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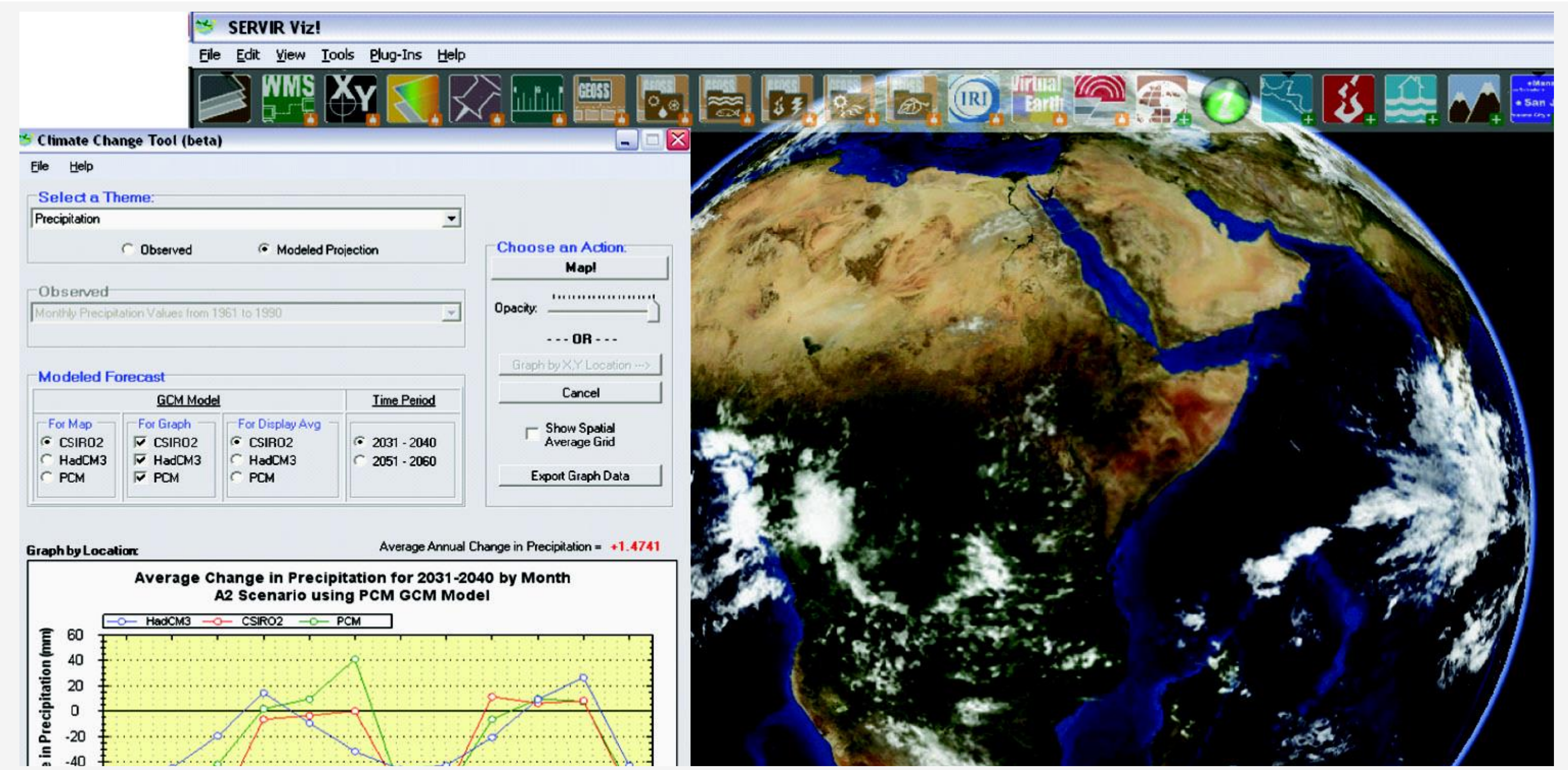

RESEARCH TECHNICAL ASSISTANCE CENTER

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Evaluating Climate-Related Migration Forecasting Models

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List of Acronyms

ABM	Agent Based Model
GDP	Gross Domestic Product
IPCC	Intergovernmental Panel on Climate Change
OECD	Ogranisation for Economic Co-operation and Development
RCP	Representative Concentration Pathways
SPEI	Standardized Precipitation Evapotranspiration Index
SSP	Shared Socioeconomic Pathways
USAID	Unites States Agency for International Development

Introduction

Climate change will have significant impacts on all aspects of human society, including population movements. In some cases, populations will be displaced by natural disasters and sudden-onset climate events. In other cases, climate change will slowly reshape the economic, social, and political realities of a place, which will influence how and where people migrate. Planning for the wide spectrum of future climate-related mobility is a key challenge facing development planners and policy makers.

Human migration brings opportunities and challenges to both sending and receiving societies. Migration is a key adaptation mechanism vulnerable households can use to cope with climate change, and whether receiving societies experience benefits or strain from population growth will depend on key investments—in housing, jobs, infrastructure, and social services. To best plan these investments requires an understanding of how future population movements will be affected by climate change.

This report reviews a number of prevailing and promising modeling approaches for forecasting the nature, magnitude, and direction of climate-related migration over the next 30 years. We pay particular attention to how well models are likely to forecast migration across geographic contexts, for different population groups (including women and marginalized groups), the degree to which models integrate other developmental or conflict-related drivers of migration, and whether models capture the potential for trapped populations. Our findings are based on a systematic literature review (see Appendix A.1 for details) and benefit from the insight and expertise of eight climate migration experts and modelers (see Appendix A.2 for details).

Our report finds that the field of climate-related migration forecasting is still in its infancy. Modeling experts caution that at this stage of model development, numerical projections to 2050 should be seen as notional at best. Modeling human behavior, including migration, is fraught with uncertainty, and adding the dimension of climate change only compounds that uncertainty. For this reason, a scenarios-based approach is preferable to an approach based on single narratives of future trends. Attention should be given to variation across the full spectrum of future scenarios, and policies oriented towards encouraging best-case outcomes.

Exposure mapping remains a useful tool to identify at-risk populations, and the United States Agency for International Development (USAID) should support a multi-pronged strategy to enhance climate resilience in vulnerable regions, including facilitating migration as an adaptive strategy, investing in in-situ adaptation, and enhancing the capacity of local and regional urban centers to accommodate and benefit from in-migration. To further strengthen foresight capacities, we recommend convening foresight exercises that bring modelers together with climate scientists, migration scholars, development practitioners, and other stakeholders to provide a more comprehensive picture of potential future trends for specific countries or regions.

Climate-related migration modeling is significantly hampered by limited data on past and present migration. To improve the frequency and accuracy of census data collection, investment in statistical bureaus of developing countries is crucial. Finding innovative ways to capture flow-data is also important to capture short-term mobility, displacement, and irregular migration trends. Continued investment in individual and household level surveys that include questions on migration aspirations, plans, ability, and non-climate-related drivers of migration will strengthen capacity to distinguish voluntary and involuntary forms of climate-related migration and immobility, and to anticipate divergent outcomes for various social groups and marginalized populations.

Background

For more than thirty years, research published by scientists and reports in the news media have warned that climate change will cause mass migration and displacement on a global scale. A predominant early assumption was that climate change and migration have a linear, cause-and-effect relationship, in which climate induced drought, rising sea levels, and natural disasters result in the movement of affected populations. Approaches to forecasting migration initially focused on exposure mapping (also called hazard mapping): identifying areas threatened by climate change and assuming the vast majority of residents of affected areas would be forced to leave. This led to catastrophic projections of climate migrations and environmental refugees (Brown 2008; McLeman 2014). Fortunately, these early projections have failed to become reality. They did not adequately account for how climate-related factors interact with non-climate related drivers of migration, the potential for in-situ adaptation, and instances in which climate change impacts may suppress mobility, particularly in low-income countries. Their shortcomings spurred more nuanced investigations of how the impacts of climate change intersect with existing mobility systems and development conditions to affect the nature, volume, direction, and composition of migration flows. Attempts to forecast climate-related migration have grown in number and sophistication in recent years, particularly since the early 2010s. Before reviewing these models, this section discusses the conceptualization of climate-related migration, the origins of climate-related migration models, and the most common types of models used today to forecast climate-related migration.

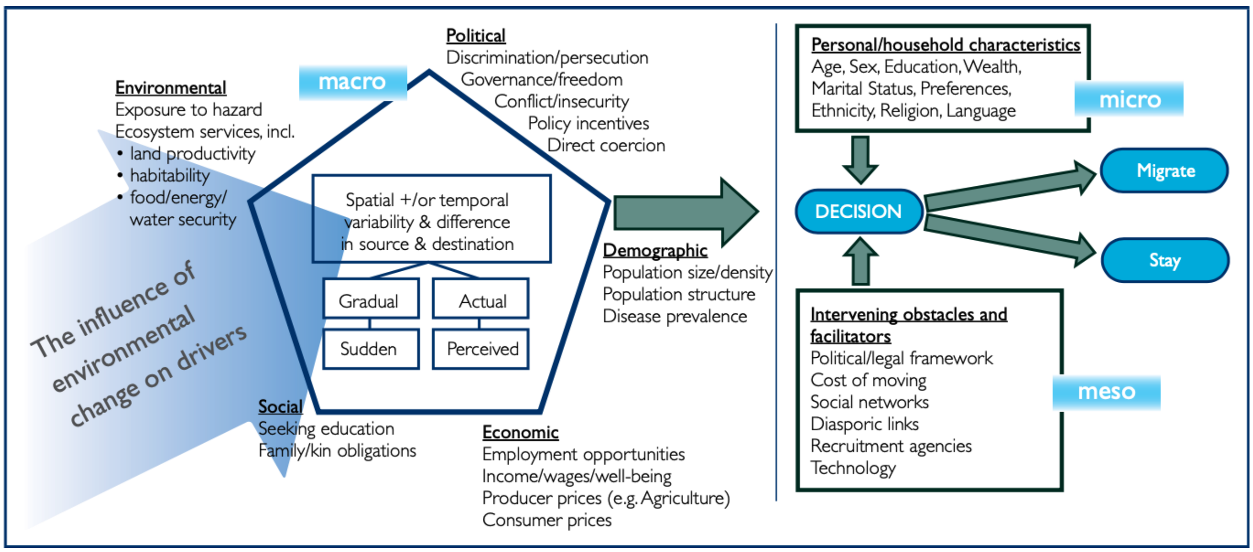
Categories of Climate-Related Migration

The International Organization for Migration, a United Nations agency, defines climate migration as "the movement of a person or groups of persons who, predominantly for reasons of sudden or progressive change in the environment due to climate change, are obliged to leave their habitual place of residence, or choose to do so, either temporarily or permanently, within a State or across an international border" (International Organization for Migration 2019). This definition is broad; it encompasses many different kinds of climate-related migration, spanning the spectrum of forced to voluntary, internal and international, temporary and permanent. This breadth poses a challenge to research, forecasting, and policy-making related to migration and climate change, because the kinds of migration being studied can vary considerably and require significantly different policy responses.

Brown and McLeman (2013) suggest climate-related migration may be categorized according to the nature of the climatic stimulus (sudden-onset climate events versus gradual changes in prevailing conditions) and the nature of the migration response (distress migration versus adaptive or amenity-seeking migration). Sudden-onset climatic events, such as floods and storms, are often associated with distress migration or displacement, in which large numbers of households abandon their place of residence at short notice. Alternatively, households can become trapped in place by sudden-onset events (e.g., floods that shut down roads). Climate-induced displacement often takes place over relatively short distances, and return migration tends to be common. The link between a sudden-onset climate event and distress migration is more direct. But where, how, and whether people move in response to that event is shaped by pre-existing migration systems, the resources and networks of affected households, government or humanitarian interventions, and the broader development context.

Slow-onset changes include increasing temperature, irregular rainfall patterns, sea-level rise, ocean acidification, soil salinization, loss of biodiversity, and desertification (de Sherbinin 2020). These slow-onset changes interact with migration outcomes indirectly and often in a non-linear fashion. Other political, economic, cultural, or conflict-related drivers of migration or immobility may be stressed by climate change, and these social phenomena mediate climate impacts and the responses of both individuals and households. For this reason, slow-onset climate changes contribute to migration but are often not the proximate cause of migration. This is why, for example, many migrants in drought-affected areas will attribute their primary reason for migrating to economic rather than climate-related factors (United States Agency for International Development Honduras Brief on Climate Change, Food Security and Migration). Some describe slow-onset climate impacts as threat multipliers—for example, drought can reduce crop yields and thus household incomes, or it can exacerbate conflict in water-scarce regions (McLeman 2014; Sofuoğlu and Ay 2020). In the context of slow-onset climate change, "thresholds" or "tipping points" become important; many populations will attempt to adapt in place despite significant livelihood stress, until in-situ adaptation fails and/or a tipping point is reached in which a significantly higher share of households choose migration as their primary adaptation strategy (McLeman 2018).

Figure 1. Conceptual Framework for the Drivers of Migration



Source: *Foresight* (2011, page 33)

Figure 1 presents a theoretical framework from the influential *Foresight: Migration and Global Environmental Change* study conducted by government of the United Kingdom in 2011. It illustrates how climate changes intersect with environmental, political, economic, social, and demographic factors at the macro- and community-level as well as micro-level variables related to personal and household characteristics and meso-level intervening obstacles and facilitators. This figure does not illustrate how the decision to migrate or stay is then affected by individual and household capabilities to migrate. Those who aspire to migrate but lack the ability to do so may become trapped or "involuntarily immobile" (Carling 2002). The potential for climate change to trap poor populations in place is as important a humanitarian concern as climate-related distress migration.

Because climate change acts indirectly on pre-existing migration systems, it is difficult to disentangle the relative impact of climate-related variables from other migration drivers. This is especially challenging for forecasting models. To date, forecasting has tended to operate under the assumption that populations are relatively fixed unless uprooted by a climate event. In reality, populations are constantly moving internally and internationally. They move in seasonal, temporary, or permanent ways for work, education, adventure, security, or family, and across stages of life (Cundill et al. 2021; Van Praag 2021). Population movements within and from a country even have a patterned relationship with levels of economic development. For example, more people move to towns and cities as economies industrialize, and in many countries, a growing percentage of the population migrates internationally as countries move from low- to middle-income status–a phenomenon referred to as a country's "mobility transition" (Zelinsky 1971; de Haas 2010; Clemens 2020; Schewel and Asmamaw 2021). This suggests that modeling should not focus exclusively on identifying climate migrants, but rather on clarifying how climate change will reshape or constrain existing mobility systems.

Population and Migration Modeling

Current approaches to forecasting climate-related migration have their roots in a longer history of forecasting population growth and distribution, which later evolved into more focused migration forecasting. Population forecasting is meant to predict future population distributions across rural and urban places based on factors like fertility, mortality, and migration. Population forecasting has been utilized by statistical agencies and development planners for many decades (Shryock and Siegel 1980). Over time, population forecasting tools have advanced, allowing researchers to incorporate a greater array of assumptions and to project more specific forecasts (e.g., by age) (Wiśniowski et al. 2015).

Migration modelers build on the sub-component of migration within population forecasting through a variety of methods. Often modelers utilize past migration data to predict future migration trends, incorporating additional variables, such as economic or demographic factors, into their models (Disney et al. 2015). All models have a certain degree of uncertainty baked into them, as no model can predict future shocks or gamechangers like wars, pandemics, or major technological breakthroughs. The lack of high quality longitudinal historic migration data in most places makes it difficult to know precisely how people have moved in the past, and thus how they might move in the future. Further, migration modelers still struggle to capture the nuanced relationship between interacting drivers of migration in different socioeconomic contexts (Lutz and Goldstein 2004). Models tend to focus on economic or demographic variables, but social, political, and cultural factors also play a role in determining who migrates, where they go, and the degree of choice in the migration process. However, we often lack reliable data to capture these non-economic drivers of migration and immobility.

Climate-related migration modeling fits into this context, as researchers incorporate climate-related indicators into population and migration models of all kinds. Climate-related variables are not yet commonly included in more general migration modeling, but a sub-field of climate-related migration modeling has emerged to address this gap. A distinct challenge to climate-related migration forecasting is the added uncertainty about what major tipping points may impact climate change in the future, along with the ability of humans to adapt to climate change via breakthroughs in technology or coordination.

Climate-Related Migration Forecasting Model Types

Researchers utilize a variety of models from different disciplines to forecast climate-related migration. Most climate-related migration forecasting modeling to date has been experimental, focusing on refining new methods. Model types include:

- **exposure models** that overlay climate-related hazards on a population distribution map to identify at-risk populations;
- **agent-based models** that simulate the actions and interactions of individual agents;

- gravity models that use population size, distance, and other variables to project future population distributions;
- **radiation models** that use population size and distance to model the flows of people between places;
- **statistical extrapolation models** or discrete history event models that model historical climate-migration interactions to project future trends;
- **systems dynamics models** that simulate the non-linear behavior of complex systems using complex econometric models and utility functions;
- **computable general equilibrium models** that use large, economic models to assess potential policy effects on real-world economic problems;
- **integrated assessment models** that integrate human systems and natural systems into one modeling framework to support informed policy making;
- **machine learning models** that have the potential to identify thresholds or tipping points in migration systems.

The above models differ significantly in assumptions made, data inputs required, and the nature of results. Each model type has advantages, disadvantages, and a preferred scope of application. For example, agent-based models (ABMs) are bottom-up, data-intensive models that tend to be better at exploring nuanced questions and mechanisms in circumscribed geographic settings such as villages, cities, and other sub-national settings. Gravity models are top-down models that tend to be better at forecasting spatial patterns over larger geographic areas, such as entire nations or regions.

Our review finds that ABMs are the most common model type used in climate-related migration forecasting. ABMs model the behavior of autonomous agents to explore how individual decision processes lead to changes at the population level. ABMs tend to require rich data inputs to calibrate the model. When this data exists, they are well-suited to explore causal and feedback mechanisms, migration motivations, and variations in migration or staying behavior based on individual and household characteristics. Typically, ABMs use data obtained through household survey (ideally longitudinal) research. One limitation to ABMs is the limited spatial precision of model outputs. ABMs tend to estimate volumes, or relative increases or decreases in migration flows from a particular area. They do not typically model source or destination areas. Like other models, ABMs are more accurate at predicting short-term changes in the volume and composition of migration flows. They are less reliable over the long-term.

Gravity models are another popular but fundamentally different alternative. The name comes from Newton's law of gravity, which states that any two bodies attract one another with a force proportional to the product of their masses and inversely proportional to the square of the distance between them. In gravity models, population size is indicative of relative “attractiveness,” but the force of attraction decays with distance. From this basic interplay of population size and distance, additional inputs can be added to explore their effects on future population distributions, including climate variables.

Gravity models do not directly model migration. Instead, climate-related migration is assumed to be the primary driver of deviations between population distributions in model runs that include climate impacts and the development-only (the “no climate”) models that include non-climate related drivers (Rigaud et al. 2018). This relatively straightforward approach makes them an attractive choice for migration modelers. However, using population as a proxy for migration can also be problematic, because population is also a function of changing administrative boundaries, fertility, and mortality. We know that fertility and mortality rates are also affected by climate change, yet in many gravity models, fertility and mortality rates are held constant.

Strengths of the gravity model include the ability to reproduce past shifts in population distribution, providing some assurance that if population trends continue to behave as in the past, these models can be trusted to forecast future trends. Gravity models are also relatively flexible in terms of data inputs and can generate results over broad geographic scales. These models also have limitations. First, much data used in global or regional models rely on sparsely collected census data over 10 year increments, which means the models may not accurately represent mobility patterns over short periods of time, short distances, and from places where census data is rarely collected. Census data typically focuses on interprovincial moves, though research suggests that in many places climate-related migration occurs mostly over short distances. Thus, as one expert shared, gravity models can overrepresent long-distance rather than short-distance movers, which may reflect different segments of society. Further, these models cannot tell us anything about migration motivations or the degree to which migration is voluntary or forced. Finally, they do not forecast migration well at a micro level. For this reason, they are not typically utilized for forecasting migration from small island states or other small geographic regions.

Another approach to forecasting climate-related migration draws on discrete history event modeling, which uses historical data to evaluate how sudden- or slow-onset climate impacts affect internal or international migration patterns. Those historical relationships are then used to project the probability of future migration under different climate scenarios. Discrete history event modeling has the advantage of basing model assumptions in real-world experiences—as one expert put it, "ground-truthing" relationships between climate change and migration—rather than extrapolating migration trends from population projections as gravity models do. These studies need to carefully control for other determinants of migration. When done well, they have been fundamental to enhancing our theoretical understanding of the climate-migration-development nexus (see, for example, Henry, Schoumaker, and Beauchemin 2004; Feng, Krueger, and Oppenheimer 2010; Nawrotzki et al. 2012; Gray and Mueller 2012; Gray and Wise 2016). Not all studies that use this approach attempt to forecast migration; nevertheless, discrete history event modeling contributes to the evidence base and theoretical assumptions that inform the development of other forecasting models, like ABMs. In this report, we refer to those that do forecast migration as statistical extrapolation models.

Although ABMs, gravity models, and statistical extrapolation approaches are some of the better-known model types, modelers continue to experiment with many others. Radiation models, for example, have been used to forecast migration flows between places with very few data inputs. As do gravity models, they rely on basic inputs related to population size, distance, and climate. The same limitations associated with using population as a proxy for migration discussed above for gravity models also apply to radiation models. Systems dynamics models offer the opportunity to explore complex systems dynamics and the potential impact of different policy scenarios, but they tend to lack spatial specificity. Computable general equilibrium and integrated assessment models share a similar focus on exploring the effects of policies on societal outcomes, but have only recently been applied to forecast climate-related migration. There is significant interest in machine learning models, but the large data-inputs required to use machine-learning significantly limits their application in data-scarce contexts.

State of the Field

To assess the state of climate-related migration forecasting models, we conducted a systematic literature search of climate-related migration forecasting models. Our search initially yielded a total of 30 models, which we coded with regard to a variety of factors including type, model prediction, geography, intervening variables, and data sources. Based on USAID's strategic interests, we removed models that focused solely on developed countries such as the United States and Australia. We focused on models that provide projections roughly over the next thirty years. We removed those that provided predictions for the year 2100 and beyond, as we judged that date to be too distant to inform USAID programming. Finally, based on our expert review, we added one statistical extrapolation model to ensure we had an example of this approach to forecasting. The final analysis included 20 models (see Appendix A.2). The following reviews the wide range of climate-related migration forecasting model types and key features of these twenty models.

Forecasting models covered multiple scales of migration (e.g., sub-national, national, regional, and global). Some forecast migration at one scale, while others combine scales and are counted twice in the summary statistics presented in Table 1. For example, 65 percent of the models forecasted trends at the national level, 30 percent at the global level, 15 percent at the regional level, and 15 percent at the community level. Of those models that focused on specific countries and fit the inclusion criteria, four focused on Bangladesh, two on Brazil, and two on Thailand. One model focused on Burkina Faso, Central America and Mexico (together), Mexico (alone), Kiribati, Maldives, and Nigeria, respectively.

Table 1. Overview of Key Characteristics of Climate Migration Forecasting Models Reviewed

Geographic Coverage	Count	Model	Count	Climate Hazard	Count	Type of Migration	Count
National	8	Agent-Based Model	7	Precipitation	11	Internal	15
National, Regional, Global	1	Gravity Model	2	Temperature	9	International	12
National, Sub-national	4	Computable General Equilibrium Model	2	Sea level rise	9	Involuntary°	3
Regional	2	Radiation Model	2	Storms	2	Voluntary°	2
Global	5	Economic Model	3	Drought	3	Permanent°	4
		Other models*	4			Temporary/ Circular/ Seasonal°	2

*Including Integrated Multi-Regional Applied General Equilibrium, Spatial Equilibrium, Statistical Extrapolation, and Systems Dynamics models.
°18 models did not state whether future migration would be voluntary/involuntary and 16 models did not explicitly consider permanent versus temporary migration.

Of the models we reviewed, 35 percent employed the agent-based model. Fifteen percent used an economic model (e.g., 2SLS, probit). Ten percent employed the gravity model, the computable general equilibrium model, and the radiation model. Integrated multi-regional, applied general equilibrium, spatial equilibrium, statistical extrapolation, and system dynamics models were each utilized once. Notably, not all models predicted migration for the same time horizon. Forty percent predicted to 2050, while others predicted to 2040, 2045, 2055, 2060, or 2080.

Model Inputs

The most common **climate-related data inputs** included in the forecasting models we analyzed were related to precipitation (e.g., average rainfall, monthly and yearly) (55 percent), temperature (e.g., average temperature) (45 percent), sea level rise (45 percent), droughts (15 percent), and storms (10 percent). The pairing of precipitation and temperature hazards was most common across all models, with 30 percent of the papers analyzing these together. Some models also included crop yields, water availability, sunshine hours, elevation, days of extreme heat, erosion, and flooding. Forecasts that take a scenarios approach most often use representative concentration pathways (RCPs) to project future climate scenarios. A RCP is a greenhouse gas concentration trajectory adopted for climate modeling and research by the Intergovernmental Panel on Climate Change (IPCC).

The most common **development-related data inputs** in the forecasting models we assessed are the shared socioeconomic pathways (SSPs). SSPs are scenarios of societal change developed by members of multiple research communities which include indicators of population, economic growth, education, urbanization, and the rate of technological development. SSPs describe scenarios for how the world might evolve in the absence of the implementation of additional climate policies. SSPs and RCPs are the most common aggregate indicators used to forecast potential future scenarios of climate change and development trajectories.

Some models include additional or independent inputs related to population distribution and the economic, political, or social context. Additional **demographic inputs** include gender, education level, age, rural or urban location, marital status, and number of children. Many of these variables are more easily incorporated into models that focus on micro-level household dynamics, such as ABMs. Some models also include population, fertility, or mortality projections.

Economic inputs—including Gross Domestic Product (GDP), household income, and occupation—are included in well over half the models we analyzed. Fewer models consider other economic factors, such as wage-differences between regions, percent of the population working in agriculture, employment data, household assets, level of education, local amenities, and local wage rates. Many models do not specify economic drivers directly, instead utilizing SSPs as proxies.

Political and social factors are not included in models as frequently as economic inputs. Of the models, only 25 percent included political inputs and 30 percent included social inputs. Political inputs can include government stability, and the freedoms, rights, and liberties enjoyed by citizens. In some cases, political inputs measure the political feasibility of climate adaptation through, for example, policies or global cooperation. Notably, only one model we assessed considered conflict. Social inputs tend to capture social networks, or the connections an individual or household has to others at origin or at a potential destination. Data can come from survey research that asks about this directly or can be implied by data on remittances or the size of the diaspora. Some papers utilized pre-existing datasets, such as those from the World Bank or United Nations.

Model Outputs

Models vary in the **type of migration** projected. Of the models we reviewed, the majority (75 percent) forecast internal migration trends, and just over half assess international migration (60 percent). Some models explore both internal and international migration. Most models do not state explicitly whether they are forecasting temporary or permanent migration. Short-term or temporary migration generally refers to migration lasting between three and 12 months, and long-term or permanent migration refers to a change of residence for one year or more. Only 20 percent of the models explicitly focus on permanent migration, while 10 percent investigate temporary, seasonal, or circular migration.[1] Only one model considers cascading migration, which refers to the impacts that in-migration may have on out-migration from the same location (De Lellis 2021). One model directly forecasts immobility (Smirnov et al. 2022). Gravity models have indirectly estimated trapped populations, suggesting many people will become trapped in a closed border scenario, but the models are not designed to directly forecast involuntary immobility (Jones 2020; Rigaud et al. 2018; Clement et al. 2021).

Some models forecast climate-related migration indirectly. For example, in gravity models, climate-related migration is assumed to constitute the difference in projected population distributions between scenarios with and without varying degrees of climate change. Other models, such as agent-based models, estimate relative changes in total out-migration, in-migration, or return migration. However, their results tend to be aspatial, meaning they do not indicate the trajectories migrants follow. Some models present numerical estimates for future climate-related migrants, while others present their findings in terms of percentage increases or decreases in migration.

Many models communicate their findings in terms of, a range of possible future trends based on different climate **scenarios**—for example, baseline, low emissions, or high emissions scenarios. Various development scenarios can also be paired with these climate scenarios. Experts consulted for this study who forecast using a scenarios-based approach encourage readers to consider the full range of possible outcomes, rather than choosing one most-probable outcome. Finally, some models may pair estimated increases in migration to urban areas with data on the food, housing, and job demands the migration would generate (Davis et al. 2018).

[1] As one expert stressed, the lack of a consistent definition of permanent migration among the studies makes comparing results challenging. This is a function of the data available to measure migration. Censuses usually include questions only about previous residences in the last year, 5 years, and 10 years. How social scientists treat a one-year move relative to a five-year move is at their discretion. The meaning of "temporary" migration can vary significantly among different societies. One expert shared that in one region where she does fieldwork, it is common to visit relatives for a month or more, which some might categorize as a temporary move while others would not.

Box 1. When are populations trapped?

Trapped populations—those who aspire to move but lack the ability to do so—are receiving increased attention in climate-migration research, but have not yet been given significant attention in forecasting (exceptions include Benveniste et al. (2022) and Smirnov et al. (2022)). According to experts interviewed, historical data can give some estimate of populations "left behind," which are then used to forecast future immobility. In gravity models, migration and trapped populations are modeled indirectly; the share of the population that does not move when exposed to climate stress is characterized as "trapped."

These estimates of trapped populations, however, are not based on data that tells us whether populations actually *want* to move. A household that chooses to stay behind and adapt in place may not see themselves as trapped. A rich body of empirical and qualitative research shows that many people do not want to move in environmentally stressed areas, even if better and more secure livelihoods could be obtained elsewhere (Zickgraf 2021; Czaika and Reinprecht 2022; Schewel 2020). Consider, for example, Indigenous populations in the Pacific Islands, where rising sea-levels and coastal degradation threaten local livelihoods, but where many prefer to remain on their ancestral homelands for cultural and spiritual reasons, including a deep connection to land and place-based identity, knowledge, and culture (Farbotko and McMichael 2019). This voluntary immobility in climate-stressed contexts has important policy implications. If populations are characterized as trapped, policy responses will naturally focus on facilitating migration and relocation programming. If populations are characterized as voluntarily immobile, more investments may be made to support in-situ adaptation (Farbotko et al. 2020; Schewel 2021).

Forecasting models cannot yet discern where and for whom future immobility will be voluntary or involuntary. A more accurate and appropriate term to describe this immobility is "resource constrained immobility," used by Benveniste et al. (2022) in their study of decreases in international migration under scenarios of climate change. Particularly for poorer and more vulnerable populations, climate change can reduce household resources and thus diminish the capacity to move *and* to invest in in-situ adaptation. ABMs are one model type well suited to discern between voluntary and involuntary immobility under conditions of climate stress; models and baseline assumptions can be calibrated using data from surveys that ask directly about migration aspirations and ability (Carling and Schewel 2018).

Nine Models

To illustrate more clearly the various approaches, strengths, and weaknesses of different climate-related migration forecasting models, we conducted an in-depth analysis of nine models purposely selected for variation across world regions, geographic scope (global, regional, or country-level forecasts), source (academic or gray literature), migration type (internal, international, and trapped populations), and model types (gravity, ABM, radiation, etc.). Key features of the models are summarized in Table 5, and a more detailed overview of each model and its data inputs/outputs is provided in Appendix A.3. The main approaches, contributions, findings, and limitations of each model are reviewed below. Models 1 and 2 are the most data- and time- intensive to produce. The first Groundswell report involved six European and

American institutions and took nearly two years to complete. It took a supercomputer four days to estimate results for just one scenario of Model 2. Both were oriented towards a broader audience and published as a World Bank report (Model 1) or long-form magazine article (Model 2). Models 3 to 9 are published in peer-reviewed journals and produced by smaller teams of academic experts.

Model 1. The Groundswell Reports

Model 1, the Groundswell reports, provide the first global picture of the potential scale of internal climate-related migration across six world regions: Sub-Saharan Africa, South Asia, and Latin America (Part I) and East Asia and the Pacific, North Africa, and Eastern Europe and Central Asia (Part II). Within each region, a country-level case study is included: Ethiopia, Bangladesh, Mexico, Vietnam, Morocco, and the Kyrgyz Republic. The Groundswell reports apply a scenarios-based gravity model to forecast future population distributions and areas that are likely to see greater in- and out-migration under different climate and development scenarios. The model applies demographic, socioeconomic, and climate impact data at a 14-square kilometer grid cell level using the Gridded World Population dataset to model likely shifts in population within countries. To address the uncertainties of analyzing migration over the next 30 years, the report considers three potential climate and development scenarios (using RCP and SSP scenarios as inputs): a pessimistic reference scenario, a more inclusive development scenario, and a more climate-friendly scenario. Climate impacts considered by the model include water scarcity, declining crop yields, and sea level rise.

Part I of the model projects that without concrete climate and development action, more than 143 million people—about 2.8 percent of the population of Sub-Saharan Africa, South Asia, and Latin America—may move within their own countries due to the slow-onset impacts of climate change. Part II, which additionally models East Asia and the Pacific, North Africa, and Eastern Europe and Central Asia—provides a global estimate of up to 216 million internal climate migrants by 2050 across all six regions. Projections tend to be higher for pessimistic scenarios versus more optimistic climate and development scenarios. However, there are interesting regional differences. In East Africa, for example, there is a larger share of climate-related migrants relative to the general population under more inclusive development scenarios as compared to the pessimistic scenario. This is largely explained by development-driven migration; more people tend to migrate as they gain access to higher education, incomes, and infrastructure (de Haas 2010). Estimates of climate migrants as a percentage of a region's total population generally fluctuates between zero and three percent of a region's total population, with North Africa being an exception where climate-related internal migration could reach as much as six percent (13 million, or half of all internal migrants) in 2050 under the pessimistic scenario.

The Groundswell reports are arguably the most ambitious climate-related migration forecasting model to date. Their findings reveal important insights into how slow-onset climate change impacts, population dynamics, and development contexts might shape future mobility trends. The model is notable for its flexible data inputs, scalability, and application across world regions. Importantly, Groundswell projections include relatively granular maps depicting which locations are likely to see more or less in- or out-migration, while many other model types lack this spatial information.

However, there are also limitations to the Groundswell model. Because it uses population as a proxy for migration, the model is subject to the same limitations reviewed above for gravity models generally. Further, the Groundswell model does not attempt to forecast international migration, planned relocation, involuntary immobility, or cascading effects. It omits many political and economic factors (like access to land, resources, jobs, conflict, or shocks) that will certainly affect future migration trends. It cannot capture migration over distances of less than 14 kilometers, and thus cannot be applied to smaller geographic areas such as small island states. The model does not include short-term climate variations or sudden-onset events. Like other forecasting models, it does not incorporate the impact of future adaptation efforts (e.g., improved crop varieties, irrigation, water conservation agriculture, or coastal defenses) into its projections.

Model 2. The Great Climate Migration Model

Model 2, the Great Climate Migration Model, provides an adapted and extended version of the Groundswell scenarios-based gravity model. ProPublica, in a collaboration with The New York Times Magazine funded by the Pulitzer Center, hired Bryan Jones, a geographer who had worked on the Groundswell report, to create a version focused on how climate change might lead to population shifts in Central America and Mexico, including how people may move within this region and to the United States. This model goes beyond the Groundswell model by forecasting international migration and highlights the potential for trapped populations.

The modeling approach consists of two modules loosely coupled over time, one focused on internal migration and the second on international migration. The internal migration module is similar to the Groundswell model, but adds additional climate hazards like flood risk, fresh water availability, and extreme heat days. It adds additional non-climate related variables including the age-sex structure of the population. The model uses the same Gridded World Population dataset used by Groundswell, but rather than uniformly distributing a population across a cell, it modifies the dataset to distribute populations in areas that show more buildings and infrastructure. The international migration module uses existing bilateral flow data to train and project the model as a function of sectoral impacts (crops, water, and productivity), political instability and corruption, global income levels (GDP per capita), and existing diaspora to estimate potential changes in origin-destination flows under five alternative futures scenarios based on different RCP and SSP combinations.

The Groundswell report projected an average of 1.4 to 2.1 million internal climate migrants in Central America and Mexico by 2050, depending on the scenario. To give a sense of scale, climate migration as a share of other internal migration ranges from 8.5 to 12.6 percent across scenarios. Model 2 does not present numerical estimates of internal migration that can be compared to Groundswell figures, but it does estimate between 680,000 to more than one million international migrants to the United States depending on government responses to climate change. The model considers the effects of more open or closed borders. It finds that closed borders reduce economic growth and urbanization in Central America and deepen poverty and hunger in rural areas, though projections for the location and scale of potential trapped populations are not reported.

The Great Climate Migration Model improves notably on the Groundswell model by including international migration, a wider array of environmental, political and population variables, and modeling policy effects related to closed or open borders. However, Jones (2020) helpfully notes several areas of uncertainty related to the socioeconomic and climactic dimensions of the model. Some inputs, such as age structure, sex ratio, built-up land, groundwater, and political stability remain constant in future projections—an assumption that is almost certainly incorrect because projections for these factors do not exist at one kilometer resolution and attempting to model them would add further uncertainty to the model. Similar to the Groundswell model, SSPs also have assumptions baked into them regarding future age-specific fertility and mortality, education, wealth, and international mobility, each of which would have significant impacts on future population outcomes but are also subject to error.

Other core limitations concern limited historical data on migration flows to calibrate the international migration model and the linear nature of climate-migration interactions in the model. For example, if a five percent decrease in water availability led to a two percent decline in the population of a given region in the past, the model assumes a future 10 percent decrease in water availability would lead to a four percent decrease in population. In reality, it is more likely that human response to climate stimuli will vary as a function of the intensity of those stimuli; as water scarcity worsens, the percent of the population that decides to leave is likely to rise in a non-linear fashion (Jones 2020; McLeman 2014). Gravity models are not yet able to capture these non-linear effects.

Finally, although the article discusses the potential for trapped populations, particularly under scenarios of closed borders, Jones is clear that the model was not designed to estimate them. Trapped populations are assumed to be those who do not move when exposed to environmental hazards, but the model has no way of determining who chooses to adapt in place and who is unable to move due to resource scarcity, disability, health problems, or family responsibilities. Because this approach models aggregate trends as opposed to household decisions, it is unable to explicitly model a decision not to migrate due to lack of resources.

Model 3. The Universal Model

Model 3, the Universal Model (Davis et al. 2018) applies a diffusion-based model of human mobility in combination with population, geographic, and climatic data to estimate the sources, destinations, and flux of potential migrants as driven by sea level rise in Bangladesh in the years 2050 and 2100. By linking the sources of migrants displaced by sea level rise with their likely destinations, the model purports to offer an effective approach for predicting climate-driven migrant flows, especially in data-limited settings. The authors describe the model as universal because it uses few data inputs and is parameter-free.

The baseline model results showed good agreement with available division-level internal migration from the 2011 Bangladesh census, meaning it successfully replicated internal migration in Bangladesh using information on population distribution and distance. However, this constitutes only a one-year projection (using 2010 data to forecast 2011 trends). By mid-century, the model estimates that nearly 900,000 people are likely to migrate as a result of direct inundation from mean sea level rise alone, and Dhaka will be the top destination for migration. In large part because of the generally high population density across Bangladesh, however, the authors find most migrants will choose destinations close to their homes. The authors also analyze the additional jobs, housing, and food that would be required to support these migrants at their expected destinations.

The model is distinct for how few data inputs are required. It builds on a radiation model published by Simini et al. (2011), which estimated internal and commuting mobility trends in the United States based on population distribution and distance estimates alone. By adding data inputs on elevation and projected sea level rise, Davis et al. (2018) present a very streamlined and simple approach to forecasting displacement from sea level rise. The model was expanded by De Lellis et al. (2021), who added a single parameter to the model on baseline migration rates, as well as a “resilience index.” These additions led to different predictions, however, namely a more country-wide distribution of migrants and a predicted outflow from Dhaka, raising concerns that radiation model outputs are too heavily dependent on the inputs and parameters modelers decide to include. Other models focused on sea level rise and migration in Bangladesh come to still different conclusions. Chen and Mueller (2018), for example, use a statistical extrapolation approach and find that inundation has negligible effects on internal migration in Bangladesh; gradual increases in soil salinity have more direct and important effects on internal and international migration trends. This suggests that, although the authors see the limited data inputs required for the universal model as a strength, it may also be a limitation.

Model 4. The Systems Dynamics Model

Model 4, the Systems Dynamics Model (Naugle et al. 2022), couples migration decision making and behavior with the interacting dynamics of economy, labor, population, violence, governance, water, food, and disease. The model is applied to a test case of migration within and beyond Mali. The model is notable for the wide range of factors incorporated beyond climate and population variables, particularly political, economic, health, and conflict-related factors, and its experimentation with how several different policy interventions might affect migration outcomes. The model outputs include the fraction of the Malian population choosing to live in each simulated region. Potential locations are rural Mali, urban Mali, neighboring countries (Burkina Faso, Cote d'Ivoire, Gabon, Gambia, Ghana, Guinea, Mauritania, Niger, Senegal), the United States, and 'the rest of the world' (as one category).

The model generally finds that as temperatures increase, economic factors make migration from Mali to other locations more attractive, and the population tends to move out of both urban and rural areas of Mali toward neighboring countries, the United States, and the rest of the world. The model examines the impact of various policy options on migration outcomes and finds that providing contraception (reducing birth rates) reduces migration by limiting pressures on the economy, resources, food availability, and water availability. Increasing the effectiveness of governance in the model improves the economic situation by increasing the internal gross regional product, and ultimately reduces migration. Increasing infrastructure and services provided by the Malian government was relatively ineffective at reducing migration pressures.

The focus of this model is on exploring feedback effects and policy interventions, which is an understudied area in climate-related migration modeling. The model does not identify geographic hotspots of out- or in-migration. This model is best interpreted as a simulation exercise, based on some unrealistic assumptions. For example, in the base case simulation, temperatures remain stable throughout the time horizon and gross regional product tracks World Bank (2017) projections. The authors do not take a position on the validity of the base case projection; rather, they emphasize the opportunity to explore the differences between this and climate change scenarios to understand the causes of variations in the results. Again, this highlights that the model is best seen as an exploration of systems dynamics and potential policy effects, rather than offering concrete numerical projections of future climate-related migration.

Model 5. The Dynamic Model

Model 5, the Dynamic Model (Entwisle et al. 2020), uses an ABM focused on land use, social networks, and household dynamics to examine how extreme floods and droughts affect migration from 41 rural villages in Northeast Thailand where rice cultivation is common. The ABM explicitly models the dynamic and interactive pathways through which climate-migration relationships might operate, including out and return migration, for each village. This model pays attention to variables that existing migration research confirms are fundamental to migration systems but are often left out of forecasting models: namely social networks, life-course dynamics, and return migration. This is one of the more sophisticated models to explore how climate change acts on already established migration processes that, as the authors describe, “are part and parcel of the life course, embedded in dynamic social networks, and incorporated in larger interactive systems where out-migration and return migration are integrally connected” (Entwisle et al. 2020, 1469).

The ABM is grounded in longitudinal survey, qualitative, spatial, social, and environmental data. Like Models 1 and 2, the model does not assume a direct “climate effect” on migration; focusing rather on how changes in precipitation affect crop yields and thus livelihoods and household assets. It incorporates potential feedback into the model, through, for example, social networks and remittances. Interestingly, the results find minimal to no climate-related effects on out-migration. One potential reason for this is that out-migration is already a normal part of social systems in this area, and these continue for other non-climate related reasons. However, the model finds that increased floods and droughts lead to a notable decline in return migration. Over time, the implication is that rural populations will decline. People will continue to leave as they always have, but many will no longer choose to return.

One strength of the ABM approach is the ability to run experiments. Running the model with and without social networks yields important differences in outcomes. In every scenario, without the facilitating effects of social networks, climate impacts decrease out-migration. This may be because social networks significantly lower the costs of moving, by sending money and helping prospective migrants (usually relatives) find housing and work. Without social networks, migration is a more individual decision and becomes costlier. The model also finds return migration stays constant without social networks. A likely explanation is that social networks are the main mechanism through which prospective return migrants learn about the hardships of floods or drought. Without social ties, decisions to return home are less affected by these climate impacts.

This model has several strengths. It is built on rich data inputs, including decades of panel survey data for this one region. Further, it looks at the full spectrum of migration, both out- and return-migration, and incorporates different propensities for migration across the life-course. Although the authors do not explore this much in their paper, the model is better suited than others to assess heterogeneity within and between villages and provide micro-level evaluations of how potential climate-related stresses might disproportionately impact marginalized or vulnerable populations.

The authors expressly state they “do not seek to replicate reality or predict any future,” rather they seek to predict the theories embedded within the model. A related limitation is that the model predicts increases and decreases in rates of out- or return-migration and yields no information on the spatial trajectories of migration flows. The data demands of this model also make it challenging to scale or apply in other areas that lack reliable, longitudinal data. Finally, this ABM model, like many other ABMs and computational models, rely on assumptions about what the underlying utility function looks like—that is, what people prioritize when they consider the costs and benefits of migration. In reality, we know utility functions can differ across populations, based on education, socioeconomic status, gender, culture, or personal disposition.

Model 6. The Inequality Model

Model 6, the Inequality Model (Burzyński et al. 2022), investigates the long-term implications of climate change on global migration and inequality. The model combines a discrete choice model with random utility and a gravity-based approach. It assumes an ambitious global scope, directly focuses on the impact of rising inequality on migration outcomes, and incorporates a range of climate variables (including changing temperatures, sea levels, and the frequency and intensity of natural disasters). The model analyzes the impact of these climate changes on productivity and utility in a dynamic general equilibrium framework. It considers slow-onset changes in temperature and sea level rise as well as sudden-onset natural disasters and extreme events, and it predicts global migration patterns at a 5 kilometer x 5 kilometer pixel level.

The model finds that climate change strongly intensifies global inequality and poverty, reinforces urbanization, and boosts migration from low- to high-latitude areas. However, it finds that only a small fraction of people suffering from the negative effects of climate change will manage to move beyond their homelands. Those who do move across borders tend to be more educated (especially those leaving Africa) compared to those who stay in their home countries. Median projections suggest that climate change will induce a permanent relocation of 62 million working-age individuals over the course of the 21st century. Massive international flows only occur under extremely pessimistic climate scenarios combined with highly permissive migration policies. The authors note that climate-related migration will be relatively small compared to migration driven by rising educational attainment and population growth differentials.

Strengths of this global model include a detailed spatial resolution of climatic and economic factors. It incorporates individuals with multiple characteristics, distinguished by age category, education levels, and origin. The model is also well suited for extensions of policy experiments. Limitations of the model include a focus only on economic, voluntary migrants. In the model, choices to stay or to relocate are made by adults between 30 and 60 years old. This choice seems unusual, considering that migration propensities are highest for adults between 18 and 35 years. The authors also make stylized assumptions about migration and migration decision-making that do not necessarily reflect real-world dynamics. For example, migration decision-making is modeled under conditions of full information, which is rarely the case. Migration decisions consider wage rates, migration costs, and the congestion externally related to the total population. This leaves out other consequential factors in migration decision-making, like the influence of social networks (see Model 6), migration ability, or place attachment.

Model 7. The Global Model

Model 7, the Global Model (Smirnov et al. 2022), applies insights from climate science and computational modeling to generate a satisfactory agent-based model that forecasts relative increases in internal and international migration and immobility in response to drought over the 21st century. ABMs are often used to capture micro-level migration decision-making at the household level at smaller geographic scales. This ABM forecasts global and national-level trends for drought-induced migration and immobility. Smirnov et al. (2022) use 16 climate models in conjunction with high-resolution geospatial population data to consider different policy scenarios. Although this model forecasts trends beyond our 2050 time horizon, we include it here because of its direct focus on forecasting immobility. No other model projecting to 2050 directly modeled climate-related immobility.

Model outputs are presented in relative terms: as the percentage change in total migration between different scenarios. The model's simulations suggest that a potential for drought-induced migration increases by approximately 200 percent under the current international policy scenario (corresponding to the current Paris Agreement targets). In contrast, total migration increases by almost 500 percent, should current international cooperation fail and unrestricted greenhouse gas emissions prevail. The authors are clear, however, that this model does not offer a representation of actual future realities. "In an effort to convey this point explicitly, we frame our key findings in relative, as opposed to absolute, terms." (Smirnov et all 2022, 3) Rather, the model should be taken as a tool to compare how the number of drought-induced migrants "might increase or decrease, in relative terms, between different climate and policy scenarios and for different countries."

This model is distinct for directly forecasting immobility. Immobile persons are defined as those exposed to extreme drought but unable to migrate due to the absence of suitable destinations in the final step of the model's algorithm. Immobility is projected to increase by about 17 percent by the end of the 21st century in the baseline scenario, which holds drought conditions based on the 2008-2017 decade constant throughout the 21st century, in contrast to 175.7 percent in the low emissions scenario and 568.2 percent in the high emissions scenario. The implication is that more severe droughts could significantly entrap populations. Interestingly, both migration and immobility increase under the high emissions scenario; greater immobility, the authors state, does not imply less overall migration.

The main sources of uncertainty in this model concern climate and population projections, the standardized precipitation evapotranspiration (drought) index (SPEI), and agent-based model parameters. The authors do not aim to explore migration motivations, causal mechanisms, or feedback dynamics. The model, by the authors' own admission, is based on coarse assumptions about human behavior and migration. "Humans are essentially automata following very basic rules… [They] do not have age, gender, resources, social capital, diaspora networks, or other characteristics, all of which undoubtedly influence migration behavior" (Smirnov et all 2022, 3). Another important limitation is that the model assumes all populations have equal exposure and vulnerability to drought within each grid cell of the world map, which does not reflect real-world heterogeneity in who is most affected by drought and who has greater or lesser capabilities to migrate or adapt in place. Finally, the model claims to forecast involuntary immobility, but does not distinguish between potential voluntary and involuntary outcomes. The model does not directly include factors that affect real-world involuntary immobility, like resource-scarcity, conflict, border restrictions, or sociocultural factors. The authors suggest future iterations of the model should include social networks, border restrictions, and other institutional constraints on international migration.

Model 8. The Small Island Model

Model 8, the Small Island Model (Speelman et al. 2021), uses an agent-based model to examine migration flows in the Maldives under various climate, political, and social scenarios to 2050. Small island states face unique climate-related challenges, including sea level rise, lack of land for managed retreat, and limited international migration pathways. Small island states pose distinct challenges to migration modelers, as they are often too small for gravity models and other approaches that rely on gridded population data. For this reason, Speelman et al. (2021) use an ABM that simulates migration from 1985 to 2014 and then forecasts a range of potential demographic futures to 2050. They develop a conceptual model for migration that highlights key push and pull factors and combine it with three factors that influence migration intentions: attitudes, subjective norms, and perceived behavioral control (Ajzen 2011). They apply the model across six possible future scenarios, each characterized by a combination of high/low population growth, little or strong government intervention, open or closed borders, and high or low emissions.

Using census data as the primary population data input, Speelman et al. show that the Maldives has been characterized by an active migration system over recent decades, with many islands having declining populations and a large urbanization trend around the capital Malé. They find that overall, across all future scenarios, these trends will continue in the decades to come. The growth of Malé continues while many other islands see population decline.[2] Revealing the importance of fertility trends, the model projects a decline in migration in the early years of the projections, due to a sharp decline in birth rates between 2000 and 2006. It rises again between 2023 and 2030 due to higher birth rates from 2006 to 2014. Overall, the findings suggest "migration in the Maldives has a strong inertia, and radical change to the environmental and/or socio-economic drivers would be needed for existing trends to change" (Speelman et al. 2021, 283).

The authors caution that the scenarios considered provide examples of future scenarios, not predictions. "Their purpose is simply to propose contrasting ways in which political and economic factors would combine to influence migration" (Speelman et al. 2021, 290). Limitations of the model highlighted by the authors include the need for more specific formulation of economic, social, political, and environmental change, linked to the need for more and better data. The model also excludes foreign residents, which is understandable given the focus on native populations. But this remains a consequential population group (~64,000 residents), and their in-migration can affect inter-island migration dynamics. Finally, the model does not integrate future shocks, adaptation, or rapid changes in demographic processes, like the short-lived but sharp decline in fertility rates in the early 2000s, which may occur again.

Model 9. The Statistical Extrapolation Model

Model 9, the Statistical Extrapolation Model (Chen and Mueller 2019), approaches model climate-migration interactions using historical data; the relationships uncovered are then used to forecast future trends. This model is used to forecast climate-induced international migration from Bangladesh. It is distinct for modeling several climate-related factors, including remote-sensing measures of flooding and rainfall and in situ measures of monsoon onset, temperature, radiation, and soil salinity. It uses nationally representative migration data to evaluate which locations and population groups are more likely to migrate across the border to other South-East Asian countries, with a particular focus on international migration to India.

Chen and Mueller find that climate variables vary in their relationships to cross-border migration. Short-term, adverse weather events are associated with decreased international migration, while increases in soil salinity increase cross-border migration. Soil salinity has a stronger effect on migration from poorer households. The model outputs do not provide an estimate of climate-related migrants by a particular date; rather, projections are based on the degree of future climate change. For example, the model predicts a total of 17,874 more migrants moving to India in response to a one standard deviation increase in soil salinity, with out-migration concentrating in the southwestern coastal regions of the country.[3] The model predicts a total of 5,754 *fewer* migrants moving to India in response to an increase in flooding of one standard deviation. The authors do not attempt to forecast when those changes in soil salinity or inundation will occur.

[2] To give a sense of the scale of change, the population of the capital of Maldives, Malé, grew from 67,939 in 2000 to 109,635 in 2014. In 2050, its population is projected to be between 169,819 and 217,976, depending on the scenario considered. The smallest island, Kandoodhoo, grew from 2,224 to 3,333 between 2000 and 2014, and is projected to have a population of between 5,260 and 3,796 in 2050. Feydhoo (Addu) grew from 2,829 to 3,397 between 2000 and 2014, and is projected to have a population of between 2,768 and 1,706 in 2050, the smallest island population projected.

[3] To give a sense of relative scale, there were 2.5 million Bangladeshi migrants in India in 2020 (MPI 2022).

Chen and Mueller examine household vulnerability to flooding and increased soil salination to explore whether households with greater human, social, or physical capital are more inclined to migrate. They also consider the impact of age, gender, and religion on migration outcomes. They find that wealthier households are less likely to migrate in response to gradual changes in soil salinity, perhaps because they are better equipped to diversify livelihoods locally, while poorer households are more likely to use international migration as an adaptation strategy as soil salinity increases. These and other related findings provide important evidence for how climate-migration interactions might vary for different social groups and more vulnerable households. Chen and Mueller do not use these more nuanced analyses, however, to forecast future trends based on household characteristics.

The authors are transparent about the limitations of their model. They lack information on the duration of each event and are unable to validate whether moves are temporary or permanent. The measure for soil salinity is relatively coarse and focuses on changes over 5 years. This misses the potential mobility implications of seasonal or annual variations. They also note that soil salinity can result from changes in landscape and deforestation along the coast, sea level rise and storm surges and ground management. It is not clear what factors are contributing most to increase soil salinization and thus where policy makers should prioritize funding for adaptive investments. Finally, they note one drawback of using a large administrative dataset in the absence of detailed survey questions that would be required to explore more carefully the reasons for migration and obstacles potential migrants face.

Table 2. Description of nine climate-related migration forecasting models

Model #	Brief title of paper	Coverage	Country	Model	Precip	Temp	SLR*	Storms	Drought**	Other	Type of Migration ***	Time horizon of prediction	Other Factors *****	Examples
1	*Groundswell I & II*	Global, Regional	Bangladesh, Mexico, Ethiopia, Morocco, Vietnam, Kyrgz Republic	Gravity			✓	✓		water and crop production	Internal	2050, 2100	Dem, Dev	population projections, SSPs
2	*The Great Climate Migration*	Regional	Central America, Mexico, United States	Gravity	✓	✓	✓			ecosystem impacts, flood, groundwater, extreme heat	Internal, International	2020-2050, 2100	Pol, Econ, Dem, Soc, Env, Dev	diaspora, instability. Violence, corruption, GDP, SSPs
3	*Universal Model*	National	Bangladesh	Radiation			✓				Internal, International	2050, 2100		
4	*Systems Model*	National	Mali	System Dynamics	✓	✓				extreme events	Internal, International	2060	Econ, Pol, Dem, Dev, Soc	labor supply, rural/urban, violence, governance, level of tech, food availability
5	*Dynamic Model*	National, Sub-national	Thailand	ABM					✓	crop production, floods	Internal, Return	25 years****	Econ, Soc	social networks household assets, remittances
6	*Inequality Model*	Global		CGEM*****		✓	✓				International	2040, 2070, 2100	Econ, Dem	education, age, wage rates, fertility projections, urbanization, GDP
7	*Global Model*	Global, National		ABM					✓		Internal, International, Immobility	2008-2100, 2081-2100	Dem, Pol	population projections, open borders
8	*Small Island Model*	National	Maldives	ABM			✓			tsunami, erosion, damages to reef	Internal	2014-2050	Dem, Pol, Soc	governance, open/closed borders, networks, population projections
9	*Statistical Extrapolation Model*	National	Bangladesh	SEM	✓	✓				flooding, soil salination, bright sun	International	Unstated	Dem, Econ, Cul	gender, age, assets, religion

*Sea level rise **We also coded for soil quality and desertification as hazards, but none of the models incorporated them. ***We also coded for cascading migration, but none of the models incorporated it. ****The authors do not look at specific years. Rather, they give data on how migration might expand over any 25 years under the climate scenarios tested. The data used was gathered in 2000 and 1990-2008, so a time horizon might be 2025 or 2033. ***** Economic (Econ), Political (Pol), Demographic (Dem), Social (Soc), Technological (Tech), Environmental Resilience (Env), Aggregate Development Indicators/Scenarios (Dev), Culture (Cul). ***** Computable General Equilibrium Model.

Summary of the Nine Models

The forecasting models reviewed above provide insight into the wide range of modeling approaches being developed to forecast climate-related migration. Overall, the authors of these models and the experts interviewed emphasized the uncertainties inherent in the models and urged caution in interpreting their results. The models are best used as tools to explore potential migration scenarios under various climate, development, and policy futures; to test theories; and to explore how climate impacts may affect broader social systems within which migration is embedded. This summary section begins with a short review of some of the climate-related migration hotspots identified in the global models we analyzed, before considering key limitations and evidence gaps that hinder the real-world applicability of these projections.

Future Climate-Related Migration Hotspots

Migration hotspots refer to locations more likely to experience higher degrees of climate-induced in- or out-migration. Hotspots of climate-driven out-migration typically identified include low-lying cities and coastlines vulnerable to sea level rise and areas of high water and agricultural stress. Climate in-migration hotspots tend to be locations with better climatic conditions for agriculture as well as cities able to provide greater livelihood opportunities (Rigaud et al. 2018).

Three of the models provided a global-level overview of potential future climate-related migration. The Groundswell report provides numerical forecasts of internal migrants for six world regions (Model 1), with detailed maps illustrating potential future migration hotspots in East Africa, South Asia, Mexico and Central America in Part I and North Africa, Lower Mekong, and Central Asia in Part II. We encourage readers to refer to the Groundswell summaries for more specific projections of migration hot spots. However, a few general findings from the six regional analyses are summarized here.

Within **East Africa**, the report predicts this region will see between 6.9-10.1 million climate migrants by 2050 depending on the climate-development scenario. Some of the major origin areas include the coastal regions of Kenya and Tanzania, western Uganda, and the northern highlands of Ethiopia. Inland hotspots are driven by declining water availability and declining crop yields, while the coastal areas reflect rising sea levels and storm surges. Migrants are projected to settle in the regional countries of the Lake Victoria Basin, the eastern highlands of Ethiopia, and the area of Lilongwe (the capital of Malawi). These destinations tend to have more favorable climate conditions and more limited impacts from climate change compared to coastal areas. These areas also tend to be already densely populated and lie along national borders.

In **South Asia**, Groundswell forecasts between 11.4 and 35.7 million migrants depending on the climate scenario. Migrants will primarily leave the eastern and northern parts of Bangladesh, the northern Gangetic Plains, the corridor from Delhi, India to Lahore, Pakistan, and metropolitan coastal cities like Mumbai and Chennai, India and Dhaka, Bangladesh. The main areas for in-migration are the southern Indian highlands, particularly between Bangalore and Chennai, northwest India, and Nepal. In general, the report finds that irrigated and rice-growing areas will see increased out-migration while rainfed areas will see more in-migration. The in-migration hotspots are driven by expected improved water availability in those areas, especially southern India.

In the region of **Central America and Mexico**, the absolute number of climate migrants is expected to be much lower than the other two regions, with a range of 0.2-3.9 million depending on the scenario. Groundswell anticipates that most climate migrants will leave the low-lying areas of Central America and Mexico, particularly along the Gulf of Mexico and the Pacific Coast of Guatemala. Some cities like

Monterrey and Guadalajara, Mexico will also be sites of out-migration. Generally, hotter, low-lying, and rain-fed areas of this region will be places of out-migration under climate change. Conversely, pastoral, rangeland, and highland areas will see populations increase due to climate migrants moving into them. The Central Plateau of Mexico and the highlands of Guatemala are projected to become hotspots of in-migration under climate change.

In **North Africa**, Groundswell predicts the region of North Africa could have between 4.5 and 13 million climate migrants by 2050. Migrants will come from the coastal areas of the region including the Nile Delta, northeast of Tunisia, northwest of Algeria, and western Morocco. The major cities of these areas will be the primary sources of out-migration in North Africa. This will be due to rising sea levels and reduced water availability. The area around the Atlas foothills in Morocco will also see reduced water availability and thus increased out-migration. The areas that will see more in-migration will be those where water availability is unchanged or increased. These areas include primarily the Nile Valley and central Delta area, southern coasts of Tunisia, eastern coasts of Algeria, and the northern part of Morocco. These are home to the major cities of Cairo, Algiers, and Tunis. Because of their higher elevations, many of these cities will see increased in-migration, despite their locations near the coast. They also are projected to have greater water availability and crop productivity.

In the **Lower Mekong region**, 3.3-6.3 million people are expected to be climate migrants by 2050. This is due to sea-level rise in the coastal areas and decreased water and crop productivity elsewhere. Specifically, the major areas for out-migration will be in northern Vietnam, the Vietnam Mekong Delta, Ho Chi Minh City, and central Thailand and Myanmar. In-migration will be concentrated in southern Thailand, the inner portions of the Mekong Delta in Vietnam, the Red River Delta in Vietnam, southern Myanmar, and parts of the Irrawaddy River. All of these in-migration locations are predicted to have greater water availability and crop productivity, but some also lie along the coast where sea-level rise and storm surges will affect them. This poses a problem for these areas with a greater population and climate change impacts.

Within **Central Asia**, 1.7-2.4 million people are expected to be climate migrants by 2050. Those migrants are expected to come from the southern border of Kazakhstan, areas surrounding the Ferghana Valley of Uzbekistan and Tajikistan, and Bishek. Minor hotspots of out-migration are along the Amu Darya River in Turkmenistan and Uzbekistan. This is likely due to decreased water availability and crop productivity. In-migration is expected in places with increased water availability like the Ferghana Valley, lower elevation areas of southern Tajikistan, and northern Kazakhstan.

The other two models that provided a global picture of future trends unfortunately do not provide similar outputs, making it difficult to compare findings across models. The second global model, Model 6 (Burzyński et al.) provides numerical forecasts for local, regional, and international migration globally. But the findings presented in the paper do not identify migration hotspots at the same granular level as Groundswell. The paper focuses instead on detailing broad trends in future movements of working-age adults with higher or lower levels of education at the global level. The model identifies major corridors of international migration under an RCP7.0 scenario in 2040, 2070, and 2100. For high-skilled international migrants, the predominant corridors are from Asia to Europe (10 million people), from Asia to North America (6 million people), from Africa to Europe (6 million people), and from South America to North America (5.5 million people). For low-skilled migrants, predominant pathways are from Asia to North America (3.6 million people), from Asia to Europe (1.5 million people), and from South America to North America (1 million people). It should be noted that although the primary focus of the published article was not to identify migration hotspots at a more granular level, the model could be applied to do so.

The third global model, Model 7 (Smirnov et al.), reports relative changes in percentage of internal and international migration and immobility by country, region and globally; it does not offer spatial information on where migration hotspots will be. Nevertheless, the model analyses RCP scenarios 8.5 and 4.5 and projects the greatest future displacement (over two percent of the world's total displacement) in Egypt, Syria, Senegal, and Guatemala, and greatest immobility (over two percent of world's immobile population) in Mali and Syria. It forecasts the top five international migration corridors (origin-destination) will be India-China, Venezuela-Colombia, Nigeria-Niger, Pakistan-India, and Morocco-Algeria.

Key Limitations and Evidence Gaps

Each model type has its own distinct strengths and limitations, which are reviewed in greater detail in the above sections. The following summarizes the general limitations and data gaps common across forecasting models reviewed in this project.

Regarding **climate hazards**, the nine forecasting models we reviewed focus primarily on slow-onset climate changes, rather than sudden-onset events. From a modeling perspective, this is understandable considering the consistency of data across hazards such as temperature or precipitation and the difficulty of predicting major natural disasters. However, sudden-onset events are likely to compound the socioeconomic and environmental impacts of ongoing slow-onset events and will be key drivers (often temporary) of displacement. Relatedly, many models forecast migration in relation to one or two climate hazards only (e.g., sea level rise, drought), when in reality, several interrelated slow- and sudden-onset climate changes will affect future population mobility or immobility. In the broader climate-migration literature, discrete history event modeling has been used to model historical responses to both sudden-onset events and multi-hazard environments, and these findings can ground future projections, even if the exact timing or severity of future natural disasters remains unknown.

Non-climate related drivers of migration remain underrepresented in the models we reviewed, including political, economic, and cultural factors, and attitudes toward destinations or host countries. Only half of the selected models include covariates for economic and political drivers, and the measures used to capture these conditions often differ significantly for each model. Economic indicators used include GDP, labor supply, employment, or wages. Political variables include indicators for governance, violence, corruption, and instability. Other dimensions related to infrastructure or technology were far less common. Indicators capturing cultural or social norms (e.g., gendered norms, place attachment) are completely omitted and remain difficult to measure, though these play an important role in shaping a given population's attitudes towards migration.

It is notable that almost all models that take a **scenarios-based approach** use RCP and/or SSP scenarios derived from the IPCC Fifth Assessment Report. These have become the go-to pathways for forecasting models to consider a range of climate and development scenarios and thus a range of potential climate-related migrations. The strengths, limitations, and uncertainties entailed in generating these climate and development pathways are beyond the scope of this report, but each brings its own set of assumptions and uncertainties to the scenarios used for migration modeling. For example, there are still many unknowns about future temperature responses to carbon dioxide emissions. Similarly, the pace of sea level rise remains challenging to predict given uncertainties about ocean heat uptake and the rate of glacier and ice sheet melt.

Regarding **intervening obstacles or facilitators**, of the nine models examined, only the dynamic (agent-based) model accounts for **social networks.** Social networks are a fundamental migration facilitator, impacting who is most likely to move and where they will migrate, yet few models are able to incorporate this dimension of migration processes. Also known as the "friends and family effect," social networks significantly reduce the informational, capital, and social costs of moving (Hatton and Williamson 1994). Some models included indicators for border controls (an intervening obstacle), but this was mostly explored in terms of open or closed border scenarios, neither of which are likely in the coming decades.

Forecasting models still tend to assume a relatively **linear relationship** between climate change and migration, and although we now know climate change and migration interact in a non-linear way, it is difficult to adequately capture future tipping points or thresholds in climate-migration relationships. Relatedly, climate-related migration forecasting models are not yet able to reliably identify or integrate potential **cascading effects**.[4] Even if research shows that cascading effects are real and occurring, experts shared the extreme difficulty of forecasting those effects with confidence.

Regarding **model output**s, future research would benefit from exploring how internal and international migration act as complements or substitutes. Internal migration can often turn into international migration. Conversely, the migration of one individual can enable a household to avoid migration, bolstered by the value of remittances from the individual (Stark and Bloom 1985). Only one model included return migration, though research suggests the pattern is common following sudden-onset disasters and displacements, and thus has important implications for post-disaster planning.

Only one of the nine models attempts to forecast suppressed mobility, immobility or **"trapped populations"**—those who aspire to migrate but lack the ability to move. In addition to the push and pull factors that encourage migration, migration trends are also shaped by **retain and repel factors**, as well as political, economic, or other constraints that deprive individuals and households of the capability to move (Schewel 2020). Retain and repel factors are not yet incorporated into the theoretical frameworks that underlie these models, which remain focused almost exclusively on push and pull factors.

Finally, no model can predict major unforeseen events, such as pandemics, wars, or technological revolutions such as the internet that may fundamentally reshape migration flows. This rather obvious point is arguably the most consequential factor undermining the accuracy of all the models' long-term projections.

Areas of Future Research

The statistician George Box famously said, "All models are wrong, but some are useful." Statistical models always fall short of the complexities of reality but that does not mean they are useless. Models can reduce uncertainty, even if they do not eliminate it completely. The models described above are some of the best early attempts to forecast climate-related migration. Modelers are well aware of existing limitations, and they are making consistent efforts to push the field forward. The field is progressing quickly, and many promising advancements have yet to be published.

The Africa Climate Mobility Initiative, a collaboration of the African Union Commission, the United Nations, and World Bank, is one ongoing initiative that explicitly builds on the Groundswell model by adding maximum rural/urban population densities, slow onset ecosystem impacts, and rapid onset events like flood risk projections. It includes additional SSP scenarios running in five-year increments and at a resolution of 4km grid cells (de Sherbinin et al. 2022). Researchers are also seeking to incorporate different forms of adaptation into the assumptions of SSPs, which currently fail to make nuanced assumptions about

[4] See De Lellis et al. (2021) for one attempt to model cascading migration.

the various ways humans are adjusting to climate change (Reimann 2022). The African Climate Mobility Initiative is also notable for its deliberate efforts to pair modeling with qualitative research and stakeholder engagement.

Beyond specific projects, expert interviews highlighted four general areas for further research. The first is establishing a multi-level modeling approach—for example, combining gravity models with agent-based models—so the strengths of one can compensate for the limitations of the other. Specifically, gravity models could be used to identify potential hotspots of migration, and agent-based models could be used in those hotspots to model rates of migration for different social groups. System dynamics models could also be integrated to better understand the effects of various policies in those locations. A second area of interest is machine learning. Machine learning offers the prospect of identifying thresholds or tipping points in climate-migration interactions–that is, identifying at what point a particular climate stress tips an existing migration system in a new direction. But because machine learning requires very large data inputs, it is difficult to apply to many regions of the world where reliable data is scarce.

Third, experts highlighted that many models are equipped to explore the impact of adaptation or development interventions, and more research attention could be directed towards this aim—for example, modeling the migration impacts of sudden flows of financial capital or the adoption of air-conditioning. Fourth, experts highlighted the need for greater trans-disciplinary collaboration between climate scientists and social scientists. Measurements and assumptions around exposure and vulnerability to climate change remain relatively coarse in current forecasting models. Regarding sea level rise, for example, it is often assumed that all households have the same level of exposure and vulnerability to inundation, whereas the duration, intensity and depth of flooding can vary significantly across a single village, and the adaptive capacity of households in that same community can be highly unequal, leading to different migration and immobility outcomes.

The most important advances in forecasting may come from modelers working on population or migration projections, not necessarily from those looking at climate-related migration. In this regard, Simini et al. (2021) recently developed a "Deep Gravity" model that generates flow probabilities, exploits many features (e.g., land use, road network, transport, food, and health facilities) extracted from voluntary geographic data, and uses deep neural networks to discover non-linear relationships between those features and mobility flows in England, Italy, and New York. Just as the earlier radiation model developed by Simini et al. (2012) influenced the Davis et al. (2018) model for Bangladesh, new advances in population or mobility modeling may set the stage for more advanced climate-related migration modeling.

Policy Implications

Modelers urge caution in interpreting the results of climate-related migration forecasts. At this stage of understanding of climate science, models and their accompanying projections are best understood as explorations of systems dynamics, ways to test theories or consider potential policy effects, and tools for considering a range of possible futures contingent on particular assumptions—what Jones (2020) calls a "a set of 'what if' scenarios." Lustgarten, the author of the New York Times Magazine report, writes, "As with much modeling work, the point here is not to provide concrete numerical predictions so much as it is to provide glimpses into possible futures. Human movement is notoriously hard to model, and as many climate researchers have noted, it is important not to add a false precision to the political battles that inevitably surround any discussion of migration."

Bryan Jones (2020) suggests "it is the variation across the different scenarios that should be considered as a starting point for discussions of potential policy intervention, areas that require additional research, or simply to start focusing on questions that will be critical to anticipating and planning for climate-induced migration appropriately." Other experts echoed this opinion. In theory, if models come to a similar conclusion about potential hotspots for out-migration or in-migration under various scenarios, or across multiple models, policy-makers could have more confidence in targeting these regions with additional investment, programming, and support. Yet at this stage there are not enough models being developed for the same geographic region to make multi-model comparisons and validation possible for many world regions where USAID works. One important exception is Bangladesh, where at least seven models have attempted to forecast climate-related migration, and a future study could systematically compare findings across these models and begin validating projections.

Exposure Modeling

Given the limitations of accepting the results of current models, one strategy is to return to the origins of climate-related migration forecasting: exposure modeling. Exposure modeling, or hazard mapping, was one of the first approaches to identifying populations at risk of climate-induced displacement. When modelers assumed all populations in at-risk regions would be forced to migrate, this gave rise to catastrophic, unrealistic migration forecasts. We now know that many populations in environmentally stressed regions do not migrate. Many will choose to stay and adapt in place; others may become trapped in place; still others may move such short distances or for such short time-periods that we do not assess this mobility as migration. Recognizing this, exposure mapping remains an important tool to identify populations whose lives and livelihoods are threatened by climate change and to target development assistance accordingly. Exposure mapping could become more sophisticated as natural scientists, social scientists, and other stakeholders work together to develop more refined maps of potential exposure, vulnerability, and adaptive capacity.

Although the precise consequences of climate stress on human mobility or immobility are difficult to predict, more general research at the climate-migration nexus support three areas of investment: 1) in-situ adaptation in climate-affected areas, recognizing that many households will prefer to stay in their home communities; 2) facilitating migration as an important adaptation strategy to cope with climate change, whether seasonally or permanently; and 3) expanding access to housing, employment, and services in urban areas and major cities neighboring climate-affected regions, as these are the most likely destinations for distress migrants. Research suggests the destinations of climate-related migrants are often within close proximity to their origin (Fussell et al. 2014). In places where international migration systems are increasingly robust – for example, between Central America and the United States, Burkina Faso and Côte d'Ivoire, or Bangladesh and India – it can be assumed that climate-related migration will also follow those established migration pathways.

Foresight Research

Foresight research constitutes another tool that may be used to anticipate potential climate-related migration trends for particular regions.[5] Foresight exercises, also referred to as "qualitative migration scenarios," bring together migration experts, stakeholders, and scholars to consider potential scenarios

[5] See 'Future Migration Trends' in the Migration Data Portal: https://www.migrationdataportal.org/themes/future-migration-trends

for future migration (Vezzoli et al. 2017). These exercises have been conducted by the Global Migration Futures project and contributed to the Future of International Migration to OECD Countries report and the British Government's influential Foresight Report (Black et al. 2011). Foresight research could be particularly useful in exploring future climate-related migration trends in particular regions to inform USAID policy. With climate migration modelers working alongside academics from a range of fields, including the natural sciences, policy-makers, and other stakeholders, migration forecasting model findings can enhance more qualitative knowledge of regional dynamics.

The benefit of foresight research is that scholars who specialize in a region may be able to identify gaps and inaccuracies in the inputs or assumptions of forecasting models, offer cultural and historical insights that might improve them, and offer key caveats about the applicability of the models' findings for particular populations or sub-regions. For example, one expert shared an anecdote about a forecasting model for Nigeria that predicted greater movement to the North of the country where land and climate conditions could sustain larger populations. The model did not account for the control of these same areas by militant groups, making it unlikely them unlikely destinations for voluntary inflows of migrants. Experts also mentioned that it is common for forecasting models to assume a standard level of exposure and vulnerability across a particular region. Natural scientists may be better equipped to look at differences in exposure and vulnerability at the household or community-level, while social scientists and migration scholars may be able to add nuance to who is most likely to use migration as a coping mechanism versus adapting in place. Where models exclude social networks, migration scholars can share information on established migration pathways that new movements are more likely to follow.

Improved Data Analytics

To further improve climate-related migration forecasting, resources may be best utilized upstream in the modeling process, where all experts agree there is a dearth of resources dedicated to the most important modeling input: data. Migration poses unique challenges to data collection, as mobility makes respondents difficult to locate, particularly for large-scale surveys. Existing longitudinal surveys with high quality tracking tend to be limited in size and scope, both temporally and geographically (Chen and Mueller 2019). Collecting high quality data at adequate scale is often not feasible in terms of time and financial resources.

Innovative ways to collect migration and mobility data are emerging in the form of cell-phone data and experiments with remote sensing and earth observation data. However, investments in high-quality and reliable censuses remain critical for larger modeling efforts; much data collected in censuses globally is inaccurate and unreliable yet forms the basis for most population projections. Investments in the statistical bureaus of host countries is one important way to build capacity for regular and reliable census data collection. In parallel, international organizations like the United Nations Department of Economic and Social Affairs, the International Organization for Migration and the United Nations High Commissioner for Refugees remain important sources of global population, migration, and displacement data, including flow monitoring.

In addition to census data, more high-quality individual and household survey data is needed to uncover migration histories, intentions, and perceptions of climate change. A major challenge of surveying to anticipate climate-related migration is that many people do not conceptualize climate change as a driver of their migration; rather, the downstream effects of climate change (e.g., loss of income) as well as other political, socioeconomic, and other factors are more often cited as the primary motivations for moving. As such, surveys must be conscious to address climate change impacts alongside other drivers of migration.

Given the need to enhance understanding about the climate-migration-development nexus, USAID could also consider systematically including questions about migration decision-making and behavior into regular monitoring and evaluation surveys in climate-stressed regions. This would expand the evidence base available to assess which population groups are more likely to migrate or to stay, and how different development interventions affect migration aspirations and ability in climate-stressed contexts.

Enhancing predictive tools also requires more foundational research, not only future-oriented research. A more robust knowledge base is needed to clarify how societies have historically and are currently responding to climate change through movement. This will improve the conceptual understanding and the theoretical frameworks that shape forecasting models. In this sense, we echo the recommendations of the 2021 United States government *Report on the Impact of Climate Change on Migration* to consider investments in research, analysis, and programming. Such investments will help build understanding and address important questions on the likely evolution and consequences of climate related migration, including but not limited to: How do different social, economic, geographic, political, and other characteristics mitigate or exacerbate the effects of climate change on migration? What geographies' conditions are most associated with the risk of immobility and trapped populations? What is the role of migration in supporting adaptation and resilience from the household to national scales?

Key Takeaways

- **The field of climate-related migration forecasting is still in its infancy.** The volume and direction of climate-related migration predicted by these models to horizons like 2050 should be taken as notional at best. Experts urged caution in using numerical estimates to inform policy and programming. Instead, they suggested, models may be better suited to explore possible future pathways, and policies oriented towards encouraging best-case scenarios.

- **The scenario-based approach is preferable to single narratives in climate-related migration forecasting, precisely because of uncertainty surrounding many inputs and the outcomes.** Modeling human behavior, including migration, is an exercise fraught with uncertainty, and accounting for climate change only compounds this uncertainty. Therefore, the full spectrum of future scenarios should be considered when using migration forecasts.

- **Climate change will affect migration, but it is one of many drivers.** Climate variation and change will increasingly affect migration decision-making and migration patterns in coming decades, but climate impacts are heavily mediated by political, economic, social, technological, and cultural factors. Although models are advancing quickly, current approaches lack the sophistication to adequately capture how climate-related factors intersect with other non-climate related drivers of migration and immobility for different social groups. The most promising advancements may come from improving general migration models that better integrate climate-related impacts.

- **Migration and immobility outcomes specific to gender or marginalized populations are not yet a major focus of climate-related migration forecasting models.** Statistical extrapolation approaches and ABMs have begun to explore these differences more robustly. Targeted data collection efforts to capture migration aspirations, plans for adaptation and migration, and migration behavior in climate-stressed contexts will contribute to more nuanced forecasting specific to gender and marginalized populations.

- **Short-term projections tend to be more accurate than long-term estimates.** When using gravity or radiation models to project future population distributions, projections in the one, five, or 10 year range are more likely to be reliable than those forecasting to 2050 or 2100. Accuracy degrades with the time horizon. We chose models forecasting to 2050 rather than 2100 for this reason, but if concrete projections are to influence policy and programming, it may be more helpful to consider projections for the coming decade.

- **Exposure mapping can highlight populations most vulnerable to climate change, and development interventions in these regions should consider both in-situ adaptation and facilitating migration as adaptation.** Distress migrants tend to move shorter distances, and supporting investments in infrastructure, housing, jobs, and social services in towns and cities of vulnerable regions will remain important.

- **Significant data collection improvements are needed to enhance forecasting.** This includes investments in statistical bureaus to improve both the frequency and accuracy of census data collection, investments in longitudinal (ideally panel) surveys to capture migration and immobility dynamics in local contexts and for different social groups, and investments in innovative ways to track migration and displacement following sudden-onset events (e.g., cell phone data). USAID could also consider mainstreaming questions about migration aspirations, plans, and ability into monitoring and evaluation surveys to expand the evidence base available to assess the impact of development interventions on migration decision-making in climate-stressed regions.

- **Foresight exercises may help policymakers anticipate future climate-related migration better than forecasting models alone.** Convening discussions with modelers, migration scholars, natural scientists, development practitioners, and other stakeholders may lead to a more comprehensive assessment of potential future mobility trends to inform policy and programming for a given region. Migration and regional scholars can identify gaps or inaccuracies in the inputs or assumptions of forecasting models and offer caveats about the applicability of the models' findings for particular populations or sub-regions. Natural scientists can offer greater insight into differences in exposure and risk at the household or community-level.

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Appendix A.1: Background on Search Strategy

Phase 1

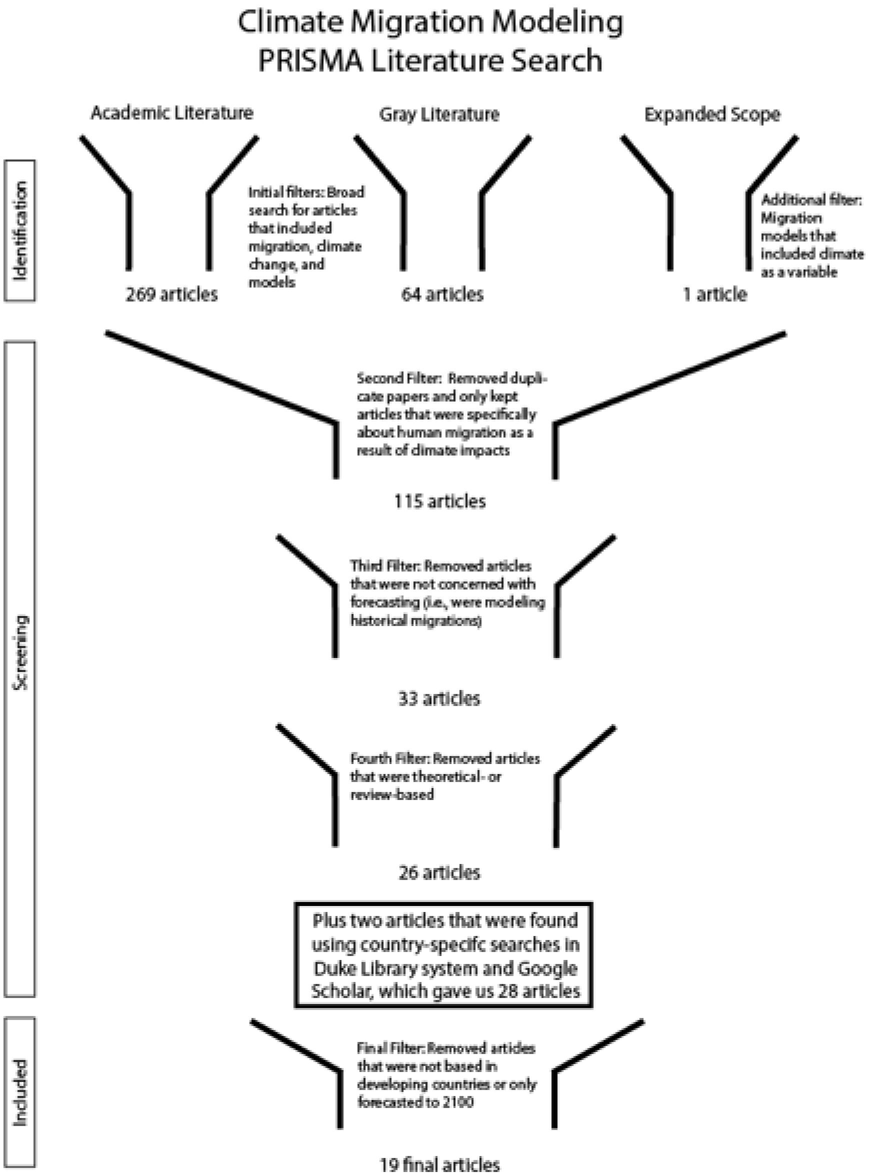
The science of forecasting climate-related migration is still nascent. Given that almost all models have emerged only since the 2010s, we did not apply a time limit in choosing models to assess. Our search strategy was three pronged. First, we used the search engines Scopus, Web of Science, Proquest, and the Duke Library system to find papers that use the terms "climate," "migration," and "model." This yielded 269 papers, primarily from academic literature. After an initial round of sorting, we identified 29 potentially relevant articles that focused on forecasting migration (rather than modeling historical trends), with the majority providing estimates at the country or regional level.

Second, to review the gray literature, we used the PAIS Index, which includes reports from the World Bank, the Brookings Institution, and the RAND Corporation. We also searched the International Monetary Fund E-Library, the OECD iLibrary, and the World Bank e-Library. In order to ensure the most comprehensive search, we utilized Google search results, particularly those at .gov or .org sites, and those mentioned in media reports. Combined, these searches yielded 64 additional papers and reports. Once duplicates were removed and each model was assessed, the gray literature search resulted in five additional models for consideration.

Third, we did a broader search of major migration forecasting models (not specifically climate-related) to see whether some included climate variables, including projections from the United Nations Population Division and Department of Economic and Social Affairs, the OECD, the International Organisation for Migration, and the Vienna Institute of Demography. This resulted in one additional model (Sander et al. 2013, 2017). Unfortunately, many estimates and projections are based on observed changes in populations or migration trends and include neither climate-related nor significant political or economic variables. We are more confident that models that do include climate-related variables would include this focus in the title or description/abstract, which would have been found via our first two search strategies.

Through this three-pronged search, we initially identified 115 potentially relevant models. Upon closer inspection we found that only 33 of these articles actually forecasted migration relating to climate change. In our sorting, we removed articles theoretical in nature or that simply reviewed other models, leaving 26 models that made future-oriented projections. The vast majority of papers modeled climate-migration interactions based on existing or historical data, rather than forecasting migration, which is why there is such a steep drop between the 115 potentially relevant models and the final 26 we included from this portion of the search. Figure 2 details our search strategy according to the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines.

Figure 2. Literature Search Process



Phase 2

After meeting with USAID, we were asked to look more closely at whether we could find models for Europe and Eurasia, the Middle East, and small island states. We conducted another literature search using Duke library database and Google Scholar, using the following broad search terms:

- In database: climate OR migration OR model OR drought OR water OR storm OR flood OR displacement OR mobility OR population movement AND country name
- In Google: migration model [country name]

This resulted in two additional models for small island states. We did not find any articles that met our criteria for the Middle East or Europe and Eurasia. This brought the total number of climate-related migration forecasting models to 30.

In order to yield a broad sense of the state of climate migration modeling, we first coded all 30 models on a variety of factors including the type of model, model prediction, geography, intervening variables, and data sources. In order to fit the USAID scope, we removed models focused solely on developed countries such as the United States and Australia. We focused on models that provide projections to 2050 (or between 2040 and 2060). We removed those that provided predictions for the year 2100 and beyond, because since we judged that date to be too distant to inform USAID programming. Finally, we added one statistical extrapolation model to ensure we have an example of this promising approach. This was an omission highlighted by one of our expert reviewers. Statistical extrapolation models (also called discrete history event modeling) were not initially included in our review for several reasons. Many discrete history event models tend to focus on modeling historical trends; those that use the relationships they uncover between climate variables and migration outcomes to project future trends do not always emphasize these projections in the title or abstract. In one paper, for example, it is a footnote. Others that focus more directly on forecasting often do not offer projections within a specific time horizon. Instead, they may examine how migration might change in relation to the degree of change of a climate-related variables (e.g., flooding, soil salinity, or a hurricane of a certain degree of severity). We decided to add one model to our review that exemplifies this approach. The final analysis included 20 models.

Phase 3

To illustrate more clearly the various approaches, strengths, and weaknesses of forecasting models, we conducted a deep analysis of nine models purposely selected for variation across world regions, geographic scope or scale (global, regional, or country-level forecasts), source (academic or gray literature), migration type (internal, international, and trapped populations), model types (gravity, ABM, radiation, etc.), and impact. The list was shared and further refined in conversation with USAID.

In selecting models for in-depth study, we originally adopted a purposive sampling approach–a non-probability approach that selects cases in a strategic way, based on their relevance to the research question. There are different types of purposive sampling techniques (typical case sampling, extreme or deviant case sampling, criterion sampling, theoretical sampling, etc.). In our first proposal, we took a variation sampling approach, meaning we wanted to identify models that would familiarize USAID with the strength and weaknesses of a wide variety of approaches to climate-related migration forecasting. We looked for variation across a range of areas:

- Geographic coverage (what regions of the world are represented)
- Geographic scope or scale (global, regional, or country-level forecasts)
- Source (academic or gray literature)
- Migration type (internal, international, and trapped populations)
- Model types (gravity, radiation, ABM, other)

Based on these focus areas, and in conversation with USAID, we selected nine models for in-depth review.

Appendix A.2: Background on Expert Interviews

In addition to this evaluation of the proposed models, our team held three individual expert interviews and an additional panel workshop. The final workshop invited the authors of the climate-related migration forecasting models to workshops to better understand what they see as the strengths, limitations, applicability, scalability, and policy-relevance of their respective models. Interviews and panel workshops addressed common questions and themes, including:

- The strengths, weaknesses, and scope of applicability of different modeling approaches
- How to interpret the results of climate-related migration forecasting models and the implications for policy
- Recent advancements in the field and areas for future research

The results of these discussions are included in the findings of the report. Participants include:

Bryan Jones, an Assistant Professor of Sustainability at the Marxe School of Public and International Affairs, Baruch College, City University of New York. His work explores the relationship between spatial population dynamics, urbanization, and climate change vulnerability. He contributed to modeling for the Groundswell report and the Great Climate Migration (ProPublica) project. (Individual interview)

Robert McLeman, a Professor in the Department of Geography and Environmental Studies at Wilfrid Laurier University. His research focuses on the human dimensions of environmental change, with particular attention to the relationship between environment and human migration, community adaptation to climatic variability and change, and fostering citizen participation in environmental science. He is a Coordinating Lead Author for the Intergovernmental Panel on Climate Change's working group on impacts, vulnerability and adaptation. (Individual interview)

Alex de Sherbinin, Deputy Director and Senior Research Scientist at the Center for International Earth Science Information Network (CIESIN), a spatial data and analysis center within the Columbia Climate School of Columbia University specializing in the human aspects of global environmental change. He is also Deputy Manager at the NASA Socioeconomic Data and Applications Center. His research focuses on the human aspects of global environmental change and geospatial data applications, integration, and dissemination. His research and teaching address climate-related mobility, climate vulnerability mapping, urban climate vulnerability, population dynamics and the environment, and environmental indicators. He contributed to modeling for Groundswell and is currently involved with modeling for the Africa Climate Migration Initiative. (Individual interview and Panel discussion)

Helene Beneviste, a postdoctoral Environmental Fellow at the Harvard University Center for the Environment, based at the Harvard Kennedy School of Government. Her research explores interactions between climate change impacts, human migration, and inequality, using Integrated Assessment Models and a scenarios-based approach. She is a lead author on a recent model forecasting resource constrained immobility for climate change scenarios. (Panel discussion)

Michael Burzyński, a researcher at Luxembourg Institute of Socio-Economic Research. His research is focused on the economics of international migration, the economic impact of climate change, selection of workers and matching on labor markets, and quantitative economic theory. He is a lead author on the "Climate Change, Inequality, and Human Migration" model assessed in this report. (Panel discussion)

Fabien Cottier, a Postdoctoral Research Scientist at Lamont-Doherty Earth Observatory of Columbia University. His research focuses on how global warming reshapes migration patterns and the implications for the risk of conflict associated with the movement of people in developing countries. (Panel Discussion)

The final report benefited from the expert review of **Arizona State University Professor Valerie Mueller**. Valerie Mueller is an associate professor in the School of Politics and Global Studies. Her research focuses on quantifying rural household vulnerability to climate variability, focusing on migration, nutrition, and health markers in Africa and Asia. Additionally, she uses randomized controlled trials to identify mechanisms to improve the delivery of rural services (legal justice for women, agricultural extension, and the equitable allocation of irrigation water) in East African countries.

Finally, the authors benefited from presentations and insights offered during an expert consultation on forecasting climate-related migration for small island states in September 2022. The workshop was organized by the Global Centre for Climate Mobility (GCCM), the Association of Caribbean States (ACS), Columbia University's Climate School, and the World Bank's Global Knowledge Partnership for Migration and Development (KNOMAD) Working Group on Environmental Migration.

Appendix A.3: Details of the Nine Models

Model 1. Groundswell Model (Rigaud et al. 2018; Clement et al. 2021)

Model type	Gravity
Type of Migration	Internal; permanent
Geographic Coverage	Regional (Sub-Saharan Africa, South Asia, Latin America, East Asia and the Pacific, North Africa, Eastern Europe, and Central Asia) National (Ethiopia, Bangladesh, Mexico, Morocco, Vietnam, Kyrgyz Republic)
Data Inputs	
Scenarios thinking	Three scenarios based on a combination of two climate scenarios and two development scenarios. **Development scenarios:** Shared socioeconomic pathways (SSP2 and SSP4). Under SSP4 only low income countries experience high population growth, coupled with substantial inequality leading to adaptation challenges. Middle income countries experience low population growth much like high income countries. SSP2 is a moderate development scenario between SSP1 ("sustainability") and SSP3 ("fragmentation") with a slow reduction in inequalities among world regions and more moderate trends in population growth, urbanization, income, and education. **Climate scenarios:** Forecasts are based on two greenhouse gas concentration trajectories using representative concentration pathways (RCP8.5 and RCP2.6). For the higher emissions scenarios, temperatures rise by 1.4°–2.6°C by 2050, and by 2.6°–4.8°C by 2100 (IPCC 2014). For the lower emissions pathway, temperatures peak at 0.25°–1.5°C above recent baseline levels by 2050 and then stabilize through the end of the century. In the higher emissions scenario, temperatures rise by 0.5°–2°C by 2050 and by 3°–5.5°C by 2100.
Environmental and Climate Impacts	Slow-onset changes; Crop yields, water availability, sea level rise Forecasts for water availability and crop yields using data from the Inter-Sectoral Impact Model Intercomparison Project, which uses computer model simulations of biophysical climate impacts. The water sector model outputs represent river discharge, measured in cubic meters per second in daily/monthly time increments. The crop sector model outputs represent crop yield in tons per hectare on an annual time step at a 0.5° x 0.5° grid cell resolution. Crops include maize, wheat, rice, and soybeans. For regions with multiple cropping cycles, yield reflects only the major crop production period. The data were converted to decadal average water availability and crop production (in tons) per grid cell. An index was then calculated that compares those values with the 40-year average for water availability and crop production for 1970–2010. Sea level rise projections from the IPCC Fifth Assessment Report, augmented by an increment for storm surges.

Population data	The population baseline used is the 2010 baseline in the Center for International Earth Science Information Network (CIESIN) Gridded Population of the World Version 4 (GPWv4) (CIESIN 2016) (Map 3.1). The gravity model was calibrated based on population change estimates for 1990 to 2000 from GPW version 3 (CIESIN and others 2005) and for 2000 to 2010 from GPWv4. GPW versions 3 and 4 model the distribution of the population on a continuous global surface based on the highest spatial resolution census data available from the 2000 and 2010 rounds of censuses, respectively. Population count grids were used that were adjusted to national-level estimates from the United Nations World Population Prospects reports. GPWv3 and v4 are gridded data products with output resolutions of 2.5 arc-minutes (a square approximately four kilometers on a side at the equator) and 30 arc-seconds (a square approximately one kilometer on a side at the equator), respectively. For model calibration and baseline population for future projections, the data were aggregated to 7.5 arc-minutes (a square approximately 14 kilometers on a side at the equator [i.e. grid cells with an area of 196 square kilometers]).
Non-climate drivers	Shared Socioeconomic Pathways
Intervening Obstacles/Facilitators	Not directly included.
Personal and HH characteristics	Not directly included.
Model Description	Deviations between population distributions in model runs that include crop and water impacts and development-only (also referred to as the SSP or "no climate impact") model runs are assumed to be driven primarily by differences in climate change–induced internal migration. The model assumes that fertility and mortality rates are relatively consistent across populations in a locale.
Outputs	Changes in population distribution (and indirectly in internal migration).
Scalability/Adaptability	The model may be customized and expanded at different scales. Gravity modeling is one of the few approaches available to take climate migration modeling to scale.
Limitations	The model cannot forecast all future adaptation efforts or conflict, cultural, political, institutional, or technological changes. Discontinuities are likely to arise as a result of political events and upheavals that can heavily influence migration behavior. The scenario framework is not designed to predict shocks to any socioeconomic or political system, such as war or market collapse. The models also cannot anticipate new technologies that may dramatically affect adaptation efforts to the degree that climate impacts become negligible. SSPs, as well as output from the global climate model and the Inter-Sectoral Impact Model Intercomparison Project, reflect plausible futures that span a wide range of global trajectories, with the caveat that extremely unpredictable or unprecedented events are explicitly excluded.

Model 2. Great Climate Migration Model (Jones 2020)

Model type	Gravity
Type of Migration	Internal, international; permanent
Geographic Coverage	Regional (Latin America)
Data Inputs	

Scenarios	**Development scenarios:** Shared socioeconomic pathways (SSP1, SSP3, and SSP5) **Climate scenarios:** Climate output consistent with three representative concentration pathways (2.6, 4.5, and 8.5) are incorporated in this work as drivers of the vulnerability and sectoral-change indicators Five plausible socioeconomic and climate futures are considered: An optimistic/reference scenario (SSP1 and RCP2.6), a pessimistic scenario (SSP3 and RCP8.5), a more climate-friendly scenario (SSP3 and RCP4.5), a more development-friendly scenario (SSP5 and RCP8.5), and a moderate scenario (SSP5 and RCP4.5).
Environmental & Climate Impacts	Water Availability, Agriculture/Crop Yields, Biomes/Ecosystem Productivity, and Flood Hazards (Inter-Sectoral Impact Model Intercomparison Project) Freshwater Availability, Sea level rise, Elevation (Socio-Economic Data and Applications Center, NASA/Columbia University Earth Institute) Extreme Heat Days (Community Earth Systems Model, National Center for Atmospheric Research) Slope Water Bodies (Environmental Systems Research Institute)
Population data	Gridded Population of the World v4 (GPW) (CIESIN), modified by the Global Human Settlement Population Grid (GHS-Pop) (European Commission Joint Research Center) Historical Bilateral Migration Flows (Migration Policy Institute, dataset by Abel and Cohen 2019)
Non-climate drivers	Shared Socioeconomic Pathways Political Stability, Control of Corruption (Worldwide Governance Indicators, World Bank) Gross Domestic Product (OECD)
Intervening Obstacles/Facilitators	Diaspora (United Nations Population Division) Man-made structures ("Built-up") (European Commission Joint Research Center) World Database on Protected Areas (International Union for Conservation of Nature)
Personal and HH characteristics	Population (Age and Sex Structure) (Gridded Population of the World Version 4.10 Basic Demographic Characteristics)
Model Description	To forecast international migration, existing bilateral flow data is used to train and project the model as a function of sectoral impacts (crops, water, NPP), political instability and corruption, global income levels (GDP per capita), and the existing diaspora, to estimate potential changes in origin-destination flows under the five alternative futures (RCP/SSP combinations) noted above. To forecast internal migration, the model authors use a modified version of the Groundswell model. The model estimates changes in the spatial population distribution (including the impact of climate change) in five-year time steps by (1) calculating a population potential surface (a distribution of values reflecting the relative attractiveness of each grid cell), and (2) allocating population change to grid cells proportionally based on potential. To generate estimates of internal migration under climate change, they then run a set of scenarios that exclude the impacts of climate change. They hold the values for all variables that are influenced by climate change constant at current day values (crop, water, NPP, heat extremes, flood hazard, and sea-level). The difference in population distribution between the five primary scenarios and these "no-climate" scenarios is attributed to migration induced by changing conditions, as the only variables that have changed are those impacted by a shifting climate.

Outputs	Changes in bilateral flow data (international migration) and population distribution (and indirectly internal migration).
Scalability/Adaptability	The model may be customized and expanded at different scales. Calibration of the model, particularly for international migration, requires reliable, historical data on bilateral migration flows. Reliable data is rare.
Limitations	Some assumptions/inputs are unrealistic (e.g., age structure, sex ratio, build-up land, groundwater, political stability, among others remain constant in future projections) Does not incorporate non-linear changes in how populations respond to climate stress. Like all other models, it cannot forecast all future adaptation efforts or conflict, cultural, political, institutional, or technological changes.

Model 3. Universal Model (Davis et al. 2018)

Model type	Radiation
Type of Migration	Internal, permanent
Geographic Coverage	Country (Bangladesh)
Data Inputs	
Scenarios	Not for 2050, where the model using RCP8.5 estimates of sea level rise. The model does use two climate scenarios for 2100 estimates.
Environmental & Climate Impacts	Sea level rise (RCP8.5 projection used for 2050 estimates; global mean sea level rise for four RCP pathways used for 2100 projection) Elevation data (Shuttle Radar Topography Mission SRTM Global 1 arc second Version 3.0)
Population data	District-(zila-)level population for the year 2010 was estimated by aggregating the Gridded Population of the World (GPWv4) dataset (30 arcsecond grid) and adjusting to United Nations medium-variant population estimates.
Non-climate drivers	Not included.
Intervening Obstacles/Facilitators	Not included.
Personal and HH characteristics	Not included.
Model Description	In the baseline model (based on Simini et al. 2012) every individual, X, leaving from location i is associated with a positive number, representing the absorption threshold for that individual. On average, individuals leaving from highly populated regions have a higher absorption threshold than those emitted from a scarcely populated location. The surrounding cities have a certain probability to absorb individual X. The individual stops in the closest location that has an absorbance greater than the individual's absorption threshold. By repeating these steps for a given number of out-going individuals (predicted emigrants), the model calculates flux among the different locations. To simulate migrations among districts of Bangladesh that are each affected differently by sea level rise, Simini et al.'s baseline model was adapted to account for the fact that migration fluxes toward inundated areas are less likely. To estimate additional food, housing, and jobs required at migrant destinations, authors multiplied the number of arriving migrants by average calorie consumption in 2010 (FAO Food Balances Sheets), average household size, and ratio of employed to total population (World Development Indicators).

Outputs	Estimates of sources, destinations, and fluxes of migrants displaced under projected sea level rise. Includes estimates of lifetime migrants and five-year migrants.
Scalability/Adaptability	The limited data inputs and parameter free model means this approach is easier to apply to other areas, particularly data-scarce regions. The model has been adapted by others to include a parameter for baseline migration rates; this addition significantly changes the results of the model (see De Lellis et al. 2021)
Limitations	Does not incorporate adaptation or temporary flows. It assumes no return migration. It uses scenarios of global mean sea level rise and national average population growth, which in reality will occur with greater spatial heterogeneity. The model does not include the potential for adaptation, non-linear change, or political, economic, and social change. The model is calibrated based on current migration patterns and decisions, and the relative importance of the factors influencing migration will likely change as climate change progresses.

Model 4. Systems Model (Naugle et al. 2022)

Model type	Systems Dynamics Model
Type of Migration	Internal, International, Permanent
Geographic Coverage	National (Mali, including potential destinations outside Mali)
Data Inputs (*Note: sources of data inputs often not clear from article)*	
Scenarios	No.
Environmental & Climate Impacts	Temperature and precipitation (The climate change scenario assumes a linear temperature increase from 2010 through 2100.)
Population data	The model creators calibrate the model with historical bilateral migration data from the World Bank (2017) and future migration data from World Population Prospects (United Nations 2017).
Non-climate drivers	Food availability Generic resource availability Resource utilization (Un)Employment Labor Supply (skilled and common) Indexed level of technology Existing Violence Governance Effectiveness Infrastructure and services
Intervening Obstacles/Facilitators	Not included.
Personal and HH characteristics	Gender, age, type of labor (skilled, common), births, mortality, and aging flows

Model Description	The model couples a model of migration choice with a multi-sectoral model of the environment in which the potential migrant functions, including feedback of migration decisions on both the sending and receiving communities. A system dynamics model simulates the influence of climate on human migration, focusing on the causal factors of economy, labor, population, violence, governance, water, food availability, and disease. The model has an annual time step extending over a 70-year time horizon, beginning in 1990 (for historical reproduction) and projecting out to 2060. Decisions about where to live are calculated using a cognitive formulation based on qualitative choice theory (McFaddin 1982). The "Migration Utility" is calculated based on a number of factors: labor type, gender, age, wage income, food availability, governance effectiveness, infrastructure and services, disease mortality, violence incongruity, income incongruity, food incongruity, unemployment rate, population, and national disaster index. The model simulates the economic situation in each region by calculating the potential gross regional product, and then adjusts this using other relevant factors to calculate the realized gross regional product for each region, which along with population dynamics, determines labor and wage dynamics. Analyses were referenced to a base case taken from population and economic projections of World Development Indicators (World Bank 2017) and World Population Prospects (UN 2017). Five policy options for reducing pressures to migrate internationally were explored: increasing contraception availability, increasing governance effectiveness, improving infrastructure and services provided by the government, increasing foreign aid to urban Mali, and increasing foreign aid to rural Mali.
Outputs	The model determines the fraction of the Malian population which chooses to live in each simulated region. Potential locations are rural Mali, urban Mali, neighboring countries (Burkina Faso, Cote d'Ivoire, Gabon, Gambia, Ghana, Guinea, Mauritania, Niger, and Senegal), the United States, and the rest of the world.
Scalability/Adaptability	The model could be applied to other world regions but requires significant data inputs.
Limitations	Researchers applied a data-intensive model to what is typically considered a data-scarce region of the world, raising questions about the reliability of the underlying data used. The authors were not clear in the article about the sources of the data.

Model 5. Dynamic Systems Model (Entwisle, Williams and Verdery 2020)

Model type	Agent-based Model
Type of Migration	Internal, permanent, return
Geographic Coverage	Sub-National (Rural region in Northeast Thailand)
Data Inputs	
Scenarios	Four climate scenarios were created based on monthly rainfall data for Nang Rong from 1900 to 2008 (accessed from the University of Delaware Center for Climate and Land Surface Change). The first scenario focuses on droughts; its middle years are marked by a seven-year period of extremely dry weather. The second focuses on floods and contains a seven-year period of extremely wet weather in the middle years. The third examines variability with a scenario whose middle years fluctuate between severe droughts and floods. Each is compared to a reference scenario, containing normal-normal weather during the middle years, which serves as a benchmark.

Environmental & Climate Impacts	Georeferenced villages, households, and the locations and attributes of plots farmed and crops grown by each household (survey data) Time Series of satellite images classified for land cover/land use Digital elevation model constructed from topographic maps Soil depth and drainage maps Observation in the field (qualitative data)
Population data	Longitudinal panel survey data that followed all individuals in 51 villages, including out- and in-migrants and return migrants (Nang Rong Project, see Walsh et al. 2013). Final model on 41 villages.
Non-climate drivers	
Intervening Obstacles/Facilitators	Social network data (kin and exchange) in villages of origin (survey data) Remittances received (survey data)
Personal and HH characteristics	Age, gender, marital status, place of residence
Model Description	The ABM simulation includes multiple types of agents: individuals, land parcels, and households. The primary pathways through which extreme climate events can influence migration patterns in this ABM include the effect on crop yields of timing and amount of rainfall (rice, cassava, and sugar are modeled separately), the way crop yields affect household assets, and how household assets and the characteristics of current and prior household members affect out-migration and return migration (households with more assets are better able to finance migration and to afford the loss of labor associated with it). There are feedbacks from migration to household assets (remittances increase assets), migration to crop yields (through labor availability), and household assets to crop yields (through inputs such as fertilizer, which must be purchased). Rainfall is assumed to be exogenous, a reasonable assumption given the focus on the experiences of individual villages over time. Because plots farmed by households vary in their vulnerability to floods and droughts in terms of elevation, distance from rivers, and soil suitability, the impact of climate shocks can vary within villages (see Walsh et al. 2013 for a complete description of this part of the model). The rules for out-migration and return migration are based on a probabilistic approach and were derived from a statistical analysis of previous survey data and as well as relevant substantive and theoretical literature. The coefficients from regression models are used in the agent-based simulation to determine individual specific probabilities of out- migration and return migration in each simulated year. Individuals are randomly selected to migrate, with the chance of doing so proportional to probabilities defined by regression-based out-migration and return migration equations. These coefficients capture the aforementioned feedback loops as well as the effects of the personal and household characteristics.
Outputs	Changes in rate of out-migration (defined as the proportion leaving of those eligible to leave in each year of the model run compared to the reference scenario) induced by different climate scenarios in 41 villages. Rates of return migration (defined as the proportion returning among those eligible to return in each model year, in comparison with the reference scenario) for all 41 villages. Note: models increases/decreases in migration response (not direction/destination)
Scalability/Adaptability	Not easily scalable. The model focuses on a small area in Northeast Thailand and a similar approach could be used only in other areas with similar panel survey data.

Limitations	The model does not derive information on migrant destinations, only climate impacts on rates of out- and return-migration. The model is calibrated based on previous migration patterns and decisions, and the relative importance of the factors influencing migration may change under future climate changes. Like other models, it does not incorporate the potential for adaptation or other political, economic, technological, or cultural changes.

Model 6. Inequality Model (Burzyński et al. 2022)

Model type	Computable General Equilibrium Model
Type of Migration	Internal (local and regional) International
Geographic Coverage	Global
Data Inputs	
Scenarios	Yes. They consider RCP7.0 as the benchmark scenario, and RCP4.5 and RCP8.5 delineate the spectrum of more optimistic and more pessimistic possibilities.
Environmental & Climate Impacts	Changes in average temperature (slow-onset) Extreme events and disasters (sudden-onset) (floods, storms, droughts, extreme heat waves) (Worldclim.org) Sea level rise projections (Jackson et al. 2016) Climate damage (SEDAC, NASA and EM-DAT) Elevation (SEDAC, NASA)
Population data	The world is divided into 198 countries, divided into 2.319 administrative regions [64 small states], divided into +7.100.000 pixels of 5km x 5km per side. Population, age and education structure by pixel (from WorldPop.org and IHME) International migration stock data by education level (OECD DIOC-E database) and South-South migration stocks imputed by using the United Nations Population Division data set Country-specific regional migration stocks by education levels are constructed using census data (IPUMS International), the WorldPop.org data (Sorichetta et al. 2016), and the Labor Force Survey data by Eurostat.
Non-climate drivers	Economic sector of locality (agricultural or non-agricultural) Wage rates endogenized with CES production function and total factor productivity (TFP) Gross Domestic Product estimates by pixels used to calculate TFP residuals (Kummu, Taka, and Guillaume 2018) Urbanization by pixel as related to whether the pixel is based in agriculture or not (WorldPop.org) Fertility projections (UNDP) Education wage gaps (Global Jobs Indicators Database (JoIn) by the World Bank) GDP levels and shares of agriculture in consumption and PPP rates (World Bank) Shares of High Skilled and educated population (Barro and Lee 2013, IHME)
Intervening Obstacles/Facilitators	Nothing is explicitly modeled as an intervening obstacle, but it does estimate a cost for migrating to approximate legal, monetary, and psychological tolls of moving.

Personal and HH characteristics	Age (under 30 and between 30 and 60) Education (college education and less education) (Inst. for Health Metrics and Eval.)
Model Description	First, the researchers model slow-onset trends and productivity losses; sea level rise, forced displacement and productivity losses; and fast-onset shocks, productivity, and utility losses. Second, they consider behavior and market responses to climate change. These behavior and market responses and productivity losses are then incorporated into a utility model as part of variables to gauge how climate change affects economic and non-economic incentives to move. They model migration decisions as an outcome of a RUM (random utility maximization) model. The utility model looks at migration as a set of three choices: a person can move pixels while staying in the same region, move regions while staying in the same country, or move to a new country. This choice is dependent on economic differences across the three levels, the costs of migrating, external effects of population congestion, and individual preference. For each choice a utility is calculated using the four components just mentioned. Each choice's utility is then used to construct aggregated probability for making that specific migration choice. These probabilities are used to estimate how many people are expected to move pixels, regions, or countries. Once a new country or region is selected, migrants are assigned to a new pixel based on expected utilities across the new region or country. When considering forcibly displaced individuals due to sea level rise, the formula is slightly adjusted because choosing not to migrate is no longer an option.
Outputs	The number of migrants leaving different areas of the world and their destinations relative to a no climate change scenario. The model further breaks these numbers down by the type of migration (local, regional, international) and the type of migrant (low or high skilled). It gives projections for migration flows for parts of the world. The model also gives an expected loss in productivity and GDP due to increased temperatures. Connected to this, the model also gives projections for how these changes will affect income distribution and inequality. Part of this includes changes in college-educated and urbanization.
Scalability/Adaptability	This global model could be adapted as needed (and as relevant data is available) and applied to particular regions.
Limitations	The model keeps climate-related policies constant, foreseeing no investment in greener technologies. The model accounts only for those direct and indirect costs that can be calibrated using existing empirical studies and time-series data.

Model 7. Global Model (Smirnov et al. 2021)

Model type	Agent-based Model
Type of Migration	Internal, international, involuntary immobility
Geographic Coverage	Global (all countries of the world)
Data Inputs	
Scenarios	Yes. Three climate scenarios: (1) constant climate fixed at 2008–2017 levels (any changes in this scenario are due to population growth), (2) *low emissions* RCP 4.5 scenario, and (3) *high emissions* RCP 8.5 scenario

Environmental & Climate Impacts	16 Global Climate Models (GCM) used to model extreme drought projections on the basis of the standardized precipitation evapotranspiration (drought) index (24 months, SPEI <−2) Spatial mask (movement constraints): Water
Population data	Baseline population distribution from LandScan (1 km spatial resolution) Population growth from United Nations medium fertility and high fertility scenarios National identification
Non-climate drivers	Not included.
Intervening Obstacles/Facilitators	No border restrictions.
Personal and HH characteristics	Not included.
Model Description	Agent-based satisficing model, based on a random choice of an acceptable destination within a feasible distance area. The population movement algorithm has five distinct steps: 1) For each grid cell of the world map, examine if the cell is occupied and affected by drought given the drought projections based on the climate model and emissions scenario used in the simulation 2) Calculate the proportion of the cell population migrating given the simulation parameters and national identification of the cell 3) Divide the migrating population into smaller groups. The groups attempt to migrate in all possible directions constrained by the maximum possible migration distance. 4) A destination cell is available for migration if it is not water, not affected by extreme drought, and the destination country is either the same (internal migration) or not significantly less developed. 5) If the initial destination is not available, search for a next available destination in the direction chosen randomly. If no destinations are available, then the population trying to migrate becomes "immobile."
Outputs	"Potential migration pressures" expressed as percentage increases or decreases in total migration.
Scalability/Adaptability	The model is scalable and other inputs could be included into the ABM.
Limitations	"The behavioral assumptions that we introduce in our model are coarse: humans are essentially automata following very basic rules [...] The agents in our model do not have age, gender, resources, social capital, diaspora networks, or other characteristics, all of which undoubtedly influence migration behavior" (3). The model does not incorporate institutional change, adaptation, or future shocks.

Model 8. Small Island Model (Speelman et al. 2021)

Model type	Agent-based Model
Type of Migration	Internal
Geographic Coverage	National (Maldives)
Data Inputs	

Scenarios	Population projections (low growth and high growth scenarios) from the Population Division of the United Nations Department of Economic and Social Affairs (UN DESA 2015). Governance: No intervention vs. strong intervention. These dynamics are based on the existing "population consolidation" and "Safer Islands" policies of the government of the Maldives. For details, see Speelman (2016) Globalization: closed borders vs. open borders. The distribution of international migrants is based on Speelman et al. (2017). High emissions, high climate impact scenario versus low emissions, low climate impact scenario. The authors use six future scenarios, taken from the United Kingdom Foresight project on migration and global environmental change (Government Office for Science 2011).
Environmental & Climate Impacts	Source for climate impacts (high and low impact scenarios) taken from the scenarios in the IPCC Special Report on Emission Scenarios (SRES) used by the United Kingdom Foresight Report (Black et al. 2011)
Population data	Census data from 1985, 1990, 1995, 2000, 2006, and 2014 Aggregated data at island level including gender, population and age structure are available at the national level for all census datasets. Annual nationally registered births and deaths Two datasets are used for the 2014 census: (1) aggregated, island level, population data (Maldives Bureau of Statistics 2015) and (2) individual data (Maldives Bureau of Statistics 2015). Note: Expatriates who (temporarily) reside in the Maldives (~64,000 residents) for employment purposes are excluded from the analysis.
Non-climate drivers	Indices for island characteristics (no further specificities found) Governance (see above)
Intervening Obstacles/Facilitators	Open vs. Closed Borders Note: the effects of social networks (as a proxy for social norms) are simulated in the model, but they are not based on "real" data inputs on social networks. Each agent in the model is connected to 50 other agents at the model start up. Information is shared about their migration moves and agents store this information for two years.
Personal and HH characteristics	For the 2006 and 2014 census datasets were made available that include a full anonymized list of the Maldivian population and corresponding characteristics such as age, level of education, marital status and migration history (Maldives Bureau of Statistics).

Model Description	Agents can develop intentions to migrate to three potential destinations: (1) to the capital Malé, (2) within an Atoll District or (3) to another island in the Maldives. The intention to migrate is shaped by three factors: (1) the attitude of an agent towards migration to different destinations, (2) personal norms and past migration behavior of their peers and (3) the diversity of agent attitudes to migration, each based on a set of statistical attributes and simulated dynamics between agents and their environment. For each simulated time step of one year, each agent determines their intention to migrate. Migration behavior of individual agents is then implemented on the basis of probability functions. These result in a new population distribution. Birth and death rates are included in each time step based on historic data or population projections, as well as aging of the population. Data on government relocation of individual populations to other islands are also included in the model. These steps are repeated for the duration of the simulation. Historic simulations run from 1985 to 2014. Demographic futures are simulated from 2014 to 2050.
Outputs	Simulated population size in 2050 for all 10 islands under six future scenarios.
Scalability/Adaptability	The model could be applied to other small island states with reliable census data.
Limitations	Does not include impacts like tsunamis, which could also lead to significant displacement. It is not clear from the paper how climate impacts are measured (e.g., whether sea level rise is given a direct focus or rather inputs relate only to high/low emissions). The model estimates social networks in a rather coarse and uniform way, which is unlikely to reflect real-world dynamics. Overall, the conceptual model is more sophisticated than the data inputs available as proxies for the most important factors.

Model 9. Statistical Extrapolation Approach (Chen and Mueller 2019)

Model type	Statistical Extrapolation Model
Type of Migration	International (cross-border from Bangladesh to India, Pakistan, Nepal, Sri Lanka, and Bhutan)
Geographic Coverage	National (Bangladesh)
Data Inputs	
Scenarios	No.

Environmental & Climate Impacts	Remote sensing measures of sub-district flooding and rainfall and in situ measures of monsoon onset, temperature, radiation, and soil salinity. With the exception of salinization, all environmental variables are reflected as anomalies over 1-, 2-, and 3-year periods to characterize migration patterns under different durations of exposure. Data on **inundation** are constructed from NASA's Moderate Resolution Imaging Spectro-radiometer (MODIS) satellite. Images are aggregated into 8-day composites that provide the best possible observation during the period, and each pixel in an image captures an area of 500 m^2. Inundation is represented by the Modified Normalized Difference Water Index (MNDWI). Data on **rainfall** are drawn from NASA's Tropical Rainfall Measuring Mission (TRMM), which generates precipitation values of 0.25 x 0.25° resolution. They focus on monthly precipitation values extracted from TRMM, aggregated up to annual measures. Annual averages of minimum and maximum **temperature** and **bright sun exposure** from the Bangladesh Meteorological Department. To capture **monsoon onset**, they use daily rainfall data (500+ weather stations) from the Bangladesh Water Development Board to generate an explanatory variable for monsoon onset. Measures of **soil salinity** are based on field surveys conducted in 18 of the 64 districts of Bangladesh by the Soil Resource Development Institute, an agency of Bangladesh's Ministry of Agriculture.
Population data	Nationally representative migration data from 2005 to 2011 are collected through the Bangladesh Bureau of Statistics vital registration records (SVRS). Sampling is stratified at the locality level, to achieve representation across rural, urban, and metropolitan areas. Approximately 200,000 households (1 million individuals) are surveyed each year.
Non-climate drivers	
Intervening Obstacles/Facilitators	
Personal and HH characteristics	Demographic and wealth variables: age, age-squared, literacy, and religion of the household head; the number of household members in eight age-sex categories (number of male/female household members 0–5, 6–16, 17–54, and greater than 54 years old); indicators for whether the household is in the coastal zone or the drought-prone areas of the Northwest; indicators for whether the household has improved water and latrine facilities (primary/secondary water source comes from tap/well, has own water source, has modern or sanitary latrine); and sources of energy (has kerosene/electricity as a source of light/fuel, has gas as a source of fuel) (from SVRS data) Migration information is reported only for individuals who have been away for at least 6 months. They focus on two migration-dependent variables, the number of migrants in the household going to South Asia and the number of migrants in the household going to India.

Model Description	The model estimates the effect of environmental factors on the flow of migrants using a negative binomial specification. The forecasting dimension of this model uses these observed relationships to predict the change in the number of migrants from Bangladesh to India (alone) and South Asian countries (together) for a 1 standard deviation increase in flooding and a 1 standard deviation increase in soil salinity. They also compare households grouped by religion, household gender composition, age groups and assets. They examine the relationship between these characteristics and environmental-migration dynamics, but do not use those estimates to project numerical estimates based on household characteristics in this paper.
Outputs	Cross-border migration (over 6 months duration) by district. Model predicts a total of 17,874 more migrants moving to India in response to a 1 standard deviation increase in soil salinity and a total of 5,754 fewer migrants moving to India in response to a one- standard deviation increase in flooding.
Scalability/Adaptability	The model can be adapted to other regions provided the same in-situ measures are available as data inputs.
Limitations	The authors are transparent about the limitations in the paper: "First, we lack confirmation of the duration of each event and, therefore, are unable to validate whether the moves are temporary or permanent. Second, the absence of spatial and temporal variation represented by our measure of soil salinity affects our ability to measure other important aspects of climate migration. By limiting the focus to changes in soil salinity over 5 years, for example, we are unable to express how mobility may be affected by seasonal or annual variations in soil salinity. Furthermore, the coarseness of our measure of salinity exposure affects our capacity to inform how policymakers should prioritize funding for adaptive investments. Soil salinity is likely a direct result of changes in landscape and deforestation along the coast, sea level rise and storm surges, and groundwater management. It remains an open question which contributing factor to soil salinity is driving the mobility patterns observed in the paper. Future research would benefit from including more refined measures of soil salinity" (118-119).