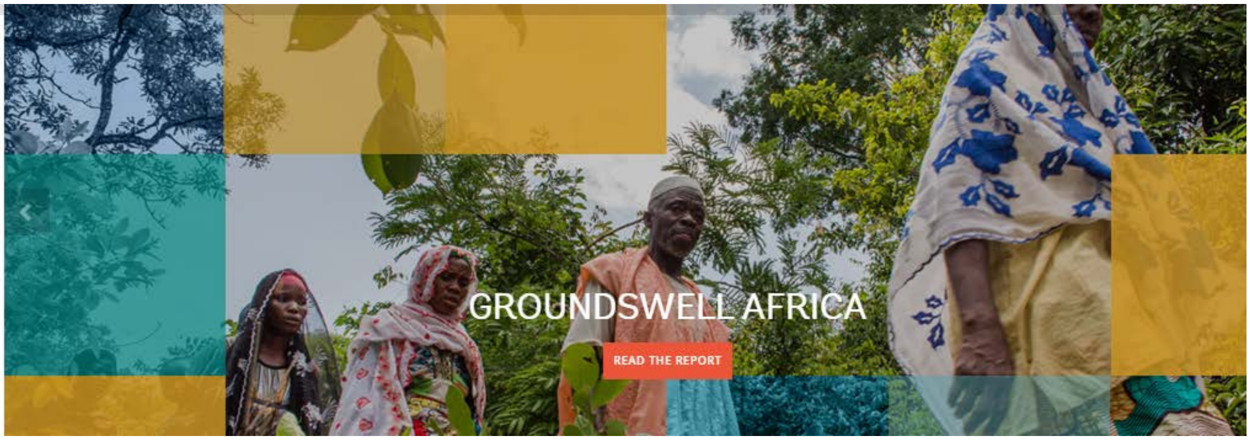
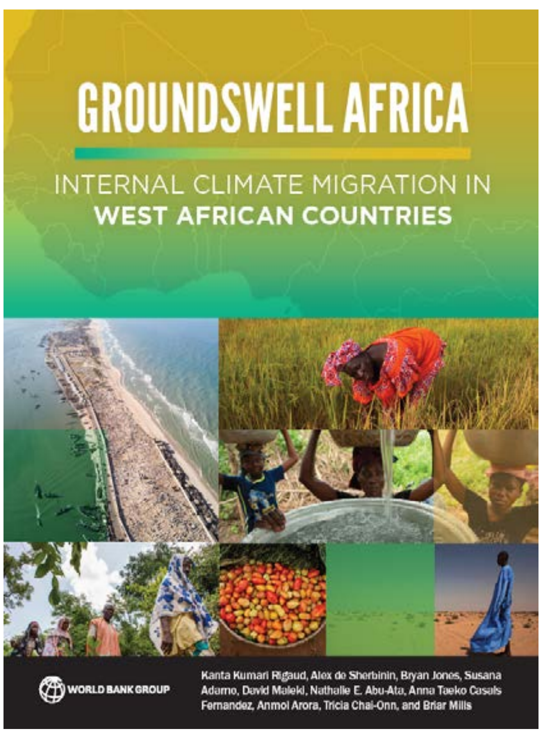


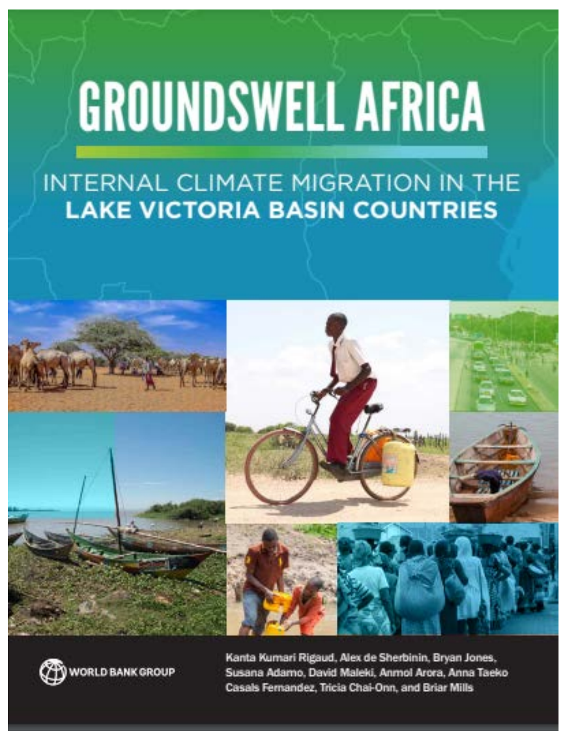
SEDAC Data Documentation

Groundswell Africa Spatial Population and Migration Projections at One-Eighth Degree According to SSPs and RCPs, v1 (2010 – 2050)

https://doi.org/10.7927/jmc9-q708

Extracted from the methods sections for the reports on
West African Countries and
Lake Victoria Basin Countries





Chapter 3

Methods: Modeling Climate Migration

3.1 CLIMATE AND NONCLIMATE MODELING

Climate change–induced migration (climate migration) is taking place, and as climate impacts intensify over the course of this century, the scale of such migration is expected to increase. The report addresses pertinent questions related to internal climate migration, such as:

- How many people will move under future climate scenarios?
- Where are potential hotspots of climate in- and out-migration?
- To what extent is climate change a driver of mobility under future scenarios?

Understanding the scale of such migration can inform our anticipatory and proactive responses. Decision-makers should view internal climate migration as a cross-cutting issue to be better understood and integrated into policy and planning based on the country's development context, institutional capacity, and climate vulnerabilities. The modeling methods in this chapter provide a pioneering approach to answering these questions.

Given environmental factors' role in mobility patterns in the past, we can expect that they will continue to play a similar role in the future, amplified by climate change. Indeed, climate variability and extremes in the landlocked portions of the Sahel are likely to drive new climate migration into the coastal zone, which will only increase the exposure of populations to the effects of sea level rise and storm surge. As in the past, climate impacts may arrive in the form of disturbances that are hard to predict, and whose ramifications for the socioecological system and migration are even harder to predict. It is against this backdrop that plausible future migration scenarios are developed that are faithful to the mechanisms that operate in the West African context—climate impacts on livelihood systems—while recognizing that the complexity of the interactions is such that precise prediction is not feasible. The results should be embedded in a deeper understanding of local development contexts and of issues addressed in literature.

This study builds on the novel scenario-based model used in the Groundswell report (Rigaud et al. 2018) **but includes several enhancements to better inform policy dialogue and action.**[27] The enhanced model and refined methods in this study include shorter time steps, higher spatial resolution, more climate impact parameters, and inclusion of nonclimate factors. Table 3.1 provides a summary of the main enhancements.

Table 3.1 Comparison between Groundswell I and West Africa Model

Groundswell I	Modifications in this work
Groundswell used a unique population gravity modeling technique to project future population distributions to the year 2050 based on socioeconomic scenarios known as the SSPs that include assumptions about future urbanization rates.	Applies maximum rural and urban population densities so that unrealistically high urban densities are not produced, as well as information on the age/sex distribution of the population that reflects gender-specific migration rates and the older age structures of urban areas.
Focus on slow-onset factors: the modeling used for the first time actual climate impact models for agriculture and water resources to understand how these would affect future population distributions, as well as sea level rise compounded by storm surge.	Includes another slow-onset impact (ecosystem impacts) and rapid onset events (as flood risk projections); incorporates conflict areas as an additional data layer.
The gravity model is driven by the population as set out in the GPW to estimate future population distribution.	Includes age and sex distribution as nonclimate factors in the gravity model, and affects the results through their relationship with population change (as derived through the spatial autoregressive calibration), and through their interaction with climate drivers.
The three scenarios are based on combinations of socioeconomic development scenarios (SSPs) and emissions scenarios (RCPs): the pessimistic (reference), more inclusive development, and climate-friendly.	Adds a fourth, optimistic scenario that combines low emissions (RCP2.6) and an inclusive development pathway (SSP2).
Scenarios were run in decadal increments from 2010 to 2050, calibrated on data from 1990 to 2010.	Scenarios are run in five-year increments, 2010 to 2050.
The future population projections incorporating climate impact scenarios were compared to future population projections without climate impacts to derive estimates of climate migration for 15-km grid cells (7.5 arc-minute).	Modeling is performed on population data at 1-km resolution (0.5 arc-minute).
Modeling supplemented with peer-reviewed literature and contextualization for illustrative case studies; with in-country consultations.	Supplemented with national, local studies/ data, where available, and validation at a workshop in Accra, Ghana (September 2019); and a virtual multistakeholder regional workshop in March 2021.

Note: GPW = Gridded Population of the World; RCP = Representative Concentration Pathway; SSP = Shared Socioeconomic Pathway.

27. For a full description of the Groundswell approach see Groundswell: Preparing for Internal Climate Migration (Rigaud et al. 2018, chapter 3, appendix A, and appendix B).

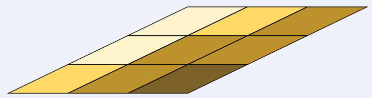
The scenarios combine development scenarios and emissions pathways, implemented in the context of a population gravity model, to estimate the potency of climate to drive internal migration. Box 3.1 summarizes the method.

Box 3.1 Modeling Approach in a Nutshell

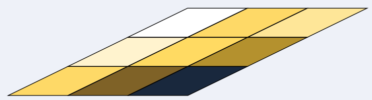
A population gravity model is used to project future population distribution for each country based on two development scenarios: an unequal development scenario representing a divided world with poor development prospects in developing countries, versus a moderate development scenario representing a more equitable future world.

Climate impacts on water availability and crops/pasturage are added to the two development scenarios, which affect the relative attractiveness of regions within countries. Areas projected to see higher water availability and productivity attract people; areas projected to see lower water availability and productivity will tend to repel people. Areas affected by sea level rise are “masked” out in a way that people cannot move into them.

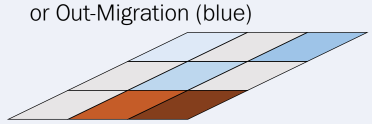
a. No Climate Change Impacts (development only) Scenario



b. Climate Change Impacts Scenario



c. Climate Impacts minus No Climate Impacts Scenario = In-Migration (red) or Out-Migration (blue)



The climate impacts are included with the development scenarios in four combinations: a pessimistic scenario with high emissions and poor development prospects, a more inclusive development scenario with high emissions and more equitable development prospects, a more climate-friendly scenario with low emissions and poor development prospects, and an optimistic scenario with low emissions and equitable development. Panels a–c (in this box) reflect the process for a hypothetical model run for one of the scenarios, in which higher population densities in 2050 are reflected by darker shades. (We produce four model runs per scenario to get a spread around the results.)

Future population projections without climate impacts are subtracted from population projections with climate impacts to yield a map of population differences. Positive differences are assumed to reflect net in-migration and negative differences are assumed to reflect net out-migration due to climate change impacts. The model is calibrated by looking at the relationship between past climate impacts and changes in historical population distributions between 1990 and 2010 (in two 10-year increments), which generates parameter estimates used to project future changes (see appendix B.2).

3.1.1 Shared Socioeconomic Pathways

To create climate change scenarios illuminating possible development pathways, this analysis builds on spatial population projections based on Shared Socioeconomic Pathways (SSPs) as developed by Jones and O’Neill (2016). SSPs represent a set of scenarios—or plausible future worlds—that underpin climate change research and permit the integrated analysis of future climate impacts, vulnerabilities, adaptation, and mitigation (Ebi et al. 2014). They can be categorized by the degree to which the scenarios represent challenges to mitigation (greenhouse gas emissions [GHG] reductions) and societal adaptation to climate change.

The analysis uses SSPs as story lines to guide the development of spatial population projections at 30 arc-second resolution (grid cells of about 1 square kilometers at the equator).[28] The five SSPs developed by O'Neill et al. (2014) span a wide range of possible future development pathways and describe trends in demographics, human development, economy, lifestyles, policies, institutions, technology, the environment, and natural resources. They are the scenario benchmarks used for adaptation planning purposes. Table 3.2 summarizes the SSP narratives; figure 3.1 relates the SSPs to one another. National-level estimates of population, urbanization, and gross domestic product (GDP) have been released for each SSP and are available through the SSP database.[29]

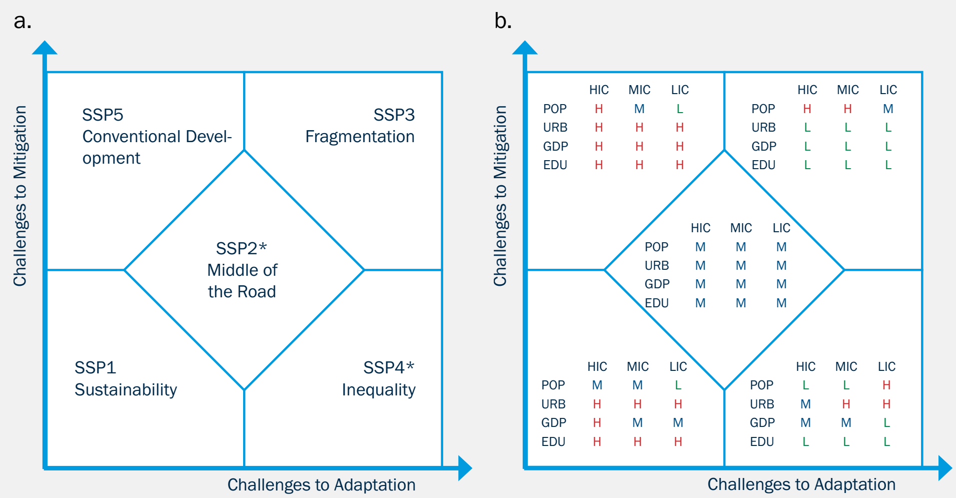
Table 3.2 Shared Socioeconomic Pathway (SSP) Narratives

SSP	Illustrative starting points for narrative	Challenge level
SSP1	Sustainable development proceeds at a reasonably rapid pace, inequalities are reduced, and technological change is rapid and directed toward environmentally friendly processes, including lower carbon energy sources and higher productivity of land.	Low for mitigation and adaptation
SSP2	Intermediate case between SSP1 and SSP3.	Moderate
SSP3	Unmitigated emissions are high because of moderate economic growth, rapid population growth, and slow technological change in the energy sector, making mitigation difficult. Investments in human capital are low, inequality is high, a regionalized world leads to reduced trade flows, and institutional development is unfavorable, leaving large numbers of people vulnerable to climate change and many parts of the world with low adaptive capacity.	High for mitigation and adaptation
SSP4	A mixed world, with relatively rapid technological development in low-carbon energy sources in key emitting regions, leading to relatively large mitigative capacity in places where it matters most to global emissions. However, in other regions, development proceeds slowly, inequality remains high, and economies are relatively isolated, leaving them highly vulnerable to climate change with limited adaptive capacity.	High for adaptation, low for mitigation
SSP5	In the absence of climate policies, energy demand is high and most of this demand is met with carbon-based fuels. Investments in alternative energy technologies are low, and there are few readily available options for mitigation. Economic development is relatively rapid, driven by high investments in human capital. Improved human capital produces a more equitable distribution of resources, stronger institutions, and slower population growth, leading to a less vulnerable world better able to adapt to climate impacts.	High for mitigation, low for adaptation

Source: Based on O'Neill et al. 2014.

28. The Groundswell projections were conducted at 7.5 arc-minutes (approximately 15 square kilometers at the equator).
29. See SSP Database (Shared Socioeconomic Pathways) - Version 2.0 at https://tntcat.iiasa.ac.at/SspDb/dsd?Action=htmlpage&page=about.

Figure 3.1 Assumptions about Changes in Population, Urbanization, GDP, and Education across Countries of Different Income Groups of the Shared Socioeconomic Pathways



Source: Jiang 2014.

Note: panel a: SSP = Shared Socioeconomic Pathway; panel b: EDU = education; GDP = gross domestic product; H = high; HIC = high-income country; L = low; LIC = low-income country; M = medium; MIC = medium-income country; POP = population; URB = urbanization.

The model in this report builds on SSP2 and SSP4, reflecting more moderate and unequal development pathways. Under the unequal development scenario (SSP4), low-income countries (LICs) and middle-income countries (MICs) follow different pathways. LICs have high population growth rates and urbanization, and low GDP and education levels. MICs have low population growth rates, high urbanization, moderate GDP, and low education levels. Inequality remains high both across and within countries, and economies are relatively isolated, leaving large, poor populations in developing regions highly vulnerable to climate change with limited adaptive capacity. SSP2 is a moderate development scenario between SSP1 ("sustainability") and SSP3 ("fragmentation"), where lower-middle-income countries (LMICs) are characterized by moderate population growth, urbanization, income growth, and education; and have moderate challenges to adaptation. These scenarios were chosen because they represent divergent development pathways. They were also selected for consistency, or the ability to be paired, with the high and low emissions scenarios (Representative Concentration Pathways [RCPs]) used in this report. The high emissions scenario (RCP8.5) can be paired with both SSP4 and SSP2; the low emissions scenario (RCP2.6) can be paired with SSP4.

The development pathways drive population and urbanization trends in a gravity model that distributes population change according to the perceived attractiveness of different locales over time under the low and high emission scenarios as framed by RCPs. 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.

The SSP population projections include international migration, but the modeling conducted in this study was limited to assessing internal climate migration. Because 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 (KC and Lutz 2014). For both SSP2 and SSP4, these flows are in the middle of the range.[30] They are 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. 2014).

3.1.2 Representative Concentration Pathways

The magnitude of future global warming is framed by the RCPs, and the internal climate migration forecasts are based on two emissions scenarios.[31] The lower emissions scenario (RCP2.6) is a world in which temperatures peak at 0.25°–1.5°C above recent baseline levels by 2050 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 GHG emissions to zero within the next 15 to 20 years (Sanderson et al. 2016). In the higher emissions scenario (RCP8.5), temperatures rise by 0.5°C to 2°C by 2050 and by 3°C to 5.5°C by 2100. It is a future consistent with scenarios of energy-intense development, continued reliance on fossil fuels, and a slow rate of technological development. RCP8.5 implies little to no climate policy. It is characterized by significant increases in CO_2 and CH_4 emissions. These two emission scenarios drive the indicators of water, agricultural, and ecosystem sector change as well as flood risk, which are incorporated in projections of future population distributions.

RCP2.6 scenario is consistent with the extremely rapid adoption of cleaner technologies, slower population growth, strong environmental policies, and well-functioning international institutions that facilitate rapid global integration. To achieve RCP2.6, new technologies would need to be widely deployed over the next five to ten years. The extended RCP2.6 scenario assumes "negative emissions" by 2070, meaning that humans remove more CO_2 and CH_4 from the atmosphere than they release. RCP2.6 is thus consistent with the Paris Agreement, which seeks to limit temperature rise to 2°C.

RCP8.5 is characterized by increasing GHG emissions, leading to high atmospheric concentrations. It is a future consistent with scenarios of energy-intense development, continued reliance on fossil fuels, and a slow rate of technological development. Pathways characterized by rapid population growth and land use intensification (croplands and grasslands) are also consistent with this scenario.

As set out in the Groundswell model, RCP8.5 is intended to be a high-end outlier in the business-as-usual world, and should not be concluded as the only or most likely outcome in a "no policy" world. RCP2.6 was closer and more in line with the Paris Agreement. In the development of the Groundswell methodology, the SSP and RCP combinations were in part driven by their compatibility. There is no perfect combination. Some argue against the plausibility and utility of RCP2.6. Comparing the RCP2.6, however, even as it may be a challenge to achieve it, provides a spread in the model runs and outcomes, to differentiate between a best case "sustainable" scenario (RCP2.6) and a high-end emission scenario (RCP8.5). What is important here is the ranges and plausibility of scenarios as the low and high end.

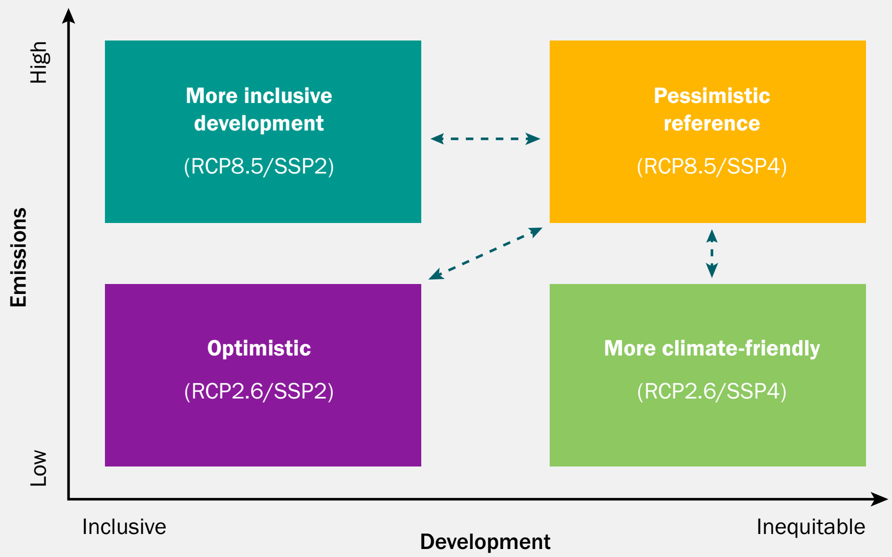
3.1.3 Scenario Combinations Used in the Model

We examined four plausible future internal climate migration scenario combinations (figure 3.2). For each scenario, the estimate represents an ensemble of model runs using combinations of crop, water, ecosystem, and flood impact models from the Intersectoral Impacts Model Intercomparison Project (ISIMIP). The four scenarios include:

30. Migration flows are considered medium across all SSPs except SSP3 ("fragmentation"), where they are low, and SSP5 ("conventional development"), where they are high. A more sophisticated set of SSP projections is under development.
31. The term emissions scenarios is technically not correct, in that the RCPs represent concentration levels of GHGs and other pollutants that warm the Earth's surface. It is used here as shorthand, because emissions contribute directly to concentration levels.

- A pessimistic/reference scenario (SSP4 and RCP8.5), in which LICs reflect continued high emissions and have unequal development and are characterized by high population growth, high rates of urbanization, low GDP growth, and low education levels. Urban growth is poorly planned, and high emissions drive greater climate impacts. This scenario poses high barriers to adaptation because of the slow pace of development and isolation of regional economies.
- A more climate-friendly scenario (SSP4 and RCP2.6), with lower emissions that reduce climate impacts, but holds the development scenario consistent with the pessimistic scenario.
- A more inclusive development scenario (SSP2 and RCP8.5), which retains high emissions because they are in the pessimistic scenario, but provides a development scenario that is more optimistic and the potential for adaptation is higher than under SSP4. Population and urban growth are lower than in SSP4 for LICs and higher for MICs, while progress in education and GDP are higher than in SSP4.
- An optimistic scenario (SSP2 and RCP2.6), which combines the lower emission scenario that reduces climate impacts and provides a development scenario that is more optimistic.

Figure 3.2 Projecting Internal Climate Migration under Four Plausible Scenarios



Source: Adapted from Rigaud et al. 2018

Note: RCP = Representative Concentration Pathway; SSP = Shared Socioeconomic Pathway.

We calibrated the model based on the historical sensitivity of past shifts in population distribution to the effects of deviations in water availability, crop productivity, and net primary productivity (NPP) from long-term baselines. Because of limitations in the underlying historical population data, only three countries had population data that met the criteria needed to undertake the calibration: Mauritania, Guinea, and Sierra Leone. The coefficients were averaged across the three calibration results for every country in the region, meaning that these countries serve as stand-ins for the other countries in the region (see appendix B.2 for details).

There are inherent uncertainties in the way climate impacts will play out in a given locale. At higher resolutions, these will affect the magnitude and patterns of climate-induced migration, including through intervening opportunities that can work in either direction depending on how climate and nonclimate factors interact (see box 3.2).

3.1.4 Climate Impacts Addressed in the Model

A key innovation of the Groundswell methodology—applied to this study—is that it incorporates actual climate impacts on critical primary sectors: water, agriculture, and ecosystem services (NPP), as well as future flood risk. Most studies seeking to understand the effects of climate change on mobility have used climate variables such as temperature and precipitation rather than actual climate impacts on different sectors.

The Groundswell model used the ISIMIP database of state-of-the-art computer model simulations of biophysical climate impacts. This climate-impact modeling initiative—aimed at contributing to a quantitative and cross-sectoral synthesis of the differential impacts of climate change, including uncertainties—offers a framework for consistently projecting the impacts of climate change across affected sectors and spatial scales.

The analysis for this study used outputs of the ISIMIP Fast Track modeling effort, which covers 1970–2010, as well as projections for 2010–50 (Piontek et al. 2013).[32] 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 UK Met Office Hadley Centre for Climate Change and the IPSL-CM5A-LR climate model developed by the Institut Pierre Simon Laplace Climate Modeling Center, in France (see appendix A for details).

The ISIMIP sectoral models of global crop, water, and ecosystem simulations—at a relatively coarse spatial scale (0.5 degrees, or roughly 55 kilometers at the equator)—are an advance over purely climate model–based indicators of rainfall and temperature, because they represent actual resources of relevance to development. The flood impact model is at 500-meter resolution and is based on projected flood depth. These climate impacts were selected because the literature shows that water scarcity, declining crop yields, declines in pasturage, and flood impacts are among the major potential climate impacts facing LICs, and these impacts will be important drivers of migration.[33] Finally, sea level rise is included as a spatial mask that does not permit people to live in areas likely to experience inundation. Each of these input layers is described in greater detail below.

The models are better at assessing long-term trends rather than individual extreme events such as drought or extreme rainfall. As devastating as they may be for rural livelihoods, brief, fast-onset events are not directly included. That said, the five-year time step in this report captures successive extremes better than the original 10-year time step used in Groundswell, in which extremes in either direction are more likely to counterbalance each other over the course of a decade. To further assess the impact of extremes, we included flood impacts (described below) in this improved model.

Water and Crop Models Used in the Gravity Model

Data on water availability and crop production were integrated into the gravity model using the following approach. The water sector model outputs represent river discharge, measured in cubic meters per second in daily and monthly time increments. The crop sector model outputs represent crop yield in tons per hectare on an annual time step at a 0.5° x 0.5° grid cell resolution. Crops include maize, wheat, rice, and soybeans; for regions with multiple cropping cycles, yield reflects only the major crop production period.[34] The data were converted to five-year average water availability and crop production (in tons) per grid cell.[35] An index was then calculated that compares those values with the 40-year average for water availability and crop production for 1970–2010 (equation 3.1):

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32. See ISIMIP Fast Track at https://www.isimip.org/gettingstarted/fast-track-simulation-protocol.
33. Water availability is influenced by rainfall and rising temperatures. Crop production is a function of rainfall, temperature, CO_2 concentrations, irrigation, and other management practices that are incorporated in the ISIMIP models.
34. The ISIMIP models seek to assess the risk that climate change will have on the potential for agriculture in a location. For this purpose, the relative changes in average yield potential are useful.
35. The models report "pure crop yields" in tons per hectare (that is, they assume that a given crop is grown everywhere, irrespective of growing conditions or where crops are actually grown). These yields were multiplied by observations-based growing areas (in 2005), separately for rainfed and irrigated yields, to obtain grid cell–level production (in metric tons) (Portmann, Siebert, and Döll 2010).

$$Index = (D_{avg} - B_{avg}) / B_{avg} \quad (3.1)$$

where D_{avg} is the five-year average crop production/water availability and Bavg 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 (0.2 indicates 20 percent above the baseline average, 1 represents a doubling, and –0.6 indicates 60 percent below the baseline average). To reduce the effect of extremes on the gravity model, increases greater than index values of 2 (meaning a tripling of yields) were capped at 2.

The ISIMIP crop and water model outputs are based on combinations of climate, crop, and water models. Applying the combinations—two global climate models driven by two emissions scenarios, which in turn drive two sets of sectoral impact models (described below)—provides a range of plausible population projections. It also gives a sense of the level of agreement across scenarios. Because the population modeling process is time consuming and computationally intensive, it was important to work with a reduced set of ISIMIP inputs.[36] The modeling 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. The crop and water models were selected 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 (ISIMIP2a) and global climate model–driven historical and future (ISIMIP fast-track) simulations. Table 3.3 presents the combinations of crop and water models used. Appendix A provides detailed information on model selection.

Table 3.3 Matrix of Global Climate Models and Crop and Water Model Combinations

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

Note: Where crop production does not take place; ecosystem (NPP) models are used to gap-fill the LPjML and GEPIC crop models, respectively. NPP = net primary productivity.

Ecosystem Productivity Models Used in the Gravity Model

Including ecosystem productivity in the gravity model was driven by two considerations. First, it is an important measure for pastoral livelihoods, just as crop production is an important metric of farm-based livelihoods. A large portion of the Sahel is inhabited by pastoralists who engage in livestock herding, and this livelihood is very climate sensitive. Ecosystem productivity is critical for this livelihood. When the original Groundswell modeling work (Rigaud et al. 2018) was done, ISIMIP ecosystem productivity models were not available.

The second reason was to fill gaps where there is no crop production. Crop production results in Groundswell were reported only for areas where the four major crops—wheat, maize, rice, and soybeans—are produced, leaving gaps in the coverage of the crop production change metrics and areas in which water stress was the sole climate-related indicator. The solution was to fill the gaps in those crop production results with the ecosystem productivity data, which are areas more likely to encompass pastoral livelihoods. Even so, in this study, ecosystem productivity is applied in the model only to those areas lacking crop productivity, since there is high spatial co-linearity between the crop and ecosystem metrics.[37]

36. Feeding all potential ISIMIP water and crop model outputs into the gravity model would have yielded 12,500 model runs: 2 RCPs * 5 GCMs * 25 crop model outputs * 50 water model outputs = 12,500.
37. This means that adding ecosystem impacts would only repeat information contained in the ISIMIP crop production impacts.

Ecosystem productivity is measured in terms of the NPP. The ecosystem models simulate the natural growth of several plant functional types, including grasses. The NPP simulated by these models thus serves as an estimate of the productivity of a location's natural biome, including grassland biomes. The NPP index is calculated in the same way as the crop and water indexes (see equation 3.1). The index used for this report are from two models: the LPJmL and VISIT models. The former is used with the LPJml crop production and water availability models (table 3.3, models 1 and 3), while the latter is used with the GEPIC crop and WaterGAP water models (table 3.3, models 2 and 4).[38] The models were driven by the same GCMs using the same RCPs as in the original Groundswell report.[39]

Flood Models Used in the Gravity Model

The original Groundswell modeling did not include flood hazards. We added flood hazards for West Africa because of their important impact on displacement, even if the impacts are highly localized. The flood hazard layer is based on projected flood depth simulated by a global flood model CaMa-Flood (Yamazaki et al. 2011) ver. 3.4.4. It primarily represents riparian (along rivers) flooding, not coastal, although it does capture rivers emptying into the ocean. Potential coastal flooding is better captured by the sea level rise mask (below). The input required by this global flood model is daily runoff simulated by multiple global hydrological models participating in the ISIMIP2b (Frieler et al. 2017) project. These hydrological models are forced by four bias-corrected climate models that include standard outputs (temperature, precipitation, radiation, etc.) from the Coupled Model Intercomparison Project phase 5 (CMIP5) (Taylor, Stouffer, and Meehl 2012). Appendix A describes the climate models, global hydrological models, and global flood model in this modeling chain.

The flood hazard data were used to calibrate the model by establishing a baseline relationship between the return rate of 100-year flood event and spatial patterns of observed population change (along with multiple additional drivers). This relationship contributed to projections of future spatial population change.

Sea Level Rise Augmented by Storm Surge

Sea level rise augmented by storm surge is not considered a driver of migration, but rather is inserted as a spatial mask in the modeling work—representing a loss of habitable land—to move populations out of inundated areas. The figures in table 3.4 represent the lower-, middle-, and upper-bound sea level rise, including storm surge, by 2030 and 2050, as reported by the Intergovernmental Panel on Climate Change (IPCC) (Church et al. 2013). Two scenarios meant to represent changes in sea level by 2050, associated with RCP2.6 and RCP8.5, were adapted by adding an increment to reflect storm surge on top of the estimates (table 3.4). According to Dasgupta et al. (2007, 6), "Even a small increase in sea level can significantly magnify the impact of storm surges, which occur regularly and with devastating consequences in some coastal areas." A comprehensive assessment of the likely levels of storm surge for all the coastal areas covered by this report was beyond the scope of this project. Nor were we able to find data on coastal erosion that cover enough of the coastline consistently. However, the coastline of Senegal (particularly Saint-Louis and Sine Saloum) and the Gulf of Guinea are among the most vulnerable to erosion because of sea level rise, whereas portions of the coast from Guinea to Liberia, along with a good portion of the Ghanaian coast, tend to rise steeply. The omission of erosion may mean that our coastal climate migration numbers are underestimated. Further details on projected sea level rise by 2050 and 2100 for a few (West Africa Coastal Areas) WACA countries are in World Bank (2020).

38. The ecosystem models are used to gap-fill the LPjML and GEPIC crop models, respectively.
39. See chapter 3 and appendix A of the Groundswell: Preparing for Internal Climate Migration report (Rigaud et al. 2018).

Table 3.4 Projected Sea Level Rise under Low and High RCPs, West Africa, 2030 and 2050

	Meters above current mean sea level					
	RCP2.6			RCP8.5		
Year	*Lower*	*Middle*	*Upper*	*Lower*	*Middle*	*Upper*
2030	0.092	0.127	0.161	0.098	0.132	0.166
2050	0.157	0.218	0.281	0.188	0.254	0.322
Storm surge increment	0.85–0.9			1.68–1.85		

Source: Church et al. 2013; CIESIN database, 2013 (storm surge).

Note: RCP = Representative Concentration Pathways.

Both the 1- and 2-meter sea level rises are based on NASA Shuttle Radar Topography Mission data, as modified by the Center for International Earth Science Information Network for the Low Elevation Coastal Zone (LECZ) ver. 2 dataset (CIESIN 2013b). Processing coastal elevation over large areas is time consuming, so using the global LECZ data expedited this work. That said, there is strong scientific grounding adding the increments (Dasgupta et al. 2007; Hallegatte et al. 2011).

In the model, the proportion of each grid cell at or below sea level is calculated for 2010 and under the projection to 2050 (for both the 1-meter and 2-meter sea level rise), and the amount is linearly interpolated for each five-year time step in between. As described in section 3.2, the model implements sea level rise by progressively removing land from occupation, thereby reducing the population that will be accommodated in a coastal grid cell over time. A supplementary analysis was conducted for coastal countries on the population movements into or out of the 5-kilometer coastal strip (because of sea level rise and other climate impacts), using the 1-kilometer grid cell model outputs (that is, not outputs aggregated to 15-kilometer grids as for the other analyses).

3.1.5 Population Data

For the population baseline, we used the 2010 baseline in the Center for International Earth Science Information Network (CIESIN) Gridded Population of the World ver. 4 (GPWv4) (CIESIN 2016). For a representation of the population distribution of West Africa based on GPWv4 for 2015 see figure 2.7). The gravity model was calibrated twice, first based on population change estimates for 1990–2010 derived from GPWv3 (CIESIN, CIAT, and FAO 2005), and second for 2000–10 from GPWv4. GPWv3 and v4 model population distribution on a continuous global surface were based on the highest spatial resolution census data available from the 2000 and 2010 rounds of censuses, respectively. We used population count grids adjusted to national-level estimates from the UN World Population Prospects reports. GPWv3 and v4 are gridded data products with output resolutions of 2.5 arc-minutes (a square approximately 4 kilometers on a side at the equator) and 30 arc-seconds (a square approximately 1 kilometer on a side at the equator), respectively. Calibration was run at two resolutions: 2.5 arc-minutes for 1990–2010 (in two decadal time steps) and 30 arc-seconds for 2000–10 to check for any variation in outcomes that might result from alternative resolution (specifically comparing 2000–10) at different resolutions. The decision to take an exploratory approach to calibration reflects the resolution at which the model was applied for future projections (1 kilometer), and the maximum number of historic periods against which to fit the model (more details below).

Uncertainties in GPWv4 2010 population count grid relate to the timeliness and accuracy of the underlying census data and to the input resolution of the census units. In West Africa, the census year ranges from 2004 in Sierra Leone to 2014 in Côte d'Ivoire, and the mean size of the input units ranges from 191 square kilometers in São Tomé and Príncipe to more than 112,000 square kilometers in Niger (table 3.5). Further uncertainties in the year 2000 estimates relate to the lowest common denominator spatial units that match between the years in GPWv3 and GPWv4, or for which growth rates are available. These units apply consistent rates of change across all subunits. So, for example, if only admin 1 units (state or province) match between censuses, population is backcast from 2010 to 2000 by using consistent rates of change across those units, even if GPWv3 and GPWv4 included population count data for 2010 at a significantly higher resolution (i.e. admin2 or admin3). This affects the confidence in the decadal population change grids used for model calibration. For

West Africa, populations for 2000 were backcast at admin 0 (country level) for Senegal and admin 1 for Liberia and Nigeria (table 3.5). All other countries had matching admin 2 or 3 units across both versions of GPW, which provided higher levels of confidence in backcast population distributions. Because of corresponding admin 3 units over each census time step, calibration of the model was performed using historical ISIMIP index values with population data from Mauritania, Guinea, and Sierra Leone.

Table 3.5 Population Data Inputs by West African Countries for GPWv4

Country	Census year	Admin level	Mean unit size (km^2)	Growth rate: start	Growth rate: end	Growth rate: admin level at which GR is applied
Benin	2013	2	3,456.1	2002	2013	2
Burkina Faso	2006	3	1,448.7	1996	2006	3
Cabo Verde	2010	2	314.2	2000	2010	2
Chad	2009	2	7,0637.4	1993	2009	1
Côte d'Ivoire	2014	4	1,226.9	1998	2014	3
Gambia, The	2013	2	536.2	2003	2013	2
Ghana	2010	2	2,923.6	2000	2010	2
Guinea	2014	3	1,315.8	1996	2014	3
Guinea-Bissau	2009	2	1,219.2	1991	2009	2
Liberia	2008	2	1,228.9	1984	2008	1
Mali	2009	4	79,610.4	1998	2009	3
Mauritania	2013	3	74,902.9	2000	2013	3
Niger	2012	2	112,392.1	2001	2012	2
Nigeria	2006	2	2,898.3	1991	2006	1
São Tomé and Príncipe	2012	2	191.1	2001	2012	2
Senegal	2013	2	8,458.2	2002	2013	0
Sierra Leone	2004	3	773.1	1985	2004	2
Togo	2010	2	2,846.9	2000	2010	2

Note: Admin level refers to governmental level. 0 = country, 1 = state/province, 2 = county (or equivalent), with levels 3 through 6 representing progressively smaller units such as local government areas or villages

Though modeling for West Africa was carried out at the original 1-kilometer spatial resolution of the GPWv4 data (30 arc-seconds), they were aggregated to approximately 15-kilometer grid cells (7.5 arc-minutes), consistent with Groundswell report. This distance better reflects attribution to migration, and the data analysis and visualization methods are appropriate only at this coarser resolution. This is primarily because the resolution at which analysis is undertaken, by proxy, defines what qualifies as a migration. This work assumes that differences between models that include and exclude climate change impacts are driven by migration. Realistically it is not possible to speak of differences at 1-kilometer resolution being due to migration, but at 15-kilometer resolution (the modeling resolution used in the original Groundswell results) these differences can feasibly be attributed to migration.[40] Similarly, at higher spatial resolution we would always obtain higher levels of migration, because aggregate differences across grid cells will be higher if the total number of grid cells is higher. Thus, it is important to balance spatial resolution with a realistic definition of the distance that constitutes a migration. Here, although we run the model at higher

40. Definitions of migration generally carry with them some minimum distance. According to the UN (1970), "A migration is (…) operationally defined as a change of residence from one civil division to another, and the volume of migration is to a considerable degree a function of the size of areas chosen for compilation." If the smallest civil division is a village or town, then in much of the world 15 kilometers is the approximate distance between settlements.

resolution than in the original Groundswell report, we aggregate to the same spatial resolution because it represents a reasonable definition of meaningful human movement. Note, however, that for analyses of the population movements into or out of the 5-kilometer coastal strip (because of sea level rise and other climate impacts) of interest in the WACA context,[41] the 1-kilometer resolution data are used.

3.1.6 Nonclimate Factors

In the West Africa modeling, we applied three additional spatial data layers to the climate impact and no-climate impact model runs. These included data on conflict occurrence over the past decade and data on the age and sex structure of the population.

Conflict

Spatial data on conflict occurrence was obtained from the Armed Conflict Location & Event Data (ACLED) database (Raleigh et al. 2010) and interpolated through spatial kriging.[42] A spatial layer was developed of the point locations of every conflict event for the 10 years spanning 2009 to 2018, and the values at each point were the number of fatalities. Spatial kriging (a form of interpolation) created a continuous surface to fill in the gaps between points, yielding a surface where each 1-kilometer pixel has a value associated with the relative amount of conflict fatalities. This surface was applied in model calibration to identify the impact of conflict on spatial population patterns and derive the coefficients (see appendix B.2 for details on the calibration results).

Demographic Characteristics—Median Age and Sex

Spatial data on the age and sex distribution per grid cell were obtained from the GPWv4.10 Basic Demographic Characteristics (CIESIN 2017). Data on median age and the sex ratio (males as a percentage of female population) calibrated the model by establishing the relationship between spatial population change and demographic characteristics of the population.

In this report the model was run at 30 arc-second (approximately 1-kilometer) resolution but aggregated to 7.5 arc-minutes for analysis and the production of maps and statistics. All modeling in the previous Groundswell report was conducted at a 7.5 arc-minute (approximately 15-kilometer) resolution, which was the original resolution of the National Center for Atmospheric Research-CUNY Institute for Demographic Research (NCAR-CIDR) model. The higher resolution reflects the spatial needs of the global change community for which the model was originally developed. In general, this resolution is adequate for spatial projections of, for example, patterns of emissions or exposure to climate hazards for applications at the global or regional scale. However, at the subnational level, it can overly generalize patterns of population change. Nevertheless, aggregation to 7.5 arc-minutes is needed, because, as noted above, at higher resolution it becomes difficult to attribute observed differences in outcomes between the climate and nonclimate scenarios to climate-induced migration.

The Groundswell report does not assume or apply any maximum population density in rural areas before they either reached carrying capacity or became urban. However, research suggests such limits may exist. In Kenya, for example, densities beyond a threshold of 500–600 persons per square kilometer resulted in no further intensification and in declining household income per adult (Muyanga and Jayne 2014), and other evidence suggests that thresholds may be reached in subsistence agricultural systems of Africa (Jayne, Chamberlin, and Headey 2014). Based on an assessment of population densities in rural areas of Africa, using each 1-kilometer grid cell of GPWv4 as a unit and identifying rural and urban areas using CIESIN's GRUMP v1 data set (CIESIN 2011), we evaluated population densities across all grid cells. See table 3.6.

41. Note that there is no universally accepted definition of the coastal zone. In Denmark, the Planning Act (1991) defines the landward boundary of the coastal zone as a 3-kilometer inland from the coast, and the seaward boundary as the shoreline, but in Spain, under the Shores Act (1988), the landward is up to 200 meters from the inland limit of the shore. Lavalle et al. (2000) adopt a definition of 10 kilometers. Our definition represents a middle ground that accounts for the modeling resolution of 1 kilometer, and assumes that livelihood activities tied to the coast are likely to be within the first 5 kilometers.
42. See The Armed Conflict Location & Event Data Project at https://acleddata.com.

Table 3.6 Population Density of Rural and Urban Areas

Rural Population Density	Urban Population Density
Maximum: n.a. 99 percentile: 614 SD: 149 Mean: 77	Maximum: 80,500 99 percentile: 11,366 SD: 2,625 Mean: 1,011

Note: n.a. = not available, SD = standard deviation.

Based on these statistics, a threshold for maximum rural population densities of 1,000 persons per square kilometer were applied, and a threshold of 50,000 person per square kilometer for urban areas. These thresholds were applied to groups of 15-square-kilometer pixels, so that while any one 1-kilometer pixel may exceed the level, on average the threshold could not surpass 1,000 persons (rural) or 50,000 persons (urban) per square kilometer.

3.1.7 Coefficients

The enhanced model includes model coefficients that show the influence of the variable on the observed deviation between observed and projected population change (spatial shifts) based on historical calibration of climate signal from 1990–2000 and 2000–10. The variables are crop production, water availability, NPP, median age, sex ratio, conflict-related fatalities, and flood risk. Crop productivity and NPP are not included in the calibration for urban populations because these are not hypothesized to have an impact in those areas (their populations are not directly dependent on cropping or animal husbandry).

The coefficients for the West African countries in table 3.7 represent the average of the coefficients across the two decades for Mauritania, Guinea, and Sierra Leone. These are the only countries whose population data met the criteria for the calibration. Note that sea level rise is not a driver of migration, but rather is inserted as a spatial mask in the modeling work to move populations out of inundated areas.

Table 3.7 Coefficient Values for West African Countries

Predictor	(Parameter) coefficient		Units
	Urban	Rural	
Crop production	n.a.	0.400	5-year deviation from historic baseline
Water availability	1.696	1.071	5-year deviation from historic baseline
Net primary productivity[a]	n.a.	0.380	5-year deviation from historic baseline
Median age	0.617	0.078	Median age of the population in years
Sex ratio	0.024	0.006	Males/females
Conflict-related fatalities	–0.025	–0.003	Number of recorded fatalities
Flood risk	0.147	0.020	5-year likelihood of flood event

Note: Data represent an average of the calibrations based on Mauritania, Guinea and Sierra Leone data. n.a. = not applicable.

a. Net primary productivity, which is intended to reflect impacts on pastoral populations, is included in the model only when crop production is not present.

Among the climate impacts, water availability is the strongest factor, particularly in urban areas, and positively correlated with population change. Therefore, increasing water availability results in increasing attractiveness, and vice versa. The coefficient for water availability in rural areas is around 2.7 to 2.8 times higher than that of either crops or NPP. Other things equal, areas with better water availability (as measured by the deviation from historic baseline) are projected to have relatively large positive population changes. In rural areas, larger values in crop yields or NPP are positively correlated with larger population change.[43] The magnitude of the coefficient is smaller, so its effect is not as strong as water availability. (As mentioned, crop production and NPP are not used to calibrate urban grid cells.)

43. Crop production is not used to calibrate urban grid cells.

Demographic variables of median age and sex (gender) distribution, introduced in this study's enhanced model, affect the climate migration projections through their relationship with population change (as derived through the spatial autoregressive calibration), and through their interaction with the climate drivers). In West Africa, the demographic variables mitigated or dampened climate migration. Results imply that while high median age tends to draw migrants to urban areas, which offer better economic opportunities, declines in water availability repel migrants, thereby offsetting each other. In short, when demographic effects are working against climate impacts, there are fewer migrants in West Africa. In contrast, in the Lake Victoria Basin (LVB) countries, the alignment between these factors means that they amplify the impact of climate (Rigaud et al. 2021a).

Flood risk is positively associated with population change, and once again, the effect is larger in urban areas by an order of magnitude. Clearly, floods do not attract populations; rather it is likely that this reflects the location of many urban areas in coastal areas and flood plains, which are prone to flooding.

3.2 POPULATION MODELING METHODS

Climate impacts on crop production, water availability, ecosystem productivity, and flood depth and extent affect the population potential of locations in the gravity model. The modeling work is based on a modified version of the NCAR-CIDR gravity model (Jones and O'Neill 2016).[44] Technical details on the model specification are in appendix B.1, and results of calibration of each input layer against changes in historical population during the 1990–2010 time period are in appendix B.2.

3.2.1 Gravity Model

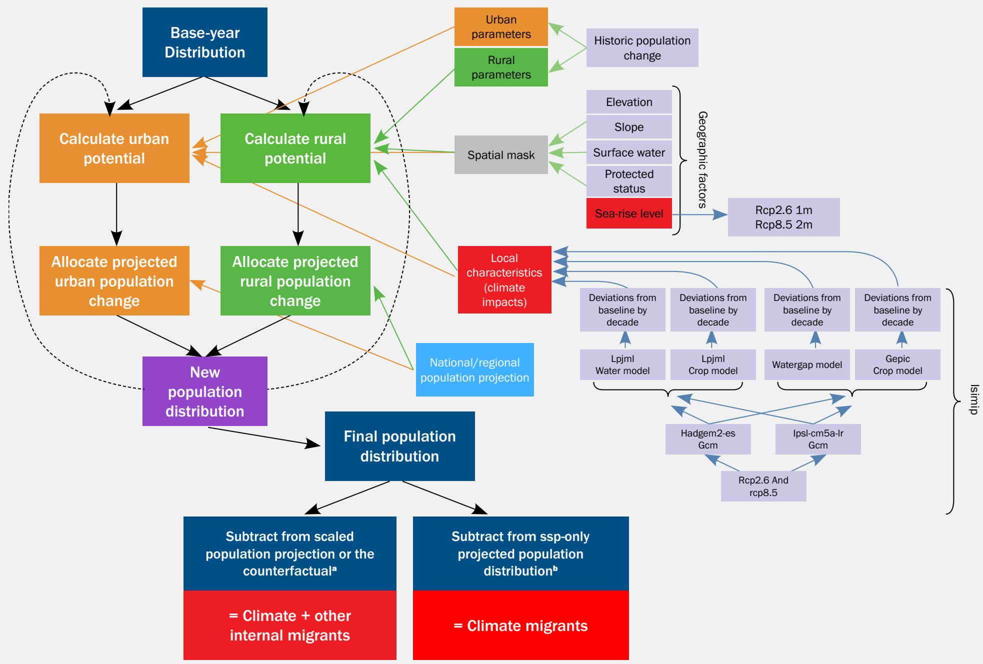
The NCAR-CIDR model uses a modified form of population potential, a distance-weighted measure of the population taken at any point in space that represents the relative accessibility of that point (for example, higher values indicate a point more easily accessible by a larger number of people). Population potential is 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 can indicate the potential for interaction between the population at a given point in space and all other populations (Rich 1980). This potential will be higher at points closer to large populations; thus, potential indicates the relative proximity of the existing population to each point within an area (Warntz and Wolff 1971). Such metrics are often used as a proxy for attractiveness, under the assumption that agglomeration is indicative of the socioeconomic, geographic, political, and physical characteristics that make a place attractive.

3.2.2 Adding Climate Impacts

The calculation of potential was modified primarily by adding variables that describe local conditions, including climate impacts, and weighting the attractiveness of each location (grid cell) as a function of the historic relationship between these variables and observed population change. Figure 3.3 shows modeling steps; boxes in red show the addition of climate impacts (or results incorporating climate impacts), demographic characteristics, and conflict-related fatalities. Population potential is, conceptually, a relative measure of agglomeration, indicating the degree to which amenities and services are available. In the original model, this value shifts over time as a function of the population; assumptions regarding spatial development patterns (for example, sprawl compared to concentration); and certain geographic characteristics of the landscape. In this expanded version of the model, the agglomeration effect is enhanced or muted as a function of the characteristics discussed above that differentiate between places. In any given grid cell, the drivers may either act in concert, reinforcing one another (for example, rural grid cells with crop production and water availability declines), or they may offset each other (for example, flood risk may increase but water availability declines).

44. Data for the original SSP-only population projections are available for download via the NASA Socioeconomic Data and Applications Center (SEDAC) at https://doi.org/10.7927/H4RF5S0P. These projections are produced using a baseline 2010 population of GPWv3 rather than GPWv4, as used here.

Figure 3.3 Modeling Steps



Note: Boxes in red represent the addition of climate impacts into the modeling framework or results that reflect climate impacts. SSP = Shared Socioeconomic Pathway.

a. The counterfactual population projection simply scales the population distribution in 2010 to country-level population totals appropriate to each SSP.

b. The no climate impacts population projection represents the population projection without climate impacts (that is, based only on the development trajectories embodied in the SSPs and the conflict and age and sex characteristics of the baseline population).

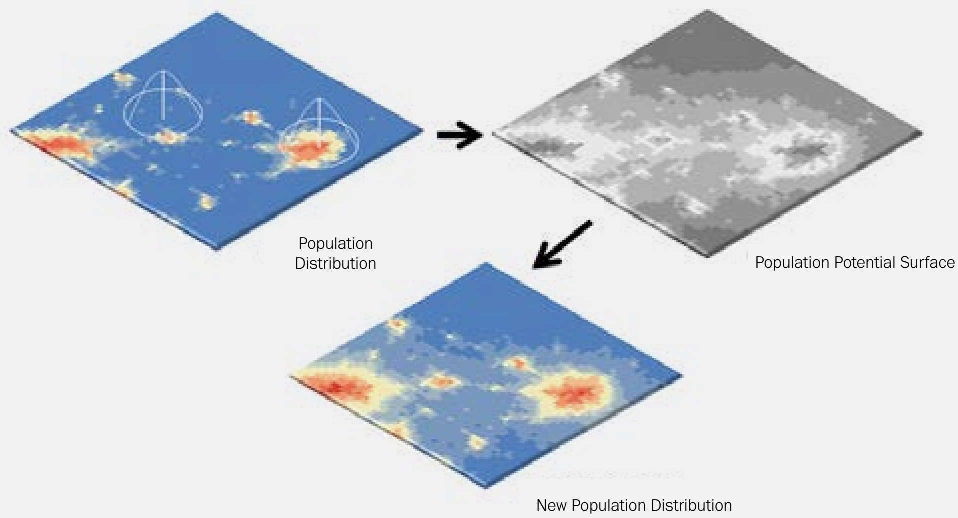
Beginning with the 2010 gridded urban-rural population distribution for each country,[45] the modeling for this report incorporated the influence of climate impacts on relative attractiveness in the following manner:

1. Calculate an urban population potential surface (a distribution of values reflecting the relative attractiveness of each grid cell).
2. Calculate a rural population potential surface.
3. Allocate projected urban population change to grid cells proportionally based on their urban potentials.
4. Allocate changes in the projected rural population to grid cells proportionally based on their rural potential.
5. Because the allocation procedure can lead to some redefinition of population from rural to urban (for example, rural population allocated to a cell with an entirely urban population is redefined as urban), this step entails redefining population as urban or rural as a function of density and contiguity of fully urban-rural cells to match projected national-level totals.

45. Urban and rural population change need to be calculated separately because the factors that influence growth of urban and rural areas are distinct. Data on the evolution of population distributions show that historically urban and rural populations exhibit very different patterns of spatial population change (Jones and O'Neill 2013). The former tends toward agglomeration over smaller geographic areas that can take several different forms (for example, dispersion/concentration), while the latter occurs over larger geographic areas, varies across a wider range of patterns (including uniform and proportional) than urban populations, and is subject to periods of substantial population decline. Further, in fitting the model to historical data we find substantial variation in many parameters driving spatial population change. These two factors suggest that modeling urban and rural populations as separate but interacting components of the total population is advantageous compared to considering the entire population as a single entity.

These steps are then repeated for each decadal time interval. Figure 3.4 illustrates steps 3 and 4 for a hypothetical population distribution. Population potential surfaces, urban and rural, are continuous across all cells; each cell may thus contain urban and rural populations.

Figure 3.4 Hypothetical Example of Gravity-Based Population Projection Model for Single Time Step (Step 3 and 4 of the Modeling Exercise)



Based on the modified NCAR-CIDR population potential (vi) is calculated as a parametrized negative exponential function (equation 3.2):

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

Where:

$\mathrm{A_i}$ = Local characteristics

$\mathrm{l_i}$ = Spatial mask

a = Population parameter etc.

P = Population

β = Distance parameter

d = Distance

(3.2)

It is weighted by a spatial mask[46] (l) that prevents population from being allocated to areas protected from development or unsuitable for human habitation, including areas likely affected by sea level rise between 2010 and 2050. P_j is the population of grid cell j; d is the distance between two grid cells. The distance and population parameters (α and β) are estimated from observed patterns of historical population change (for the urban and rural populations, separately). The β parameter is indicative of the shape of the distance-density gradient describing the broad pattern of the population distribution

46. Spatial masks are used in geospatial processing to exclude areas from consideration. The effect is that the algorithm is not applied in these areas. Examples would include protected areas or places where the terrain is too rugged to inhabit.

(for example, sprawl compared to concentration), typically a function of the cost of travel (with lower costs leading to residential patterns more indicative of sprawl). The α parameter captures returns on agglomeration externality, interpreted as an indicator of the socioeconomic, demographic, and political characteristics that make a place attractive or not.

The SSPs include no climate impacts on aggregate total population, urbanization, or the subnational spatial distribution of the population. We modified the NCAR-CIDR approach by incorporating spatial data including the ISIMIP sectoral impacts, demographic characteristics, and the distribution of conflict-related fatalities, all of which would likely affect population outcomes. The index A_i is a weight on population potential calibrated to represent the influence of these factors on the agglomeration effect that drives changes in the spatial distribution of the population. 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 population's demographics and the likelihood of dangerous conflict. The model is calibrated over two decadal periods (1990–2000 and 2000–2010) of observed population change relative to observed climatic and demographic conditions as well as safety (for example, conflict-related fatalities).
Details on the modeling methodology, including the methods used for calibration, and drivers of migration discovered during the calibration process, are in appendix B.

Andrea Borgarello / World Bank

3.2.3 Characterizing the Model

This modeling provides credible, spatially explicit estimates of changes in the population distribution (and indirectly migration) as a function of climate, demographic, and development trends. It is important to understand what the model does and does not do. Gravity models, in their simplest form, can reconstruct and quantify past evolutions of population distributions based on observed agglomeration effects over large geographic regions, under varying conditions, and at alternative spatial scales. They can also be refined and expanded to incorporate additional details, such as environmental parameters that affect the relative attractiveness of locations, typically improving the capacity of the model to accurately replicate past trends and thus, theoretically, project into the future.

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 (in our model crop production, ecosystem productivity, water availability, and flood risk) and the development-only (also referred to as the SSP, or no climate, models that include only the demographic and conflict metrics). Both types of models include the agglomeration effect. Migration is a “fast” demographic variable compared with fertility and mortality; it is responsible for much of the decadal-scale redistributions of population. Without significant variation in fertility or mortality rates between climate-migrant populations and nonmigrant 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. The model assumes that fertility and mortality rates are relatively consistent across populations in a locale. Note that the model does not provide any information about the directionality of migration. In other words, it cannot be inferred that migrants are moving from a given area of out-migration (for example, a hotspot of climate out-migration) to a given area of in-migration. Rather, the model reflects broader changes in the spatial distribution of population because of climate impacts, with the distribution changing incrementally with each time step.

For each climate migration scenario, the model produces a range of estimates that reflect variation in the underlying inputs to the model, which in turn reflect scientific uncertainty over likely future climate projections and impacts and development trajectories (box 3.2). In any scenario, outcomes are a function of the global climate models and the sectoral impact models that drive climate impacts on population change. For each of the four scenarios, there are four models, consisting of different global climate model/ISIMIP 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. While some may prefer to have just one figure, in a complex issue such as climate-related migration, a scenario-based approach of plausible outcomes is preferable. It would be desirable to have even more scenarios to better assess the uncertainty (or conversely confidence) in the results. However, time and resource constraints prevented more than four realizations for the model per climate-development combination.

Box 3.2 Sources of Uncertainty in Modeling Climate Migration

The climate migration modeling results incorporate five main sources of uncertainty that can affect the estimated number of internal climate migrants or the differences between the four scenarios and the development-only scenario.

ISIMIP impacts vary across models. The differences result in different effects in the gravity model; models with the highest negative impacts repel more people from affected areas than those projecting fewer extreme outcomes. Similarly, in isolated cases (a small number of grid cells) different ISIMIP models can disagree on the positive or negative nature of changes, leading one model to attract population and the other to repel.

Variations between the two global climate models—HadGEM2-ES and IPSL-CM5A-LR—can amplify the ISIMIP differences. The global climate models were selected in part because their future precipitation trends differ substantially in magnitude, and partly even in sign (see appendix A). This variance in precipitation affects the water, crop, and NPP models.

The modeling has a temporal component that can influence population distribution trajectories. Stronger sectoral impacts early in the 40-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 predicted to deteriorate severely during that period, the impact on migration will be greater than if the deterioration occurred during a more demographically stable period.

If the no climate impacts model finds that a place is relatively attractive and the sectoral climate impacts are positive or neutral (relative to other areas that see negative impacts), it will reinforce the attractiveness of that area. Conversely, in remote areas experiencing population decline and negative climate impacts, “push” factors will be reinforced. This phenomenon creates spatial momentum.

Model parameterization affects the results. The model was calibrated using actual population changes and actual climate impacts (represented by ISIMIP model outputs) for two periods, 1990–2000 and 2000–10. This calibration was done using the two separate sets of model combinations: the LPJmL water and crop models and the WaterGAP water and GEPIC crop models (supplemented by the LPJml and Visit NPP models). Different parameters correspond to the different models. If the parameter estimates are close across the crop or water models, there will be less variation in the population distribution projected by each model. The uncertainty around the ensemble mean (measured using the coefficient of variation) will therefore be lower. Conversely, if parameter estimates are not close, there will be greater uncertainty around the ensemble mean.

The model is analyzed at spatial and temporal scales that capture migration well. With grid cells of about 15 square kilometers at the equator, population shift can be a form of short-distance migration. The temporal scale of five-year increments from 2010 to 2050 is adequate to capture the longer-term shifts in population caused by changes in water availability, crop conditions, ecosystem productivity, and flood risk. The five-year temporal resolution of the model corresponds to the temporal resolution most national censuses consider when attempting to capture and quantify migration trends.[47] The model does not capture shorter-term and seasonal migration.

The focus is on the 30 years between 2020 and 2050, which represent a meaningful planning horizon, especially considering the social dimension of migration. Chapter 4 of Rigaud et al. (2018) considers water and agriculture sector impacts beyond 2050 by examining ISIMIP outputs for 2050–2100. The authors suggest that, if anything, the climate signal will become far stronger toward the end of the 21st century. Appendix C of this report provides those projections for West Africa. Under RCP8.5, the western portions of the region (Senegal, The Gambia, parts of Guinea-Bissau, and southern Mali) and in some cases the southern portions (from Côte d'Ivoire in the west to Benin and even Nigeria in the east) are projected to get much drier by the end of the century. If these projections materialize, they will amplify further the impacts on migration.

The model cannot forecast all future adaptation efforts, conflicts, or cultural, political, institutional, or technological changes. Discontinuities are likely to arise because of political events and upheavals that can heavily influence migration behavior. Armed conflict may have nonlinear links to climate variability and change, but models are generally not sophisticated enough to forecast the changing nature of armed conflict or state failure with any precision. The scenario framework is not designed to predict shocks to any socioeconomic or political system, such as large-scale war or market collapse. The models cannot anticipate new technologies that may dramatically affect adaptation efforts to the degree that climate impacts become negligible. The SSPs, as well as output from the global climate model and ISIMIP, reflect plausible futures that span a wide range of global trajectories, with the caveat that extremely unpredictable or unprecedented events are explicitly excluded. The SSPs assume certain levels of adaptation and a continuation of the business as usual, and the projected scale of migration is not cast in stone. The scenario-based results in the study should be seen as a plausible range of outcomes rather than precise forecasts to spur policy and action to counter distress-driven climate migration.

47. Migration data are sporadic in national censuses, but when present, they are typical based on a "five-year question," which prompts respondents to indicate where they lived five years ago.

Chapter 4

Modeling Results: Climate Impact Projections

This chapter presents the modeling results of the projected climate impacts on water availability, crop production, net primary productivity (NPP), and flood risk (derived on the basis of the Intersectoral Impacts Model Intercomparison Project [ISIMIP] simulation models) and for sea level rise compounded by storm surge. Results are presented relating to the nonclimate factors: demographic (including median age and sex) and conflict. These climate and nonclimate impact results form the basis of the modeling outcomes of the plausible future climate migration scenarios presented in chapter 5.

4.1 CLIMATE IMPACT MODELS

Panels in figures 4.1 to 4.3 present the average projected changes in water availability, crop production, and NPP for the 2010–50 time period, respectively. NPP is used to gap-fill areas where there is no crop production. These projections represent the inputs for estimated future population shifts induced by climate change as a proxy of climate migration.[48]

4.1.1 Water, Crop, and Ecosystem Productivity

Water availability is the strongest factor that will influence migration in West Africa over the next few decades. The water models project drying in the western Sahel (Senegal into western Mali) and wetting in the eastern Sahel (Burkina Faso and Niger), consistent with patterns in the Coupled Model Intercomparison Project phase 5 (CMIP5) archive (Biasutti 2019, see also Chapter 2.3). Figure 4.1 depicts the average index values across the model runs for the 2010–50 period for the water models. The extreme values in the northern Sahel and into the Sahara Desert are a function of extremely low baselines. Appendix C has projections from 2050–2100. The maps show the same patterns, but with accentuated impacts in the western Sahel, but also the south under the IPSL-CM5A-LR global climate model, especially under Representative Concentration Pathway 8.5 (RCP8.5).

48. Since NPP is used in the migration model only to gap-fill areas where there is no crop production in rural areas, this does not apply to Nigeria because there is no part in the country without crop production.

The water modeling results vary considerably among West African countries. The climate models project that by 2050 Senegal is almost certain to become drier in the western and coastal areas, and that under some models the whole country will become drier, in some cases significantly (for example, for the WaterGAP models under RCP8.5). Ghana will see modest wetting in the north and drying across several models in the south. Drying may be high: up to 50 percent to 70 percent reductions in water availability in the Accra metropolitan area under the IPSL-CM5A-LR global climate model (GCM) coupled with WaterGAP by 2050. Results suggest that Mauritania will become drier in the western and coastal areas under the Had-GEM2-ES GCM, and that water availability will more than triple in some of the arid interior areas, but against a very low baseline such that changes may not be that significant from a livelihoods' perspective. Côte d'Ivoire will see an increase in water availability between now and 2050 under most model runs. Only under the IPSL-CM5A-LR GCM is there some drying in the eastern portion of the country.

The projections for crop models are more nuanced than for the water models. Figure 4.2 depicts the average index values for the crop models for the 2010–50 period. The LPJmL crop model projects more widespread decreases of 10 percent to 30 percent across much of the region (except Sierra Leone and Liberia and the northern Sahel), whereas the GEPIC model produces a patchwork of mostly increases with some decreasing crop production. Appendix C has projections from 2050–2100. The maps show the same patterns, but with accentuated impacts, especially under RCP8.5.

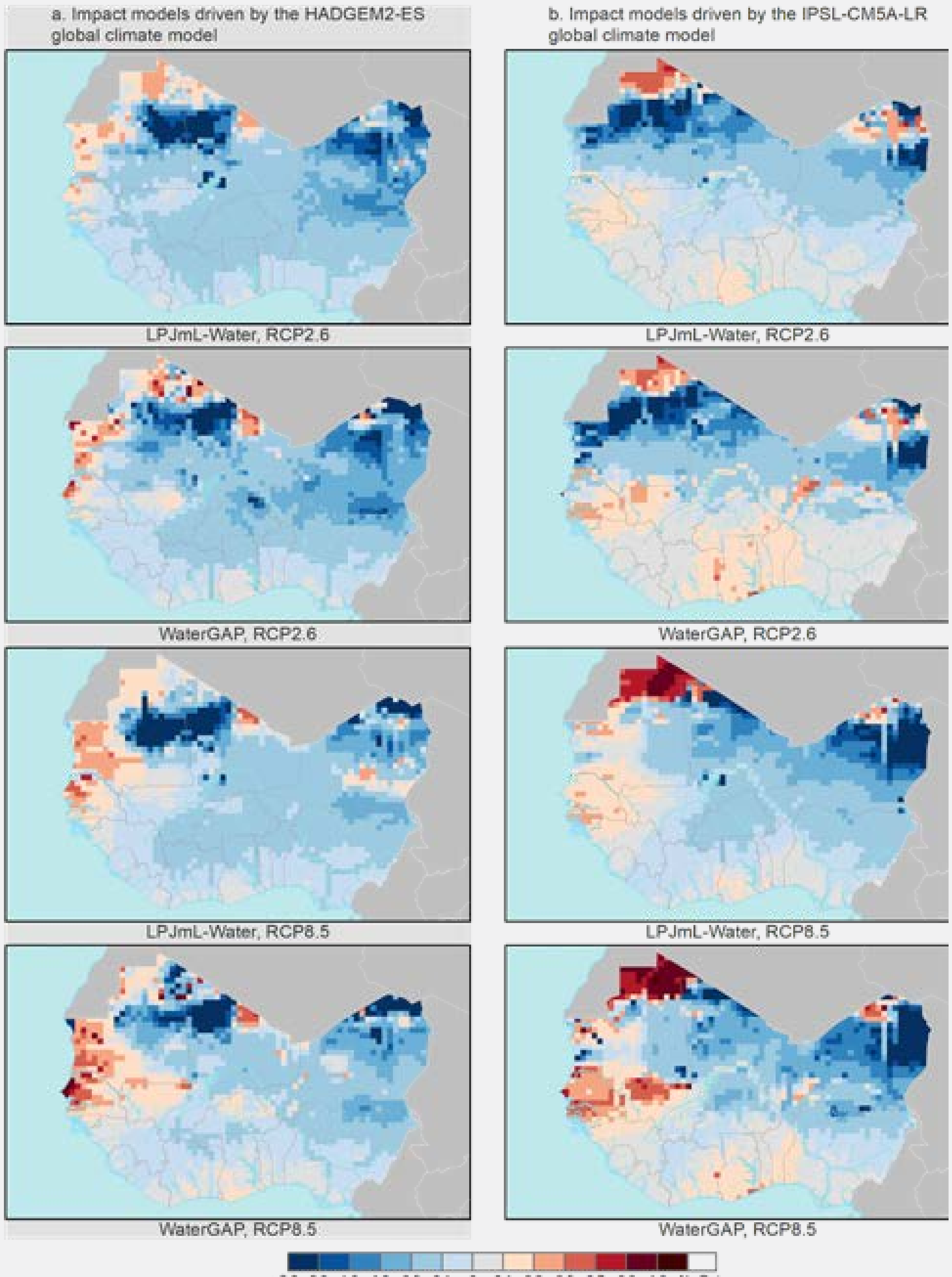
Model runs show mixed crop production among the countries. In Nigeria, by 2050 the LPjML model shows 10 percent to 30 percent declines in the middle belt of the country (away from the river basins), and GEPIC shows more mixed results, including areas with increases in crop production. The notable increase in water availability in the north and northeast reflects increases in crop production, particularly under the GEPIC models. In Côte d'Ivoire, agriculture is largely stable or there are increasing yields for staple crops, though with patches of decline. In the south of Mauritania, crop production declines under most model runs.

In rural areas, high values in crop yields and NPP are positively correlated with larger population change. Ecosystem productivity models—enhancements to the original Groundswell modeling work (Rigaud et al. 2018) —are important measures for pastoral livelihoods. A large portion of the Sahel is inhabited by pastoralists who engage in livestock herding, and this livelihood is very climate sensitive. Ecosystem productivity or NPP models are used only in areas lacking crop productivity data, since there is high spatial co-linearity between crop and ecosystem metrics.[49]

Generally, the wetting in climate models used to assess NPP suggests great increases in plant biomass in the northern Sahel and into the Sahara, but these are against a very low baseline productivity (figure 4.3). For example, the dramatic changes in NPP in Mauritania, similar to precipitation patterns, are against a very low baseline, and should be interpreted in this light (figure 4.3). In some cases, the NPP model outputs are shown only for information purposes (because there are very limited parts of the countries without crop production, for example, Nigeria).

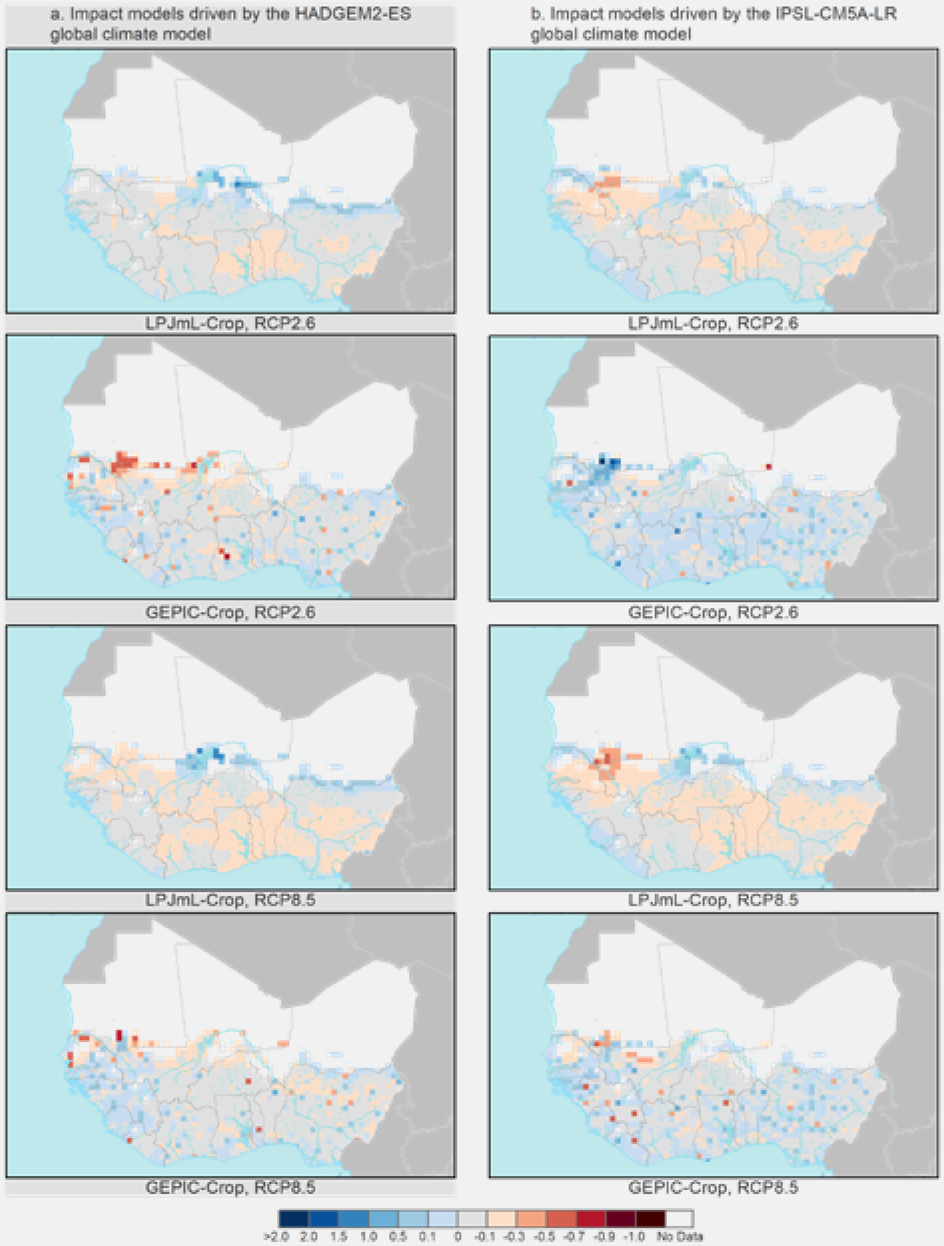
49. This means that adding ecosystem impacts would only repeat information in the ISIMIP crop production impacts.

Figure 4.1 ISIMIP Average Index Values against 1970–2010 Baseline for Water Availability, West Africa, 2010–50



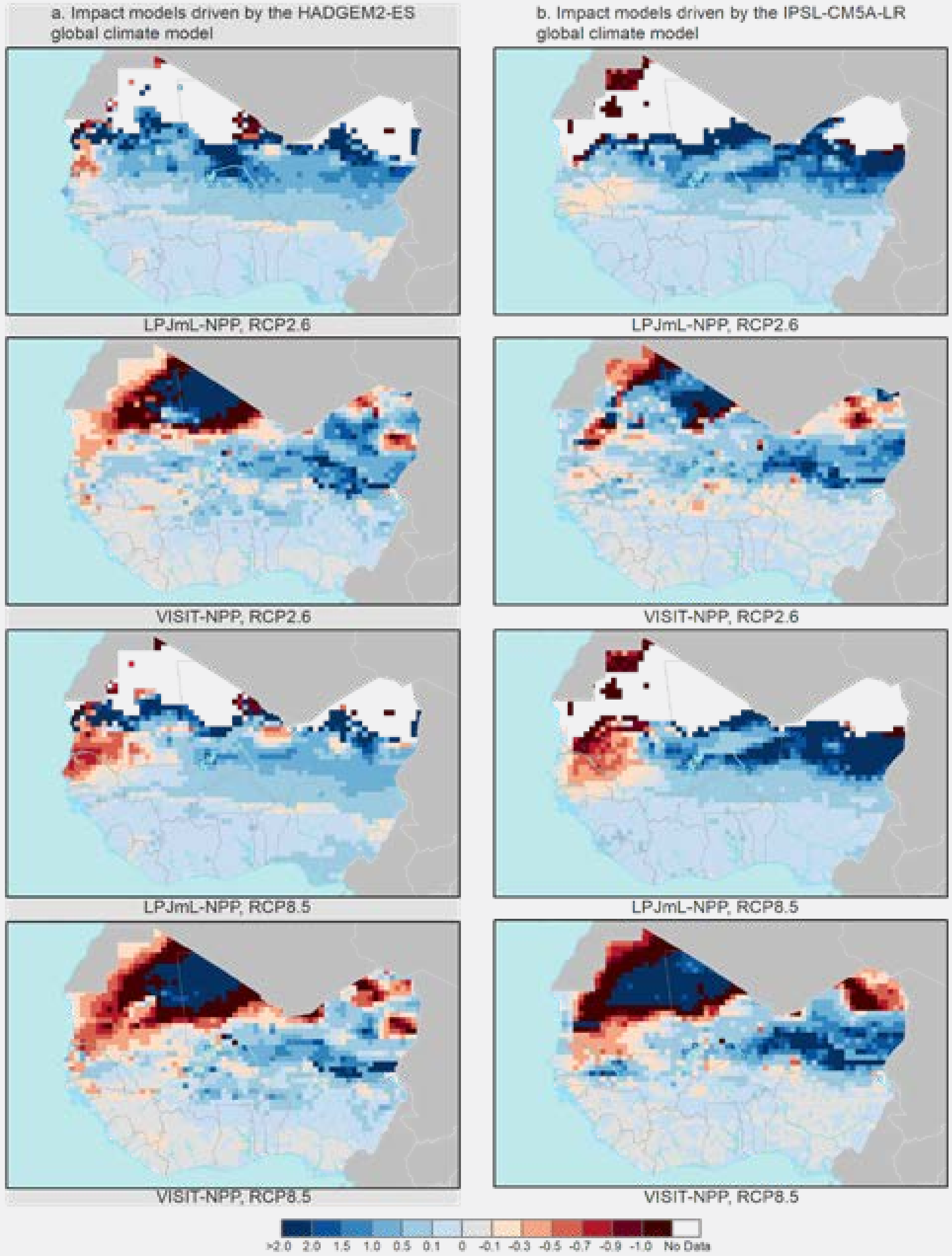
Note: Data calculated against 1970–2010 baseline for water availability from HadGEM2-ES (panel a) and IPSL-CM5A (panel b) climate models, with RCP2.6 model runs in the top four maps and RCP8.5 model runs in the bottom four maps. Blue areas indicate wetting relative to the historical baseline, and gray to tan to red areas indicate drying.

Figure 4.2 ISIMIP Average Index Values against 1970–2010 Baseline for Crop Production, West Africa, 2010–50



Note: Data calculated against 1970–2010 baseline for crop production, driven by the HadGEM2-ES (panel a) and IPSL-CM5A (panel b) climate models, with RCP2.6 model runs in the top four maps and RCP8.5 model runs in the bottom four maps. Blue areas indicate crop production increases relative to the historical baseline, and gray to tan to red areas indicate crop production decreases. White areas do not grow the four major crops: these gaps were filled with projections of ecosystem productivity.

Figure 4.3 ISIMIP Average Index Values against 1970–2010 Baseline for Ecosystem NPP, West Africa, 2010–50



Note: Data calculated against 1970–2010 baseline for ecosystem NPP, driven by the HadGEM2-ES (panel a) and IPSL-CM5A (panel b) climate models, with RCP2.6 model runs in the top four maps and RCP8.5 model runs in the bottom four maps. Blue areas indicate higher NPP relative to the historical baseline, and tan to red areas indicate lower NPP. These projections were used to gap-fill areas without crop production projections. Extreme index values under the VISIT model in the Sahara are against very low baselines. NPP = net primary productivity.

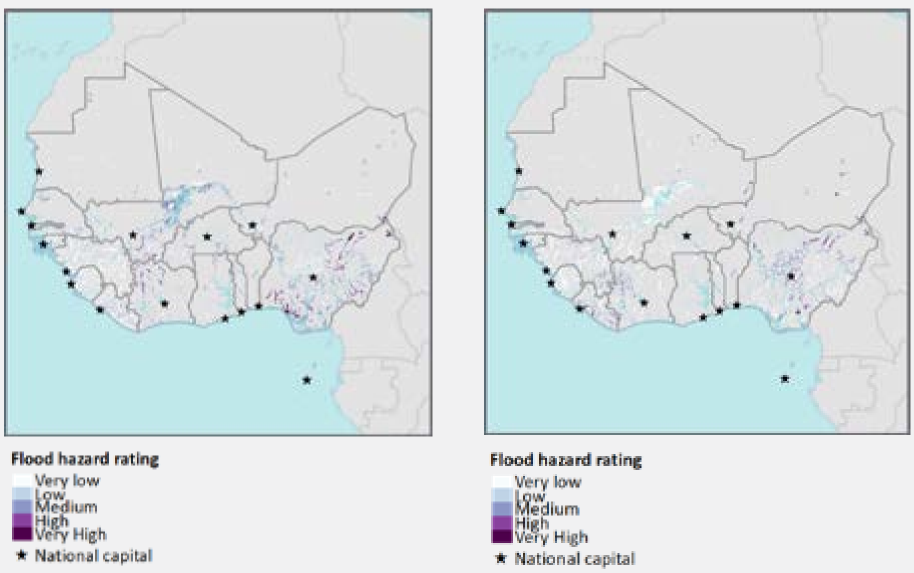
4.1.2 Flood Models Used in the Gravity Model

Flood risk is positively associated with population change, and the effect is larger in urban areas by an order of magnitude. Figure 4.4, panels a and b, depicts flood risk data for West Africa under RCP2.6 and RCP6.0, representing low and high emission scenarios, respectively. Flood hazards are higher and more extensive under higher emissions—along main rivers—including the Niger River Basin from Mali through to Nigeria, Sasandra River in Côte d'Ivoire, and the Lake Faguibine system in Mali, which experiences seasonal flooding. The model runs for RCP2.6 were used in the climate-friendly and optimistic scenarios, and the model runs for RCP6.0 were used in the more inclusive development and pessimistic scenarios.

Paradoxically, flooded areas tend to attract population in the gravity model, because riparian areas have been historically more accessible and often host urban areas. Thus, flood risk will tend to attract new migrants rather than repel them; and this is consistent with the literature on flood risk in developing countries. For example, Jongman et al. (2012) state that "over the period 1970–2010 the number of people exposed to flooding globally has increased by 2.7 percent more than total population growth. Developing countries have, conjoint with general high population growth, experienced the strongest increase in exposed relative to total population." In addition, there is the well-documented trend in migration toward, and consequently population growth in, low-lying and flood-prone coastal areas (de Sherbinin et al. 2011; Neumann et al. 2015).

Figure 4.4 Projected Flood Hazard Rating, West Africa, 2040, RCP2.6 and RCP 6.0

a. RCP2.6 b. RCP 6.0



4.1.3 Sea Level Rise

The analysis considers sea level rise projections from the Intergovernmental Panel on Climate Change (IPCC) Fifth Assessment Report, augmented by an increment for storm surges. Under RCP2.6, the increment for storm surge was 0.85–0.9 meters, for a total of 1 meter; under RCP8.5, the increment was 1.68–1.85 meters, for a total of 2 meters. These assumptions are applied to all coastlines. They represent the loss of habitable land because of sea level rise plus storm surge in each coastal grid cell.

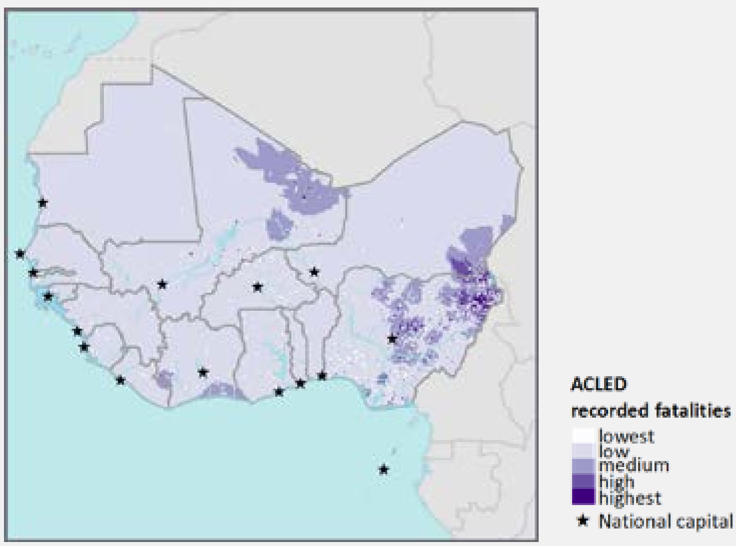
4.2 NONCLIMATE FACTORS

4.2.1 Conflict

Conflict hotspots tend to be associated with slow or declining rural population growth and slightly more rapid urban growth because when civil conflicts break out people tend to flee rural areas in search of protection in urban areas. Conflict-related fatalities are moderately negatively correlated with population change, decreasing attractiveness, again with a stronger effect in urban areas. However, the coefficients are small.

Spatial kriging (a form of interpolation) created a continuous surface to fill in gaps between points, yielding a surface where each 1-kilometer pixel has a value associated with the relative amount of conflict fatalities (figure 4.5). This surface was applied in model calibration to identify the impact of conflict on spatial population patterns. Spatial data on conflict occurrence was obtained from the Armed Conflict Location & Event Data Project (ACLED) database. A spatial layer was developed of the point locations of every conflict event between 2009 and 2018, and the values at each point were the number of fatalities.

Figure 4.5 Interpolated Conflict Surface, West Africa, 2009–18



Source: Adapted from CIESIN interpolation of Armed Conflict Location & Event Data (ACLED) for 2009-18.

Note: The fatality levels across the 10 years for each of these classes are as follows: lowest = 0, low = 1–34, medium = 35–102, high = 103–270, highest = 270–8,600.

4.2.2 Demographic Characteristics

Data on median age and the sex ratio (males as a percentage of female population) were used to calibrate the model by establishing the relationship between spatial population change and demographic characteristics of the population. The coefficient on median age used to calibrate the model was high in the West Africa region (table 3.6), meaning that it was influential. The reason is that urban areas typically have higher median ages than rural areas (figure 4.6) because of higher fertility rates in rural areas and patterns of rural-to-urban migration that typically syphon off working age adults from rural areas, adding them to the population of urban areas. The strong signal on a nonclimate-related parameter in West Africa may have contributed to the lower number of estimated climate migrants relative to the original Groundswell work (Rigaud et al. 2018). For example, the attractiveness of higher median age in urban area, as an underlying demographic pattern in West Africa, dampened the effects of water stress, which would otherwise drive climate out-migration. This is observed in the coastal areas of Senegal and Bight of Benin region from Côte d'Ivoire to Nigeria. Similarly, conflict-related fatalities are negatively correlated with population change, decreasing attractiveness of localities, with a stronger effect in urban areas, but here the coefficient is small. This is discussed further in appendix D. See figure 4.7, panels a and b.

In most regions, because of the propensity of youth to migrate to urban areas, rural areas would typically have higher median age. Also, lower sex ratios (more females than males) would typically be associated with rural areas (Siegel and Swanson 2004), and areas with higher sex ratios (more males per females) would typically be associated with urban areas. For future projections we assume that variability in the sex ratio and median remain constant over space.

Figure 4.6 Median Age, West Africa, 2010

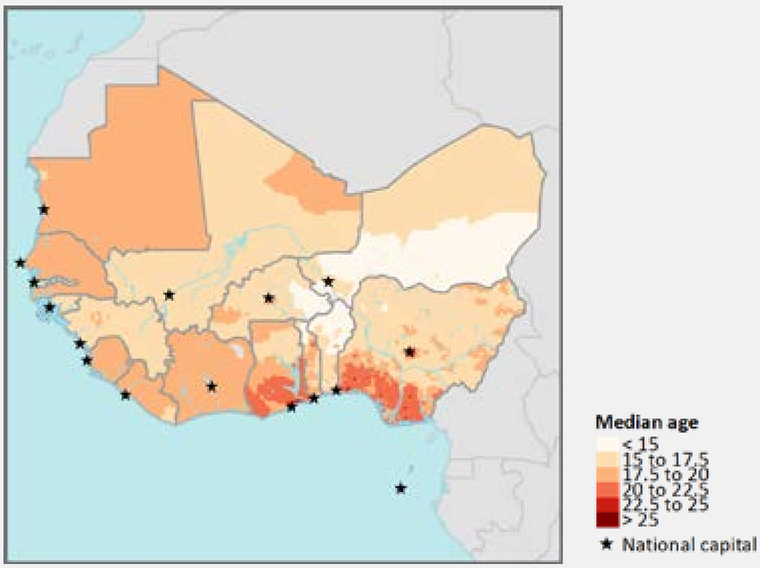
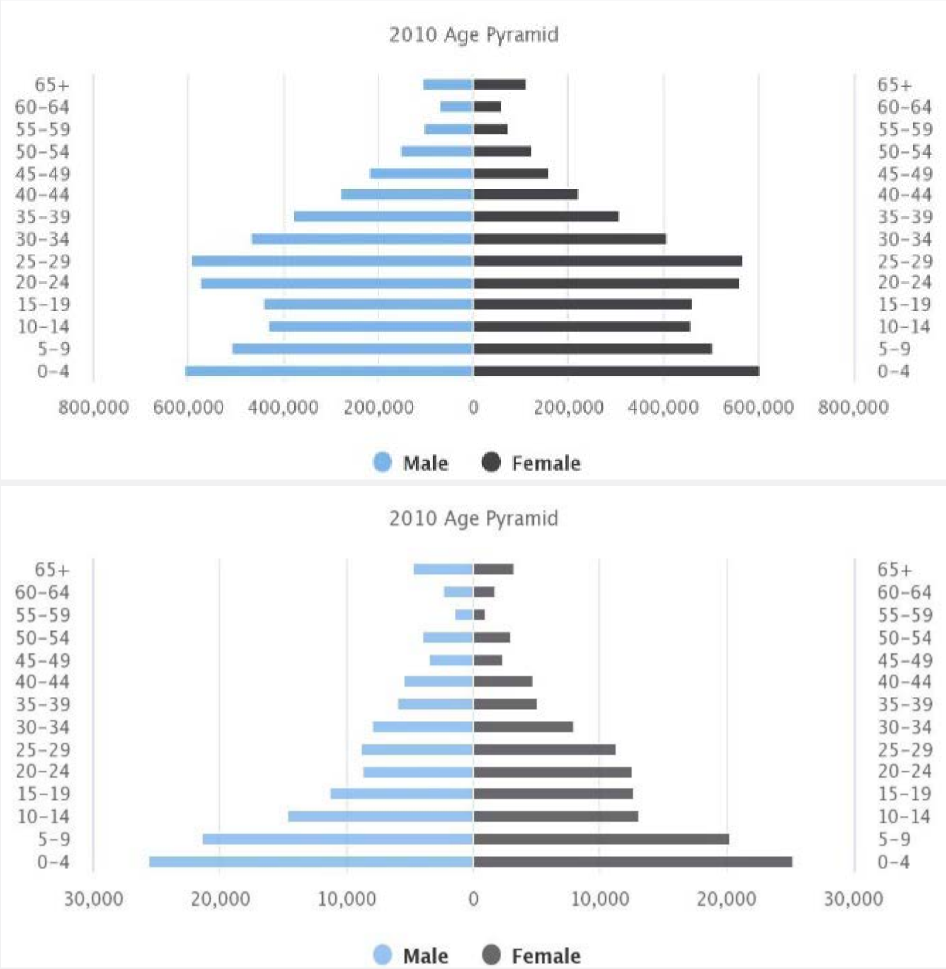
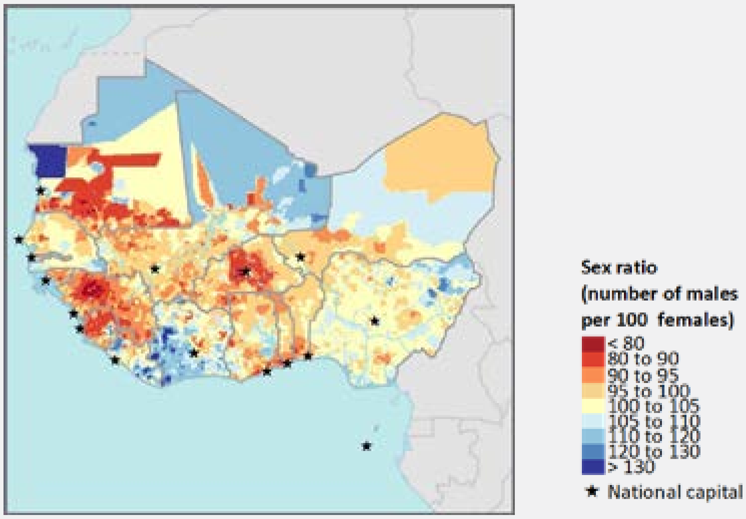


Figure 4.7 Age Pyramid for Lagos Area (top) and Rural Northern Nigeria (bottom), 2010



Source: CIESIN 2018a.

Figure 4.8 Sex Ratio, West Africa, 2010



Chapter 4

Modeling Results: Climate Impact Projections

This chapter presents the modeling results of the projected climate impacts on water availability, crop production, net primary productivity (NPP), flood risk (derived based on the Intersectoral Impacts Model Intercomparison Project [ISIMIP] simulation models), and sea level rise compounded by storm surge. Results relating to the nonclimate factors (demographic, including median age and sex, and conflict) are also presented. The climate and nonclimate impact results form the basis of the modeling outcomes of the plausible future climate migration scenarios presented in chapter 5.

4.1 CLIMATE IMPACT MODELS

Figures 4.1–4.3 present the average projected changes in water availability, crop production, and NPP for the 2010–2050 time period, respectively. NPP is used to gap-fill areas where there is no crop production. Appendix C has projections for the 2050-2100 time period. These projections represent the inputs for the estimation of future population shifts induced by climate change as a proxy of climate migration.

4.1.1 Water, Crop, and Ecosystem Productivity

The analysis reveals that populations are most sensitive to historical deviations in water availability (in both rural and urban areas), followed by historical deviations in crop productivity and changes in NPP that affect rural farmers and pastoralists. This means that positive deviations in water availability, crop productivity, or NPP are associated with increases in population density in the past. The coefficients are set out in table 3.7.

Water availability is the strongest factor that will influence migration in the Lake Victoria Basin (Lake Victoria Basin) over the next few decades. This implies that greater water availability results in increasing attractiveness of a location, and vice versa. The coefficient is particularly high in rural areas, meaning that, other things being equal, areas with better water availability (as measured by the deviation from historic baseline) are projected to have relatively large positive population changes. Figure 4.1, panels a and b, depicts the average index values across the model runs for the 2010–50 period for the water models.

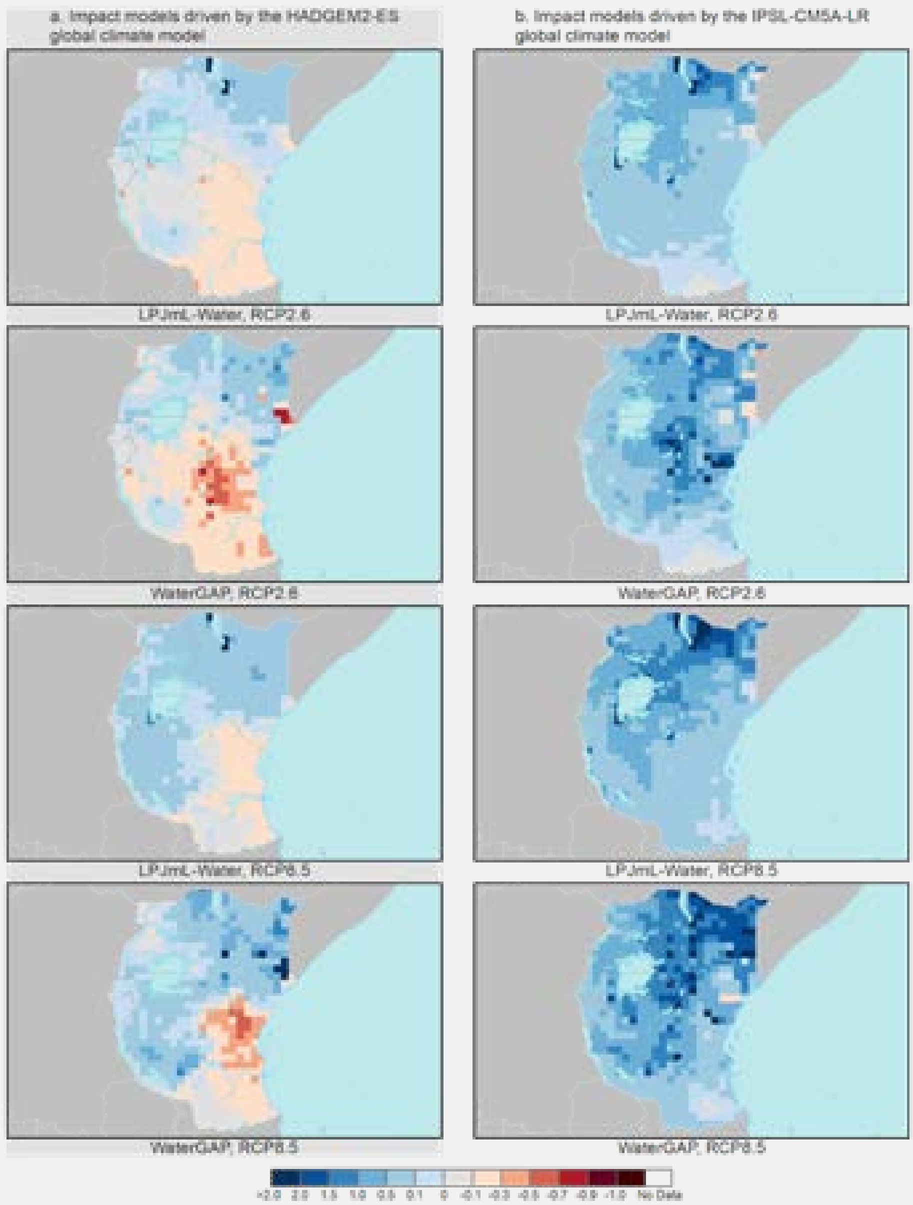
Consistent with patterns found in the Coupled Model Intercomparison Project ver. 5 (CMIP5) archive, the water models all show wetting in northern Uganda and Kenya. The models disagree on Tanzania, which under the Hadley model (HADGEM2-ES) is projected to get drier, while under the IPSL model it is projected to get wetter.

The modeling results vary considerably among Lake Victoria Basin countries. The climate models project contrasting results for water availability between 2010 and 2050 in Tanzania. The IPSL-CM5A-LR model projects increase in water availability across most of Tanzania, with the northeast projecting the highest increase in water availability. The HADGEM2-ES model, however, projects drying in the east and northeast (against very low baselines) and increase in water availability in the west and north, with some variations. In Uganda, the average projected water availability from the ISIMIP model runs for the 2010–50 period suggest that Uganda is likely to become wetter, particularly in the east, while some models indicate a drying trend in the northwest and west-central areas.

In rural areas, high values in crop yields and NPP are positively correlated with larger population change. The magnitude of the coefficient is smaller, so its effect is not as strong as water availability. Crop production and NPP are not used to calibrate urban grid cells because populations are assumed not to be as dependent on crops and livestock for livelihoods. Figure 4.2, panels a and b, depicts the average index values for the crop models for the 2010–50 period.

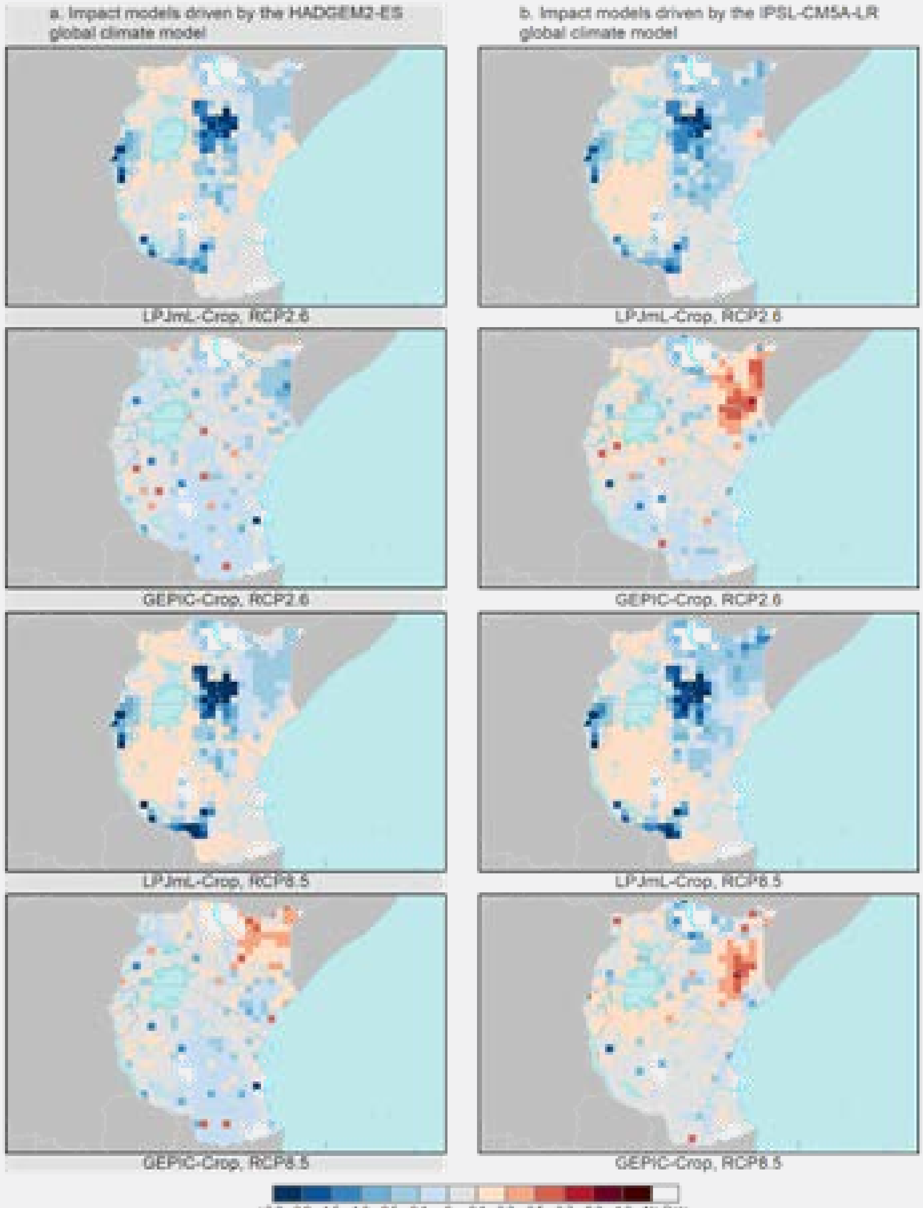
The crop models are more varied than the water models. Under the LP-JmL model, the highland areas around Mount Elgon on the Uganda-Kenya border and stretching through the highlands toward the southeast, along throughout Rwanda and Burundi, show significant increases in yields. It also consistently shows declines in western Tanzania. The GEPIC model shows declines in crop productivity in northeastern Uganda as well as western Tanzania. Under RCP8.5, declines are significant throughout the region. The results of NPP presented in figure 4.3, panels a and b, should not be seen as very influential except in those few areas of gaps in cropping.

Figure 4.1 ISIMIP Average Index Values against 1970–2010 Baseline for Water Availability, Lake Victoria Basin, 2010–50



Note: Data calculated against 1970–2010 baseline for water availability, from LPJmL/water (panel a) and WaterGAP (panel b), forced with the HadGEM2-ES climate model (top four maps) and IPSL-CM5A (bottom four maps) under RCP2.6 and RCP8.5. Blue areas indicate wetting relative to the historical baseline, and tan to red areas indicate drying.

Figure 4.2 ISIMIP Average Index Values against 1970–2010 Baseline for Crop Production, Lake Victoria Basin, 2010–50



Note: Data calculated against 1970–2010 baseline for crop production, from LPJmL/crop (panel a) and GEPIC (panel b), forced with the HadGEM2-ES climate model (top four maps) and IPSL-CM5A (bottom four maps) under RCP2.6 and RCP8.5. Blue areas indicate crop production increases relative to the historical baseline, and tan to red areas indicate crop production decreases. White areas do not grow the four major crops: these gaps were filled with projections of ecosystem productivity.

Figure 4.3 ISIMIP Average Index Values against 1970–2010 Baseline for Ecosystem NPP, Lake Victoria Basin, 2010–50

Note: Data calculated against 1970–2010 baseline for ecosystem NPP, from LPJmL (panel a) and VISIT (panel b), forced with the HadGEM2-ES climate model (top four maps) and IPSL-CM5A (bottom four maps) under RCP2.6 and RCP8.5. Blue areas indicate higher NPP relative to the historical baseline, and tan to red areas indicate lower NPP. These projections were only used to gap-fill in areas without crop production projections. NPP = net primary productivity.

4.1.2 Flood Models Used in Gravity Model

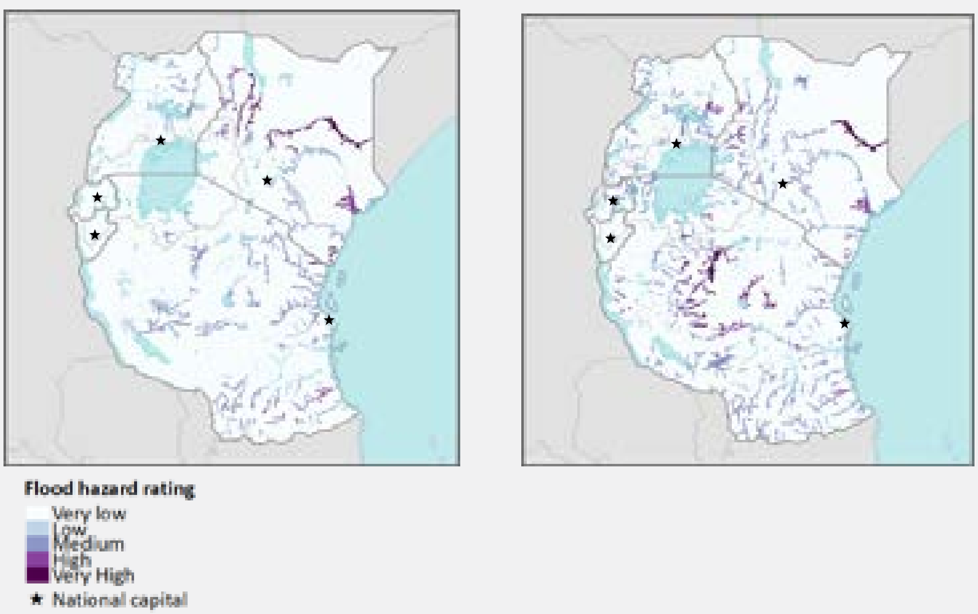
Flood risk is positively associated with population change, and the effect is larger in urban areas by an order of magnitude. Figure 4.4, panels a and b, depicts flood risk data for the Lake Victoria Basin under RCP2.6 and RCP6.0, representing low and high emission scenarios, respectively. The model runs for RCP2.6 were used in the climate-friendly and optimistic scenarios, and the model runs for RCP6.0 were used in the more equitable development and pessimistic scenarios. Flood hazards are higher and more extensive under higher emissions: along Tanzania's section of the Lake Victoria Basin south to Lake Eyasi and Kitangiri. The risks are also high around Lake Kyogo in Uganda and north of the Basin in Kenya.

Paradoxically, flooded areas tend to attract population in the gravity model, since riparian areas are historically more accessible and often host urban areas. Thus, flood risk will tend to attract new migrants rather than repel them. This is consistent with the literature on flood risk in developing countries. For example, Jongman, Ward, and Aerts (2012) write that "over the period 1970–2010 the number of people exposed to flooding globally has increased by 2.7 percent more than total population growth… Developing countries have, conjoint with general high population growth, experienced the strongest increase in exposed relative to total population." There is a well-documented migration trend toward, and consequently population growth in, low-lying and flood-prone coastal areas (de Sherbinin et al. 2012; Neumann et al. 2015). A new World Bank Study "The Ebb and Flow: Water, Migration and Development" (Borgomeo et al. 2021; Zeveri et al. 2021) found that on average, water deficits result in five times as much migration as do water deluges, even though floods are much more likely to gain national or international attention.

Figure 4.4 Projected Flood Hazard Rating, Lake Victoria Basin, 2040, RCP2.6 and RCP6.0

a. RCP2.6

b. RCP6.0



4.1.3 Sea Level Rise

The model implements sea level rise and storm surge by progressively removing land from occupation, thereby reducing the population accommodated in a coastal grid cell over time. The analysis uses sea level rise projections from the IPCC Fifth Assessment Report, augmented by an increment for storm surges (table 3.4). Under RCP2.6, the increment for storm surge was 0.85–0.9 meters, for a total of 1 meter; under RCP8.5, the increment was 1.68–1.85 meters, for a total of 2 meters. These assumptions are applied to all coastlines; they represent the loss of habitable land because of sea level rise plus storm surge in each coastal grid cell. In the model, the proportion of each grid cell at or below sea level is calculated for 2010 and under the projection to 2050 (for both the 1-meter and 2-meter sea level rise), and the amount is linearly interpolated for each five-year time step in between.

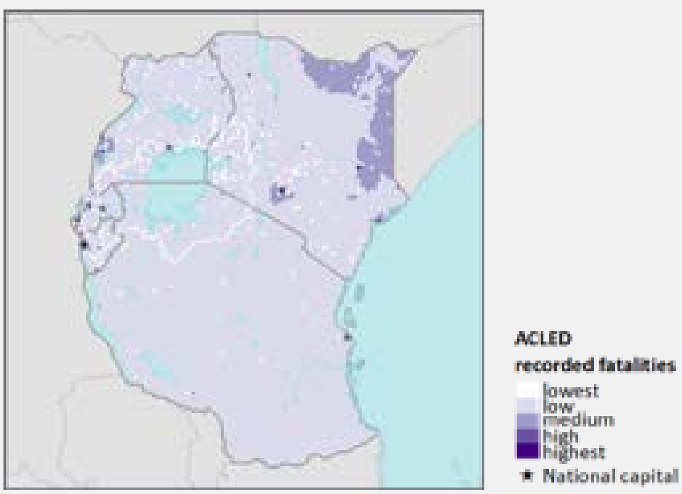
4.2 NONCLIMATE FACTORS—CONFLICT AND DEMOGRAPHIC CHARACTERISTICS

4.2.1 Conflict

Conflict hotspots tend to be associated with slow or declining rural population growth and slightly more rapid urban growth, because when civil conflicts break out people tend to flee rural areas in search of protection in urban areas. Conflict-related fatalities are moderately negatively correlated with population change, decreasing attractiveness, again with a stronger effect in urban areas. However, the coefficients are small.

Spatial kriging (a form of interpolation) created a continuous surface to fill in gaps between points, yielding a surface where each 1-kilometer pixel has a value associated with the relative amount of conflict fatalities (figure 4.5). This surface was applied in model calibration to identify the impact of conflict on spatial population patterns. Spatial data on conflict occurrence were obtained from the Armed Conflict Location & Event Data Project (ACLED) database.[43] We developed a spatial layer of point locations of every conflict event between 2009 and 2018, and the values at each point were the number of fatalities.

Figure 4.5 Interpolated Conflict Surface, Lake Victoria Basin, 2009–18



4.2.2 Demographic Characteristics—Median Age and Sex

Data on median age and sex ratios used to calibrate the model by establishing the relationship between spatial population change and demographic characteristics of the population show weak impacts (see table 3.7 on coefficients). This is unlike the pattern in the West Africa, in which the attractiveness of higher median age in urban areas, as an underlying demographic pattern in West Africa, dampened the effects of water stress, which would otherwise drive climate out-migration.

43. Armed Conflict Location & Event Data Project (ACLED) (database), accessed September 2018, Madison, WI, http://www.acled.org.

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Appendix A

ISIMIP Data Inputs

The modeling team needed to choose among a number of global climate models (GCMs) and crop, water, net primary productivity (NPP), and flood models. This appendix provides the rationale for the GCMs and models.

A.1 CLIMATE MODELS USED IN CROP, WATER AND NET PRIMARY PRODUCTIVITY MODELING

Of the more than 30 GCMs that participated in the Coupled Model Intercomparison Project phase 5 (CMIP5) (Taylor, Stouffer, and Meehl 2012), five models were used in the Intersectoral Impacts Model Intercomparison Project (ISIMIP) Fast Track to drive the crop, ecosystem, and hydrological models. These cover a large percentage of temperature and precipitation projections across the CMIP5 ensemble, although the entire range cannot be represented with only five models (Warszawski et al. 2014; McSweeney and Jones 2016). For this study, the climate model ensemble was further reduced to make its application in the population modeling framework feasible. From the five ISIMIP GCMs, the HadGEM2-ES and IPSL-CM5A-LR models were chosen. One reason for choosing these models is that the future precipitation trends differ substantially in magnitude, and partly even in sign, between these models for the case study regions of this report (Schewe et al. 2014). For these regions, a large range of possible future climate changes can be covered with only these two models. Further, both models produce new impact simulations within the ISIMIP2b project (Frieler et al. 2017), so that this analysis could easily be updated when those new impact simulations are available. Moreover, the HadGEM2-ES model has a particularly fine native resolution, potentially rendering it more realistic than other models at the regional scale.

While it would be desirable to use climate impacts data at a higher spatial resolution, no consistent set of impact model simulations is available that have been forced by regional climate models (RCMs). The use of global impact simulations in this study presents an advance over using purely climate model–based indicators because they represent actual resources (crops, ecosystem productivity, and water) relevant for human livelihoods.

A.1.1 Crop Models

Müller et al. (2017) evaluated global crop models by comparing simulations driven with observations-based climate input (within the ISIMIP2a project) to reported crop yields. Six of these models contributed future simulations within the ISIMIP FastTrack, which could have been used in the work underlying this report. Among these, at the global level, one of the best-performing models (in terms of time series correlation and mean bias in global yield) for both maize and wheat is LPJmL (Bondeau et al. 2007). For maize, GEPIC (Liu et al. 2007) also performs very well; both models also have a reasonable performance for rice. Another advantage of this choice is that LPJmL is an ecosystem model, while GEPIC is a site-based model; thus, two of the major structural model types are covered.

For some crop-country combinations, very few models show a good performance at the national scale in terms of time series correlation and mean bias (Müller et al. 2017), which is, however, not to say that they cannot capture longer-term trends. To reflect overall agricultural productivity, the four major crops (maize, wheat, rice, and soybean) were combined into a total production index. Depending on the country, other crops are also important, but are not simulated by most of the global crop models.

A.1.2 Water Models

The ISIMIP hydrological models have so far been evaluated (Gosling et al. 2017; Hattermann et al. 2017) mainly for 11 large river basins, of which only the Ganges (Bangladesh) and Blue Nile (Ethiopia) are relevant for the present set of case study countries. Moreover, in these studies, the models have been anonymized, that is, individual models cannot be identified. One criterion that narrows the choice is that only a few models can provide simulations, including human water abstraction, dams, and reservoirs, which are major nonclimatic human influences on the water cycle. These simulations are normally closer to observed discharge. Of the models that participated in both ISIMIP2a and the ISIMIP FastTrack, these are available from H08, WaterGAP, PCR-GLOBWB, MPI-HM, or LPJmL. From these, LPJmL and WaterGAP (Döll, Kaspar, and Lehner 2003; Flörke et al. 2013) were selected. LPJmL integrates crop yields, water resources, and ecosystems in a single model. WaterGAP can be calibrated separately for each basin and therefore matches observed river discharge better than other global models in many river basins. None of the ISIMIP global models include glacier dynamics. Work is ongoing to include glacier dynamics both in PIK's regional hydrological model SWIM and in WaterGAP.

A.1.3 Net Primary Productivity Models

The choice of net primary productivity or ecosystem models follows similar considerations as that of crop and water models. Out of four global ecosystem models (also called biome models) that participated in both the ISIMIP Fast Track and ISIMIP2a, three provided future simulations with both HadGEM2-ES and IPSL-CM5A-LR climate model forcing: LPJmL, VISIT, and JULES. LPJmL is among the best-performing global ecosystem models according to recent studies evaluating models' interannual variability and extreme events (Ito et al. 2017; Schewe et al. 2019), and was therefore chosen for this report. In addition, VISIT serves as an alternative model to gauge the potential influence of modeling uncertainty on the final estimates. We note however that the VISIT historical (ISIMIP2a) simulations do not account for historical changes in human land use.

A.2 CLIMATE MODELS USED IN FLOOD MODELING

Of the more than 30 GCMs that participated in CMIP5, four models (IPSL-CM5A-LR, GFDL-ESM2M, MIROC5, and HadGEM2-ES) were used in the ISIMIP2b to drive the hydrological models. These cover a large fraction of the range of temperature and precipitation projections across the whole CMIP5 ensemble, although the entire range cannot be represented with only four models (McSweeney and Jones 2016; Warszawski et al. 2014). One reason for choosing these models in ISIMIP2b is the availability of variables and time span that satisfies the requirement of all impact model sectors within ISIMIP. Priority orders were defined for the four GCMs, such that the hydrological models with limited computational resources will complete all experiments for IPSL-CM5A-LR first, followed by GFDL-ESM2M, MIROC5, and HadGEM2-ES. All the GCMs provide forcing data for the two Representative Concentration Pathways (RCPs) investigated in the ISIMIP2b project: RCP2.6 (low level of global warming under strong climate mitigation) and RCP6.0 (business as usual).

A.2.1 Flood Models

Six global hydrological models (GHMs): H08, LPJmL, MPI-HM, PCR-GLOBWB, ORCHIDEE, and WaterGAP2, uploaded results for all required experiments at the start of this investigation. They vary in representation of hydrological processes on land, and their performance has been evaluated for river basins worldwide, including the Blue Nile Basin (Ethiopia) (Hattermann et al. 2017). Of the six models, MPI-HM is forced only by the first three GCMs (not HadGEM2-ES), and ORCHIDE is forced only by IPSL-CM5A-LR and GFDL-ESM2M. The other four GHMs are forced by all four GCMs, making a total of 21 GCM-GHM combinations that generate daily runoff at 0.5 by 0.5 degrees (about 50- by 50-kilometer) resolution for the globe.

Global Flood Model

Global flood models represent the hydrodynamic process that route the gridded runoff along river networks and compute the flood inundation patterns as potential results of the routing. The GHMs often include river routing schemes. However, none of the six GHMs used here provide flood inundation depth. While other global flood models such as ISBA-TRIP (Decharme et al. 2012) and HyMAP (Getirana et al. 2012) exist, the CaMa-Flood is one of the first and only open source global river model available that can simulate floodplain dynamics and backwater effects by solving the diffusive wave equation (Yamazaki et al. 2011). CaMa-Flood generally improves the peak river discharge simulation compared to the native routing schemes employed in the GHMs (Zhao et al. 2017). CaMa-Flood has been widely used in global flood studies, and its performance has been shown in detail (Dottori et al. 2018; Hirabayashi et al. 2013). CaMa-Flood is forced by the projected daily runoff for the 2010–49 period from the GHMs, and daily discharge at 0.25 by 0.25 degree resolution is generated.

Definition of Flood Hazard Ratings

The annual maximum discharge results from CaMa-Flood forced by the 21 GCM-GHM combinations and the two RCPs (RCP2.6 and RCP6.0,[88] representing low and high emissions pathways) are extracted for West Africa and downscaled to 500-meter resolution annual maximum flood inundation depth (either flooded or not flooded at 500-meter resolution) based on topography information. Downscaling and mapping to observational-driven flood depth to avoid bias from the global climate models are described in the supplementary text of Hirabayashi et al. (2013), Wilner et al. (2018), and Dottori et al. (2018). The annual maximum flood inundation depth at 500-meter resolution considers flood defenses in West Africa, which are usually very low (can protect only against floods with return period of two to five years) according to Scussolini et al. (2016). Only those exceeding the protection return period, based on statistics from an accompanying preindustrial control run, are kept unchanged for the simulated flood depth, under the assumption of levee break (so it is as if flood protection does not exist). Floods below the protection return period threshold are set to 0 flood depth.

According to global flood depth damage functions compiled at the Joint Research Center of the European Commission, a 1-meter flood depth would lead to near 40 percent damage for residential buildings in sampled African countries (Huizinga, de Moel, and Szewczyk 2017). This is used as threshold to define damaging flood and convert the annual maximum flood inundation depth at 500 meters to 1/0 for above/below this threshold. For each decade (2010–19, 2020–29, 2030–39, 2040–49), the occurrence of damaging annual maximum flood events is then aggregated for each model combination and serve as a base for the flood hazard rating, which is defined as below:

- Very high (3): at least 70 percent models agreeing on at least five years of damaging flood in the decade.
- High (2): at least 70 percent models agreeing on at least two years of damaging flood in the decade, excluding areas with very high (3) rating.
- Medium (1): at least 50 percent models agreeing on at least one year of damaging flood in the decade, excluding areas with very high (3) or high (2) rating.
- Low (0): more than 50 percent models agreeing on no damaging flood in the decade.

These definitions consider absolute flood depth, flood defenses in West Africa, and model agreement for each decade, although the thresholds chosen could be changed to define a smaller or larger area for each category. The relative areas of flood hazard ratings are expected to change between the decades not only from global warming trends but also from large interannual and decadal climate variations.

88. At the time of this modeling work, flood modeling had not yet been performed for RCP8.5, so RCP6.0 serves as a stand in for the high emissions pathway represented by RCP8.5.

Appendix B

Population Gravity Model and Coefficients

This appendix provides technical details on the population gravity model. It also describes the coefficients derived from the historical population distribution data, which help explain the drivers of future climate migration.

B.1 TECHNICAL DETAILS OF THE MODEL

As described in section 3, the value A_i (from equation 3.2) is calculated as a function of these indicators, and represents an adjustment to the relative attractiveness of (or aversion to) specific locations (grid cells) reflecting current water availability crop yield, and net primary production (NPP) relative to "normal" conditions, in addition to flood risk, sex ratio, median age, and risk of conflict. To carry out the procedure, model estimates of the α and β parameters for the urban and rural populations are necessary, and (equation 3.2) must be calibrated. Two separate procedures are employed and carried out for the urban and rural population distributions. Urban and rural populations interact in the model, but changes in both are projected separately at the grid-cell level in the same manner. Here the procedure is described once, and, unless otherwise noted, the process is redundant for urban/rural components.

The α and β parameters capture broad-scale patterns of change in the distance-density gradient, which is represented by the shape/slope of the distance decay function (parabolas) depicted in equation 3.2. The negative exponential function described by equation 3.2 is very similar to Clark's (1951) negative exponential function, which has accurately captured observed density gradients throughout the world (Bertaud and Malpezzi 2003). To estimate α and β, the model in equation 3.2 is fitted to the 1990–2000 urban and rural population change from GPWv3 and to the 2000–10 urban and rural population change data from GPWv4, and we compute the values of α and β that minimize the sum of absolute deviations (equation B.1):

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

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 decadal time steps (1990–2000 and 2000–10) 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 or socioeconomic conditions. The modeling approach requires that the relationship between A_i and the sectoral impact, flood risk, demographic, and conflict indicators is estimated, which are hypothesized to affect population change. When α and β are estimated from historical data (for example, observed change between 2000 and 2010), a predicted population surface is produced that reflects optimized values of α and β, such that absolute error is minimized. Figure B.1 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 such as to eliminate (from figure B.1) for each individual cell (which is labeled observed) (equation B.2):

$$\Delta P^{obs}_{i,t} = A_i * \Delta P^{mod}_{i,t} \tag{B.2}$$

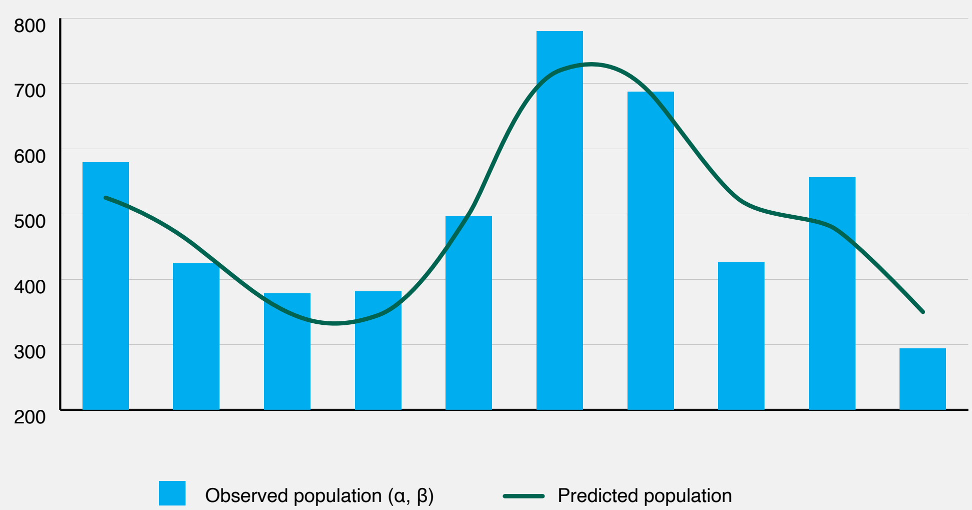
where $P^{obs}_{i,t}$ and $P^{mod}_{i,t}$ are the observed and modeled population change for each cell i and A_i is the factor necessary to equate the two.

The second step is to estimate the relationship between observed index and the different potential drivers of spatial population metrics by fitting a spatial lag model (equation B.3):

$$A_{i,t} = pW A_{i,t} + \beta_1 C_{i,t} + \beta_2 H_{i,t} + \beta_3 N_{i,t} + \beta_4 F_{i,t} + \beta_5 M_{i,t} + \beta_6 S_{i,t} + \beta_7 K_{i,t} + \varepsilon_{i,t} \tag{B.3}$$

where *C, H,* and *N* are the five-year deviations from the historic baseline on crop yield, water availability, and NPP, respectively, *F* is the flood risk metric, M is median age, S is sex ratio expressed as (male/female), and K is the conflict-related fatalities metric. These seven variables and their respective coefficients constitute the set of explanatory variables that produce index A_i For any grid cell in which *C* (crop yield) is a nonzero value, the value of *N* (NPP) is automatically set to zero, so that only one of the two variables is contributing to the index A_i Finally, is the spatial autocorrelation coefficient and *W* is a spatial weight matrix. From this procedure, a set of cell-specific α values is estimated for urban and rural population change.

Figure B.1 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 are used of $C_{i,t}$, $H_{i,t}$, $N_{i,t}$, and $F_{i,t}$, and current values of $M_{i,t}$, $S_{i,t}$, and , $K_{i,t}$ are used along with their respective coefficient estimates from equation B.3 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 Shared Socioeconomic Pathways (SSPs) (for example, the SSP4 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. Finally, exogenous projections of national urban and rural population change are incorporated and the model applied as in equation 3.2.

Because of testing, cells meeting certain criteria are excluded from the calibration procedure. First, cells that are 100 percent restricted from future population growth by the spatial mask (*l,* equation 3.2) are excluded, because 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 include significant outliers that skewed coefficient estimates in equation B.3. In most cases, these values correspond with very lightly populated cells where a small over- or underprediction of the population in absolute terms (for example, 100 persons) is quite large relative to total population within the cell (large percentage 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 B.3 would have a substantial impact on coefficient estimates. To combat this problem, the most extreme 2.5 percent 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 percent urban over the decade (2000–10) were excluded because 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 they are the result of a definitional change. In most cases these exclusions eliminate 5 percent to 10 percent of grid cells.

B.2 DRIVERS OF MIGRATION

Table B.1 provides coefficient estimates derived from fitting the spatial autoregressive model to historic population distribution change data for the periods 1990–00 and 2000–10 for each potential driver of spatial population change. The coefficients are derived from an equation that includes each of the potential drivers of migration described in section 3: the index for each decade of water availability, crop production, and ecosystem NPP compared to the historical baseline, as well as the median age and sex ratio of the population in each grid cell, conflict-related fatalities, and flood risk. Because urban and rural populations evolve in fundamentally different ways, we fit the model to observed change in each component of the population separately.

The coefficients should be interpreted as the influence on the *observed deviation between observed population change and predicted population change given only the agglomeration effect*. The values represent the contribution of each driver to the weight on potential (A_i) necessary to eliminate prediction error, which indicates the relative attractiveness of each location. The coefficients are unstandardized. Therefore, they cannot be directly compared (except for the ISIMIP crop, water, and NPP values), because their value can be understood only in relation to the ranges in the values of each data layer. For the ISIMIP values (apart from flood risk) the range is 0–2, whereas the range for median age is roughly 11–26, and for sex ratio the range is 62–250. This means the coefficients for the demographic variables, particularly median age, which is already high, will have a disproportionate impact on future population distribution compared to the climate impact variables. Table B.2 provides the descriptive statistics for each nonclimate variables plus flood risk.

The coefficients in table B.1 represent the average of the coefficients across the two decades, and across three countries used for regional calibration: Mauritania, Guinea, and Sierra Leone. Only these three countries had matching population and population growth rates at the same administrative level across the three time steps from 1990 to 2010.[89] Sea level rise is not considered a driver of migration, but rather is inserted as a spatial mask in the modeling work to move populations out of inundated areas.

Table B.1 Coefficient Values Derived from Calibration for Mauritania, Guinea, and Sierra Leone

Indicator (driver)	(Parameter) coefficient		Units
	Urban cells	Rural cells	
Crop production	n.a.	0.400	5-year deviation from historic baseline
Water availability	1.696	1.071	5-year deviation from historic baseline
Net primary productivitya	n.a.	0.380	5-year deviation from historic baseline
Median age	0.617	0.078	Median age of the population in years
Sex ratio	0.024	0.006	(Males/females) ratio
Conflict-related fatalities	−0.025	−0.003	Number of recorded fatalities
Flood risk	0.147	0.020	5-year likelihood of flood event

Note: n.a. = not applicable.

a. Net primary productivity, which is intended to reflect impacts on pastoral populations, is included in the model only where crop production is not present.

The coefficients are unstandardized, and therefore cannot be directly compared (except for the ISIMIP crop, water, and NPP values), since their value can only be understood in relation to the ranges in the values of each data layer. So for the ISIMIP values (apart from flood risk) the range is 0–2, whereas the range for median age is roughly 11–26, and for sex ratio the range is 62–250. This means the coefficients for the demographic variables will have a higher impact on future population distribution than the coefficient values might otherwise suggest. Table B.2 provides the descriptive statistics for each of the non-climate variables plus flood risk, while Table B.3 provides examples of the multiplication of the minimum and maximum values times the rural coefficients.[90] While water availability still has the biggest absolute range in values (3.213) followed by crop production (1.200), median age and sex ratio[91] still have ranges in values of more than 1, which rival the values for crop production and net primary productivity. The impact of the conflict and flood risk variables is, by comparison, very small.

89. Were calibration to be applied in countries without matching population and population growth rates at the same level, results would be spurious because changes in population could be due to the changing administrative units used to construct the population grids in each time period.
90. For example, for median age, the minimum value of 11, when multiplied by the rural coefficient of 0.078, yields a value of 0.858, while the maximum value of 26, when multiplied by the same coefficient yields a value of 2.028.
91. Sex ratios are read as males per 100 females. The negative coefficient suggests that the higher the sex ratio in an area, the stronger the population decrease, meaning areas with many more males than females typically will see higher declines in population. Compared to the climate variables, the effects are still quite small, but they are higher than for the other non-climate impact variables.

Table B.2 Descriptive Statistics for West Africa for Data Layers

	Min.	Max.	Mean	SD
Median Age	11.0	26.0	17.8	2.3
Sex Ratio	61.5	250.0	105.6	19.9
Conflict-related fatalities	1.0	259.0	5.1	3.9
Flood Risk	0.0	4.0	0.2	0.6

Note: The minimum and maximum values for the ISIMIP values (crop production, water availability, and net primary productivity) are 0 and 2, respectively. SD = Standard deviation.

Table B.3 Results of minimum and maximum values times sample rural coefficients

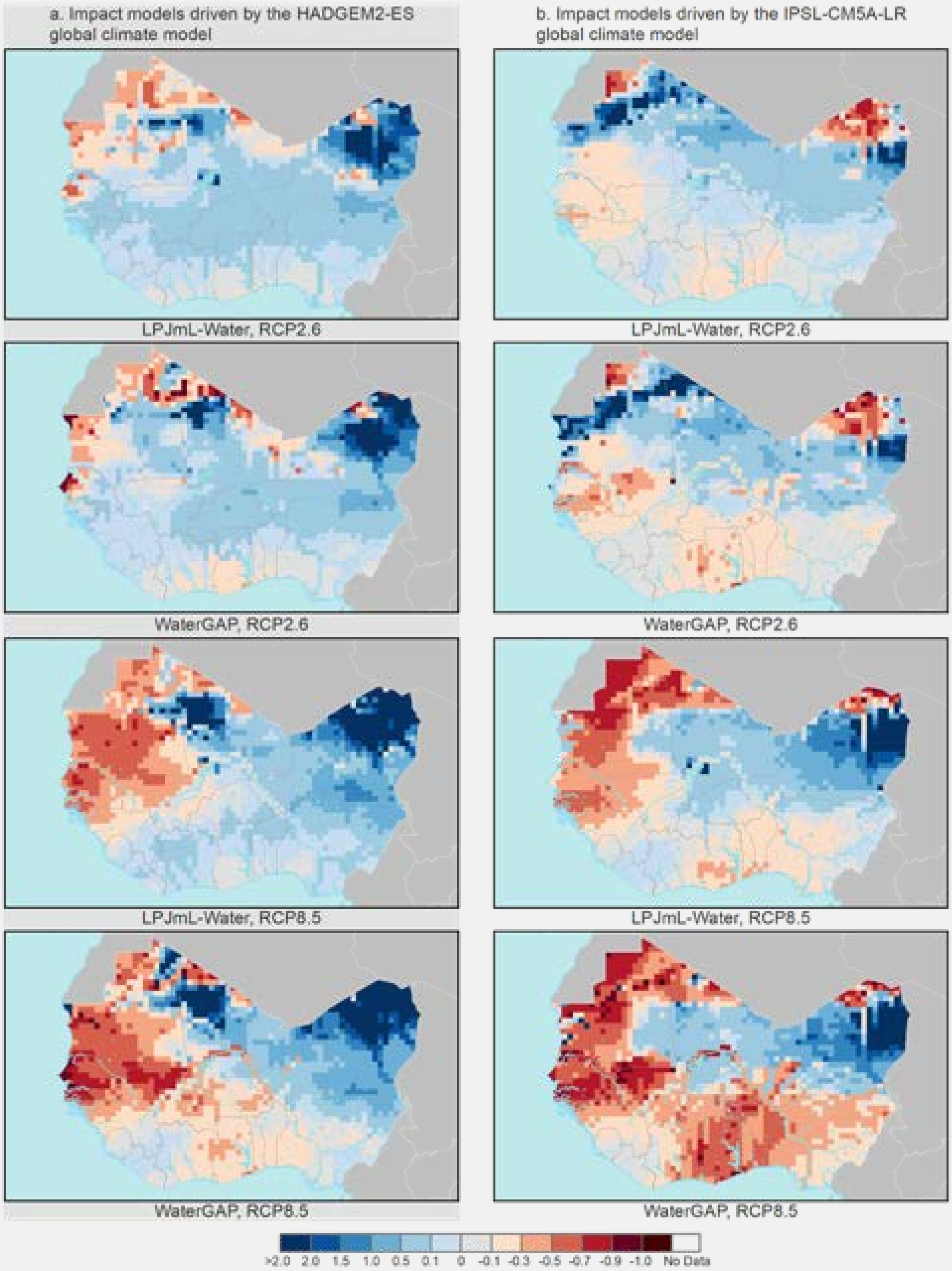
	Min.	Max.	Coefficients (rural)	Min. x Coefficient	Max. x Coefficient	Absolute Range
Crop production	-1	2	0.4	-0.400	0.800	1.200
Water availability	-1	2	1.071	-1.071	2.142	3.213
Net primary productivity	-1	2	0.38	-0.380	0.760	1.140
Median Age	11	26	0.078	0.858	2.028	1.170
Sex Ratio	61.5	250	0.006	0.369	1.500	1.131
Conflict-related fatalities	1	259	-0.003	-0.003	-0.777	0.774
Flood Risk	0	4	0.02	0.000	0.080	0.080

Appendix C

ISIMIP Projections to 2050–2100

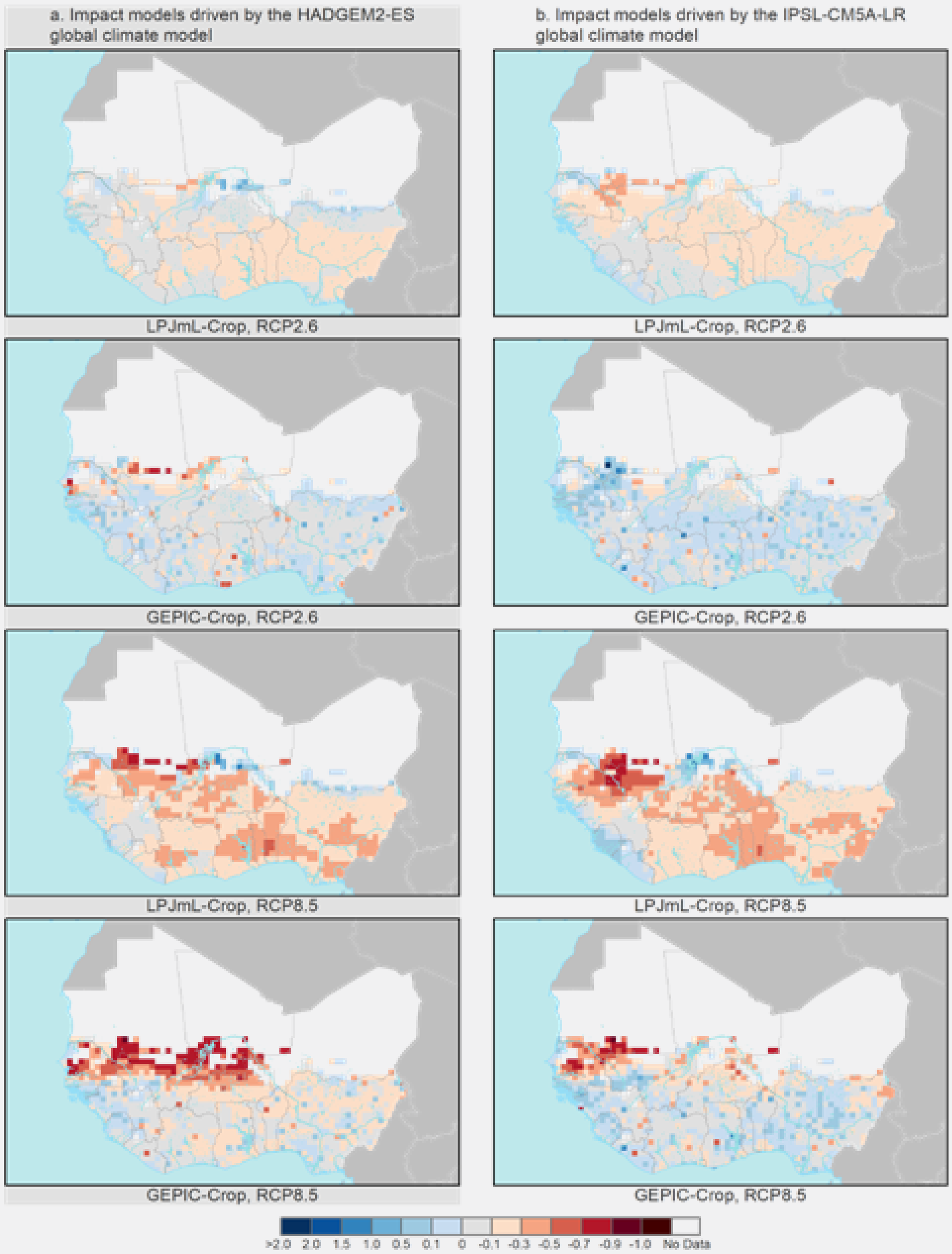
This appendix presents the projections for the water, crop, and ecosystem models out to 2050–2100 using the index defined in equation 3.1, in which the historical baseline value is subtracted from the projected value and then divided by the historical baseline value. Positive index values are capped at 2, which represents a tripling of the baseline value (whether it be water availability, crop production, or ecosystem productivity.

Figure C.1 ISIMIP Average Index Values against 1970–2010 Baseline for Water Availability, West Africa, 2050–2100



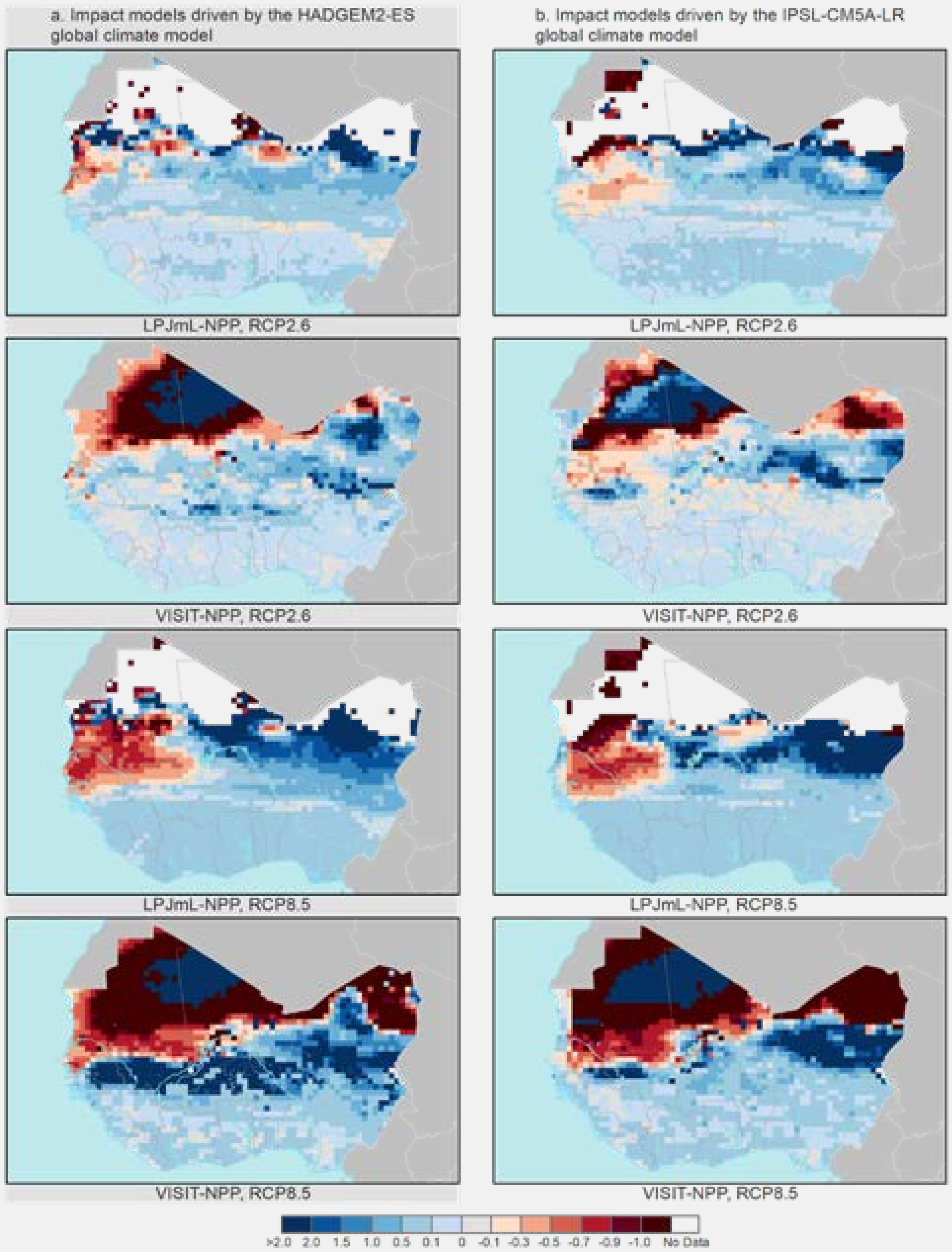
Note: Data compiled from LPJmL/water (panel a) and WaterGAP (panel b), forced with the HadGEM2-ES climate model (top four maps) and IPSL-CM5A (bottom four maps) under RCP2.6 and RCP8.5. Blue areas indicate wetting relative to the historical baseline, and gray and tan areas indicate drying.

Figure C.2 ISIMIP Average Index Values against 1970–2010 Baseline for Crop Production, West Africa, 2050–2100



Note: Data compiled from LPJmL/crop (panel a) and GEPIC (panel b), forced with the HadGEM2-ES climate model (top four maps) and IPSL-CM5A (bottom four maps) under RCP2.6 and RCP8.5. Blue areas indicate wetting relative to the historical baseline, and tan to red areas indicate drying. White areas do not grow the four major crops.

Figure C.3 ISIMIP Average Index Values against 1970–2010 Baseline for Ecosystem NPP, West Africa, 2050–2100



Note: Data compiled from LPJmL (panel a) and VISIT (panel b), forced with the HadGEM2-ES climate model (top four maps) and IPSL-CM5A (bottom four maps) under RCP2.6 and RCP8.5. Blue areas indicate higher NPP relative to the historical baseline, and tan to red areas indicate lower NPP. NPP = net primary productivity.

Appendix D

Comparison Between Groundswell and West Africa Results

Comparing the estimated number of internal climate migrants in the original Groundswell report (see table 4.2 in Rigaud et al. [2018]) with the results of this report (denoted as Groundswell Africa) reveals commonalities and differences for three out of four scenarios (there was no optimistic scenario in the original Groundswell report). Similar to the Groundswell model, trajectories of climate migration are highest under the high emission pessimistic (reference) scenario followed by the high emission inclusive development scenario, and lowest under the climate-friendly scenario. The spatial patterns of in- and out-migration hotspots are also broadly similar. Yet overall, estimates for the original Groundswell model are higher than estimates for the Groundswell Africa model. This section provides explanations for these differences before comparing results.

D.1 EXPLANATIONS

A summary list of differences between the two models is found in table 3.1, with additional details found in section 3. Differences between the model outputs come down to two primary factors: the Groundswell Africa model includes more data layers (for example, biome, rapid onsets) that influence the population potential (relative attractiveness) of grid cells during each time step, and the modeling was carried out at a higher resolution.

Additional Data Layers

The Groundswell Africa model includes several additional spatial layers that influence the population potential at each time step. In addition to the effect of climate impacts on crop production, water availability, and sea level rise on future population distributions included in the original Groundswell model, the new model includes spatial data layers representing climate impacts on net primary productivity (NPP) and flood risk, differences in age and sex composition, and conflict-related fatalities. Each of these layers exerts an influence on the relative attractiveness of each grid cell at each time step. This is a function of the magnitude of the value for each variable (for example, strongly positive or negative NPP relative to baseline conditions), the coefficient values obtained from the calibration based on historical climate impacts, and the change in population distribution (from 1990 to 2000 and 2000 to 2010). The coefficient values for the original Groundswell report are in table D.1, and the coefficient values for the new model are in table D.2. Higher coefficient values (positive or negative) equate to higher impacts on the attractiveness of grid cells for any given increment of change for each additional data layer.

The expanded set of covariates and the resolution at which they are applied can lead to lower estimates of the number of internal climate migrants. First, because the Groundswell Africa model is fit to higher-resolution (1-kilometer) data, the coefficients on each covariate are going to vary because of the additional information in the higher resolution spatial data (both the population data used to measure migration and the potential drivers of migration). Tables D.1 and D.2 indicate variability in the crop and water coefficients between the two models. For example, the signal on crop yields on rural population change is noticeably stronger in the version 1 application, while the signal on water stress is very similar (and is the largest explanatory factor). Rural populations are quite large across the region. Therefore, the smaller signal on crop yields would suggest a dampened response to changes in agricultural productivity in the Groundswell Africa model relative to the original Groundswell model.

Finally, the coefficient on median age was high in this region (especially in urban areas), meaning that higher median age distributions were associated with greater attractiveness. This makes sense because urban areas have older age distributions. However, the strong signal on a nonclimate-related parameter in Groundswell Africa may have contributed to the lower number of estimated climate migrants relative to the original Groundswell work. The map of median age distribution (figure 4.6) shows higher median ages coincide with many areas where projected water availability will decline significantly. Water is the climate variable with the strongest effect on future population distribution across urban and rural areas. The result is that while the median age draws migrants to urban areas (particularly along the coasts of Senegal and the Bight of Benin region from Côte d'Ivoire to Nigeria), declines in water availability repel migrants, thereby offsetting each other.[92] Because urban areas are the engines of regional growth and are attractive to migrants, declining water availability dampens their influence. When demographic effects are working against climate impacts, there are fewer migrants. In addition, the short period over which we calibrated (1990 to 2010) may be a further factor, because the uncertainty is large around the coefficients.

Table D.1 Coefficient Values for West African Countries from Groundswell I

Indicator (driver)	(Parameter) coefficient		Units
	Urban cells	Rural cells	
Crop production	0.599	1.077	10-year deviation from historic baseline
Water availability	0.712	1.111	10-year deviation from historic baseline

Source: Rigaud et al. 2018.

Table D.2 Coefficient Values for West African Countries from Groundswell Africa

Indicator (Driver)	(Parameter) coefficient		Units
	Urban cells	Rural cells	
Crop production	n.a.	0.400	5-year deviation from historic baseline
Water availability	1.696	1.071	5-year deviation from historic baseline
Net primary productivitya	n.a.	0.380	5-year deviation from historic baseline
Median age	0.617	0.078	Median age of the population in years
Sex ratio	0.024	0.006	(Males/females) ratio
Conflict-related fatalities	−0.025	−0.003	Number of recorded fatalities
Flood risk	0.147	0.020	5-year likelihood of flood event

Note: Data represent an average of the calibrations using historical data for Mauritania, Guinea and Sierra Leone. N.a.= not applicable.

a. Net primary productivity, which is intended to reflect impacts on pastoral populations, is included in the model when crop production is not present.

Finally, because the Groundswell Africa modeling work included the nonclimate layers in both the climate impact and the no climate impact (SSP-only) model runs, their inclusion could serve to dampen (reduce) the difference between the climate and no climate model runs for each scenario. In other words, because the Groundswell Africa model includes a substantially larger number of drivers, there is an increased chance that, at any given location, two or more drivers are essentially compensating for one another (or canceling

92. For example, consider an urban location that is experiencing a particularly dry period, but that is also demographically characterized by an older, male-dominated population. While the drying trend would act to push people out of the region (a positive coefficient on water stress means that as water availability declines the attractiveness of a grid cell will also decline), the demographic profile of the city would have a dampening effect on that push, as shown by the positive coefficients on median age and sex ratios (table D.2).

each other out). While the increased number of covariates increases the likelihood of this phenomenon, it also reflects a more realistic representation of the wide range of factors that affect migration trends. In short, the potential for climate to drive migration is not lower. The relative level of the climate parameters has not changed much from the Groundswell modeling work, but the portion of migration the model attributes to them is changing because of the addition of the demographic data layers.

An example specific to Groundswell Africa relates to including NPP. Changes in crop productivity have an influence only where crop production is actually practiced. But large areas of the region do not have arable land because of climatic or other constraints. In such areas, the migration trends predicted by the original Groundswell model were based only on projected water availability (because there is no crop production). It is very likely that in the Groundswell Africa model, changes in NPP had a significant dampening effect on the influence of water across parts of the Sahel and southern Sahara where, in the Groundswell model, movement was projected solely on the basis of changes in water availability.

Including projected changes in NPP in the model will moderate the impact of projected changes in water availability. This interaction is likely the primary cause of the increase in estimated migration in eastern Niger in the Groundswell Africa model (relative to the original version). Instead of moderating the impact of water availability, NPP exacerbates the impact because both NPP and water availability are strongly positive in this region (see figures C.1 and C.3). This hypothesis is borne out by the fact that the Groundswell Africa model produces higher climate migration estimates in Niger than for the original Groundswell model, which apart from the tiny island nation of São Tomé and Príncipe, is the only country in the region in which Groundswell Africa climate migration estimates are substantially higher.

Finally, the crop yield covariate was applied to both urban and rural areas under the original Groundswell model but not in the Groundswell Africa model. This decision is directly tied to the resolution of the models. At coarser resolution, urban areas are less precisely captured by the gridded distribution, which means that it is possible (and even likely) that there are meaningful agricultural effects and urban landscapes within the same approximately 14-square-kilometer grid cell. On the ground this is simply agricultural land existing close to an urban landscape, common throughout the region. However, at 1-square-kilometer resolution it is far less likely that a grid cell exhibits both urban and agricultural characteristics. Quantitatively, this was evident in the statistically significant coefficient on crop yields generated by the original Groundswell model, and the coefficient derived under the Groundswell Africa model was insignificant in urban grid cells (as it was for the NPP variable). It is likely this logical decision contributes to the observed variation in estimated migration across the two models.

Different Resolution and Spatial Definition of a Migrant

For both the original Groundswell and the Groundswell Africa model, we hold the spatial definition of a migrant constant. To be considered a migrant, a person must cross the boundary of a 7.5 arc-minute grid cell, which equates to a move of approximately 14 kilometers, depending on where that person is within the grid cell. This is a reasonable definition. Longer moves suggest more in the way of fundamental life changes (new jobs, livelihoods, educational opportunities, etc.) that we tend to associate with migrants. Shorter moves, here less than approximately 14 kilometers, are more likely associated with a move that reflects less fundamental life changes. Of course, these assumptions may not be applicable everywhere, but in general the definition here fits with those often used by major statistical and government agencies.

The differences between the original Groundswell and Groundswell Africa models may be explained by the concept of intervening opportunities. Under the original Groundswell model, if climate impacts result in changes in population distribution, those changes will be manifested at the resolution of the model, which is 7.5 arc-minutes. This can be interpreted as follows: if a person is compelled to move, then the mover will cross a 7.5 arc-minute grid cell boundary, since that is the smallest areal unit considered by the model. However, for the Groundswell Africa model, the gravity model is run at the resolution of 1 kilometer, and results at that resolution are summarized at the 14-kilometer resolution (to conform to the spatially defined concept of migration). Thus, changes in population distribution that occur at the 1-kilometer resolution are averaged over the 7.5 arc-minute grid cell so that the population change may be attenuated. When interpreted in terms of migration, potential movers are offered destinations (intervening opportunities) that, if selected, would not qualify them as migrants because the distance is too small. For example, if a person leaves a 1-kilometer grid cell for another grid cell 5 kilometers away, but that does not cross a 7.5 arc-minute grid cell boundary, that person does not count as a migrant.

Conceptually, this approach is probably more realistic; however, compared to the original model, when conditions varied between 7.5 arc-minute cells such that a place became less attractive, movers either had to migrate or not migrate; short distance moves were not an option. Thus, if the same population were hypothetically exposed to the same risk of migrating but offered a different set of destinations that vary by resolution, it is likely that the model offering shorter-distance options will produce an estimate of total migrants lower than that of the model that does not, because the former has intervening opportunities that do not meet the definition of migration here.

In the Groundswell Africa model, coastal migration numbers are calculated at the 1-kilometer resolution using the outputs of the gravity modeling but are summarized in the 5-kilometer coastal band for the entire country. This means that the definition of a climate migrant is changed in this special case, because it is likely that many people will simply move back from the coastline a sufficient distance to avoid the effects of sea level rise and storm surge.

D.2 COMPARISON OF RESULTS

Estimates for the original Groundswell model are higher than those for the West Africa model, except in the cases of Niger and São Tomé and Príncipe. Table D.3 compares the projected number of internal climate migrants in West African countries in the original Groundswell and Groundswell Africa (West Africa).

Table D.3 Comparison of Model Results for West Africa

The optimistic scenario was only conducted for the Groundswell Africa study.

Country	Scenario	Projected total population in the original Groundswell report	Projected number of internal climate migrants in the original Groundswell	Projected internal climate migrants in the original Groundswell (SD)	Total population in Groundswell Africa (West Africa)	Projected internal climate migrants in Groundswell Africa (West Africa)	Projected iternal climate migrants in Groundswell Africa (West Africa) (SD)	Difference in projected number of internal climate migrants between Groundswell Africa (West Africa) and the original Groundswell (Groundswell Africa (West Africa) - orignal Groundswell)
Benin	Optimistic	-	-	-	19,213,739.01	99,084.09	2,157.71	-
Benin	More climate-friendly	23,690,197	339,795	48,726	21,014,523.41	161,630	2,132	**-178,165**
Benin	More inclusive development	21,546,150	631,161	86,824	19213739.01	225,898	3,088	**-405,263**
Benin	Pessimistic (reference)	23,552,010	818,855	128,077	21,014,523.45	339,838	2,652	**-479,017**
Burkina Faso	Optimistic	-	-	-	38,601,849.38	113,189.54	97,036.42	-
Burkina Faso	More climate-friendly	48,672,201	741,885	229,997	45,887,153.94	107,031	111,706	**-634,854**
Burkina Faso	More inclusive development	41,066,593	1,563,352	938,872	38601849.38	358,588	261,094	**-1,204,764**
Burkina Faso	Pessimistic (reference)	48,676,466	2,206,195	1,330,056	45,887,153.94	298,256	209,469	**-1,907,939**
Cabo Verde	Optimistic	-	-	-	573,207.66	2,472.33	829.69	-
Cabo Verde	More climate-friendly	487,981	12,426	3,640	520,584.31	3,046	1,003	**-9,380**
Cabo Verde	More inclusive development	498,743	22,341	5,543	573207.4857	15,963	16,478	**-6,379**
Cabo Verde	Pessimistic (reference)	510,642	27,701	7,659	520,584.16	16,141	15,498	**-11,561**
Côte d'Ivoire	Optimistic	-	-	-	30,619,321.34	23,418.84	4,733.74	-
Côte d'Ivoire	More climate-friendly	39,261,854	502,102	81,083	37,294,515.05	49,276	10,641	**-452,826**
Côte d'Ivoire	More inclusive development	32,427,837	564,843	149,425	30619321.02	52,510	13,911	**-512,332**
Côte d'Ivoire	Pessimistic (reference)	39,262,499	1,093,126	271,184	37,294,514.66	116,840	37,782	**-976,286**
Gambia, The	Optimistic	-	-	-	3,273,075.62	3,023.24	956.56	-
Gambia, The	More climate-friendly	4,621,775	81,737	28,389	3,729,752.27	4,649	1,165	**-77,089**
Gambia, The	More inclusive development	4,089,157	255,068	87,322	3273075.706	13,772	5,298	**-241,296**
Gambia, The	Pessimistic (reference)	4,770,421	376,336	138,869	3,729,752.36	56,997	47,074	**-319,340**
Ghana	Optimistic	-	-	-	46,376,231.38	102,408.07	32,289.44	-
Ghana	More climate-friendly	57,830,154	811,651	164,890	54,060,789.33	147,152	52,109	**-664,498**
Ghana	More inclusive development	49,665,186	1,387,923	409,590	46376231.41	228,468	66,042	**-1,159,455**
Ghana	Pessimistic (reference)	57,818,067	2,194,162	669,726	54,060,789.35	327,176	133,298	**-1,866,986**
Guinea	Optimistic	-	-	-	15,479,772.10	7,229.48	823.72	-
Guinea	More climate-friendly	19,615,661	159,311	57,112	17,599,029.31	11,991	866	**-147,319**
Guinea	More inclusive development	17,394,016	353,586	35,072	15479771.72	26,137	1,159	**-327,449**

Country	Scenario	Projected total population in the original Groundswell report	Projected number of internal climate migrants in the original Groundswell	Projected internal climate migrants in the original Groundswell (SD)	Total population in Groundswell Africa (West Africa)	Projected internal climate migrants in Groundswell Africa (West Africa)	Projected iternal climate migrants in Groundswell Africa (West Africa) (SD)	Difference in projected number of internal climate migrants between Groundswell Africa (West Africa) and the original Groundswell (Groundswell Africa (West Africa) - orignal Groundswell)
Guinea	Pessimistic (reference)	19,704,317	538,605	56,900	17,599,028.97	46,053	1,161	**-492,552**
Guinea-Bissau	Optimistic	-	-	-	2,488,421.53	1,366.86	628.77	-
Guinea-Bissau	More climate-friendly	3,460,118	47,589	9,942	2,733,208.83	2,722	1,190	**-44,868**
Guinea-Bissau	More inclusive development	3,211,673	178,064	43,954	2488421.413	7,286	3,457	**-170,778**
Guinea-Bissau	Pessimistic (reference)	3,670,554	266,687	116,586	2,733,209.27	13,941	4,855	**-252,746**
Liberia	Optimistic	-	-	-	11,093,543.89	10,806.39	4,239.72	-
Liberia	More climate-friendly	13,720,318	101,855	51,791	12,453,786.00	11,446	2,938	**-90,410**
Liberia	More inclusive development	12,204,987	217,205	121,937	11093544.16	26,967	8,253	**-190,238**
Liberia	Pessimistic (reference)	13,734,446	270,708	154,550	12,453,786.28	27,532	6,957	**-243,176**
Mali	Optimistic	-	-	-	35,910,201.17	164,338.31	7,391.14	-
Mali	More climate-friendly	42,911,212	955,099	331,551	41,045,328.86	91,357	22,546	**-863,743**
Mali	More inclusive development	37,661,103	2,372,533	520,502	35910201.17	526,066	204,132	**-1,846,467**
Mali	Pessimistic (reference)	43,042,918	3,057,370	776,613	41,045,328.86	340,006	119,458	**-2,717,364**
Mauritania	Optimistic	-	-	-	6,271,098.33	28,511.51	5,074.08	-
Mauritania	More climate-friendly	8,319,214	275,667	16,960	7,151,487.41	34,435	10,898	**-241,231**
Mauritania	More inclusive development	7,587,610	888,538	221,987	6,271,098	100,231	53,163	**-788,307**
Mauritania	Pessimistic (reference)	8,826,114	1,143,404	269,442	7,151,487.41	91,085	24,102	**-1,052,318**
Niger	Optimistic	-	-	-	50,943,358.67	5,581,698.29	8,786,035.91	-
Niger	More climate-friendly	68,877,181	3,171,600	1,114,904	63,203,161.20	6,222,214	9,633,910	**3,050,615**
Niger	More inclusive development	56,712,462	5,630,935	1,246,286	50943358.67	7,506,778	10,068,496	**1,875,843**
Niger	Pessimistic (reference)	70,010,615	7,602,129	1,896,305	63,203,161.20	8,499,456	10,842,256	**897,327**
Nigeria	Optimistic	-	-	-	371,695,000.02	1,119,370.37	704,792.12	-
Nigeria	More climate-friendly	437,216,780	10,417,671	6,462,415	431,132,379.65	3,919,560	2,019,869	**-6,498,111**
Nigeria	More inclusive development	376,852,304	22,850,623	5,029,929	371695000	5,140,615	1,536,759	**-17,710,008**
Nigeria	Pessimistic (reference)	437,470,422	31,766,020	7,277,850	431,132,379.65	8,321,962	1,089,574	**-23,444,058**
Sao Tome and Principe	Optimistic	-	-	-	211,017.25	65.62	19.78	-
São Tomé and Príncipe	More climate-friendly	239,697	48	14	239,633.93	52	44	**4**
São Tomé and Príncipe	**More inclusive development**	**211,232**	**90**	**38**	**211166.3132**	**163**	**46**	**73**

Country	Scenario	Projected total population in the original Groundswell report	Projected number of internal climate migrants in the original Groundswell	Projected internal climate migrants in the original Groundswell (SD)	Total population in Groundswell Africa (West Africa)	Projected internal climate migrants in Groundswell Africa (West Africa)	Projected iternal climate migrants in Groundswell Africa (West Africa) (SD)	Difference in projected number of internal climate migrants between Groundswell Africa (West Africa) and the original Groundswell (Groundswell Africa (West Africa) - orignal Groundswell)
São Tomé and Príncipe	Pessimistic (reference)	239,697	121	44	239,632.99	177	41	57
Senegal	Optimistic	-	-	-	24,251,961.22	91,573.64	32,147.64	-
Senegal	More climate-friendly	32,865,674	1,062,589	161,503	30,505,192.30	133,769	64,786	-928,820
Senegal	More inclusive development	26,337,344	3,344,603	976,437	24,251,961.21	382,214	232,987	-2,962,389
Senegal	Pessimistic (reference)	32,843,285	5,551,508	2,114,996	30,505,192.14	602,646	421,798	-4,948,862
Sierra Leone	Optimistic	-	-	-	11,279,031.12	28,186.16	6,562.01	-
Sierra Leone	More climate-friendly	12,885,479	57,827	20,632	12,220,808.41	30,074	4,511	-27,753
Sierra Leone	More inclusive development	11,885,089	122,232	12,027	11279030.82	114,696	23,864	-7,536
Sierra Leone	Pessimistic (reference)	12,883,912	156,826	21,659	12,220,808.08	125,253	20,713	-31,573
Togo	Optimistic	-	-	-	10,349,349.25	13,723.88	3,440.52	-
Togo	More climate-friendly	14,259,033	162,146	53,847	11,059,249.99	29,394	10,976	-132,751
Togo	More inclusive development	13,227,650	254,902	68,059	10349348.87	31,040	4,237	-223,862
Togo	Pessimistic (reference)	14,313,135	409,220	107,192	11,059,249.56	74,583	24,230	-334,637
West Africa	Optimistic	-	-	-	676,141,757.40	7,389,099.75	8,814,921.11	-
West Africa	More climate-friendly	791,594,251	17,940,358	6,978,888	789117375.4	10,959,798	9,844,409	-6,980,560
West Africa	More inclusive development	678,347,510	38,464,857	6,640,606	676141905.3	14,757,392	10,193,563	-23,707,465
West Africa	Pessimistic (reference)	791,594,251	54,401,044	9,785,078	789117373.1	19,297,942	10,908,761	-35,103,102

Appendix C

ISIMIP Projections to 2050–2100

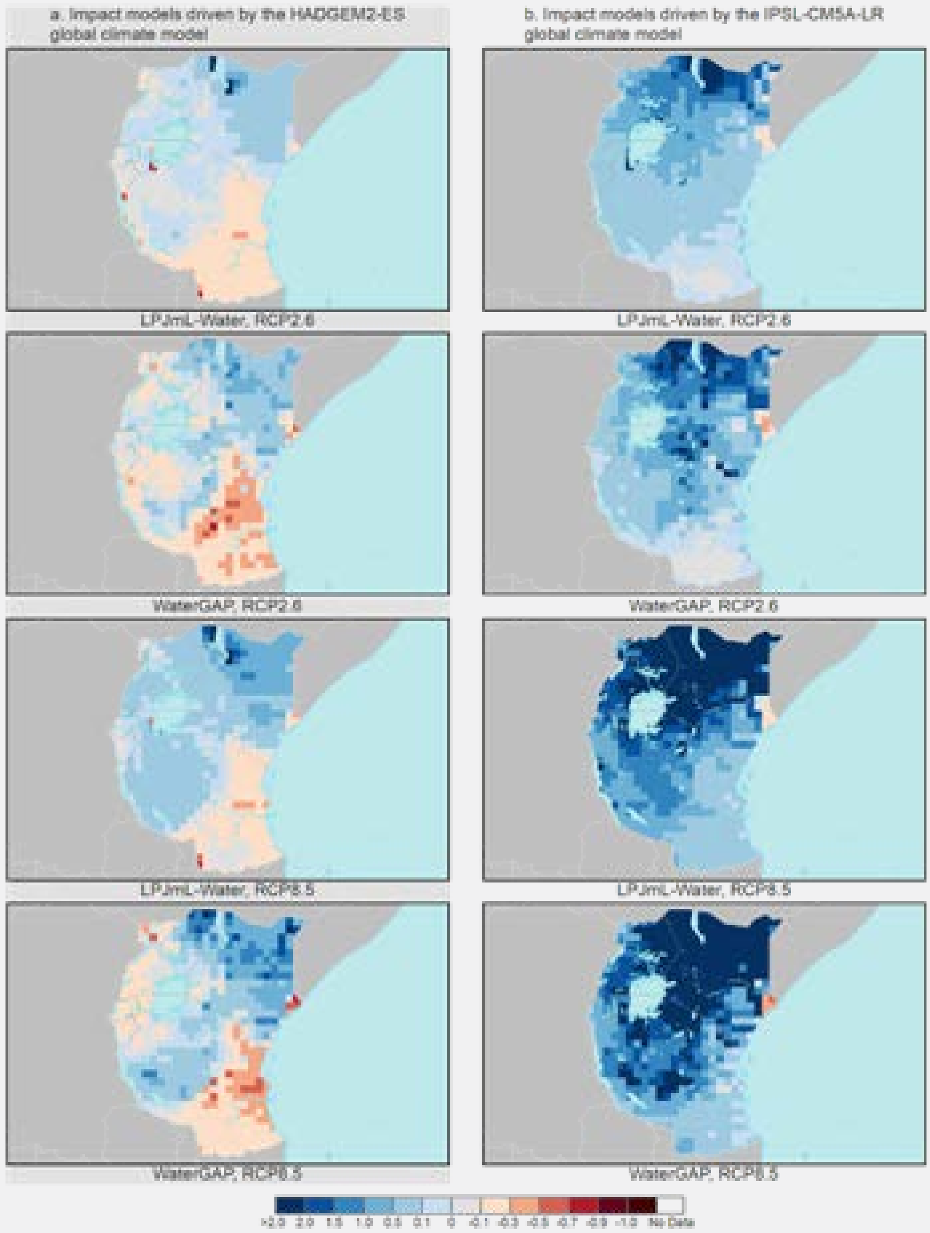
This appendix presents the projections for the water, crop, and ecosystem models out to 2050–2100 using the index defined in equation 3.1, in which the historical baseline value is subtracted from the projected value and then divided by the historical baseline value. Positive index values are capped at 2, which represents a tripling of the baseline value (whether it be water availability, crop production, or ecosystem productivity).

Figure C.1, shows that water availability will continue some of its earlier trajectory. The Hadley model (HADGEM2-ES) shows drying in the south of the Lake Victoria Basin (LVB) region and wetting in the north. The IPSL-CM5ALR model shows mostly a wetting pattern across the region, but with modest drying in southern Tanzania under the LPJmL-water model.

The water model runs are highly consistent across the two GCMs (figure C.2). A number of models show strong declines in crop productivity in northeastern Kenya and in western Tanzania and Uganda. The LPJmL Crop model shows a strong increase in water availability across all model runs in the southeastern corner of Kenya near Lake Victoria.

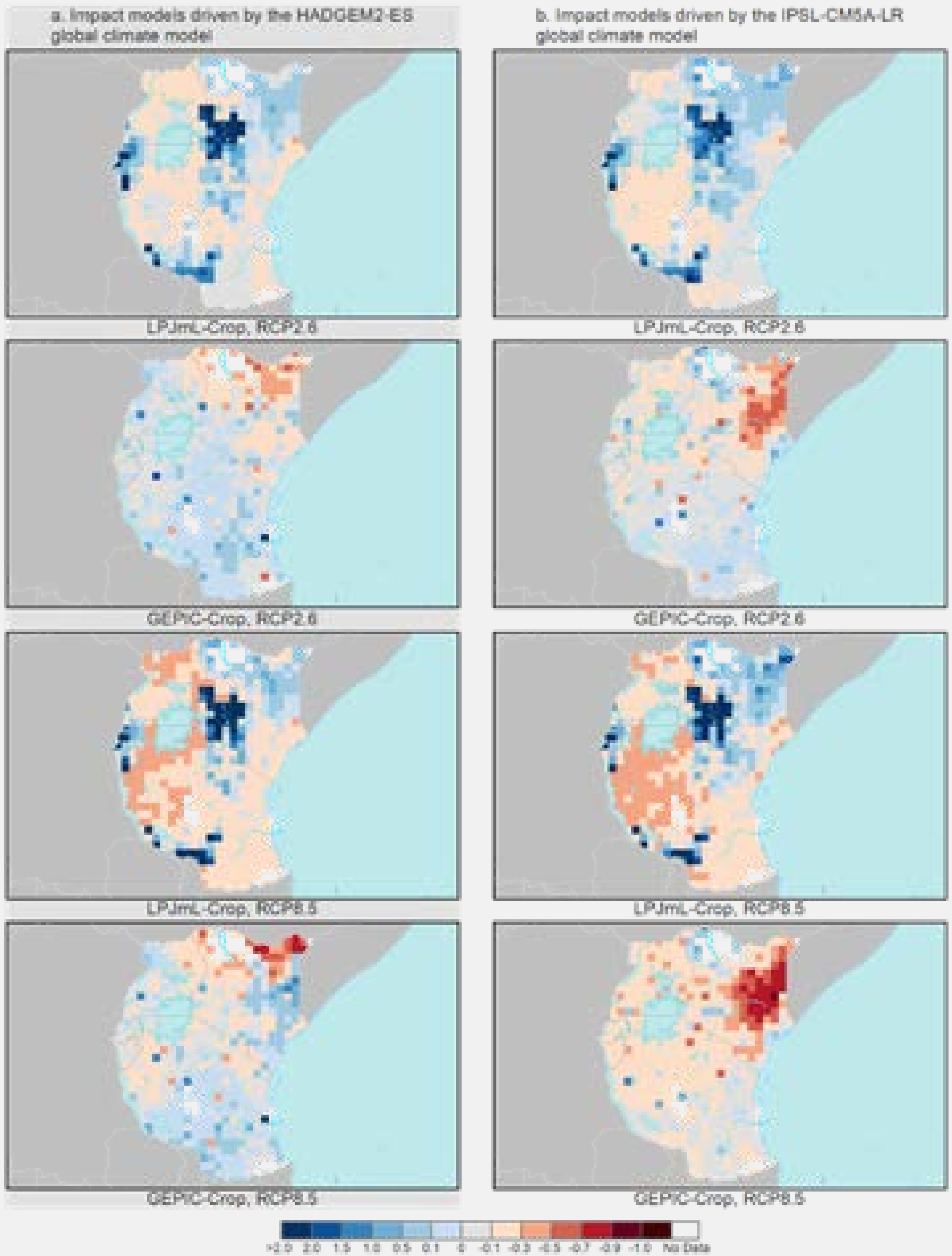
Net primary productivity (NPP) models to the end of the century show mostly increases in NPP except for modest areas of decline along the eastern coastal areas that vary in intensity and location by model.

Figure C.1 ISIMIP Average Index Values against 1970–2010 Baseline for Water Availability, Lake Victoria Basin, 2050–2100



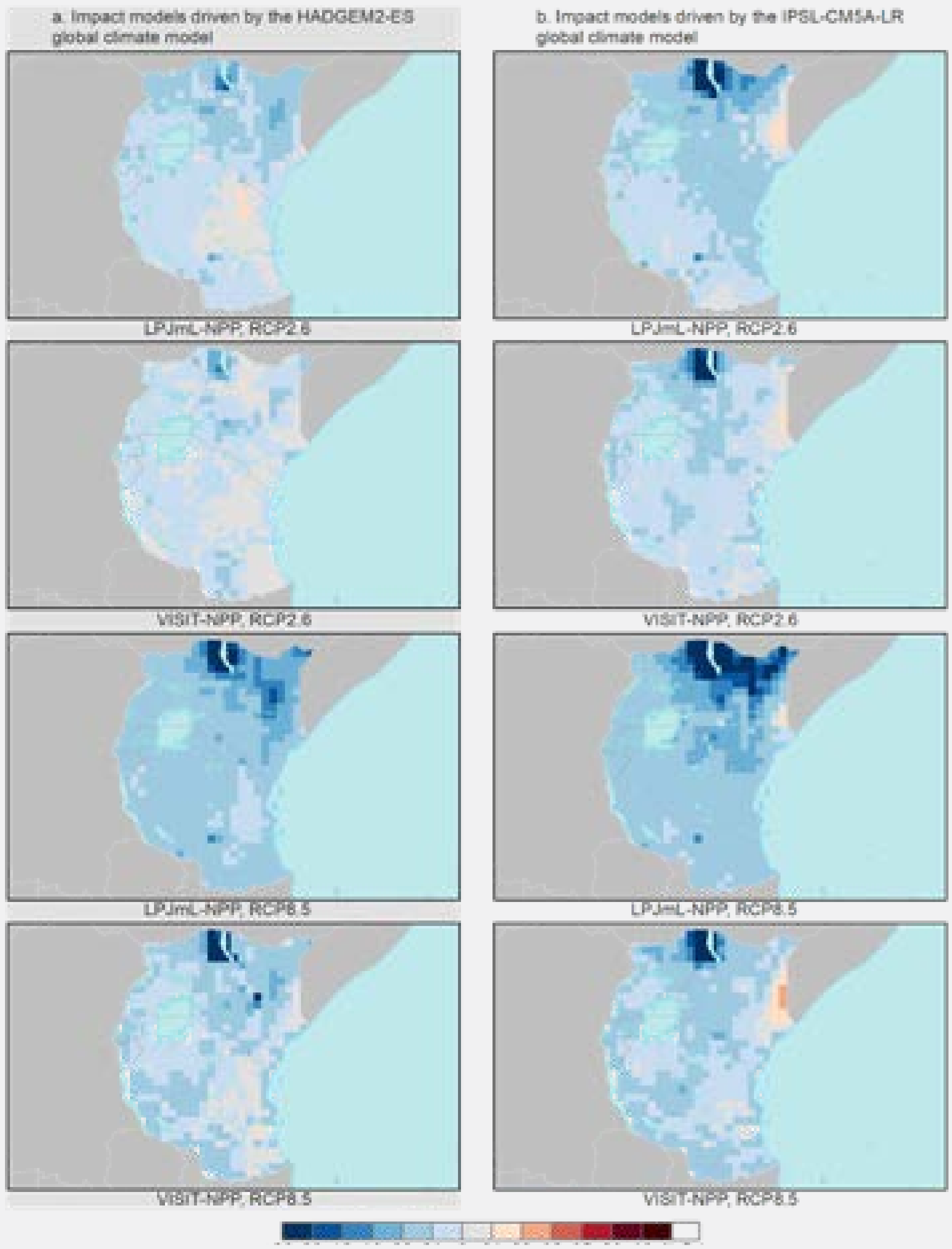
Note: Data calculated against 1970–2010 baseline for water availability, from LPJmL/water (panel a) and WaterGAP (panel b), forced with the HadGEM2-ES climate model (top four maps) and IPSL-CM5A (bottom four maps) under RCP2.6 and RCP8.5. Blue areas indicate wetting relative to the historical baseline, and tan to red areas indicate drying.

Figure C.2 ISIMIP Average Index Values against 1970–2010 Baseline for Crop Production, Lake Victoria Basin, 2050–2100



Note: Data calculated against 1970–2010 baseline for crop production, from LPJmL/crop (left) and GEPIC (right), forced with the HadGEM2-ES climate model (top four maps) and IPSL-CM5A (bottom four maps) under RCP2.6 and RCP8.5. Blue areas indicate wetting relative to the historical baseline, and tan to red areas indicate drying. White areas do not grow the four major crops.

Figure C.2 ISIMIP Average Index Values against 1970–2010 Baseline for Ecosystem NPP, Lake Victoria Basin, 2050–2100



Note: Data calculated against 1970–2010 baseline for ecosystem NPP, from LPJmL (panel a) and VISIT (panel b), forced with the HadGEM2-ES climate model (top four maps) and IPSL-CM5A (bottom four maps) under RCP2.6 and RCP8.5. Blue areas indicate higher NPP relative to the historical baseline, and tan to red areas indicate lower NPP. NPP = net primary productivity.

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Appendix D

Comparison Between the Original Groundswell and Lake Victoria Basin Results

Comparison of the estimated number of climate migrants reported in the original Groundswell report (Rigaud et al. 2018) with the results for the custom modeling for the Lake Victoria Basin (LVB) countries in this report reveals some commonalities and differences for three out of four scenarios (there was no optimistic scenario in the original Groundswell report) (table D.1). Similar to the original Groundswell model, trajectories of climate migration are highest under the high end of the pessimistic (reference) scenario, with a total 38.5 million climate migrants by 2050. The high end of the inclusive development scenario is a close third, with 30.6 million climate migrants, just after the climate-friendly scenario, with 33.6 million climate migrants. Also, the hotspots of in- and out-migration generally occur in the same locations. Yet overall, estimates for the Lake Victoria Basin model are higher than estimates for the Groundswell model. This section provides explanations for these differences.

The enhanced modeling applied in the Lake Victoria Basin study differs in several important ways (see chapter 3) from the modeling approach developed for the first Groundswell report. As such, it stands to reason that the results of this study might vary from the original Groundswell report. It is common in modeling for results to diverge as new features are captured. For example, the climate modeling community has noted higher variance across model runs in the recently released CMIP6 global climate models as new features of the climate system are captured. As Eyring et al. note (2019, 102):

> “The latest generation of climate models feature increases in spatial resolution, improvements in physical parameterizations (in the representation of clouds, for example) and inclusion of additional Earth system processes (such as nutrient limitations on the terrestrial carbon cycle) and components (such as ice sheets). These additional processes are needed to represent key feedbacks that affect climate change, but are also likely to increase the spread of climate projections across the multimodel ensemble.”

Thus, models of increasing complexity often demonstrate increased variability relative to simpler models, because more moving parts and interactions may drive results in disparate directions. To better contextualize the results of the Lake Victoria Basin study, we will explain ways in which the outcomes projected here are both similar to and different from the Groundswell study, and the mechanisms through which differences may occur.

In general, the Lake Victoria Basin and Groundswell studies project very similar geographic patterns of climate migration, and thus, similar hotspots of in- and out-migration. These similarities, given the different modeling approaches, suggest that these results are robust, and should be taken with a fair degree of confidence. Moreover, the relative magnitude of projected climate migration across the scenarios common to Groundswell and the Lake Victoria Basin study are similar as well, suggesting that the pessimistic scenario will produce the most climate migration. The optimistic scenario, featuring low emissions and a more favorable development context, produces the lowest levels of climate migration. However, the studies do not agree on the magnitude of projected climate migration: the Lake Victoria Basin study projects levels four to five times higher under each of the comparable scenarios.

Differences in the magnitude of projected climate migration, that is, the total number of projected climate migrants, between studies may be because of changes in the Lake Victoria Basin modeling relative to the original Groundswell model. However, there is nothing about the Lake Victoria Basin model that will inherently lead to higher numbers. The Lake Victoria Basin study approach was also applied, for example, to Ethiopia and 16 West African countries. In the case of the former, the model projected more climate migrants than the original Groundswell approach; however, in West Africa the enhanced model projected climate migration of a lesser magnitude (in both cases geographic patterns and the relative magnitude of migration across scenarios were fairly stable). Here, the increase in magnitude relative to Groundswell can be attributed to four broad factors: (i) the higher spatial resolution of the Lake Victoria Basin model, (ii) the higher temporal resolution of the Lake Victoria Basin model, (iii) the addition of demographic variables in the Lake Victoria Basin modeling, and (iv) the relatively short historic data record against which to estimate model parameters.

The Lake Victoria Basin model is applied at 1-kilometer (0.5 arc-minute) resolution, while the original Groundswell model was applied at a 15-kilometer (7.5 arc-minute) resolution. The difference in spatial resolution can lead to disparate results through two primary mechanisms. First, models calibrated at different resolutions (even if the input data are similar) may yield different parameter estimates. That is, the strength of the signal on the variables of interest may be different because the model may pick up on patterns at 1-kilometer resolution that are muddled at the 15-kilometer resolution, or vice versa. Relative to the original Groundswell model, the signal on the water stress variable was considerably stronger, which in this case, contributed to a higher number of projected climate migrants.

The second mechanism relates to the resolution at which the model is applied, and that at which migration is measured. Despite application at different resolutions, in the Lake Victoria Basin model results were aggregated to 15 kilometers for purposes of estimating the number of migrants. However, this is done after intercell migration is projected by the model (i.e., the final results are aggregated). Because potential migrants have more possible destinations in a higher resolution model, it is possible that the higher resolution model will predict either more or fewer migrants as a function of which cells are most and least attractive, and how far those cells are from one another.

The temporal resolution of the model can have a similar amplifying or dampening effect on the projected number of climate migrants. Because the Lake Victoria Basin model is applied in five-year time steps as opposed to 10-year (as in the Groundswell model), there is more detailed information regarding the changing conditions that might lead someone to move (or not). For example, if water stress, when measured over a 10-year period, does not appear to deviate much from the historic baseline for a given location, then the model will not predict much movement in or out of that location as a function of water stress. However, if in reality there were a particularly dry five-year period followed by a wet five-year period in this location (which cancel one another out in the 10-year data), there may have been movement out of the region initially, followed by return migration or movement by others into the region later. The coarser temporal model will miss this movement, while the higher resolution model will capture it.

Table D.1 Comparison of Model Results for Groundswell and Lake Victoria Basin modeling work for Lake Victoria Basin countries by 2050

The optimistic scenario was only conducted for the Groundswell Africa study.

Country	Scenario	Projected total population in the original Groundswell report	Projected number of internal climate migrants in the original Groundswell	Projected internal climate migrants in the original Groundswell (SD)	Total population in Groundswell Africa LVB	Projected internal climate migrants in Groundswell Africa LVB	Internal climate migrants in Groundswell Africa LVB (SD)	Difference in projected number of internal climate migrants between the original Groundswell and Groundswell Africa LVB (Groundswell Africa LVB-original Groundswell
Burundi	Optimisitc	-	-	-	16,810,184	586,741	387,048	-
Burundi	More climate-friendly	21,471,620	89,312	56,901	18,099,239	493,874	292,607	404,561
Burundi	More inclusive development	19,882,568	122,417	56,289	16,810,184	551,565	400,402	429,148
Burundi	Pessimistic (reference)	21,510,653	124,953	67,323	18,099,239	629,321	378,104	504,368
Kenya	Optimisitc	-	-	-	78,055,622	4,221,245	1,295,917	-
Kenya	More climate-friendly	96,303,160	695,815	243,602	91,674,704	4,913,378	1,787,385	217,562
Kenya	More inclusive development	81,996,237	1,010,947	185,178	78,055,622	4,320,894	842,519	3,309,947
Kenya	Pessimistic (reference)	96,280,481	1,281,636	516,969	91,674,704	5,872,851	1,760,866	4,591,215
Rwanda	Optimisitc	-	-	-	22,953,347	812,653	304,841	-
Rwanda	More climate-friendly	30,019,189	175,366	104,381	26,032,569	756,594	190,675	581,227
Rwanda	More inclusive development	26,526,152	247,587	104,682	22,953,347	942,204	231,139	694,617
Rwanda	Pessimistic (reference)	30,004,920	188,660	47,699	26,032,569	1,136,773	90,517	948,113
Tanzania	Optimisitc	-	-	-	102,253,936	9,781,741	3,382,959	-
Tanzania	More climate-friendly	123,952,110	1,491,249	907,081	119,048,184	11,433,170	4,278,700	9,941,921
Tanzania	More inclusive development	106,694,062	2,796,693	797,939	102,253,936	11,185,512	2,756,064	8,388,820
Tanzania	Pessimistic (reference)	123,954,637	2,677,400	808,312	119,048,184	13,394,939	3,305,488	10,717,539
Uganda	Optimisitc	-	-	-	93,253,351	7,089,913	691,976	-
Uganda	More climate-friendly	114,738,215	1,400,628	1,003,919	112,336,667	8,647,304	938,452	7,246,677
Uganda	More inclusive development	95,383,646	1,951,039	1,005,618	93,253,351	8,810,974	679,506	6,859,935
Uganda	Pessimistic (reference)	114,723,428	2,179,599	1,072,572	112,336,667	10,870,185	1,193,479	8,690,586
LVB	Optimisitc	-	-	-	313,326,440	22,492,294	3,720,938	-
LVB	More climate-friendly	386,484,294	3,852,370	2,315,884	367,191,364	26,244,319	4,743,910	22,391,949
LVB	More inclusive development	330,482,665	6,128,682	2,149,707	313,326,440	25,811,148	2,996,865	19,682,466
LVB	Pessimistic (reference)	386,474,119	6,452,248	2,512,875	367,191,364	31,904,069	3,949,993	25,451,820

Note: GS = Groundswell; LVB = Lake Victoria Basin.

A third (and likely most important) potential source for variation in the projected total number of climate migrants is the introduction of the demographic variables to the Lake Victoria Basin model. Introducing complexity into any model potentially increases the variability in outcomes, because for every new variable there are an increasingly large number of complex interactions driving outcomes. Here, the demographic variables (age and sex distribution by grid cell) introduced in the enhanced model affect the results through their relationship with population change (as derived through the spatial autoregressive calibration) and their interaction with the climate drivers. Thus, the degree to which additional demographic variables will affect estimates of climate migrants depends on whether the projected impact of age and sex structure on migration runs counter to or aligns with the direction of movement driven by climate, and on the degree to which the impact of age and sex structure either mitigates or enhances the signal (coefficients from calibration) on climate effects. Through the course of the Lake Victoria Basin modeling, and previous modeling of Ethiopia and the West Africa Coastal Areas (WACA) region, we have found inconsistency in the impact of demographic characteristics of the population of future outcomes. In the WACA region, the signal on the demographic variables was strong, which mitigated or dampened climate migration. In the Lake Victoria Basin and Ethiopia the opposite was true, and including demographic variables has amplified the impact of climate. These results demonstrate how added complexity can lead to increasingly disparate outcomes.

A final potential source of inconsistency in the total number of climate migrants between the Groundswell and Lake Victoria Basin modeling relates to the short historic period for which we have data to fit the model. Given only a small sample of countries for which multiple censuses and data points may fit a model, the exercise is vulnerable to the impact of outliers, or short-term aberrations in the historic data. As seen in table D.2, the parameter estimates from the calibration in the original Groundswell report vary by country in the Lake Victoria Basin because different countries were used for calibration in different parts of East Africa. The estimates are also far lower, particularly for water availability, than the parameters in the Lake Victoria Basin model (Table 3.7). Unfortunately, there is little that can be done to combat this problem, and the results must be considered within the context of the existing data constraints.

While these results may not be considered desirable from a policy communication perspective, this reflects the reality that this is partly a research project and partly a policy project. The research part means that we are testing different approaches and sometimes the results are unanticipated.

Table D.2 Coefficient Values for the Lake Victoria Basin Countries, Groundswell Modeling

	Urban		Rural	
	Crop	Water	Crop	Water
Burundi	0.023303	0.037088	0.096555	0.890003
Kenya	0.016749	0.033076	0.067242	0.570891
Rwanda	0.023303	0.037088	0.096555	0.890003
Tanzania	0.023303	0.037088	0.096555	0.890003
Uganda	0.016749	0.033076	0.067242	0.570891

Source: Rigaud et. al. 2018.