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Modeling Climate Driven Urban Migration in the United States

Julia Beckwith
Scripps College

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Abstract: Though research on climate driven migration has become more prevalent, the majority of recent studies model migration patterns in the Global South. While these inquiries are rightfully focused on populations that will be disproportionately affected by climate change, countries in the Global North are not impervious to these effects. As global population distributions shift, it will be necessary to know which urban areas in the United States might be best equipped to handle influxes of people. Drawing on existing climate-migration frameworks, the agent-based model detailed in this paper utilizes available demographic and climate data to simulate climate-driven migration between key urban areas in the United States. The model ultimately serves as a tool for guiding larger conversations about the future of urban populations.

1 Introduction

As ecosystem services are impacted by changing climates, humans are figuring out how to adapt. One strategy, which has been utilized for centuries, is migration. Over the past twenty years, there has been a growing impetus to examine how a changing global climate will redistribute human populations. The excess of carbon dioxide in the atmosphere is expected to result in an increase in extreme weather and natural disasters, as well as rising sea levels: events that will physically destroy inhabitants' residences and prompt immediate relocation [19].

Not all climate-driven migration is quite as obvious, though. Climate is defined as the long-term patterns of temperature and precipitation in a given location, and these patterns are also changing: the earth is becoming warmer. This is a subtle, nefariously slow process. Drivers like heat and drought have less straightforward effects on human migration. While the gradual pace of climate change can render its effects invisible and trivial, its accretive nature simultaneously allows for the opportunity to intelligently adapt and prepare for impending heat and change [21].

This paper outlines an agent-based model (ABM) that can be used to understand how urban population landscapes of the United States might shift over the next fifty years. Utilizing data from climate prediction models, the U.S. Census, and American Community Surveys, as well as theories of human decision-making, the model grants the user a sandbox in which they can explore the complex process of migration and the many interlocking drivers at play. The paper first establishes the connection between climate-driven migration and agent-based modeling, providing examples of existing ABMs. The next section provides a comprehensive, detailed overview of the model's various functions, per the "Overview, Design, Details, and Decision" protocol standard for ABMs. The rest of the paper explores the sensitivity of the model to different input parameters. Finally, suggestions for further expansion and exploration of the model are offered.

2 Related Work

Since the early 2000's, the link between climate and migration has been a growing field of study. Much of the literature is theory-based. The dominant framework for understanding climate-driven migration emphasizes that climate is rarely a direct cause of migration but instead affects existing social, demographic, political, economic, and environmental forces [4].

Due to the already-complex nature of human migration dynamics, a common approach to simulating and predicting these movements is agent-based modeling. The key feature of agent-based modeling is its ability to detect patterns in large populations based on individual decision-making processes [16]. With these types of models, the complex factors that contribute to migration can be accurately represented on an individual level, and then large-scale patterns of migration can be identified.

While many migration models disregard the environment, there are a handful that explicitly model environmental factors in order to get a better sense of the relationship between climate change and migration [22]. Table 1 provides a comparative overview of existing climate-migration agent-based models.

Author, Year	Location	Climate Factors
Kniveton et. al., 2011	Burkina Faso	Rainfall
Hassani-Mahmooei et. al., 2012	Bangladesh	Drought, flood, cyclone, sea-level rise
Walsh et. al., 2013	Thailand	Rainfall, soil quality,
Magallanes et. al., 2014	Peru	Rainfall, glacier melt
Hailegiorgis et. al., 2018	Ethiopia	Rainfall, livestock production, crop yield vegetation growth

Table 1: Existing Climate Migration ABMs

When observing the "Location" column of Table 1, it becomes apparent that all existing climate-driven migration agent-based models are simulating countries in the Global South. While it is important to pay attention to countries that will feel disproportionate effects of climate change, it should also be noted that countries in the global north are not invincible to the effects of climate change. Moreover, when they open their borders to international climate migrants from other countries, they should have a sense of how their existing population distributions might look.

There has been limited research examining climate-driven migration within the United States, but the existing literature is . Hauer et. al. look at the movement of Americans affected by sea level rise, projecting future destinations through unobserved component modeling. Under a 1.8 meter sea level rise, they anticipate significant migration to Austin, TX, Orlando, FL, Atlanta, GA, Phoenix, AZ, and Myrtle Beach, SC and significant migration from Miami, FL, New Orleans, LA, New York City, NY, and Los Angeles, CA [12]. Ultimately, they stress that sea-level rise could result in migration to landlocked areas unprepared for large-scale in-migration. Fan et. al. use a computable general equilibrium model coupled with a random utility model to examine the potential economic effects of migration; specifically, the fluctuations in wage and housing prices associated with climate-change-induced migration. Broadly, their model predicts that the Northeast, West, and California will experience an increase in population, which in turn will lead to a higher Gross Regional Product. The converse is true for the South and Midwest [7]. Notably, neither utilize agent-based modeling.

Though there are existing agent-based models that examine climate-induced migration, none have been created to examine migration patterns in the United States. The research on climate-driven migration within the United States utilizes different modeling techniques. Therefore, this model bridges the gap between these two knowledge bases.

3 Methodology

This section follows the standard Overview, Design, Details, and Decision protocol (ODD+D) for describing agent-based models [20]. Note that this model uses Cutler's 2017 model "Climate Change Adaptation in Coastal Regions" as inspiration [6].

3.1 Overview

3.1.1 Purpose

The purpose of this model is to provide a preliminary computational framework to understand how urban populations in the United States will change as a result of climate change. As of now, it is designed for use in an academic setting as a teaching tool; however, it is also a starting point for a more robust model that could eventually serve as an invaluable tool for informing future urban policy and infrastructure planning.

3.1.2 Entities

The model contains two entities: counties and households. Each household is located within a county. The counties were selected before the creation of the model; they contain all of the cities in the United States with populations over 250,000. A complete list and visual representation of the counties can be found in the Appendix. The counties are located within a network, which is represented by a K_{74} complete graph. The edges of the graph are weighted by the great-circle distance between the centroid of each county, in miles. The exogenous driver of the model is climate change, as represented through county-level heat and drought predictions for 2060 from the U.S. Government's Climate Explorer tool [8].

3.1.3 Attributes

Model attributes, agent attributes, and graph attributes (both node and edge) are detailed below.

Attribute	Type	Description	Fixed?
`num_agents`	`int`	Number of agents	
`num_counties`	`int`	Number of counties modeled	×
`G`	`graph`	NetworkX K_{74} graph	×
`nodes`	`list`	List of graph nodes	×
`limited_radius`	`bool`	Presence of migration radius	×
`upper_network_size`	`int`	Maximum network size	×
`network_type`	`string`	Type of network	×
`climate_threshold`	`list`	Migration threshold	×
`county_climate_ranking`	`list`	Counties sorted by climate	

Table 2: Model Attributes

Attribute	Type	Description	Fixed?
`unique_id`	`int`	Unique ID	×
`age`	`int`	Age	
`pos`	`int`	Agent's current location	
`original_pos`	`int`	Agent's original location	×
`income`	`int`	Income bracket	
`tenure`	`bool`	Homeowner/Renter	
`connections`	`list`	List of connected agents	
`family`	`list`	List of family members	
`preference`	`int`	Agent's migration preference	×
`probability`	`float`	Likelihood of migration	

Table 3: Agent Attributes

Attribute	Type	Description	Fixed?
`agent`	`list`	List of all agents	
`u25income`	`list`	Income distribution, age < 25	×
`income2544`	`list`	Income distribution, age 25-44	×
`income4564`	`list`	Income distribution, age 45-64	×
`income65a`	`list`	Income distribution, age > 65	×
`tenure`	`list`	Ownership probability by income	×
`heat`	`float`	Days above 90°F	
`dry`	`float`	Days without rain	
`slr`	`float`	% of county affected by sea-level rise	×
`median_house`	`int`	Median house price	×

Table 4: Node Attributes

Attribute	Type	Description	Fixed?
`distance`	`int`	Distance between each pair of nodes	×
`net_migration`	`int`	Net migration between each pair of nodes	

Table 5: Edge Attributes

3.1.4 Time

The model is run for 47 years (simulating the time period from 2013-2060). One time step is one year.

3.1.5 Process Overview and Scheduling

For each time step, the following processes run:

1. Update climate: *Each county's climate is updated in a linear manner based on the two climate data points from 2013 and 2060.*

2. Rank counties by climate: *Based on the updated climates, counties are ranked from most desirable climate to least.*

3. Update county climate ranking: *The attribute* `county_climate_ranking` *is updated to reflect the current rankings.*

4. Update agents

   (a) Update age: *As each time step models 1 year, age increases by 1.*

   (b) Update income: *When an agent reaches a new age bracket, their income is randomly updated, with a skew towards upward mobility until they reach retirement age.*

   (c) Update tenure: *If the agent's income has been updated, their tenure is also updated based on the new income.*

(d) Update network: *Based on the model attribute* `network_type` *networks are updated appropriately. If an agent's network isn't too big, the agent has a 30% chance of adding a new networked agent from their current county.*

(e) Calculate migration probability: *See Section 3.2.2*

(f) Make migration decision: *See Section 3.2.2*

5. Update county populations: *Based on U.S. mortality curves and birth rates, agents are removed and new agents are added* [2] [3].

6. Collect data

3.2 Design Concepts

3.2.1 Theoretical and Empirical Background

The model attempts to concretize the theory of climate-driven migration put forth by Black et. al., which states that climate is rarely the only driver of migration; instead, multiple drivers interact and climate influences these other drivers. This is implemented in the model through the integration of demographic data, social networks, family structures, and median house prices, the model's key drivers of migration. The model takes seriously the premise that different demographic traits affect one's likelihood to migrate. Drawing from a U.S. Census Bureau report focusing on the relationship between geographic mobility and demographic characteristics from 2005-2010, the model relies on specific mover rates for people of different ages and home ownership statuses [14].

3.2.2 Individual Decision-Making

First, every agent's migration probability is calculated based on their age and tenure. Then, a random number between 0 and 1 is generated. If this number is less than the agent's migration probability, the agent prepares to migrate.

If the model parameter `limited_radius` is set to true, a migration radius is generated based on the agent's income. Then, all of the counties within this radius are added to a temporary list of possible migration locations. The number of times each county is added to the list is based on distance: the furthest county is added once and the closest county is added fifteen times. This effectively reflects the phenomenon that people are more likely to migrate to places closer to them. The radius is such that the agents in the top income bracket are able to move anywhere. If the model parameter `limited_radius` is set to false, then all counties are added to the agent's list of potential locations, with no distance weighting.

Next, the agent's family and network are taken into account. The location of the agent's family is added to the list, even if it is the same as the agent's current location and regardless of whether it falls within the migration radius.

If the agent's preference is set to family, the family member's location is added five times. Then, all of the locations of networked agents are added. Note that this process is implicitly weighted: if there is more than one networked agent in a certain location, it will be added to the list multiple times. If the agent's preference is set to network, all of the networked locations are re-added to increase the probability that the agent will move somewhere they have a connection.

Now, the median house prices of each county in the list of possible destinations is considered. If the agent is within the lower two-thirds of possible income brackets, the agent will prioritize a lower cost of living more. If the median house price divided by 100,000 is less than the agent's income bracket number, the county is re-added to the list of locations. If the agent's preference is set to cost of living, the counties are re-added based on the difference between income and house price. In this way, places with a cheaper cost of living will have a higher probability of being chosen. If the agent is within the top one-third of possible income brackets, the agent will not prioritize a lower cost of living as much. A rich agent will only re-add counties where the absolute difference between income bracket and scaled house price is less than 3, unless their preference is set to cost of living, in which case, all counties with a median house price less than their income bracket are re-added, weighted by difference.

Depending on the model parameter `climate_threshold`, some agents' list will be filtered according to each county's climate. There are two possible types of climate thresholds: absolute and relative. An absolute threshold is a specific number of days above 90°F and a specific number of days without rain. Any agent in a county whose climate data is above this threshold will have their lists subject to climate review. A relative threshold considers the agent's county's climate in relation to other counties' climates. The model attribute `county_climate_ranking` keeps track of the counties, sorted by climate. If an agent's county is below a certain index specified by `climate_threshold`, their list of counties to migrate to will be filtered by climate. If the agent's preference is set to climate, their list will also be filtered by climate, regardless of how the agent's county compares to either threshold.

The climate filtering process illustrates how climate is not necessarily an explicit driver of migration, but instead another component to consider within the larger decision process. If the agent is located within a county whose climate ranking is in the top 20% of counties, their list remains unchanged, unless their preference is set to climate. Then, all of the counties in their list with a better climate ranking are re-added to the list, with a slight weight for the top three counties. If the agent's preference is set to climate, all counties with a better climate ranking are added, regardless of distance. The top 7 counties are weighted. Then, every county in the agent's list with a worse climate has a 50% chance of being completely removed, even if it appears more than once. If the agent's preference is set to climate, all instances of counties with worse climates are removed.

Finally, sea-level rise is taken into consideration. Using results from Hauer et. al., counties are flagged depending on their vulnerability to sea-level rise.

Hauer et. al. provide estimates of the percentage of counties' populations at risk from sea-level rise [13]. These percentages are stored in the model. If a county in the climate-filtered list will be impacted by sea-level rise, a random number is generated. If the number is less than the percentage of the population that will be at risk, all instances of the county are removed from the list. If the agent's preference is set to climate, all instances of any county vulnerable to sea-level rise are removed.

If the list of possible counties is not empty, the agent randomly chooses a county to migrate to. Though this is technically a random decision, the list of counties is weighted based on distance, family, network, and climate. Note that the chosen county could be the same county as their current location, in which case they don't end up migrating. If it is a different county, the agent moves and migration metrics are updated.

3.2.3 Learning

Individual learning is not implemented in the model.

3.2.4 Individual Sensing

Agents are able to sense their climate and the climates of all of the other counties.

3.2.5 Individual Prediction

Individuals are unable to predict future climates.

3.2.6 Agent Interaction

Upon initialization, every agent is assigned a network of other agents, based on the model parameter `upper_network_size`. At least half of these agents are located in the same county as the agent, and the rest (anywhere from 0 to `upper_network_size`; this quantity is randomly determined for each agent) are located outside of the agent's original county. Depending on the type of network specified by `network_type`, an agent will have either a random network, an income-based network (where all of their connections are in the same income bracket or above/below one bracket) an age-based network (where all of their connections are within 5 years of their age), or an income and age-based network (where both constraints apply). A connection is two-way; if an agent is added to a network, the network's agent is also added to the agent's network.

All agents are also assigned a family of at least one other agent. Depending on their income, they are connected with a family member in their original location, or one in a random location. According to a New York Times analysis of data from the Health and Retirement Study, those with less means are more likely to live close to their parents [5]. Thus, in the model, agents whose income is in the lower three-fourths of possible income brackets are assigned family members in the same county, and agents whose income is in the top one-fourth are assigned family members all over the country.

As agents migrate, their location updates; this location is accessible by the other agents in their network and family. When making the decision to migrate, the agent's network and family provide an additional pull factor: the more connected agents in a place, the more likely the agent is to migrate there. The role of agent interaction in the decision-making process is expanded upon in Section 3.2.2.

3.2.7 Heterogeneity

Each agent is assigned attributes based on ACS demographic data. The agents vary in their age, income, and tenure. These attributes inform their decision-making. Agents' networks and families are also heterogeneous. Finally, each agent's preference enables different decision modules to run for each agent.

3.2.8 Stochasticity

When agents are assigned networks/families, this process is completely random. Every time the model is initialized, agents have different networks/families. Preferences are also assigned stochastically upon initialization.

3.2.9 Observation

The key output observed is movement of agents. At each time step, county population and migrant flux are collected. The net migration for each of the 2,701 county pairs are collected once the model has finished running. Income distribution by county is collected at the beginning and end of the model. Model-wide preference distribution is collected upon preference assignment.

3.3 Details

3.3.1 Implementation

This model is implemented in Python 3.5.2 using the Mesa 0.8.6 package for agent-based modeling [15]. Other packages utilized include NetworkX 2.3, NumPy 1.16.4, and Pandas 0.24.2.

3.3.2 Initialization

Initialization data from the 2013 American Community Survey 5-year estimates were accessed using the Python package CensusData 1.3 [17]. Climate data were obtained from the Climate Explorer application, part of the U.S. Climate Resilience Toolkit [8]. Median house price data came from the National Association of Realtors [1]. When initialized, the model simulates the populations and climates of each county in 2013. As the agents are added to the counties, they are first assigned an age based on the age distribution in each county. Then, based on their age, they are assigned an income. Finally, based on their income, they are assigned a house ownership status (tenure). Once all of the agents have been added to the model and assigned the aforementioned three attributes, they are connected to other agents in their networks and families. Then, if the model attribute `preferences` is set to true, agents are randomly assigned preferences.

3.3.3 User Input

The model takes in the following parameters from the user: `network_type`, `climate_threshold`, and `limited_radius`, allowing the user to explore different scenarios. Some of these scenarios are detailed in Section 5.

4 Results

For the purposes of this project, the main result is the model itself; however, the patterns the model currently produces are also interesting to note. The default settings are a relative climate threshold of 51, preferences, random networks, and a limited radius. For these default settings, the following trends emerge. The counties that experience the biggest relative population growth are: Allen, IN; Dane, WI; Durham, NC; Erie, NY; Fayette, KY; King, WA; Lancaster, NE; Lubbock, TX; Lucas, OH; and Ramsey, MN. The counties that experience the biggest relative population depletion are: Los Angeles, CA; Miami-Dade, FL; Maricopa, AZ; Pinellas, FL; San Diego, CA; Orange, CA; Harris, TX; New York, NY; Dallas, TX; and Hillsborough, FL. The top migration pathways are: Erie, NY to King, WA; Allegheny, PA to Erie, NY; Cuyahoga, OH to Erie, NY; Los Angeles, CA to Santa Clara, CA; Los Angeles, CA to San Diego, CA; Cuyahoga, OH to Allegheny, PA; Multnomah, OR to King, WA; Wayne, MI to Allegheny, PA; Wayne, MI to Cuyahoga, OH; and Wayne, MI to Erie, NY. The migration pathways expose an unexpected phenomenon: staggered waves of migration. When looking at the overall population trends for the counties over 47 time steps, it becomes apparent that agents will first move to places with average climates closer to their original location, and then move to places with the best climates. The following section explores other scenarios, effectively demonstrating how sensitive the model is to different parameters.

5 Sensitivity Analysis

5.1 Climate Threshold

Three different climate thresholds were input to the model: a low (36), medium (51), and high (66) value. While all three inputs demonstrated similar patterns to those described in Section 4, there were some differences when comparing the low threshold to the high threshold. When agents had a low climate tolerance, places with good climates experienced much bigger relative growth. Agents relocated multiple times in order to live in the places with the best climates. When agents had a high climate tolerance, places in the mid-Atlantic and north Texas had an increase in relative population. This is because the agents are able to withstand worse climates and therefore will live in places that are only marginally better climate-wise, prioritizing closeness to their original location.

5.2 Income-Based Radius

When the model is run without an income-based radius, there is a lot more movement to the West Coast. Given that the majority of the model's agents are located on the East Coast, this makes sense. When the radius was implemented, agents would perform a series of moves to get closer to the counties with the best climates; however, without this limit, agents move straight there.

5.3 Network Type

When the model was run at a medium climate threshold with all four types of networks (random, income, age, and income/age), there were no significant differences in the output. This could be due to the relatively uniform distribution of agents by income and age throughout the counties. If a user was curious about isolating the effects of the different networks, this could be easily achieved by omitting the other factors in the migration decision.

6 Conclusion

This model is merely a starting point for a larger conversation. In terms of technical improvements, the model could be optimized to run on a computing cluster and thus allow the user to explore scenarios on a larger scale. Though parallelizing the model was attempted, the limitations of Python as an interpreted language proved to be more challenging than anticipated.

A more robust agent decision process would also be another opportunity for extending the model. There are existing socio-cognitive theory of individual adaptation strategies to climate change that could be integrated into the model, such as the MPPACC framework put forth by Grothmann and Patt [9]. Along with a theory-based decision process, implementing agent memory and agent prediction would allow for a more realistic simulation. Currently, the model has a linear climate trend but given that climate prediction models are becoming more sophisticated, climate data could be more refined. Simulating in natural disasters could also open up many more possibilities. Allowing agents to move in and out of cities could also prove interesting. Factoring in different economic metrics and allowing them to change over time, as opposed to the current static median house price data would undoubtedly add to the model. If the model were to extend even further into the future, some measure of the city's preparedness for climate change and/or access to ecosystem services would help to inform people's decision-making.

Though there are many possibilities for expanding and improving the model, the biggest opportunity for improvement would be implementing an aspect of social inequality: what happens when someone's environment becomes uninhabitable but they are unable to migrate? How can this effect be accurately modeled? Given that climate change will disproportionately affect under-resourced populations, it is necessary to figure out which populations are most vulnerable to climate change and create adaptive strategies in their interest.

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8 Appendix

County	State
Alameda	California
Allegheny	Pennsylvania
Allen	Indiana
Arapahoe	Colorado
Baltimore City	Maryland
Bernalillo	New Mexico
Bexar	Texas
Clark	Nevada
Collin	Texas
Cook	Illinois
Cuyahoga	Ohio
Dallas	Texas
Dane	Wisconsin
Davidson	Tennessee
Denver	Colorado
District of Columbia	District of Columbia
Douglas	Nebraska
Durham	North Carolina
Duval	Florida
El Paso	Colorado
El Paso	Texas
Erie	New York
Essex	New Jersey
Fayette	Kentucky
Franklin	Ohio
Fresno	California
Fulton	Georgia
Guilford	North Carolina
Hamilton	Ohio
Harris	Texas
Hennepin	Minnesota
Hillsborough	Florida
Hudson	New Jersey
Jackson	Missouri
Jefferson	Kentucky
Kern	California
King	Washington

County	State
Lancaster	Nebraska
Los Angeles	California
Lubbock	Texas
Lucas	Ohio
Maricopa	Arizona
Marion	Indiana
Mecklenburg	North Carolina
Miami-Dade	Florida
Milwaukee	Wisconsin
Multnomah	Oregon
New York	New York
Nueces	Texas
Oklahoma	Oklahoma
Orange	California
Orange	Florida
Orleans	Louisiana
Philadelphia	Pennsylvania
Pima	Arizona
Pinellas	Florida
Ramsey	Minnesota
Riverside	California
Sacramento	California
San Diego	California
San Francisco	California
San Joaquin	California
Santa Clara	California
Sedgwick	Kansas
Shelby	Tennessee
St. Louis County	Missouri
Suffolk	Massachusetts
Tarrant	Texas
Travis	Texas
Tulsa	Oklahoma
Virginia Beach	Virginia
Wake	North Carolina
Wayne	Michigan
Webb	Texas

Table 6: A list of the 74 modeled counties.

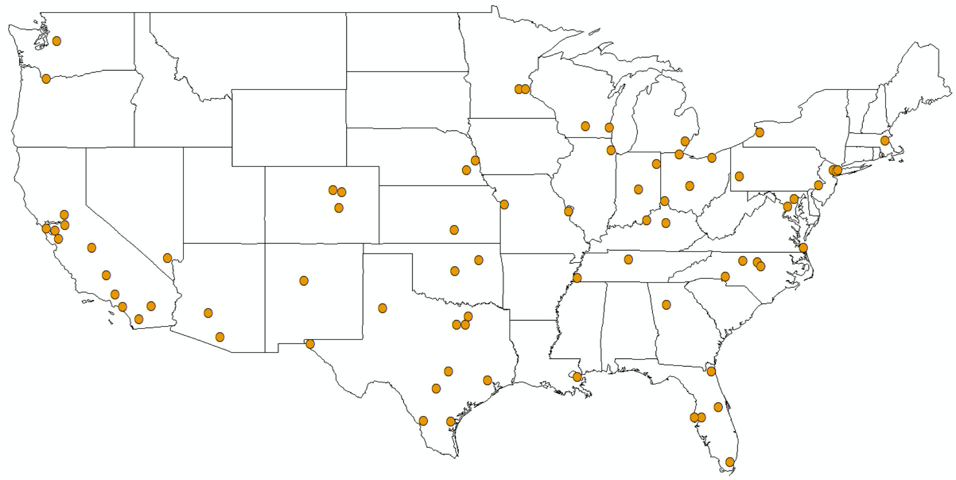

Figure 1: A visual representation of the 74 modeled counties.