Modeling Climate Change-Induced Migration in Central America & Mexico
Methodological Report

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1. Introduction

Climate change poses one of the greatest threats to human communities, ecosystems, and development goals. Vulnerability to climate risks, typically characterized as a function of exposure, sensitivity, and adaptive capacity (e.g., Adger 2006), is often highest in the world's poorest communities. The potential loss of ecosystem services threatens the livelihoods of many marginal populations, and a lack of resources in poorer communities exacerbates sensitivity and severely limits adaptive capacity. In many countries, rapid population growth, coupled with urbanization, place further pressure on the capacity of already stressed public and private institutions to provide essential services.

The physical effects of climate change, such as sea-level rise, stronger and more frequent coastal storms, changing precipitation patterns, and increased incidence of drought and heat extremes have environmental, socioeconomic, and political consequences that are not mutually exclusive but instead augment one another. For example, increasing heat extremes and drought influences water availability and agricultural productivity, which in turn threatens food security, economic productivity, and political stability as competition for scarce resources is amplified. These connections often increase exposure and confound adaptation options. Further complicating matters, these relationships vary over space and operate at different scales as a function of existing socio-political conditions. Given these compounding threats, and with limited adapt-in-situ options, it is highly likely that patterns of human mobility will shift in response to climate change (IPCC 2014), including through migration as adaptation, forced displacement, planned relocations, and entrapment.

The IPCC's 5th Assessment Report recognizes migration as an important adaptation response to climate risks. Migration is a complex phenomenon driven by multiple, interacting processes that vary substantially over space. Certain baseline regularities relative to, for example, age-structure and gender, exist worldwide (e.g., De Jong 2000; Rogers and Castro 1981). However, unique regional and local patterns born out of complex decision-making processes are evident. The migration decision is informed by a diverse set of factors, including economic and political conditions, health and family considerations, the presence or absence of social and physical amenities, historic and cultural influences, and intangibles such as place attachment (Hatton and Williamson 2005). The relative importance of these factors will vary across regions, countries, segments of the population, and individuals as a function of cultural and societal norms, education, age and gender, and wealth. Rather than acting independently, climate/environmental factors tend to work through the various drivers of migration as seen in Figure 1, particularly so in regions economically dependent on threatened ecosystem services (Black et al. 2011; Tacoli 2009), and in urban areas. Substantial variation in the nature and distribution of environmental change, and the capacity of populations to mitigate and adapt, is likely to exacerbate geographic disparity in migration in the coming decades (Gemenne 2011; Raleigh et al. 2008).

Climate-induced migration has the potential to impact existing public infrastructure, such as food, water, and energy distribution systems as well as public health capacity. Additionally, migration will fundamentally change the distribution of climate exposure and vulnerability, reducing threats in some places while enhancing or introducing new threats in others. Migration is a multi-scale process, occurring over varying distance and along alternative pathways, often as a function of underlying characteristics of the migrant stock and regional and/or local socioeconomic and political conditions. The characteristics of migrants matter to both sending and receiving regions, as the structure of the population will determine which services are most critical and what new patterns of climate-related vulnerability might emerge. As such, it is critical that national, regional, and local planners have some mechanism for anticipating the potential movement of people in response to climate change. Couching migration processes in the physical and socioeconomic impacts of climate change is paramount to identifying potential migration hot spots, that is, places likely to be large net senders and receivers of climate migrants possessing certain characteristics. In doing so, the appropriate agencies operating at and across multiple scales will be better situated to integrate migration-related issues into the development and implementation of climate resilient policy aimed at protecting lives and livelihoods.

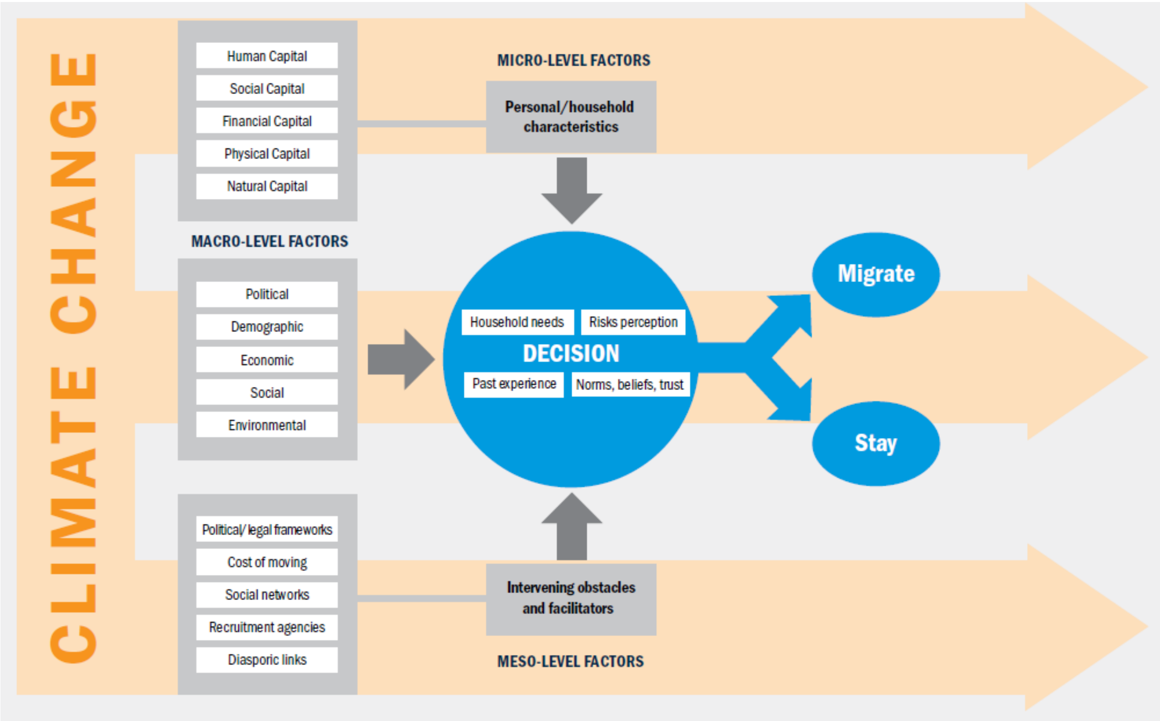


Figure 1. Foresight model adapted to illustrate climate change, livelihoods, and household migration behavior (Source: Rigaud et al. 2018)

The purpose of this report is to review the data and methods used to characterize the nature, scope, and scale of migration under a changing climate in Central America and Mexico. We aim to project potential migration outcomes under a range of climate and demographic/socioeconomic scenarios to further inform productive dialogue regarding the impact of policy decisions. In addition to broad estimates of international and internal migration intensity, the combination of spatially explicit models of climate change, sectoral impacts, and socioeconomic/demographically informed population change will reveal migration "hot spots" (in and out) that may benefit from specific interventions to mitigate against negative impacts or in support of potential positive outcomes. Additionally, to help target efforts we aim to characterize the uncertainty in outcomes across alternative climate and societal outcomes. Underlying the project are three broad assumptions: (1) migration and displacement are likely consequences of and/or important adaptation responses to climate change, (2) patterns of climate-related migration will vary spatially, temporally, and as a function of scale (e.g., international vs. internal), and (3) climate-related migration trends are a function of the complex relationship between physical/environmental change, socioeconomic and demographic characteristics of populations, history and existing connections, political systems, and geographic characteristics of the landscape.

In 2018, the Center for International Earth Science Information Network (CIESIN) and the CUNY Institute for Demographic Research (CIDR), under the overall direction of the World Bank, released the World Bank flagship report *Groundswell: Planning for Internal Climate Migration* (Rigaud et al. 2018). The novel methodological approach to estimating the impact of climate change on internal migration patterns was built from spatial methods of projecting future population distributions that can be calibrated to reflect the impact of difference potential drivers of change. This work builds upon the *Groundswell* methodology, incorporating a number of refinements and expanding the set of variables that influence change in the spatial distribution of the population. The report is organized as follows: Section 2 briefly introduces the challenges associated with identifying and projecting climate migration, Section 3 will review the scenario framework we adopt for this project, Section 4 introduces the data used in the modeling approach, and finally Section 5 introduces the modeling approach itself, and finally Section 6 discusses some of the important limitations of the modeling approach and best practices for consuming the results.

2. Understanding Climate Migration

Over the past three decades, the scientific community has focused significant time and effort on understanding the physical effects of anthropogenic climate change. Comparatively less attention has been given to the societal dimensions of global change, and only in recent years have studies forecasting climate impacts on human populations really begun to proliferate. Efforts to model the impact of climate change on migration remain in their infancy, owing in part to significant data constraints and the difficulty in disentangling a causal human/environment relationship from dynamic societal processes (Hugo et al. 2012; Brown 2008; Black 2001). Baseline migration data, particularly intra-national, are difficult to come by and inconsistently compiled. Additionally, substantial population growth and redistribution in the developed world (forecast in the absence of climate change), and significant uncertainty in climate outcomes at the local level (both extreme events and slow-onset change), further confound estimates of climate-induced migration and displacement (Hugo et al. 2012). As such, modeling potential outcomes represents a substantial challenge, and existing estimates are often contentious, described at times as "excessively alarmist" and "well-educated guesswork" (Hugo et al. 2012; Kolmannskog 2008).

Despite these challenges and criticisms, there is real value in attempting to quantify the potential impacts of climate change on migration, particular from a policy perspective. Unanticipated movements are potentially detrimental to poverty eradication efforts, and yet it is quite likely that, in certain cases, migration represents an appropriate adaptation response to changing physical and socioeconomic conditions. Beginning to understand geographic variation in the intensity and directionality of migration, while acknowledging the uncertainty associated with any such projections, will help to understand the potential impacts of climate-induced migration and, subsequently, help frame the policy debate. To date, however, there is little consensus regarding the probable number of climate-induced migrants, and methods are disparate. In this section we review the methodological challenges associated with projecting migration under climate change as well as some of the early attempts to do so.

2.1 Methodological Challenges

A fundamental difficulty associated with identifying and projecting the number of future climate migrants is the definition of climate-induced migration itself. Often referred to as "environmental migration," there is no universally agreed upon definition of what broadly constitutes a climate migrant. The literature notes confusion regarding the various classes of climate migrants such as the distinction between forced and voluntary migrants, or the definition of internally displaced persons and climate refugees (Waldinger 2015; Hugo et al. 2012; Crisp 1999). In many cases, these terms are used interchangeably (Hugo et al. 2012). It is also likely that a certain percentage of climate migrants may fit into more than one class over time. For example, can a displaced person eventually become a voluntary migrant (by choosing not to return home), and if so, what is the appropriate passage of time? Similarly, the interaction of climate, socioeconomic, and political conditions confound classification schemes. How do we classify the refugees of conflict that has been exacerbated by climactic conditions? Scale also presents a major impediment to definitional questions as well. Hugo (1996) suggests that moves motivated by environmental reasons tend to occur over short distances, which raises the question of how far one must travel in order to be counted. Definitional issues represent an impediment to the accurate characterization of climate-induced migration, which is likely to vary in scale, intensity, and causality over different parts of the world. These issues also impede the quest to count existing and project future climate migrants, as definitional inconsistency renders estimates incomparable. Furthermore, the intensity of the phenomenon in invariably tied to the definition (Hugo et al. 2012).

Estimates of future climate-induced migration flows are often driven by vulnerability assessment and assumptions regarding adaptations strategy. Vulnerability and adaptation strategy, and subsequently any effort to attach numbers to the climate-induced migration question, are subject to several significant sources of uncertainty. The impacts of climate change will unfold concurrent to shifting socioeconomic and political conditions, globalization, continued urbanization, and substantial changes in the relative distribution of the global population. Vulnerability and the feasibility of alternative adaptation options will vary as a function of these demographic, socioeconomic, and political factors. These conditions themselves are difficult to project, and yet it is impossible to characterize vulnerability and anticipate adaptation options (including migration) in their absence. Further confounding the equation is uncertainty associated with projections of climate change, particular at the local scale. Climate modeling techniques have advanced rapidly over the past several decades, and scenario-based estimates of climate change at the global-scale are perceived as fairly robust. However, it is still very difficult to accurately anticipate the impact of climate change on regional climate and weather, and geographically specific projections of extreme events are probabilistic and themselves fraught with uncertainty.

A further challenge to producing estimates of future climate-migrants are the difficulties associated with disentangling climate-induced migration from that driven by other socioeconomic/demographic forces (Jonsson 2010; Jäger et al.2009). It will be very difficult to, for example, distinguish between voluntary climate migrants and other urban-to-rural migrants, particularly in rapidly urbanizing regions of the developing world. Additionally, multi-causality is a common characteristic of migration, and it can be difficult to classify migrant types even in the absence of environmental factors. Correlation between drivers, including climate drivers, complicate the application of traditional statistical techniques, and good data on migration are difficult to come by, particularly internal migration (Brown 2008). There is agreement in the literature that climate change is best considered one of many possible drivers of migration (Waldinger 2015; Raleigh 2010). However, as climate change is likely to present conditions and challenges not yet experienced in many parts of the world, it will be both difficult to anticipate how populations react to different types of climate-related hazards and furthermore to extract the effect of these hazards from the many other factors known to drive migration.

The media attention given to climate change and migration almost demands some attempt to quantify the potential impact of the former on the latter. However, it should be acknowledged up front that the challenges associated with doing so are extreme. Climate, socioeconomic, political, and demographic conditions all contribute to the phenomenon, and they do so within the context of local culture and history. The uncertainty associated with the drivers of migration and differential vulnerability and adaptation strategy are such that any estimate of the climate-change impact on migration should be taken with a healthy degree of skepticism. These caveats and limitations should be made clear, but they should not dissuade serious consideration of migration in crafting climate-resilient policy.

The methods presented in this report represent a next generation approach to the assessment of migration under climate change. The modeling adopts and expands upon a scenario-based approach (Rigaud et al. 2018) that disaggregates the portion of future changes in population distribution that can be attributed to climate migration. The model, a gravity-based spatial allocation-type framework, consists of two primary modules, international and internal, that are loosely coupled to produce estimates of cross-border and internal migration. Scenarios are combinations of socioeconomic and climate (emissions) projections. The development scenarios drive internal population and urbanization trends in a gravity model that distributes population change according to the perceived attractiveness of different locales over time. Future population distributions are influenced by climate impacts on the water and agriculture sectors, ecosystem impacts, and future flood risk, all of which influence attractiveness. The model estimates the number of climate migrants and their future locations by comparing population distributions that incorporate climate impacts with scenarios based on development trajectories only, which themselves include know drivers of migration such as GDP, diaspora (in the case of the international module), and stability/governance.

3. Scenario Framework

In this work, we adopt a scenario framework, a common approach in the climate change community, but less so in demographic research. As such, studies of vulnerability are less often based on this type of approach (Birkmann et al. 2015). Scenarios are generally designed to illustrate different plausible development pathways, often to make the future more realistic and logical for decision-makers (Birkmann et al. 2015). Furthermore, scenarios help us to characterize and interpret uncertainties in key outcomes, to identify potentially desirable and undesirable outcomes, and to identify advantageous policies designed to improve outcomes (Birkmann et al. 2015; Preston et al 2009; Hallegatte et al. 2011; van Vuuren et al. 2012). For this study, we adopt the IPCC Representative Concentration Pathways (RCPs) and Shared Socioeconomic Pathways (SSPs) scenario framework.

The development scenarios in this work are taken from the Shared Socioeconomic Pathways (SSPs), and they include two "high development" and one "low development" scenarios. The high development scenarios assume rapid convergence in socioeconomic conditions, higher levels of educational attainment, lower fertility rates and subsequently lower population growth, and high urbanization rates. However, the two scenarios differ in that the one assumes an ecofriendly future in which the primary fuel mix is dominated by clean renewables and planning/policy is oriented around efficiency and environmental preservation. The other assumes socioeconomic growth that is driven by the expanded use of, and continued reliance on, fossil fuels, and relatively little in the way of environmentally friendly policy. Under the low development scenario, developing countries are characterized by high population growth, low urbanization, very slow income growth, and significant inequality. Furthermore, in the low development future, nations take a very closed approach toward migration. These scenarios are discussed in more detail in the next section.

Climate forecasts are based on three emissions scenarios. The lower emissions scenario is a world in which temperatures peak at 1.0°–2.2°C above pre-industrial levels by midcentury and then stabilize through the end of the century (IPCC 2014). This is the world of the Paris Agreement, in which countries work together to reduce greenhouse gas emissions to zero within the next 15–20 years (Sanderson et al. 2016). In the higher emissions scenario, temperatures rise by 2.0°–3.2°C by 2050 and by 3.2°–5.6°C by 2100. The moderate emissions scenario falls between the two extremes, with temperatures rising 1.5°–2.6°C by 2050 and by 1.7°–3.2°C by 2100.

3.1 The Representative Concentration Pathways (RCPs)

Developed in advance of the IPCC 5th Assessment Report, the RCPs represent the latest generation of global scenarios for climate change research (van Vuuren at al. 2014). The RCPs are trajectories of greenhouse gas (and other pollutants) concentrations resulting from human activity corresponding to a specific level of radiative forcing in 2100. For example, RCP8.5 implies a future where radiative forcing of 8.5 W/m^2 is achieved by the end of the century. An important characteristic of the RCPs is that they do not rely on a fixed set of scenario specific assumptions regarding economic development, technological change, or population growth. Instead, there are many different socioeconomic futures or pathways that may lead to the same level of radiative forcing. This framework allows researchers to consider alternative policy decisions with combinations of societal, economic, and technological change. As such, a future with high population but rapid development of clean technology may achieve the same level of radiative forcing as a world characterized by low population growth but continued reliance on fossil fuels. This framework is very useful from a policy analysis perspective, as it allows researchers to specify specific levels of global change (e.g., 2°) and then explore alternative policy options to achieve emissions levels consistent with the goal. Previous scenarios, by contrast, specified the socioeconomic conditions from which climate change/impacts were then calculated.

Climate output consistent with three RCPs (2.6, 4.5, and 8.5) are incorporated in this work as drivers of the vulnerability and sectoral-change indicators (introduced below) proposed for inclusion in the international and internal migration models (see Section 4). In many cases (e.g., the Inter-Sectoral Model Intercomparison Project; ISIMIP) indicators have been projected and are incorporated directly into this work. In others we have proposed projecting an existing indicator (or set of indicators) into the future (e.g., the World Risk Index, see section 3.4.1). We propose, where necessary, using the climate output available as part of the ISIMIP (discussed in more detail in section 3.5.1) such that the climate outputs are consistent across the entire project. The three RCP scenarios considered in this work are now discussed in more detail.

RCP2.6 is a low emissions scenario. Greenhouse gas emission begins to decline by 2020, and radiative forcing peaks by midcentury before declining to near current levels by 2100. This scenario is consistent with the extremely rapid adoption of new, cleaner technologies, slower population growth, and strong environmental policy. To achieve an RCP2.6 future, new technologies would need to be widely employed in the next 5-10 years. The extended RCP2.6 scenario assumes “negative emissions” by 2070, meaning humans are removing more CO_2 and CH_4 from the atmosphere than they are releasing.

RCP4.5 is an intermediate emissions scenario. It is consistent with a future including relatively ambitious climate policy, stable CH_4 emissions, and CO_2 emissions that peak by midcentury before declining. Societal pathways including rapid adoption of new, less energy intensive technologies, declining agricultural land use, slower population growth and more organized urban development, and the implementation of environmental conscious programs such as reforestation are all consistent with an RCP4.5 future.

RCP8.5 is characterized by increasing greenhouse gas emissions over time, leading to high atmospheric concentration. It is a future consistent with scenarios of energy intense development, continued reliance on fossil fuels, and slow rate of technological development. Alternatively, pathways characterized by rapid population growth and land use intensification (croplands and grasslands) are also consistent. RCP8.5 implies little to no climate policy, and it is characterized by significant increases in CO_2 and CH_4 emissions.

3.2 Shared Socioeconomic Pathways (SSPs)

The five SSPs, described in more detail in O’Neill et al. (2015), span a wide range of possible future development pathways and describe trends in demographics, human development, economy and lifestyle, policies and institutions, technology, and environment and natural resources. Broadly, they are organized according to the respective challenges to adaptation and mitigation in each future world (see Figure 2). Importantly, climate change impacts are not directly included in these scenarios, however they can be thought as consistent with broad assumptions regarding the primary factors driving challenges to adaptation and mitigation, namely population and emissions, respectively. National-level estimates of population, urbanization, and GDP have been released for each SSP and are available through the SSP database (https://tntcat.iiasa.ac.at/SspDb/dsd?Action=htmlpage&page=about).

Population estimates include assumptions regarding international migration, however, once again these assumptions are made in the absence of any information regarding climate change, exposure, and vulnerability. In this work we will attempt to model the potential impacts of climate change on international migration. No assumptions are made regarding internal migration. In this work we will consider SSP1, SSP3, and SSP5, described here in more detail.

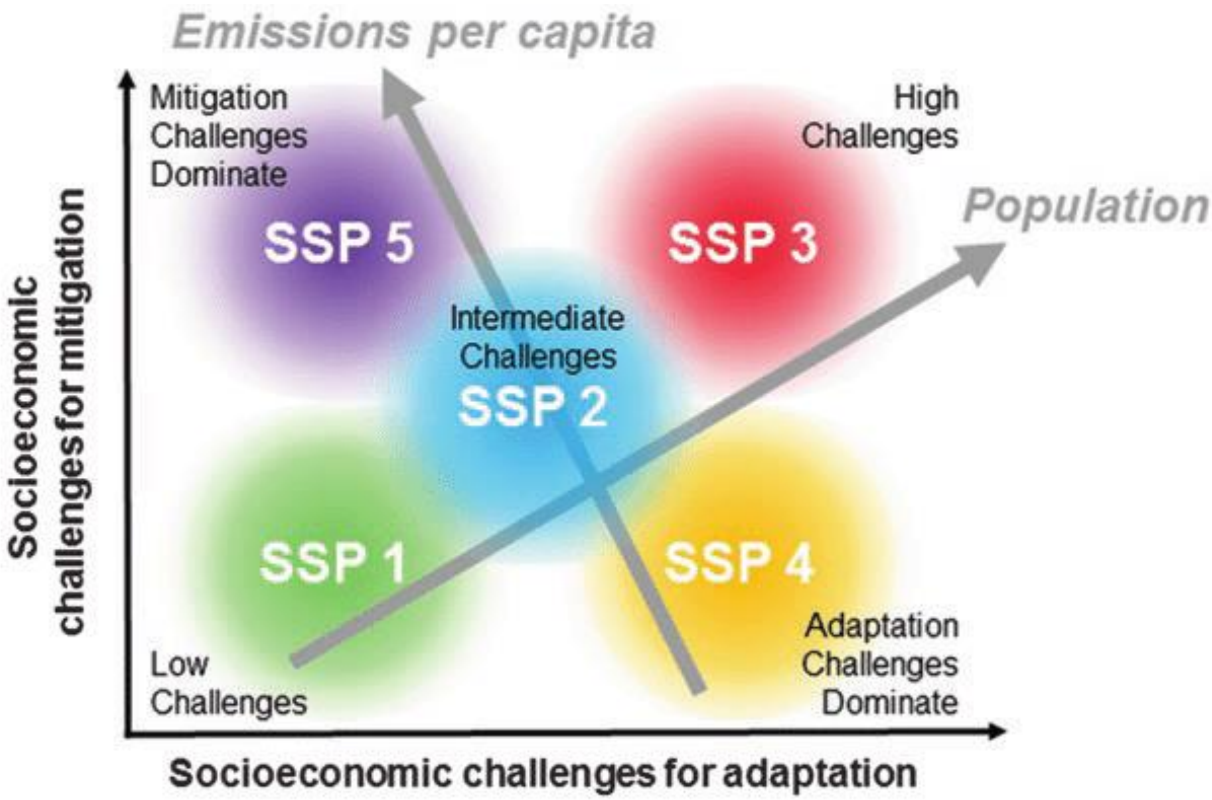


Figure 2. The five Shared Socioeconomic Pathways (SSPs) (O'Sullivan 2018)

Two SSPs describe worlds in which societal conditions are hypothesized to present (on balance) lower challenges to adaptation. SSP1 (Sustainability) envisions a development path with a gradual shift toward greater emphasis on environmental protection, reduced inequality, and enhanced cooperation internationally and among different segments of society. There is increased investment in education and health and relatively high-income growth, leading to a relatively rapid demographic transition and therefore low population growth in the high-fertility countries. In contrast, in currently low-fertility countries, optimism about economic prospects sustains fertility at medium levels (somewhat below replacement levels of about two children per woman). Migration is moderate and urbanization, though rapid, is well managed and sprawl and urban de-concentration are minimized. SSP5 (Fossil-Fueled Development) has a greater emphasis on competitive markets, innovation and globalization than does SSP1, and also a greater reliance on fossil fuels (with less concern for global environmental consequences). But it also has several similarities in terms of human capital and demographic outcomes. Strong investments in education and even more rapid income growth than in SSP1 lead to similarly low fertility (and low population growth) in high-fertility countries and even higher fertility in the currently low-fertility countries (at or around replacement level). Migration levels are high, and urbanization (as in SSP1) is rapid. However, unlike SSP1, urban planning has difficulty keeping up with high urbanization rates, and sprawling patterns of development dominate.

SSP3 (Regional Rivalry) describes a world in which conditions are assumed to present high challenges to adaptation. Nationalism and security concerns lead to regionalization (rather than globalization), with weak institutions, slow technological change and economic growth, and little environmental protection. Relatively low investments in human capital lead to relatively high fertility and population growth rates in the currently high fertility countries. In contrast, economic uncertainty leads to relatively low fertility rates and low population growth (or decline) in the currently low-fertility countries. The low assumed migration rates do little to contribute to growth in these regions. Limited urban employment opportunities lead to slow urbanization, and urban settlements are poorly planned, particularly in developing countries, where inequality and fragmentation lead to a mixed pattern of urban change (e.g., pockets of wealthier, deconcentrated settlements alongside more concentrated slum-type growth).

3.3 Scenario Combinations Used in the Model

Following the logic of the Groundswell approach, here five plausible socioeconomic and climate futures are considered, four of which are based on the various combinations of SSPs 3 and 5 and RCPs 4.5 and 8.5. This matrix of scenarios allows us to examine the relative importance of different climate and societal futures in driving potential migration outcomes as, for example, we can assess each climate scenario (RCP) within the context of different societal outcomes (SSPs) by holding the former constant and varying the latter (and vice versa). The final scenario is the most optimistic SSP/RCP combination, and it serves as a point of reference against which to measure the less optimal outcomes. The scenarios can be characterized as follows:

1. An optimistic/reference scenario (SSP1 and RCP2.6), in which climate impacts are rapidly reduced on a global scale and there is regional convergence toward higher levels of development across Central America and Mexico.
2. A pessimistic scenario (SSP3 and RCP8.5), in which climate change impacts are on the high end of current plausible scenarios and significant challenges to socioeconomic development exist throughout the region, exacerbating the gap between Central America and the United States.
3. A more climate-friendly scenario (SSP3 and RCP4.5), which pairs a less-extreme climate outcome with the same challenging socioeconomic future as the pessimistic scenario (Scenario #2).
4. A more development-friendly scenario (SSP5 and RCP8.5), which follows the pessimistic climate future but assumes a more inclusive development pathway in which regional economic growth occurs quickly.
5. A moderate scenario (SSP5 and RCP4.5), in which socioeconomic development occurs rapidly throughout the region accompanied by a moderate level of climate change.

4. Data

In this section, we review the data inputs to the model in detail. Table 1 includes a complete list of data products and variables, it and indicates whether the product was used in the international or internal model (or both, in some cases).

Table 1. Datasets, variables, and sources

Product	Source	Resolution	Time Series	Time Step	Indicator	Model
Water Availability	ISIMIP	0.5°	1970-2100	5-year	Devaition from baseline	Internal/International
Agriculture/Crop Yields	ISIMIP	0.5°	1970-2100	5-year	Devaition from baseline	Internal/International
Biomes/Ecosystem Productivity	ISIMIP	0.5°	1970-2100	5-year	Devaition from baseline	Internal/International
Flood Hazard	ISIMIP	1km	1970-2060	5-year	5-year risk of flooding	Internal
GRACE Groundwater	SEDAC	3°	2002-2016	n/a	Trends in terrestial groundwater	Internal
Extreme Heat days	CESM	0.5°	1970-2100	1-year	Average annual heat wave days	Internal
Sea-Level Rise (ACE2)	SEDAC	Vector (Poly)	2020-2100	5-year	Changes in coastline	Internal
Political Stablility/No Violence	WGI	National	1996-2018	variable	Likelihood of political instability/violence	International
Control of Corruption	WGI	National	1196-2018	variable	Use of public resources for private gain	International
Gross Domestic Product	OECD	National	1980-2100	5-year	GDP per capita (derived)	International
Population (Historic)	EC-JRC	250m, 1km, National	1975, 1990, 2000, 2015	n/a	Population Count	Baseline data
Disapora	UNPD	National	2010	n/a	Forigen-born by country of origin	International
Man-made structures ("Built-up")	EC-JRC	38m, 250m, 1km	1975, 1990, 2000, 2015	n/a	Portion of grid cell that is "built-up"	Internal
Age and sex structure	SEDAC	1km	2010	n/a	Age cohorts by sex	Internal
Altimeter Corrected Elevation	SEDAC	30m, 90m, 1km	1994-2005	n/a	Corrected elevation	Internal
Slope	n/a	30m, 90m, 1km	1994-2006	n/a	Average slope (parcel of land)	Internal
Water Bodies	ESRI	Vector (Poly)	2019	n/a	Presence of surface water	Internal
World Database on Protected Areas	IUCN	Vector (Poly)	2019	n/a	Mandate for protection	Internal

Data Sources

Acronym	Full Name	Host/Providor
CESM	Community Earth Systems Model	National Center for Atmospheric Research
EC-JRC	European Commission Joint Research Center	European Commission
ESRI	Environmental Systems Research Institute	n/a
ISIMIP	Inter-Sectoral Impact Model Intercomparison Project	Potsdam Institute for Climate Impact Research
IUCN	International Union for Conservation of Nature	n/a
SEDAC	Socio-Economic Data and Applications Center	NASA/Columbia University Earth Institute
UNPD	United Nations Population Division	n/a
WGI	Worldwide Governance Indicators	World Bank

4.1 Historical Bilateral Migration Flows

The historic international migration data used to calibrate the model were obtained from two sources. First, for movement from each Central American country and Mexico to the United States, data for 1990, 2000, and 2015 were accessed through the Migration Policy Institute (MPI 2019), which for 2000 and 2015 includes the data found in the Yearbook of Immigration Statistics from the Department of Homeland Security (e.g., USDHS 2015). Flows include all migrants to the United States who have been granted legal status, which includes green card (permanent residents) and visa holders (temporary nonimmigrants), and refugees/asylum-seekers. These data are supplemented by the bilateral flow data produced by Abel and Cohen (2019), who estimate bilateral migration flows between all origin-destination country pairs based on migrant stock data published by the World Bank and United Nations. The Abel and Cohen dataset is the source of all flows between Central American countries (including Mexico), as the bilateral flow data between countries is not provided by national statistical offices, is not compiled consistently or over the appropriate time steps, or does not exist. For purposes of consistency across all countries in the study, the MPI data have been scaled to reflect the trends reflected in the Abel and Cohen dataset.

4.2 Inter-Sectoral Model Intercomparison Project

The Inter-Sectoral Impact Model Intercomparison Project (ISIMIP) is an ongoing community-driven modeling effort organized by Potsdam Institute for Climate Impact Research (PIK) designed to provide a framework for comparing multi-scale, cross-sectoral climate impact projections (Warszawski et al. 2014). Based on the RCPs and SSPs, ISIMP facilitates a quantitative assessment of impacts across multiple sectors and models based on common climate and socioeconomic background scenarios and climate model inputs. A major goal of the project is the development of policy-relevant metrics. Over the course of this century, policymakers will be tasked with assessing the costs associated with mitigation efforts against those of adapting to a warmer world. In that spirit, the project is motivated by and organized around a central question: how do impacts vary between 2°C, 3°C, and 4°C of global warming? Research is designed to isolate "tipping points," the level of environmental change associated with rapid increase in negative sectoral impacts.

The ISIMP "fast track," completed in 2013 and published in 2014, included 28 global impact models representing five different sectors (water, biomes, agriculture, coastal infrastructure, and health). Fast-track results were published in a special issue of *The Proceedings of the National Academy of Sciences* and are available for public use through PIK. Impact models were driven by common gridded climate data from five different climate models spanning the full range of RCPs. Data are organized on a 0.5° x 0.5° global grid for the period 1960-2100. More detail on the climate inputs, impact models, and scenarios can be found in Warszawski et al. (2014).

This project uses outputs of the ISIMIP Fast Track modeling effort for crop production, water availability, and ecosystem impacts, which covers 1970–2010, as well as projections for 2010–50 (Piontek et al. 2013). Under the Fast Track, the future sectoral impact models are driven by a range of general circulation models. This project used two general circulation models that provide a good spread for the temperature and precipitation parameters of interest: the HadGEM2-ES climate model developed by the Met Office Hadley Centre for Climate Change (United Kingdom) and the IPSL-CM5A-LR climate model developed by the Institut Pierre Simon Laplace Climate Modeling Center (France). The crop, water, and ecosystem simulations — at a relatively coarse spatial scale (0.5°) — represent indicators that capture the impact climate may have on specific types of livelihoods, the viability of which will figure into the migration decision (e.g., climate acting *through* other mechanisms; see Figure 1). These climate impacts were selected because the literature shows that water scarcity, declining crop yields, and declines in pasturage are among the major potential climate impacts facing lower-income countries and these impacts will also be very important drivers of migration.

4.2.1 Water and crop models

The primary ISIMIP drivers included in this analysis were water availability and crop yields. Output from the water sector model are representative of river discharge, measured in cubic meters per second in daily/monthly time increments, and are influenced by rainfall and changing temperatures. Crop sector model outputs estimate annual crop yield of four staple crops (maize, wheat, rice, and soybeans) in tons per hectare at a 0.5° x 0.5° grid cell resolution, and they are a function of rainfall, temperature, CO_2 concentrations, irrigation, and other management practices. Because the impact of climate change on local conditions, that is the deviation from historic local norms, is more indicative of potentially disruptive change than absolute yields, here we adopt the approach used in the Groundswell report in which the data are transformed to reflect periodic deviation from the 40-year historic baseline. The data were converted to five-year average water availability and crop production (in tons) per grid cell, and an index was then calculated that compares those values with the 40-year average for water availability and crop production for 1970–2010:

$$Index = (D_{avg} - B_{avg}) / B_{avg} \qquad \text{(Eq. 1)}$$

where D_{avg} is the five-year average crop production/water availability and B_{avg} is the baseline average crop production/water availability for the 40-year period 1970–2010. The indexes for water availability and crop production represent deviations from the long-term averages.

We also adopt the Groundswell approach to selecting ISIMIP crop and water model outputs based on different combinations of climate, crop, and water models. Applying the combinations — two global climate models driven by two different emissions scenarios, which in turn drive two sets of sectoral impact models (described below) — provides a range of plausible population projections while also indicating regions where the models tend toward agreement (Rigaud et al. 2018). The modeling for this assessment employed the HadGEM2-ES and IPSL-CM5A-LR global climate models, which drive combinations of the two water models and two crop models: the LPJmL water and crop models, the WaterGAP2 water model, and the GEPIC crop model (Table 2). The crop and water models were selected by experts at PIK based on several criteria, including model performance over the historical period, diversity of model structure, diversity of signals of future change, and availability of both observationally driven historical and global climate model-driven historical and future simulations. Table 2 (below) presents the combinations of models used.

Table 2. Matrix of global climate models and crop/net primary productivity (NPP) and water model combinations (adopted from Rigaud et al. 2018)

	Crop/NPP simulation			
Water simulation	*HadGEM2-ES, LPJmL (crop) LPJmL(NPP)*	*HadGEM2-ES, GEPIC (crop) Visit (NPP)*	*IPSL-CM5A-LR, LPJmL (crop) LPJmL (NPP)*	*IPSL-CM5A-LR, GEPIC (crop) Visit (NPP)*
HadGEM2-ES, LPJmL (water)	Model 1			
HadGEM2-ES, WaterGAP2		Model 2		
IPSL-CM5A-LR, LPJmL (water)			Model 3	
IPSL-CM5A-LR, WaterGAP2				Model 4

4.2.2 Ecosystem productivity

In the same way that crop production is an important metric of farm-based livelihoods, ecosystem productivity is an important measure for pastoral livelihoods. Throughout most of Central America, agriculture is more prevalent than pastoralism or other livestock operations, however there are regions (particularly in Mexico) where such livelihoods dominate. In this project, ecosystem productivity is applied as a potential driver in non-urban areas where the crop data indicate that agriculture is not taking place (e.g., those places likely suitable for pastoralism). Using ecosystem productivity only in areas lacking crop productivity data was deemed preferable to including an overlay of NPP on top of the crop production, since there is high spatial co-linearity between the crop and ecosystem metrics.

Ecosystem productivity is estimated in terms of net primary productivity (NPP). The ecosystem models simulate the natural growth of several different plant functional types, including grasses, thus, NPP simulated by these models serves as an estimate of the productivity of a location's natural biome, including grassland biomes that may potentially support pastoral livelihoods. Like the water and crop metric, NPP is transformed to represent local periodic deviation from the historic baseline. The NPP sectoral models used in this work are the LPJmL and Visit models — the former is used with the LPJml crop production and water availability models, while the latter is used with the GEPIC crop and WaterGap water models — and the models were driven by the same general circulation models as the water and crop models.

4.3 Flood hazard

Flood hazards are known to have a substantial impact on displacement throughout Central America, particularly in those places vulnerable to tropical weather systems. The flood hazard layer is based on projected flood depth simulated by a global flood model CaMa-Flood (Yamazaki et al. 2011) version 3.4.4, which itself is driven by inputs (daily runoff) from multiple global hydrological models included in the ISIMIP2b (Frieler et al. 2017) project. The hydrological models are forced by four bias-corrected climate model outputs (temperature, precipitation, radiation, etc.) from the Coupled Model Intercomparison Project phase 5 (CMIP5; Taylor et al. 2012). In this assessment, the historic relationship between flood hazard, as characterized by the return rate of 100-year flood, and spatial population change was established (controlling for other variables). This relationship was assumed to remain constant and contributed to projections of future spatial population change.

4.4 GRACE Groundwater

The Trends in Global Freshwater Availability from the Gravity Recovery and Climate Experiment (GRACE), 2002-2016, is a global gridded dataset at a spatial resolution of 0.5° that presents trends (rate of change measured in centimeters per year) in freshwater availability based on data obtained from 2002 to 2016 by NASA GRACE. Terrestrial water availability storage is the sum of groundwater, soil moisture, snow and ice, surface waters, and wet biomass, expressed as an equivalent height of water. GRACE measures changes in the terrestrial water cycle by assessing small changes in Earth's gravity field. This observation-based assessment of how the world's water cycle is responding to human impacts and climate variations provides an important tool for evaluating and predicting emerging threats to water and food security (Rodell at al. 2019).

4.5 RCP-based Extreme Heat Outcomes

The extreme heat projections for this assessment are taken from the Benefits of Reduced Anthropogenic Climate Change (BRACE) project (O'Neill and Gettelman, 2018). The National Center for Atmospheric Research–Department of Energy (NCAR-DOE) Community Earth System Model (CESM) large ensemble (29 members) was used to produce projections of future conditions under the RCP8.5 climate scenario (Kay et al. 2014) and the medium ensemble (14 members) for projections of future conditions under the RCP4.5 climate scenario (Sanderson et al. 2015). For the RCP2.6 scenario, we assume the current temperature regime persists. Global projections of temperature are considered at the ~1° native CESM grid and bias corrected before computing heat extreme metrics (Oleson et al., 2015).

There is no universally agreed upon definition of a heat wave, so once again we draw on the BRACE project to develop a locally adaptive method for characterizing heat extremes (e.g., Anderson et al., 2016; Jones et al., 2018). At the grid-cell level, we define a heat wave to account for two basic features of the problem: local conditioning (i.e., the range of temperatures to which local population is acclimated) and a minimum intensity, to ensure that a heat wave actually consists of dangerously warm days. We achieve this by specifying two thresholds that must be met for any two or more consecutive days: an average daily temperature ($\bar{T}$) that is greater than a relative threshold ($\bar{T}_{rel}$) specified as a percentile of the current distribution of daily mean temperature, and a maximum daily temperature ($\hat{T}$) that is greater than an absolute temperature threshold (T_{abs}). That is, a heat wave day must have:

$$\bar{T} > \bar{T}_{rel} \quad , \quad \hat{T} > T_{abs} \qquad \text{(Eq. 2)}$$

To implement this definition, we assume that the relative threshold is given by the 98th percentile of the present-day (1981-2005) distribution of daily mean temperature ($\bar{T}_{98}$), and that the absolute threshold is a daily maximum temperature of 35°C (T_{35}), a commonly used heat threshold (Wilder et al. 2013; Jones et al. 2015).[1] As such, an extreme heat event is comprised of two or more consecutive days meeting the following criteria:

$$\bar{T}_{GCA} > \bar{T}_{98,GCA} \quad , \quad \hat{T}_{GCA} > T_{35,GCA} \qquad \text{(Eq. 3)}$$

In this work we consider extreme heat in a twofold manner. First, we assess the historic relationship between spatial population change and average annual exposure to extreme heat measure in person days (number of extreme heat days * population). In many cases, there is no meaningful relationship (with some notable exceptions throughout drier regions of Mexico and some lowland regions of Central America). The second application of these data is to project changes in exposure to heat extremes over time. Thus, whereas in some regions the impact of heat on migration may be difficult to characterize, we are able to speak to the potential change in exposure under different climate/socioeconomic scenarios that is an important component of assessing future vulnerability to climate extremes.

4.6 Instability, Violence, and Corruption

Broad data on governance are from the Worldwide Governance Indicators (WGI) project, which covers over 200 countries and territories, measuring six dimensions of governance starting in 1996: voice and accountability, political stability and non-violence, government effectiveness, regulatory quality, rule of law, and control of corruption. The aggregate indicators are based on several hundred individual underlying variables, taken from a wide variety of existing data sources. The data reflect the views on governance of survey respondents and public-, private-, and NGO-sector experts worldwide. The WGI also explicitly report margins of error accompanying each country estimate. These reflect the inherent difficulties in measuring governance using any kind of data. Even after taking these margins of error into account, the WGI permit meaningful cross-country and over-time comparisons (Kraay et al. 2010). In this project we use the (1) political stability and non-violence index, defined as "capturing perceptions of the likelihood of political instability and/or politically-motivated violence, including terrorism" and the (2) control of corruption index, which "captures perceptions from firms and households survey respondents and public, private, and NGO sector experts worldwide of public power exercised for private gain,

[1] The most deadly extreme heat events of the past several decades have demonstrated maximum daily highs in exceedance of 40°C for several consecutive days (e.g., India 2015; France/Europe 2003; Chicago/Midwestern US 1995) while daily mean temperatures hovered between the 32-36°C range.

including both petty and grand forms of corruption, as well as 'capture' of the state by elites and private interests."

4.7 Gross Domestic Product (GDP)

Long-term scenarios (up to 2100) of national-level GDP are from the Organization for Economic Co-operation and Development (OECD) and are based on the five SSPs. The projections assume a convergence process and places emphasis on the key drivers of economic growth in the long run: population, total factor productivity, physical capital, employment and human capital, and energy and fossil fuel resources (specifically oil and gas). The projections are subject to large uncertainties, particularly for the later decades, and disregard a wide range of country-specific drivers of economic growth that are outside the narrow economic framework, such as external shocks, governance barriers and feedbacks from environmental damage. Hence, they should be interpreted with sufficient care and not be treated as predictions, but instead as scenarios that are consistent with the qualitative narratives embodied by the SSP (Dellink et al. 2017). In this work, national-level GDP is used along with population scenarios to derive GDP per capita, a proxy for income/wage rates and an important driver of cross-boundary migration.

4.8 The Global Human Settlement Layer (GHSL)

The Global Human Settlement Layer, produced by the Joint Research Center (JRC) of the European Commission, is a remote sensing-derived global data product that represents built-up land for different points in time over 40 years (1975, 1990, 2000, and 2014) at approximately 38 meters resolution, aggregated to 250 meters (Corbane et al. 2018). The original resolution data are binary, indicating either the presence or absence of a built structure in each 38 meter grid cell (Pesaresi et al. 2013; 2016). The aggregated data are constructed from the 38 meter cells to quantify the percentage of each cell that is built-up. This construction implies an aggregation of the original data to 304 meters and a subsequent resampling step to 250 meters to facilitate compatibility with other 1 kilometer global land cover and population data products. A recent validation study has generally confirmed the accuracy of the GHSL data layers for the different points in time in urbanized settings but also reported higher levels of classification errors in rural regions (Leyk et al. 2018).

4.9 The Global Human Settlement Population Grid (GHS-Pop)

GHS-Pop is a high-resolution spatial raster dataset that depicts the distribution and density of population, expressed as the number of people per cell at 250 meter and 1 kilometer resolution for 1975, 1990, 2000, and 2015 (Schiavina et al 2019). To derive residential population estimates for each period, population data from census or administrative units, provided by the Center for International Earth Science Information Network (CIESIN) Gridded Population of the World v4 (GPW), were disaggregated to grid cells. The process was guided by the distribution and density of built-up area as indicated by the GHSL global layer for each period. The GPW gridded distributions are minimally modeled population counts (or population density grids) produced using the best (highest resolution) available administrative census data for each time period. Data are transposed from census units to grids proportionally according to the area of each census unit comprised by each grid cell after masking for water and ice (CIESIN 2016). The algorithm does not change over time, ensuring consistency and comparability across census periods. In this work the 2015 distribution of GHS-Pop serves as the base-year distribution for the internal migration model, and the historic distributions (1990, 2000) are included for model testing and validation.

4.10 Diaspora

The presence and size of a foreign-born population within a host country is often indicative of the strength of social networks that exist between sending and receiving nations. In this work, we use the foreign-born population in each Central American country (and the United States) originating in another Central American country as a measure of the strength of the social connection between countries. Migrant stock data are from the United Nations Department of Economic and Social Affairs - Population Division, and they are expressed as counts (UN 2017).

4.11 Population Age and Sex Structure

Spatial data on the age and sex distribution per grid cell was obtained from the Gridded Population of the World Version 4.10 Basic Demographic Characteristics (CIESIN 2017). Data on median age and the sex ratio (males as a percent of female population) were used to calibrate the model by establishing the relationship between spatial population change and demographic characteristics of the population. For future projections, we assume that variability in sex ration and median remain constant over space.

4.12 Elevation, Slope, Surface Water, and Mandate for Protection

The spatial population model includes a geospatial mask that acts as a multiplier, proportionally scaling the population potential for each grid cell as a function of the area within each cell deemed suitable for human habitation. We construct the mask from four geospatial data layers: surface water, elevation, slope, and protected land. We overlay these data to produce a single mask from which we extract the portion of each cell suitable for habitation. We use the ESRI World Water Bodies (DeLorme 2013) dataset to mask global surface water. Elevation and slope data are from the Global Multi-Resolution Terrain Elevation Data 2010 (GMTED2010; Danielson and Gesch 2011). We use the elevation of the highest permanently populated settlement in each continent as a ceiling to exclude land from future habitation as a function of high elevation. In general, development costs increase substantially on land exhibiting a slope greater than 15%, which is also the point at which many municipalities impose development regulations (e.g. Theilacker and Anderson 2010). Here we account for the likelihood that improved technology will reduce the costs associated with excess slope and instead impose a threshold of 25%, an oft-cited “no-development” threshold in municipal regulations across the United States (Houck 2005). Finally, we use the International Union for the Conservation of Nature (IUCN) World Database on Protected Areas (WDPA) to mask land as a function of mandate for protection (IUCN 2015). Specifically, any area classified under IUCN categories Ia (strict nature reserve), Ib (wilderness area), II (national park), III (national monument or feature), or IV (habitat/species management area) is masked as not suitable for development/habitation.

In some cases, we found existing base-year population in cells otherwise completely masked as a function of mandate for protection. There are two possible explanations. First, the algorithm used to distribute the existing population across grid cells in the GPW base-year data does not specifically account for protected land, and as such population and protected land may overlap in the base-year. Second, in many cases new mandates for protection grandfather in existing populations (e.g. people living in newly designated national forest land in the United States). For modeling purposes, we treat both of these cases identically. For example, cells that are 100% masked as a function of mandate for protection are not eligible to receive any projected future population growth. However, these cells are allowed to lose people during periods of population decline. This decision reflects our perception of real-world population change in areas with both existing population and prohibitions on new development.

5. Modeling Methods

The modeling approach, broadly, consists of two modules that are loosely coupled over time. First, the international model projects five-year movement across international boundaries[2] within Central America and Mexico, to and from the United States, and to and from the rest of the world (aggregate). International movement is then fed into the second component of the model at each five-year time step, the internal model. The internal migration model projects population change over 1 kilometer grid-cells within each country individually.

5.1 International Model

While there is currently little empirical evidence to suggest that the large-scale movement of people across national boundaries is a likely consequence of climate change across large regions of the globe, there is also very little in the way of historic precedent for the environmental changes likely to occur as a result of a shifting climate. Here we introduce a method for identifying origin-destination international migration flows that could potentially intensify or decline as a result of environmental change. We take advantage of existing bilateral flow data (Abel and Cohen 2019), to train and project our 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. The proposed international model will operate at the country level, and we apply the model to each of the proposed RCP/SSP scenarios.

5.1.1 Procedure

The Abel and Cohen (2019) international migration flow data include origin-destination counts of migrants for each of four periods: 1990-1995, 1995-2000, 2000-2005, 2005-2010. From these data, we will calculate historic outmigration rates for each country over each of the four periods. We will then model national-level outmigration as a function of the components from Table 1 using a Poisson log-linear regression model:

$$\log(\mathrm{m}_{ij,t}) = \propto + \beta_1 G_{ij,t} + \beta_2 V_{i,t} + \beta_3 C_{i,t} + \beta_4 A_{i,t} + \beta_4 W_{i,t} + \beta_4 D_{ij,t} + \log(P_{i,t}) \qquad \text{(Eq. 4)}$$

where $\mathrm{m}_{ij,t}$ is the count of migrants from country i to j at time t, G is the difference in GDP per capita between country i and j, V is the value of the instability/violence index, C is the value of the corruption index, A is the five-year deviation of crop yield/NPP from historic baseline, W five-year deviation in water availability from historic baseline, D is the size of the population born in country i currently residing in country j, and $P_{i,t}$ is the population of country i at time t.

[2] The SSP population projections include an estimate of international migration based on an existing global-level matrix of in- and out-migration (Abel and Sander 2014) and adjusted to reflect assumptions regarding, for example, conflict and political changes and the degree of openness of national borders in each SSP (O'Neill et al. 2015). As this study builds on the SSPs, by definition it also includes the bilateral migration flows included in the national-level population projections that correspond to each SSP (Samir and Lutz 2014). For SSP1 these flows are in the middle of the range , for SSP3 they are low, and for SSP5 they are high.

5.1.2 Validation

Validation of the international model was carried out in a relatively straightforward fashion. To validate our approach, we will fit the model to the observed bilateral flow data for the period 1990-1995 and projected migration flows for the subsequent three periods: 1995-2000, 2000-2005, 2005-2010. Errors varied substantially over time, ranging from lows hovering between 1% and 5%, to over 80% in some of the lesser traveled migratory routes (e.g., Belize to Panama, which average less than 100 migrants in each five-year period). Like many similar models, it is very difficult to project shocks that might dramatically change migratory flows, particularly sudden economic crises and/or wars. As such, error tends to be higher when unexpected shocks occur. Conversely, the model performs at a higher level when conditions in the sending and receiving countries of any given flow remain somewhat stable and predictable.

5.2 Internal Model

Hugo (1996) shows that the majority of environmental migrants stay close to their former home and within the boundaries of their country. Similarly, the vast majority of future climate migrants and displaced persons are expected to move internally (e.g., Raleigh et al. 2008; Waldinger 2015; Hugo 1996). Measuring internal migration is challenging as there is no standard definition regrading what constitutes a migration (e.g., distance or temporal duration). Furthermore, the lack of consistent data regarding historic migration patterns in many countries confounds efforts to model future migration.

5.2.1 The Gravity Model

The model adopted in this work is based the approach from the Groundswell report (Rigaud et al. 2018), which itself was adapted from the INCLUDE gravity-based downscaling model (Jones and O'Neil 2013, 2016). The INLCUDE model downscales national population projections to subnational raster grids as a function of geographic, socioeconomic, and demographic characteristics of the landscape and existing population distribution. Gravity-type approaches, commonly used in geographic models of spatial allocation and accessibility, take advantage of spatial regularities in the relationship between population agglomeration and patterns of population change. These relationships can then be characterized as a function of the variables known to correlate with spatial patterns of population change.

The INCLUDE model uses a modified form of population potential, a distance-weighted measure of the population taken at any point in space that represents the relative accessibility of that point (for example, higher values indicate a point more easily accessible by a larger number of people). Population potential can be interpreted as a measure of the influence that the population at one point in space exerts on another point. Summed over all points within an area, population potential represents an index of the relative influence that the population at a point within a region exerts on each point within that region, and (Rich 1980) it can be considered an indicator of the potential for interaction between the population at a given point in space and all other populations. Population potential will typically be higher at points close to large populations, thus it is also an indicator of the relative proximity of the existing population to each point within an area (Warntz and Wolff 1971). Historically, population potential is often considered as a proxy for attractiveness, under the assumption that agglomeration is indicative of the various socioeconomic, geographic, political, and physical characteristics that make a place attractive.

For this assessment, the calculation of potential was modified primarily by adding variables that describe local/regional conditions, including climate impacts on economic livelihoods, and weighting the attractiveness of each location (grid cell) as a function of the historic relationship between these variables and observed population change. Population potential is, conceptually, a relative measure of agglomeration, indicating the degree to which amenities and services are available. In the INLCUDE model, this value shifts over time as a function of the population distribution, assumptions regarding spatial development patterns (e.g., sprawl vs. concentration), and of certain geographic characteristics of the landscape. The Groundswell approach expanded the model by considering the local impact of climate on certain key sectors. In this further expanded version of the model, the agglomeration effect is enhanced or muted as a function of additional local characteristics that aid in differentiating between places. Furthermore, the version of the model applied here operates at high resolution (1 kilometer) and considers cross-boundary influences.

Beginning with the 2015 gridded population distribution for each country, 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, we then run a set of scenarios that exclude the impacts of climate change. That is, we 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. Figure 3 provides a full flowchart of the modeling steps.

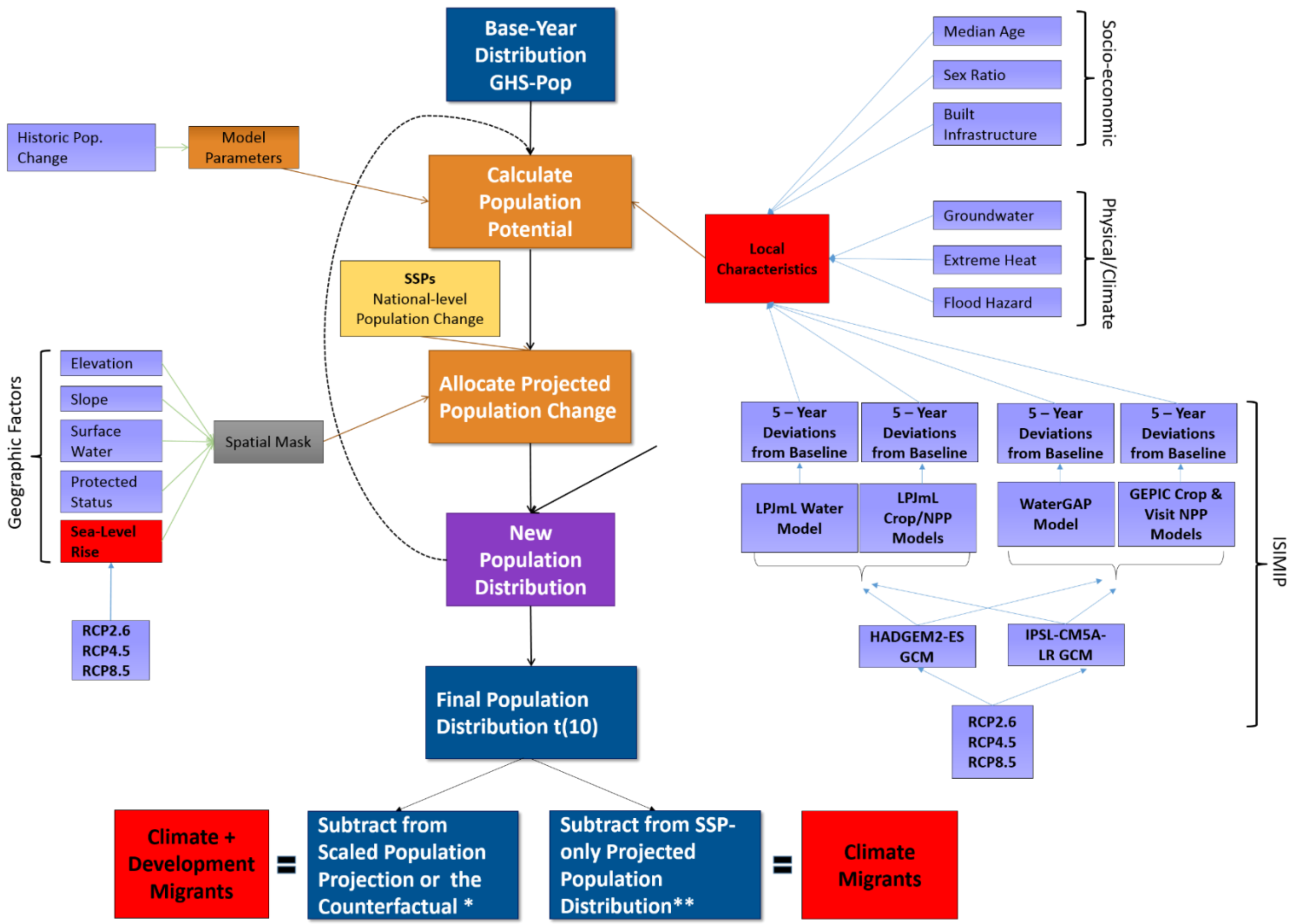
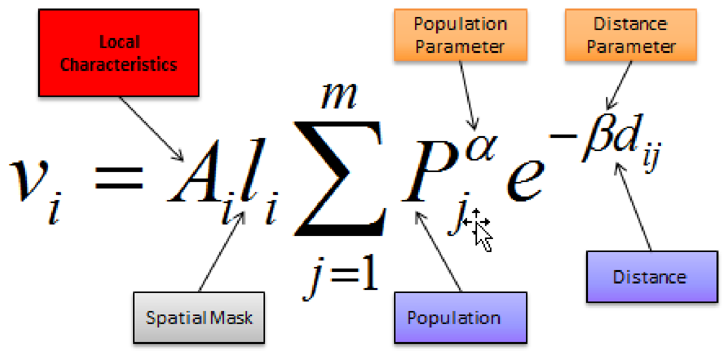


Figure 3. Flowchart of modeling steps (adapted from Rigaud et al. 2018)

* The counterfactual population projection simply scales the population distribution in 2010 to country-level population totals appropriate to each SSP.
** The no climate impacts projection does not include any climate impacts (i.e., based only on the development trajectories embodied in the SSPs and the conflict and age and sex characteristics of the baseline population).

In this modified version of the INCLUDE model, population potential (v_i) is calculated as a parametrized negative exponential function:



$$v_i = A_i l_i \sum_{j=1}^{m} P_j^{\alpha} e^{-\beta d_{ij}}$$

(Eq. 5)

where spatial mask (l) prevents population from being allocated to areas that are protected from development or unsuitable for human habitation, including areas that will likely be affected by sea level rise between 2010 and 2050. P_j is the population of grid cell j, and d is the distance between two grid cells. The population and distance parameters (α and β) are estimated from observed patterns of historical population change. The β parameter is indicative of the friction of distance or the cost of travel that generally determines the shape of the distance–density gradient in and around urban areas (e.g., sprawl vs. concentration). The α parameter captures returns on agglomeration externality, interpreted as an indicator of the characteristics that make a place more or less attractive.

Importantly, the SSPs include no climate impacts on aggregate total population, urbanization, or the subnational spatial distribution of the population. The INCLUDE approach was modified by incorporating additional spatial data including the ISIMIP sectoral impacts, projections of groundwater availability, flood hazard, and extreme heat, demographic characteristics of the population, and characteristics of the built environment, all of which are likely to affect population outcomes. The index A_i is a weight on population potential that is calibrated to represent the influence of these factors on the agglomeration effect that drives changes in the spatial distribution of the population. All of the data are incorporated into the model as 1 kilometer gridded spatial layers. The ISIMIP data represent five-year deviation from long-term baseline conditions, the demographic data are observed median age and sex ratio, and conflict-related fatalities are interpolated from point data. The value A_i is calculated as a function of these indicators. Numerically, it represents an adjustment to the relative attractiveness of (or aversion to) specific locations (grid cells), reflecting current water availability, crop yields, and ecosystem services relative to "normal" conditions, as well as the demographic composition of the population and the likelihood of dangerous conflict.

5.2.2 Calibrating the Model

The model is calibrated over two decadal periods (1990–2000 and 2000–2015) of observed population change relative to observed climatic, demographic, and socioeconomic conditions. As noted above, the value A_i is calculated as a function of these different climatic, demographic, and socioeconomic indicators and acts as an adjustment to relative attractiveness. In order to carry out the procedure, model estimates of the α and β parameters are necessary, and A_i must be calibrated. Two separate procedures are employed.

The α and β parameters are designed to capture broad-scale patterns of change found in the distance-density gradient, which is represented by the shape/slope of the distance decay function from Equation 5. The negative exponential function described by Equation 5 is very similar to Clark's (1951) negative exponential function, which has been shown to accurately capture observed density gradients throughout the world (Bertaud and Malpezzi 2003). To estimate α and β, the model in equation 5 is fitted to the 1990-2000 and 2000-2015 population change from GHS-Pop, and we compute the values of α and β that minimize the sum of absolute deviations:

$$S(\alpha, \beta) = \sum_{i=1}^{n} \left| P_{i,t}^{mod} - P_{i,t}^{obs} \right| \qquad \text{(Eq. 6)}$$

where $P_{i,t}^{mod}$ and $P_{i,t}^{obs}$ are the modeled and observed populations in cell i, and S is the sum of absolute error across all cells. We fit the model for two time steps (1990-2000 and 2000-2015) and take the average of the α and β estimates.

In this modified version of the population potential model, the index A_i is a cell-specific metric that weights the relative attractiveness of a location (population potential) as a function of environmental and/or socioeconomic conditions. The modeling approach requires that the relationship between A_i and the different local indicators is estimated, which are hypothesized to impact population change. When α and β are estimated from historic data (e.g. observed change between 2000 and 2015), a predicted population surface is produced that reflects optimized values of α and β, such that absolute error is minimized. Figure 4 includes a cross section (one dimension) of grid cells illustrating observed and predicted population for 10 cells. Each cell contains an error term that reflects the error in the population change projected for each cell over a 10-year time step. It is hypothesized that this error can at least partially be explained by a set of omitted variables, including environmental/sectoral impacts. To incorporate these effects, we first calculate the value of A_i such as to eliminate ε_i (from Figure 4) for each individual cell (which is labeled observed A_i):

$$\Delta P_{i,t}^{obs} = A_i * \Delta P_{i,t}^{mod} \qquad \text{(Eq. 7)}$$

where $\Delta P_{i,t}^{obs}$ and $\Delta P_{i,t}^{mod}$ are the observed and modeled population change for each cell i and A_i is the factor necessary to equate the two.

The second step is to estimate the relationship between observed index A_i and the different potential drivers of spatial population metrics by fitting a spatial lag model:

$$A_{i,t} = \rho W A_{i,t+} \beta_1 C_{i,t} + \beta_2 H_{i,t} + \beta_3 N_{i,t} + \beta_4 F_{i,t} + \beta_4 E_{i,t} + \beta_4 W_{i,t} + \beta_5 M_{i,t} + \beta_6 S_{i,t} + \beta_7 K_{i,t} + \varepsilon_{i,t} \qquad \text{(Eq. 8)}$$

where C,H and N are the five year deviations from the historic baseline on crop yield, water availability, and net primary production, respectively, F is the flood risk metric, *W* is groundwater availability, *E* is incidents of extreme heat, *M* is median age, *S* is sex ratio expressed as (male/female), and K is the built-up metric (GHSL). Together these nine variables and their respective coefficients constitute the set of explanatory variables that go into producing index A_i. Note that for any grid cell in which C (crop yield) is a non-zero value, the value of N (net primary production) is automatically set to zero, so that only one of the two variables is contributing to the index A_i. Finally, ρ is the spatial autocorrelation coefficient and W is a spatial weight matrix. From this procedure, a set of cell specific *A* values is estimated.

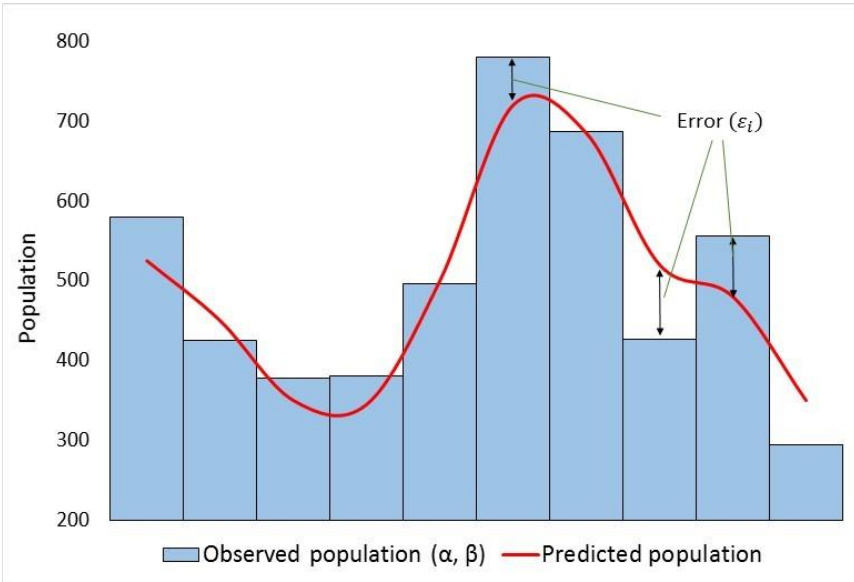


Figure 4: Cross section of grid cells illustrating observed and projected population distributions. Note: The error term is used to calibrate the index A(i).

For future projections (for urban and rural populations), projected values of each independent variable are used along with their respective coefficient estimates from Equation 8 to estimate spatially and temporally explicit values of A_i. Finally, to produce a spatially explicit population projection, estimates of α and β are adjusted to reflect the SSPs (e.g. the SSP1 storyline implies a more concentrated pattern of development than SSP5, see Jones and O'Neill 2016) to produce estimates of the agglomeration effect, to which the spatio-temporally variant estimates of A_i for the RCPs described above are applied, and finally exogenous projections of national urban and rural population change are incorporated and the model applied as specified above.

Past testing of the model indicated that cells meeting certain criteria should be excluded from the calibration procedure. First, cells that are 100% restricted from future population growth by the spatial mask (l, Equation 5) are excluded, as the value of v_i in these cells (0) renders the observed value of A_i inconsequential. Second, the rural and urban distributions of observed A_i were found to include significant outliers that skewed coefficient estimates in Equation 8. In most cases, these values were found to correspond with very lightly populated cells where a small over/under prediction of the population in absolute terms (e.g. 100 persons) is actually quite large relative to total population within in the cell (e.g. large percent error). The value of A_i (the weight on potential), necessary to eliminate these errors, is often proportional to the size of the error in percentage terms, and thus can be quite large even though a very small portion of the total population is affected. Including these large values in Equation 8 would have a substantial impact on coefficient estimates. To combat this problem, the most extreme 2.5% of observations are eliminated on either end of the distribution. Third, because the model is calibrated to urban and rural change separately, cells in which rural population was reclassified as 100% urban over the decade (2000-2015) were excluded, as the effect would be misleading (in the rural distribution of change it would appear an entire cell was depopulated, while in the urban change distribution the same cell would appear to grow rapidly). It would be incorrect to attribute these changes to sectoral impacts when, in fact, they are the result of a definitional change. In most cases, these exclusions eliminate 5-10% of grid cells.

5.2.3 Estimating Internal Climate Migrants

Gravity models do not directly model internal migration. Instead, internal 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 the non-climate related drivers). Migration is a "fast" demographic variable compared with fertility and mortality; it is responsible for much of the decadal-scale redistributions of population (Rigaud et al. 2018). Without significant variation in fertility/mortality rates between climate-migrant populations and non-migrant populations, it is fair to assume that differential population change between the climate impact scenarios and the development-only scenarios occur as a function of migration. Thus, for each grid cell we consider the impact of climate change to be the difference between the "climate" and "no-climate" scenario (e.g. SSP3/RCP8.5 vs. SSP3/No-Climate). To estimate total internal migration under any scenario, we sum the positive differences at the grid-cell level between any scenario and its corresponding no-climate scenario.

6. Limitations

The model adapted and applied in this work is a "top-down" type model that is designed to capture and estimate broad trends in spatial population change. This type of approach is well suited for large-scale application over larger regions or globally, and it has been shown to, in general, capture and replicate observed patterns of broad spatial change with a high degree of accuracy (Jones and O'Neill, 2013). However, this type of approach does come with certain limitations. Furthermore, any attempt to estimate future patterns of climate migration will carry with it certain limitations, regardless of the choice of model. In this section, we discuss limitations both directly related to the modeling applied here, and more broadly to models of climate migration in general.

6.1 Uncertainty

Modeling certain human behaviors, such as migration, is often fraught with uncertainty. Adding the dimension of climate change to such an exercise will compound existing uncertainty. Broadly, uncertainty exists in both the socioeconomic and physical (climatic) dimensions of the modeling applied here — both the international and internal models. Here we will discuss the primary sources of uncertainty in more detail.

Beginning on the physical/climate side, for each climate migration scenario (SSP/RCP combination), the model produces a range of estimates that reflect variation in the underlying inputs to the model. Five of these inputs (crops, water, NPP, flood hazard, and heat extremes) vary over time as a function of climate, meaning they take different values and distributions as a function of the prescribed climate scenario (RCP) and the model that was used to produce them (e.g., global climate model; sectoral impact model). Variation across RCPs reflects uncertainty regarding the future degree to which climate change will occur and, in turn, impact migration. Conversely, variation across models within the same RCP reflects scientific uncertainty over climate processes (e.g., different results across global climate models under the same RCP) and climate impacts on each of the variables that impact the migration decision. In any scenario, outcomes are a function of the global climate models, the sectoral impact models, and the flood/heat models that drive climate impacts on population change. For each of the five scenarios, there are four models (ensemble members), consisting of different global climate model/ISIMIP/flood hazard/heat combinations. The ensemble mean (or average) of the four models is reported as the primary result for each scenario. Uncertainty is reflected in the range of outcomes (across the four models) for each grid cell and at different levels of aggregation. The scenario-based approach is preferable to adopt a single model in this type of research precisely because of the uncertainty surrounding many of the inputs and the outcomes, and attention should be given to the variation across the full ensemble for each SSP/RCP scenario.

The remaining inputs to the internal model, age structure, sex ratio, built-up land, and groundwater, are held constant into the future, primarily because we don't have projections of these factors will evolve at 1 kilometer resolution over time. Attempting to model change in these factors is beyond the scope of this work, it and would introduce more uncertainty into the model. In the absence of projections, the conservative decision is to hold values constant, however, it is also quite likely that this assumption will be incorrect, and as such one must consider the impact of this decision on the results. Similarly, in the international model the metrics representing stability and corruption are held constant. History, however, indicates that Central America has experienced its fair share of change, going through periods of increasing and decreasing political stability, for example. It is very difficult to predict political change and/or shocks, and we don't attempt to do so here, so one must interpret the international migration results as assuming unchanged levels of political stability, which again is an uncertain outcome.

The SSPs were designed to encompass a wide range of conditions in support of the scenario-based approach to climate impacts, and in this regard they are extremely useful. However, there is a fair degree of uncertainty around the demographic (population) and socioeconomic (GDP) assumptions and projections that accompany each scenario. For example, the national-level population projected for each country under each scenario depends on assumptions regarding future age-specific fertility and mortality, education, wealth, and broad assumptions regarding international mobility. Each one of these components will impact population outcomes, and deviation from the assumed level of each input can lead to substantial variation in outcomes. We cannot assess this uncertainty in the same way that we can the uncertainty in climate models, as each SSP is accompanied by a single projection produced by a single model. That said, it should be considered when interpreting the results of this work that the assumptions that go into each SSP are subject to error.

A further source of uncertainty relates to the calibration of the model. We have at our disposal only a very short historic record from which to estimate the empirical relationship between population change and the hypothesized drivers. Additionally, we have only a few countries in which the historic data are of higher quality and compiled over the appropriate spatial units (Mexico, Guatemala, Belize, and El Salvador). As such, the empirical relationship identified in the calibration of the model is itself subject to uncertainty.

Finally, and related to the aforementioned sources of uncertainty, is the temporal and spatial momentum that sometimes develops within the model. The modeling has a temporal component that can influence population distribution trajectories. Stronger sectoral impacts early in the 35-year projection period will have greater influence than the same impacts later in that period, because those early impacts affect the gravitational pull of locations, creating "temporal" momentum over which later climate impacts may have less influence. Similarly, the timing of population change (growth or decline) projected by the SSPs relative to the development of sectoral impacts can influence outcomes. For example, for most countries in the study, projected population growth is greatest during the first decade; if conditions are also predicted to deteriorate severely during that period, the impact on migration will be greater than if the deterioration took place during a more demographically stable period. Similarly, the relative location of predicted positive or negative climate impacts may produce substantial nodes of growth or decline, particularly if they fall over regions with larger populations and take place earlier in the 40-year period. Put more simply, time and space matter, and the degree to which the inputs to the model project a confluence of events over time and space will substantially impact outcomes. Thus, variations in the projected timing and location of certain changes will lead to increased temporal and spatial variation in outcomes.

6.2 Non-Linear Changes

The model applied in this assessment is empirically estimated using historic data. We do so to identify how people have responded to certain climate and non-climate related factors in the past. This information is used to inform our projections into the future, importantly, under the assumption that people will continue to respond in the same manner. In this sense the model is linear. For example, if a 5% decrease in water availability has, in the past, led to a 2% decline in the population of a given region through out-migration, then given a future projection of a 10% decrease in water availability in the same region (holding all other factors constant) our model will project a 4% decline in population due to out-migration. The assumption of linearity should be considered conservative, as it is widely posited that the human response to climate stimuli will vary as a function of the intensity of that stimuli. More simply, this is to say that as water scarcity worsens, it is not illogical to believe the percent of the population making the decision to leave might rise. Here we have chosen to use only information that can be historically verified to drive our model as opposed to making assumptions regarding how the human response might change as the intensity of conditions changes. We do so, in part, because the conditions projected by the climate models are, in many cases, outside the range of historic conditions for which we have observations, thus we have no empirical data to predict how the response might vary.

In light of this decision, the intensity of climate migration projected in this work should be considered conservative. Given the conditions projected by the climate models across much of Central America and Mexico (over which there is a fair degree of uncertainty), it is more likely that our model will underestimate mobility rather than overestimate, if all other potential drivers are held constant.

6.3 Defining Migrants

As mentioned above, there is no consensus on the definition of a “climate migrant.” Because our modeling approach extrapolates climate migrants by comparing scenarios that include projections of future climate change with projections that assume no change, we can feel confident asserting that climate was a factor in the outcome. However, the top-down type of model applied here does not capture all the dimensions of so-called climate migration. First, the temporal and spatial scale of the model is instrumental in determining who is a migrant. For example, the model iterates over five-year periods and the 1 kilometer results are aggregated to 7.5’ grid cells. It is at this spatio-temporal resolution that we compare the climate and no-climate scenarios to extrapolate estimates of climate-induced migration. Thus, to be considered a migrant a person has to be located in a grid cell different from the one they were located in five years earlier. Practically, this means a person must move roughly 10 kilometers minimum and remain in the new location for a prolonged period of time. Within these parameters, we are capturing/projecting more of the long-term, longer distance migration that results from slow-onset change. Missing from these projections would be short-term migrants who return home after a sudden onset event like a storm, or seasonal migrants who begin looking for short-term work in urban areas to supplement declining farm income.

Top-down models of migration are designed to estimate the aggregate results of household-level decisions that influence migration (de Sherbinin et al. 2008), but they do not build directly on the evidence (or data) from microlevel studies. It considers such factors only at an aggregate level. The focus is on the 30 years between 2020 and 2050. This period represents a meaningful planning horizon, especially when considering social dimension of migration at the national and international level. A consequence of the decision to focus on these factors, however, is that behaviors related to climate change that take place over shorter time periods or shorter distances (e.g., moving back from an encroaching coastline) are not included here, and one must be careful when attributing the results to certain household-level behaviors.

6.4 Trapped Populations

The modeling for this analysis was designed explicitly to assess mobility. Unanticipated, climate-induced migration has the potential to be politically and practically disruptive to both sending and receiving regions. Properly assessed and planned for, climate-migration will present opportunities that both sending and receiving regions may capitalize on, thus the focus on mobility is justified and critical. However, often overlooked is another critical group, so-called trapped populations. Trapped populations comprise those people who, given the resources to do so, would likely respond to climate change/hazards by moving but for various reasons find themselves unable to do so. Unsurprisingly, socioeconomic hurdles are often to blame for the immobility of trapped populations, as many are simply too poor or lack the necessary resources to move. Others may be unable to move because of health considerations or family responsibilities. Trapped populations are among the most vulnerable to climate-related hazards, as they reside in locations that are experiencing adverse conditions, and they generally lack the economic resources not only to move, but also to adequately adapt in place.

For two primary reasons, the approach applied in this work is unable to estimate trapped populations. Theoretically, trapped populations are included in the spatially explicit projections produced by the model, as the parameters calibrated from the historic data reflect the degree to which people respond to different stimuli. Trapped populations, broadly, don't respond, and thus the presence of trapped populations in the historic data would, again theoretically, weaken the estimated response. However, the model has no way to determine who is choosing not to move and who is simply unable to move. In the presence of adverse conditions, those who choose not to move are often capable of adapting to new conditions in place, indicating access to resources. Trapped populations, those who would move if they could, do not enjoy the same adaptive capacity. Secondly, and related, because our approach is based on modeling aggregate trends as opposed to household-level decisions (the latter being a "bottom-up" approach more typically applied in studies considering smaller geographic regions), we are unable to explicitly model the decision not to migrate due to lack of resources.

It is important to acknowledge the presence of this population, and in the academic literature it is widely suggested that future work focus more specifically on this particularly vulnerable population. It is, however, beyond the scope of this work to do so.

6.5 A Final Word on the Results

The description of model limitations is meant, primarily, to aid in interpreting the results of this assessment. Broadly, the outcomes presented here should be considered as a series of possible futures contingent on a set of assumptions, a set of "what if" scenarios. None of the scenarios should be considered a "most-likely" outcome, nor should the emphasis be on the any one projection of the total magnitude of migration. Instead, 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 questions that will be critical to anticipating and planning for climate-induced migration appropriately. Furthermore, the geographic information presented here (e.g. international flows, sub-national hot spots) should help to focus the attention of planners and policymakers on regions that are very likely to experience impacts, be it in- or out-migration. Even if there is uncertainty in the likely magnitude of those impacts, identifying critical geographic zones is crucial to fine-tuning policy intervention.

Finally, the work presented here represents a step forward in complexity of the family of gravity-based top-down models for assessing climate-induced migration over large regions at high resolution. The modeling itself should be scrutinized and continued refinements applied. Modeling climate-induced migration is a very challenging undertaking, rife with uncertainty. This should not, however, preclude the scientific community from attempting to do so as the exercise itself is necessary to generate the important conversations that will allow society to effectively manage this challenge.

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