table 2.2: Stage 1 and Stage 2 decision variables

$$\min \quad \sum_{i\in N_o}\sum_{j\in N_h} c_{ij}^{(1)}\cdot x_{ij}^{(1)} + \sum_{i\in N_o} b_i^{(1)}\cdot y_i^{(1)} + \sum_{j\in N_h}\left(o_j^{(1)}\cdot q_j^{(1)} + m_j^{(1)}\cdot r_j^{(1)}\right) \tag{1a}$$

$$+ \sum_{s\in S} p^s \left(\sum_{i\in N_o}\sum_{j\in N_h} c_{ij}^{(2)}\cdot x_{ij}^{(2,s)} + \sum_{i\in N_o} b_i^{(2)}\cdot y_i^{(2,s)} + \sum_{j\in N_h}\left(o_j^{(2)}\cdot q_j^{(2,s)} + m_j^{(2)}\cdot r_j^{(2,s)}\right)\right)$$

$$\min \quad \sum_{i\in N_o}\sum_{j\in N_h} k_{ij}^{(1)}\cdot x_{ij}^{(1)} + \sum_{s\in S} p^s \left(\sum_{i\in N_o}\sum_{j\in N_h} k_{ij}^{(2)}\cdot x_{ij}^{(2,s)}\right) \tag{1b}$$

s.t.

$$\sum_{j\in N_h} x_{ij}^{(1)} + y_i^{(1)} = s_i^{(1)}, \quad \forall\, i\in N_o \tag{1c}$$

$$\sum_{j\in N_h} x_{ij}^{(2,s)} + y_i^{(2,s)} = s_i^{(2)} + y_i^{(1)} + \sum_{j\in N_h}\left(x_{ij}^{(1)}\cdot(1-\alpha_{ij}^s)\right), \quad \forall\, i\in N_o, \forall\, s\in S \tag{1d}$$

$$\sum_{i\in N_o} x_{ij}^{(1)} + z_j^{(1)} = cap_j^{(1)}, \quad \forall\, j\in N_h \tag{1e}$$

$$\sum_{i\in N_o} x_{ij}^{(2,s)} + z_j^{(2,s)} = cap_j^{(2)}, \quad \forall\, j\in N_h, \forall\, s\in S \tag{1f}$$

$$x_{ij}^{(1)} \le M(G_j - G_i)\cdot\delta_{ij}, \quad \forall\, i\in N_o,\ \forall\, j\in N_h \tag{1g}$$

$$x_{ij}^{(2,s)} \le M(G_j - G_i)\cdot\delta_{ij}, \quad \forall\, i\in N_o,\ \forall\, j\in N_h, \forall\, s\in S \tag{1h}$$

$$\sum_{i\in N_o} x_{ij}^{(1)} \le r_j^{(1)}\cdot cap_j^{(1)}, \quad \forall\, j\in N_h \tag{1i}$$

$$\sum_{i\in N_o} x_{ij}^{(2,s)} \le r_j^{(2,s)}\cdot cap_j^{(2)}, \quad \forall\, j\in N_h, \forall\, s\in S \tag{1j}$$

$$r_j^{(1)} \le q_j^{(1)}, \quad \forall\, j\in N_h \tag{1k}$$

$$r_j^{(2,s)} \le \sum_{t'=1}^{2} q_j^{(2,s)}, \quad \forall\, j\in N_h, \forall\, s\in S \tag{1l}$$

There are two objectives that the model optimizes: (1a) minimize resettlement operation cost, and (1b) minimize cultural distance. In Stage 1, we minimize the costs of refugee allocation, retention at the host, and facility construction and operation, while also minimizing the overall cultural distance of the allocation decisions. Then, in stage two, we minimize the *expected* transfer cost, refugee retention costs, facility-related costs, and cultural distance across all given scenarios. This "here-and-now" approach creates action plans for the several probabilistic scenarios that can occur, so that the decision-maker has informed options upon realizing the uncertainty at the end of the first resettlement stage.

From top to bottom, constraints (1c) and (1d) are supply-balancing constraints. (1c) guarantees that the supply at a given origin must equal the sum of allocated and unallocated refugees in the first stage; and with (1d), the number of allocated and unallocated refugees must equal the sum of the stage two supply, unallocated refugees from stage one, and the failed resettlement from stage one. This constraint implicitly makes the stage two supply scenario-dependent by appending to it the failed resettlement and unallocated refugees from stage one. (1e) and (1f) are capacity-balancing constraints that limit the number of refugees that can be allocated to any given host in each stage, stating that the sum of the allocated refugees and the unmet capacity of the host must equal the overall capacity. Constraints (1g) and (1h) are related to the ND-GAIN index and prohibit refugee allocations from origin countries that have a higher climate resilience score than their planned host. Operational accommodation constraints (1i) and (1j) ensure that refugees may only be allocated to a host that has an operational facility. (1k) and (1l) only allow for a facility to be operational ($r_{jt} = 1$) if it has previously been constructed.

Chapter 3

Application and results

The purpose of this formulation was to enrich current planning insights by integrating actual resettlement rates into resettlement planning. Data associated with the estimated refugee supply at the 29 origins (Table 3.1), host capacities, and facility- and resettlement-related costs were compiled from [14] and [15]. Origin countries were chosen based on the threat posed to them by climate change, gathered from [21]. The names of the host countries are excluded to avoid potential controversy or bias.

Table 3.1: Origin Countries by Region and Subregion

Region	**Origin Countries**
Africa	
Central Africa & Great Lakes	Burundi, Central African Republic, Equatorial Guinea, Dem. Rep. of Congo, Congo, Republic of Congo
East Africa	Chad, Eritrea, Ethiopia, Somalia, South Sudan, Sudan
West Africa	Cameroon, Guinea, Guinea-Bissau, Niger, Nigeria
Southern Africa	Angola, Zimbabwe
Middle East & North Africa (MENA)	Mauritania, Iraq, Syria, Yemen
Asia & the Pacific	
South-West Asia	Afghanistan, Pakistan
South Asia	Bangladesh
Central Asia	Tajikistan, Turkmenistan
Americas	Haiti, Venezuela

Each origin's supply values, retrieved from [14], were estimated with an understanding of their population growth rate, their vulnerability to climate change's effects, and their inclination to resettle. As for the hosts and their capacities, [15] calculated these values based on proportions of the host's total population to ensure fairness and that the impact of a larger resettlement is minimized. The hosts themselves were chosen based on their historical resilience to migration and climate impacts, as well as their global economic strength [15].

We optimize allocations across 6 different scenarios: "normal high," "normal average," "normal low," "extreme high," "extreme average," and "extreme low." These scenarios derive from the collected UNHCR data from 2011 to 2024. The "normal" scenarios reflect resettlement trends during periods with no specific catastrophic destruction to global resettlement channels, while "extreme" scenarios represent the opposite. Specifically, resettlement data taken from 2019 through 2021 appear to be *drastically* lower on a global scale than the preceding and succeeding years, and while the COVID-19 pandemic was not necessarily climate-induced, this data serves as a proxy to understand how global resettlement may react to a large-scale, climate-induced resettlement disruption.

The applications [14] and [15] utilize a resettlement horizon of 20 years; however, our approach focuses on highlighting the more immediate effects of failed resettlement and therefore models a 10-year resettlement horizon, 2030 to 2040. Data was collected from [11] to assist in creating the α_{ij}^s values, as the UNHCR is one of the primary sources through which formal international resettlement submissions occur. The UNHCR has collected overall resettlement versus resettlement needs data since 2011, as well as more granular data surrounding origin to host resettlement, although sparse. Nevertheless, if data existed on the country level, it was integrated into α_{ij}^s calculations. If not, the overall resettlement proportion was utilized as a baseline.

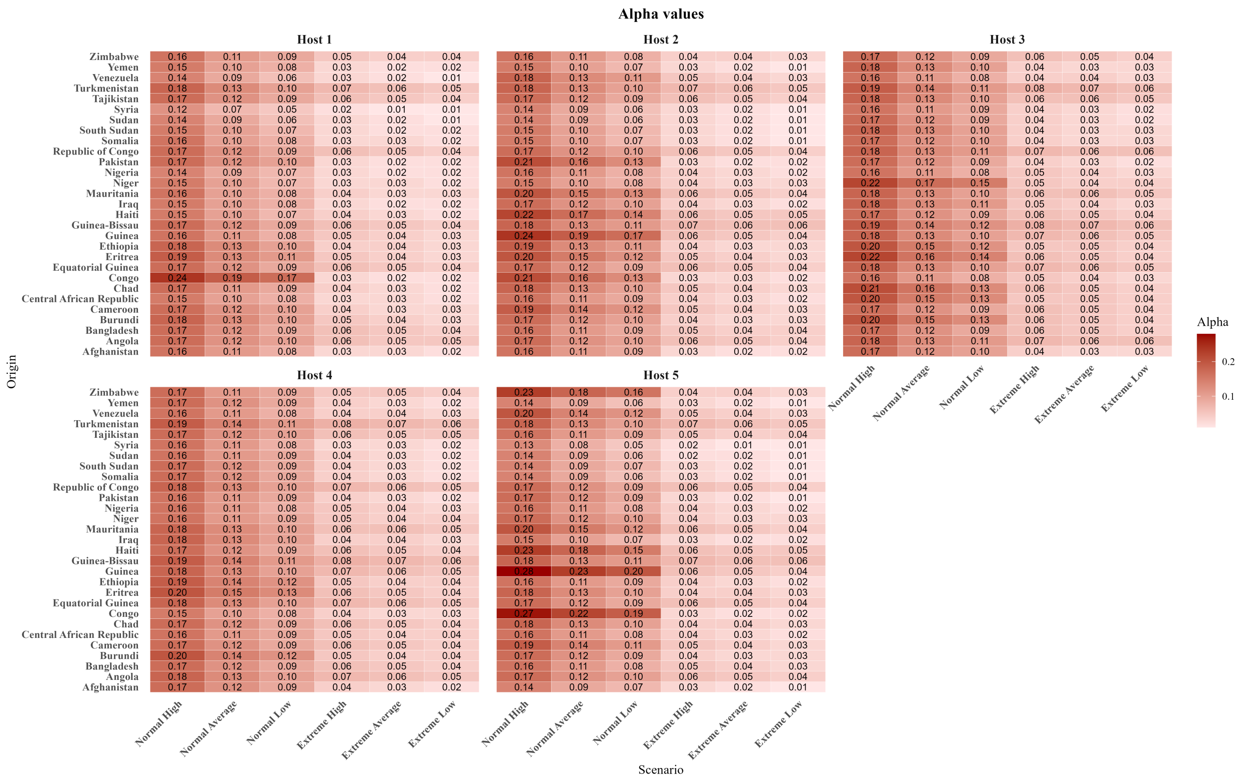

Figure 3.1: Heatmap of α values by scenario, host, and origin.

As can be seen above, α_{ij}^{s} values tend to be more variable in hosts with existing historical data, but the combination of compatibility scores (cost of living, geographical distance), the baseline α_{ij}^{s} value, and the Global Peace Index (GPI) assisted where historical data was not available.

The GPI was integrated to show the effect of emergent civil unrest or general conflict on resettlement trends. Generally, data has shown that differing types of conflict in a country have varied effects on migration, but this application applies an inverse relationship between α_{ij}^{s} and GPI. We assume that greater conflict levels, especially violent conflict, limit a refugee's ability to consider international resettlement due to a lack of income, unsafe or closed travel channels, and the lack of access to formal resettlement opportunities [22][23].

In the first stage, the model allocates refugees from origin to host, minimizing the total cost of the resettlement operation, along with the cultural distance between the origin-host pairs. In our context, these are the resettlement outcomes we would realize in the perfect scenario, before any realization of uncertainty. The optimal allocations given by the model are shown in Table 3.2.

Table 3.2: Stage 1 allocations

Origin	**Host**	**[2030-2035)**
Afghanistan	Host 2	993,934
Afghanistan	Host 5	356,066
Angola	Host 5	1,390,000
Bangladesh	Host 1	2,239,430
Bangladesh	Host 5	2,210,570
Burundi	Host 4	490,000
Cameroon	Host 5	1,060,000
Central African Republic	Host 3	180,000
Chad	Host 3	480,000
Congo	Host 5	3,720,000
Equatorial Guinea	Host 5	60,000
Eritrea	Host 3	130,000
Ethiopia	Host 3	5,120,000
Guinea	Host 5	800,000
Guinea-Bissau	Host 5	80,000
Haiti	Host 5	1,050,000
Iraq	Host 4	1,910,000
Mauritania	Host 5	200,000
Niger	Host 3	870,000
Nigeria	Host 5	15,840,000
Pakistan	Host 2	2,410,000
Republic of Congo	Host 5	180,000
Somalia	Host 4	360,000
South Sudan	Host 5	430,000
Sudan	Host 5	293,419
Sudan	Host 4	1,416,581
Syria	Host 4	1,540,000
Tajikistan	Host 5	150,000
Turkmenistan	Host 4	80,000
Venezuela	Host 5	1,370,000
Yemen	Host 3	654,908
Yemen	Host 4	205,092
Zimbabwe	Host 5	460,000

Stage one demonstrates the interplay between origin-host transfer cost and culture score difference. The allocations shown demonstrate the case where minimized cultural distance was weighted slightly higher than the transfer cost (60 and 40 per cent, respectively), resulting in 17 origins being allocated to hosts with their closest cultural proximity and 9 origins being allocated to hosts with the lowest transfer costs. Because we implement non-flexible capacity constraints, the model will not always be able to allocate countries to their preferred hosts if capacity does not allow. As the decision-maker's priorities shift between minimizing the tangible costs of the resettlement process and the cultural impacts incurred by the hosts, the weights may be adjusted to account for those needs.

The model fully utilized all supplies and capacities in the first stage, making it an efficient, idealized plan. But when we integrate historical resettlement statistics, cost of living, geographical distance, and the conflict status of the origin countries into such an idealized plan, we begin to visualize realistic outcomes of the first stage's execution.

The "Normal" high, average, and low scenarios have baseline α_{ij}^{s} values of 0.1522, 0.1011, and 0.0754, respectively. These likelihoods are consistent with resettlement outcomes from 2011 to 2024 (except 2020 - 2021), before the incorporation of more personalized data [11].

Figure 3.2: Resettlement outcome comparisons separated by host in the "Normal" scenarios

In Fig. 3.2, we compare the failed resettlement (red) to the successful resettlement (green) across the "Normal" scenarios. One aforementioned assumption of this model is that both failed resettlement outcomes and unallocated refugees are reintegrated into the supply of the origin in stage 2 via constraint (1d), resulting in a supply surplus for every origin. For example, 15.84 million Nigerian refugees were allocated to Host 5, the highest capacity host, and 13.4 million refugees did not successfully resettle in the best-case scenario presented in this application. Therefore, 13.4 million refugees *in addition to* Nigeria's second stage supply of 16.82 million will require resettlement. Hence, it becomes increasingly evident that, at this rate, Nigeria will not be able to allocate its full supply by the target year of 2050 without significant intervention.

The issues from the "Normal" scenarios are greatly exacerbated in the "Extreme" scenario, as the baseline α_{ij}^s values for the high, average, and low scenarios are 0.0397, 0.0318, and 0.0239, respectively. The α_{ij}^s values were even further decreased by higher normalized GPI values, representing cases where the conflict levels in the origin countries are especially high

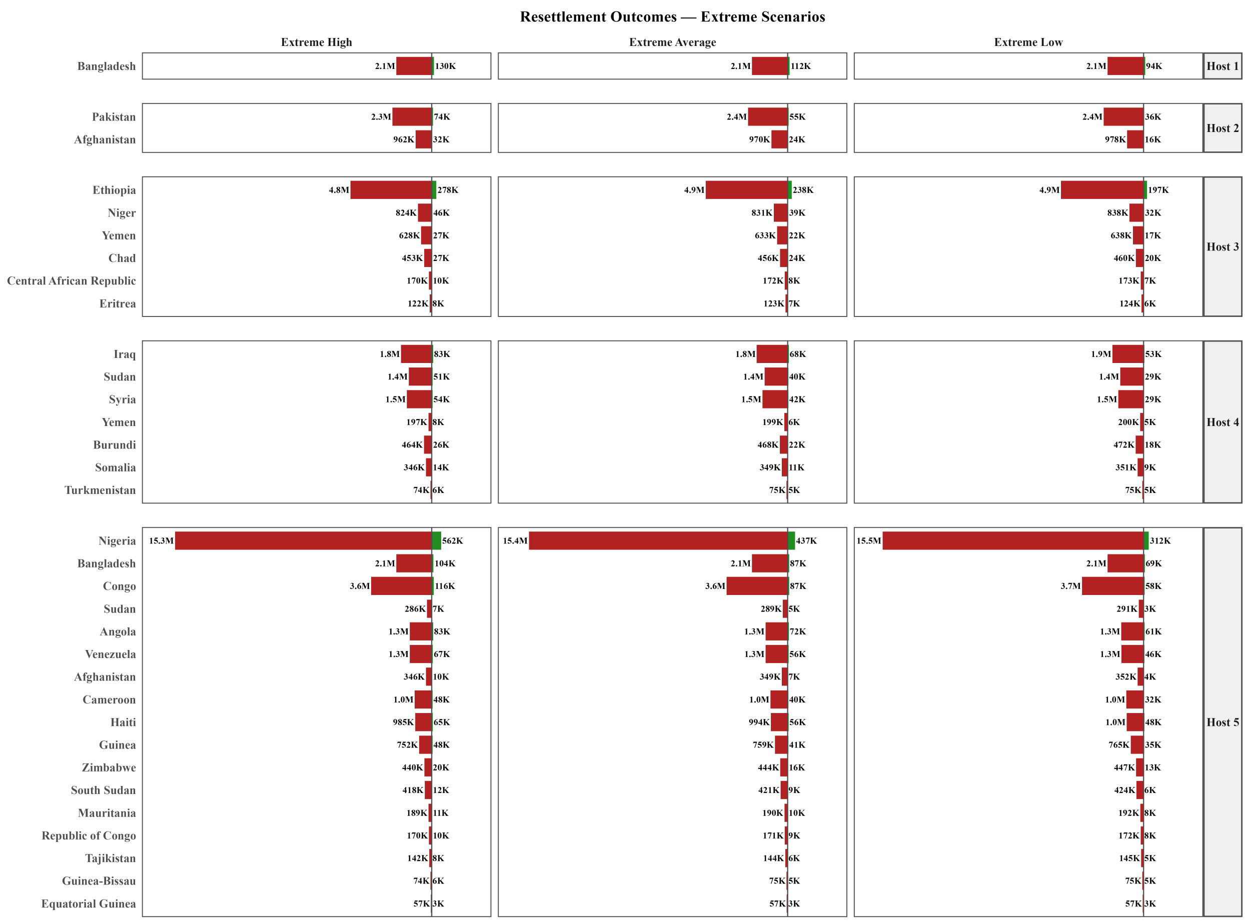

Figure 3.3: Resettlement outcome comparisons separated by host in the "Extreme" scenarios

and likely intensified by extreme climate-induced events, and refugees have little to no access to formal resettlement channels. Conversely, there are situations in which GPI may not necessarily warrant a decrease in α_{ij}^{s}, like if the decision-maker planned to expend substantial resources in higher conflict countries to ensure resettlement, or if conflict was believed to drive a higher proportion of resettlement, but these circumstances are tuneable in the model's parameters.

The question then becomes: how do, or can, we adjust host capacities to accommodate a much larger supply of refugees than what was previously planned? In this modeling approach, we constrained the host capacities in the second stage to the originally planned parameter. In Fig. 3.4, each host's given capacity is compared with the capacity it would require to fully resettle all of the refugee supply at their assigned origins. Host 5, with the highest capacity at 31.52 million, would still require 19.06 million capacity to reach its demand. In most cases, the decision to increase planned capacity by 160 per cent over 5 years is not feasible. These results highlight the urgent necessity for more dynamic capacity planning approaches that lessen the burden of extreme resettlement failures.

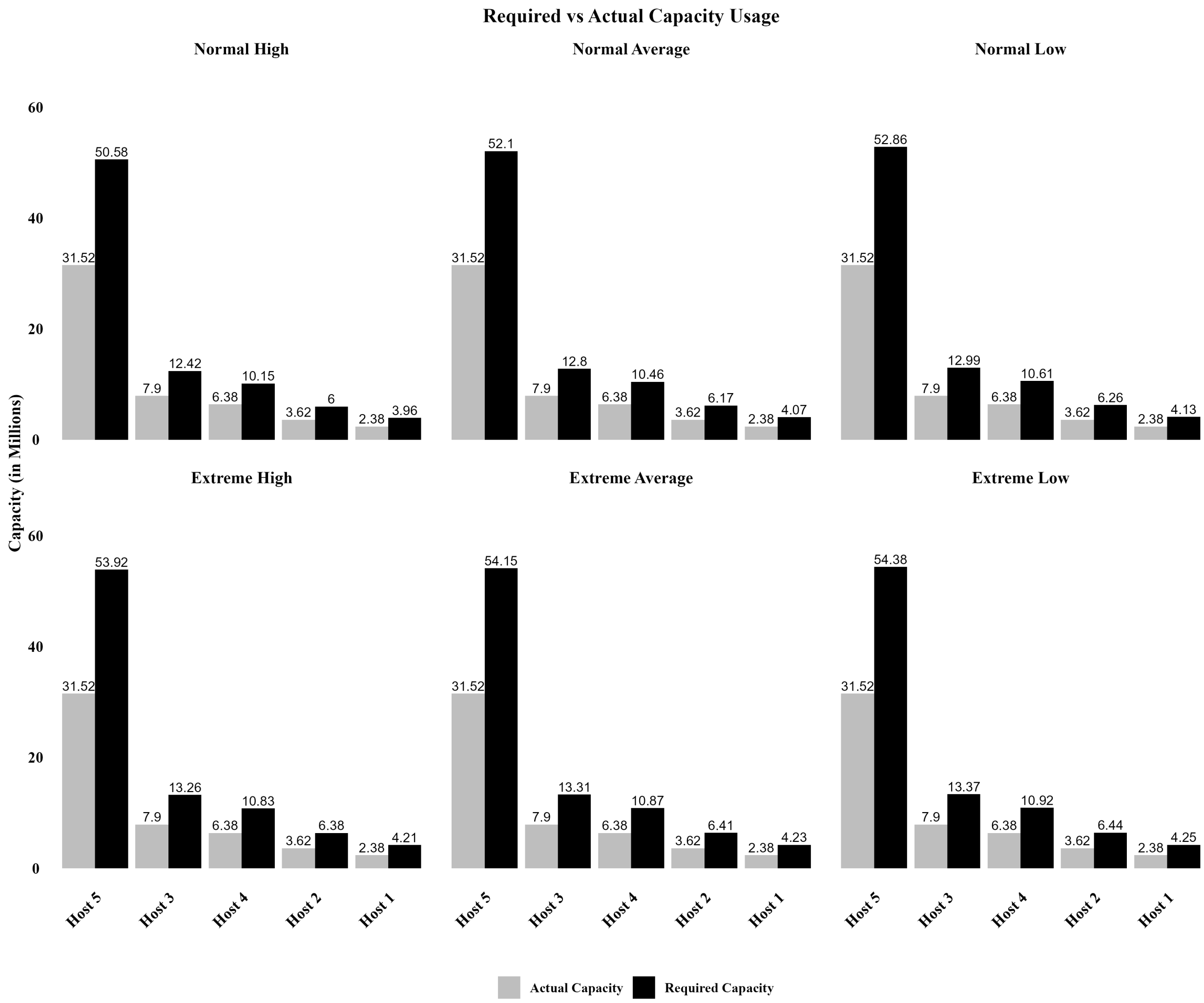

Figure 3.4: Additional refugee capacity required at each host in each scenario to meet the full demand.

With such uncertainty surrounding the resettlement process and how refugees will make movement decisions, the model optimizes the second stage allocations based on the minimized expected cost and cultural distance of its decisions. Now, each origin possesses a surplus in supply from failed resettlement in the first stage, and the amount of unallocated supply across several of the origins dramatically increases (shown in Tables 3.3 and 3.4). There is simply not enough capacity across the five hosts to fully utilize all supply.

Table 3.3: Stage 2 Supply: Normal Average Scenario

Origin	**Used**	**Unallocated**
Afghanistan	2,636,017	
Angola	0	2,791,623
Bangladesh	8,423,021	0
Burundi	0	958,996
Cameroon	2,065,353	0
Central African Republic	0	352,810
Chad	0	945,035
Congo	6,178,444	877,777
Equatorial Guinea	112,832	0
Eritrea	0	248,683
Ethiopia	0	9,829,509
Guinea	1,476,220	0
Guinea-Bissau	149,292	0
Haiti	1,874,649	0
Iraq	0	3,699,780
Mauritania	380,419	0
Niger	1,731,123	0
Nigeria	18,789,544	12,197,183
Pakistan	4,600,026	0
Republic of Congo	0	358,595
Somalia	0	728,016
South Sudan	860,267	0
Sudan	0	3,375,079
Syria	0	2,934,323
Tajikistan	0	293,163
Turkmenistan	0	149,016
Venezuela	2,532,786	0
Yemen	0	1,663,968
Zimbabwe	0	865,429

Table 3.4: Stage 2 Supply: Extreme Average Scenario

Origin	**Used**	**Unallocated**
Afghanistan	2,748,664	0
Angola	0	2,887,950
Bangladesh	8,731,406	0
Burundi	0	1,008,048
Cameroon	2,170,062	0
Central African Republic	0	371,775
Chad	0	996,372
Congo	5,765,350	2,007,705
Equatorial Guinea	116,990	0
Eritrea	0	263,174
Ethiopia	0	10,362,410
Guinea	1,618,800	0
Guinea-Bissau	154,836	0
Haiti	2,003,775	0
Iraq	0	3,871,853
Mauritania	400,474	0
Niger	1,840,994	0
Nigeria	17,769,556	14,453,373
Pakistan	4,924,564	0
Republic of Congo	0	371,069
Somalia	0	758,649
South Sudan	890,911	0
Sudan	0	3,514,894
Syria	0	3,058,484
Tajikistan	0	303,558
Turkmenistan	0	154,560
Venezuela	2,673,610	0
Yemen	0	1,741,793
Zimbabwe	0	933,860

In contrast to the first stage, where the model was able to fully utilize all supplies and capacities in its plan, the reality is that, as a result of failed resettlement, the global supply increased from 51.81 million to 94.08 million in the "Normal Average" scenario, and to 98.87 million in the "Extreme Average" scenario. Even further, Nigeria and the Democratic Republic of the Congo (referred to as "Congo") utilized nearly half of the total capacity across all five host countries in each scenario. As a direct impact of failed resettlement in the first stage, 15 of the 29 origin countries are unable to formally resettle their refugees because host capacities are fully met.

Chapter 4

Limitations and Future Work

The resettlement process involves multiple actors who each influence the final resettlement decision. Host countries determine their capacity and whether to admit refugees, the UNHCR defines refugee status, and refugees themselves decide whether to move. While the proposed mathematical optimization model accounts for uncertainty at the country level, it does not explicitly model the refugee as a decision-making agent with individual objectives. Incorporating this level of behavioral granularity could help identify probabilistic resettlement outcomes that were beyond the reach of this framework. However, with refugee flows from 29 origin countries, individual behavior is highly variable, and data availability remains a major limitation. The current global dataset remains sparse concerning individual-level migration intent and choice modeling, limiting how deeply these dynamics can be integrated into a quantitative framework. Future extensions could benefit from the integration of agent-based or discrete choice models, if such data become available.

This study provides a 10-year snapshot of the effects of failed resettlement under climate-induced migration scenarios, but does not fully capture the compounding effects of uncertainty across the full 20-year period to 2050. Although we apply rate-based extrapolation to create a broad understanding of longer-term trends, a multi-stage, time-evolving formulation could offer more accurate forecasts of resettlement duration and host system strain over time. Future work should explore longitudinal applications over a full planning horizon to better inform durable policy decisions under long-term climate risk.

Refugee-related policies continue to be a controversial subject of conversation in countries that are sought out to be hosts. Especially so, as of late, due to the more stringent policies emerging in more influential countries, where host countries' populations are taking more negative views on immigration and open borders [24]. We did not integrate the current hosts' policies into the calculation of their capacities, nor did we integrate host-country political relationships into the creation of α_{ij}^{s} values. Incorporating more nuance into the host capacity calculations in future applications can offer even more accurate allocation decisions and resettlement behaviors.

Chapter 5

Conclusion

Climate change and its effects are quickly intensifying and creating unlivable situations for many countries across the globe. As a result of climate change, civil unrest and violent conflict, economic hardship, and natural disasters are all but inevitable across the affected regions, greatly exacerbating the need for a mass resettlement of refugees. With such a great resettlement looming so shortly, governing bodies must have a long-term resettlement plan prepared to ensure efficient execution over the resettlement horizon. However, the plan must be adapted to account for the true performance of current resettlement efforts rather than an idealized situation.

There is much uncertainty in the global outcomes of refugee resettlement in the present setting. Therefore, to capture the effects of that uncertainty, we propose a scenario-based, two-stage stochastic model with objectives to minimize the resettlement costs and cultural distances. Our modeling approach provides insight into the consequences of planning for the idealized state, or deterministically allocating, as seen in the current literature. Due to the realistic under-performance of global resettlement efforts and the uncertainty with which refugees make decisions, catastrophically large levels of supply backlog and fully utilized capacities could push the resettlement timeline back by many years, even in the best-case scenario.

This model contributes a highly flexible construction to the field of climate-induced refugee resettlement planning by its ability to incorporate historical resettlement data, estimated supply and capacity levels, proxies for refugee preferences and behavior, and scenario-based analysis. Because the model provides several different scenarios of outcomes, decision-makers can plan for a wide range of possibilities, enhancing their execution of the global resettlement operation. Additionally, the model adapts to changing cultural differences and operational costs, allowing decision-makers to allocate their resources between cost and maximizing the likelihood of societal integration. Ultimately, the given model provides crucial insight into the outcomes of climate-induced resettlement efforts while considering real-world resettlement statistics, providing decision-makers with a nuanced understanding of refugee behavior and the likely consequences of idealized, inflexible planning.

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