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A Multi-Hazard Approach to Climate Migration: Testing the Intersection of Climate Hazards, Population Change, and Location Desirability from 2000 to 2020

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Abstract: Climate change intensifies the frequency and severity of extreme weather events, profoundly altering demographic landscapes globally and within the United States. This study investigates their impact on migration patterns, using propensity score matching and LASSO techniques within a larger regression modeling framework. Here, we analyze historical population trends in relation to climate risk and exposure metrics for various hazards. Our findings reveal nuanced patterns of climate-induced population change, including “risky growth” areas where economic opportunities mitigate climate risks, sustaining growth in the face of observed exposure; “tipping point” areas where the amenities are slowly giving way to the disamenity of escalating hazards; and “Climate abandonment” areas experiencing exacerbated out-migration from climate risks, compounded by other out-migration market factors. Even within a single county, these patterns vary significantly, underscoring the importance of localized analyses. Projecting population impacts due to climate risk to 2055, flood risks are projected to impact the largest percentage of areas (82.6%), followed by heatwaves (47.4%), drought (46.6%), wildfires (32.7%), wildfire smoke (21.7%), and tropical cyclone winds (11.1%). The results underscore the importance of understanding hyperlocal patterns of risk and change in order to better forecast future patterns.

Keywords: climate risk; community impacts; climate migration; socioeconomic impacts; climate change



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1. Introduction

The increasing frequency and severity of climate hazards are becoming evident world-wide due to the ongoing impacts of climate change. According to the Intergovernmental Panel on Climate Change (IPCC), extreme weather events, such as hurricanes, floods, wildfires, droughts, and heatwaves, have become more frequent and intense over recent decades. The IPCC's Sixth Assessment Report highlights that the global temperature has risen by approximately 1.1 °C since the pre-industrial era, contributing to the increased energy in the climate system that fuels these extreme events [1]. These changes are not isolated but part of a broader pattern of climate-related disruptions impacting ecosystems, causing physical damage, and directly altering the risk behaviors of individuals as risk awareness increases [1–3]. The socioeconomic impacts of these heightened climate hazards are profound. For instance, the World Bank reports that the economic costs of extreme weather events have surged, with annual losses from natural disasters tripling over the past three decades [4]. In recent years, the United States has experienced a significant increase in

damages from climate events, with the National Oceanic and Atmospheric Administration (NOAA) reporting that the number of billion-dollar disasters has risen sharply, averaging 18 events per year from 2016 to 2020 compared to an average of 6.5 events per year in the 1980s [5]. This escalation in both the frequency and severity of climate-related disasters has led to unprecedented economic costs, exemplified by the 2017 hurricane season, which caused over USD 300 billion in damages, making it the costliest season on record [6].

Beyond the directly observable economic damages of the increased frequency and severity of climate exposure in the U.S., recently, scholars have begun focusing more attention on less directly observable indirect impacts, particularly on larger community-level outcomes (see [7] as an example). These include property value decreases, changing demographic composition of the population, negative impacts on macro-level economic indicators (e.g., GDP), and commercial viability. Underlying these impacts is the belief that risk behavior and decision-making processes will qualitatively shift as awareness around risk continues to increase at both the individual [8,9] and the community/policy-making level [10].

Of particular interest to the current research is the work by Shu and colleagues [7], who found that between the years 2000 and 2020, flood risk at the neighborhood level directly impacted approximately 7.3 million residential moves in the US. Interestingly, most of those residential moves occurred in areas that continued to grow, what the authors called “risky growth” areas, and, therefore, were hidden as an impact on community growth. More directly impactful were the 3.2 million people that left areas categorized as “climate abandonment areas”—areas that lost population over the 20-year period despite overall national growth and had statistically significant negative impacts from the local flood risk in the area. The research went on to posit that negative population change would lead to a series of community-level consequences, affecting tax structures, property values, commercial activity, and the ability to effectively adapt to the increasing risk. For example, a study by Keenan et al. [8] on climate gentrification in Miami-Dade County underscores how flood risk influences property values and migration patterns, with higher elevations becoming more desirable as flood-prone areas are increasingly seen as uninhabitable.

Other research in this area documents recent trends in climate migration within the US to reveal that an increasing number of individuals and communities are relocating due to climate-induced hazards, such as hurricanes, wildfires, and sea-level rise [11–13]. The Internal Displacement Monitoring Centre (IDMC) reports that in 2020 alone, nearly 1.7 million Americans were displaced by natural disasters, a significant proportion of which were climate-related [14]. Additionally, studies by the Environmental Protection Agency (EPA) indicate that regions such as the Gulf Coast and California are experiencing higher rates of out-migration as residents seek safer and more stable environments due to issues of extreme heat, flooding, and air quality [15].

While the work of Shu et al. [7] and others has significantly advanced our understanding of climate-induced migration, their findings are largely limited to analyzing one hazard at a time, particularly flood risk. Current U.S.-focused research on climate migration is predominantly centered on flood risk and neglects the impact of other climate hazards. Studies like the Internal Displacement Monitoring Centre (IDMC)’s reports highlight that flooding is one of the leading causes of displacement, but this narrow focus in the current literature limits our understanding of the full scope of climate-induced migration and its downstream impact on communities across various climate hazards [14]. This growing body of research, while underscoring the need for robust strategies to address flood-induced migration, raises a crucial question: “How do climate migration and residential mobility patterns relate to exposure to multiple climate hazards beyond flooding?” This research aims to address this gap by examining the relationship between residential mobility patterns and increased exposure to a range of climate risks, including flooding, wildfires, wildfire smoke, extreme heat events, hurricane winds, and drought. By broadening the scope, we seek to provide a more comprehensive understanding of climate-induced migration patterns and their multifaceted impacts on communities. This research tests that research question,

with the hypothesis that there are emerging patterns associated with residential mobility patterns historically and the increased exposure/risk to wildfires, extreme heat events, tropical cyclone winds, drought conditions, and poor air quality from wildfire smoke. Our conceptual framework builds upon Shu and colleagues' [7] findings, which demonstrated that the relationship between flood risk and population change was both nonlinear and confounded by the larger economic context of the local area. They found that low levels of climate exposure could be perceived as an amenity, but beyond a critical threshold, areas gained reputations for risk, deterring potential residents. Additionally, they observed that economically desirable areas and areas seen as amenity-rich (good schools, an abundance of job opportunities, etc.) could continue to grow despite flood risk, suggesting that some amenities could outweigh climate-related disamenities. Said another way, the impact of flooding was not powerful enough as a "push-factor" to counter the "pull-factor" qualities of other amenities.

We extended the framework developed by Shu et al. [7] to multiple climate hazards, hypothesizing that similar nonlinear relationships and economic moderating effects will be observed across various types of climate risks. To test these hypotheses, we developed a series of models predicting population change from 2000 to 2020, incorporating exposure and risk data for multiple climate hazards. We explored the impact of area desirability by comparing comprehensive models with simplified models for areas experiencing population growth or decline, using these as proxies for an area's overall desirability. This approach allowed us to disentangle the effects of climate risks from other factors influencing migration patterns, providing a more comprehensive understanding of climate-induced residential mobility across the United States over the next 30 years.

The remainder of this paper will highlight trends in climate migration in the US context, walk through the methods employed in the analysis, present the major results, and discuss the potential ways in which this research could be useful from a policy perspective. Section 2 is structured in a way that highlights the development and integration of the population projection data, climate hazard data, and the major decisions that were made in order to prepare the disparate data sources for analysis. The results are presented at both a national and case-study level, and Section 4 of the paper takes a step back to better understand the ways in which these data might be used for policy and decision-making processes in the US.

Climate Migration in the US Context

Climate migration in the United States has historically been influenced by various environmental factors. In the past, migration patterns were often linked to natural disasters, such as hurricanes, floods, and droughts. For instance, events like Hurricane Katrina in 2005 led to significant displacement from affected regions, such as New Orleans, highlighting the immediate impact of extreme weather events on population movements [16]. Throughout history, domestic migration shifts have been a primary adaptive response to economic and environmental shocks, compelling households (and firms) to relocate to regions offering enhanced utility and economic opportunities [17–19]. However, the frequency at which these shifts have occurred has been small enough that it generally has been seen as an exception versus the rule.

More recently, climate migration in the US is increasingly driven by long-term environmental changes exacerbated by climate change. Rising sea levels threaten coastal communities, forcing residents to consider relocation options [20]. Additionally, changes in temperature and precipitation patterns impact agricultural viability, influencing migration from rural to urban areas in search of better economic opportunities [21]. The recent work by Shu and colleagues [7] found that by simply changing the scale at which we generally analyze domestic climate migration, we are able to uncover clear statistical patterns, including the phenomena of "lost growth" in highly desirable areas. This highlights a dilemma, which is often hidden due to the absolute increases in population overall, where areas attracting migration due to economic advantages also face escalating climate risks.

Looking ahead, future climate migration trends in the US are projected to intensify as the effects of climate change become more pronounced. Coastal states, like Florida and Louisiana, are expected to experience continued population displacement due to sea-level rise and more frequent hurricanes [18]. Moreover, regions historically prone to wildfires in the western US may see increased migration as fire seasons lengthen and intensify [22]. In response to these challenges, policymakers are exploring strategies to mitigate the impacts of climate migration. Initiatives range from coastal zone management and urban planning to enhance resilience against sea-level rise [23]. Furthermore, equitable adaptation measures are crucial to address the needs of vulnerable communities, ensuring that climate migration does not exacerbate existing social inequalities [24–26].

Understanding future population change as a potential response to climate risks is critical for a number of different sectors and stakeholders within our society, from the individual homeowner to government officials, and for decision-making processes in industry. Research has already highlighted that in the United States, increasing exposure to climate hazards, such as floods, cyclonic winds, droughts, and intensified heatwaves, is anticipated to drive significant population realignments [9,27–29]. As we project future climate exposure into the future only a few decades, climate risk may become a more regular consideration in the home buying process, retail site analysis, and the selection of locations for various other purposes [18,30].

In order to fully measure and account for the impact of climate migration, it must be understood within the larger framework of economic context. The interplay between environmental disamenities (such as flood risks) and socioeconomic amenities (such as jobs, good schools, etc.) complicates migration dynamics, influencing both “pull-factors” and “push-factors” for specific regions [31]. Historically, shifts in migration patterns reflect broader socioeconomic changes. For example, the 1970s saw significant migration from the Northeast to amenity-rich southern and western states, driven by increased demand for natural amenities amidst urbanization pressures [19]. While amenities will likely continue to “pull” people to certain areas, the growing disamenities of climate risk and exposure are expected to increasingly “push” people away from vulnerable regions. Therefore, any investigation into climate migration must consider these relationships within this larger context of competing factors influencing population movement.

2. Methodology

As an extension to the work by Shu and colleagues [7], we focused on assessing population change across census block groups in the contiguous United States (CONUS) from 2000 to 2020 in relation to climate hazard exposure. Our analysis incorporated exposure to multiple climate hazards, including floods, wildfire smoke, droughts, wildfires, heatwaves, and tropical cyclone winds. In order to isolate the effect of climate, the research study was designed to disentangle the historical relationships between natural hazard exposures to each of the model climate hazards and other factors significantly related to migration [20,24]. Once those relationships were identified, we extrapolated them into the future under various climate scenarios and socioeconomic pathways (SSPs) for the next three decades. By integrating climate hazard data with socioeconomic pathway population projections, we aimed to provide climate-adjusted population projections specifically driven by observed historical relationships, which also integrate future variations in the social, economic, and political context built into the 5 SSPs.

2.1. Climate Hazards

This analysis incorporates 6 different climate hazards detailed below:

1. Flood Risk was operationalized as the inundation of properties based on the First Street Flood Model [32];
2. Wildfire Risk was operationalized as the burn probability of a given area based on the First Street Wildfire Model [33];

3. Wildfire Smoke Risk was operationalized as the number of “Orange Plus” poor air quality days based on the First Street Air Quality Model [34];
4. Extreme Heat was operationalized as the probability of experiencing a heatwave relative to local temperature and based on the First Street Extreme Heat Model [35];
5. Tropical Cyclone Wind Risk was operationalized as exposure to damaging wind speeds based on the First Street Wind Model [36];
6. Drought Risk was operationalized as weeks at or above Moderate (D2) Drought levels based on the US Drought Monitor [37].

2.2. Dimension Reduction Process for Climate Risk Data

In order to address the issues of multicollinearity within hazards, a single metric was used for each of the climate indicators. This is particularly important for flood, wind, wildfire smoke, and drought, which all have multiple categories or return periods associated with the models used to operationalize these measures. The approach produces an expected value $E(X)$, which is the sum of the impact of the hazard (x multiplied by the probability of the event $P(x)$), as shown in Equation (1). Table 1 denotes the climate hazard and the associated categories/return periods evaluated with their equivalent probabilities used in Equation (1) below. In addition, the probability of wildfires and the probability of heatwaves were directly used as the single measures of those events. The expected value specification of the climate hazard metrics is specified in Equation (1):

$$E(X) = \sum_x x \cdot P(x) \quad (1)$$

where

- $E(X)$ is the expected value of exposure in an annualized form;
- x is the hazard-specific value of risk for each climate hazard;
- $P(x)$ is the probability associated with risk for each climate hazard.

Table 1. Periods (return period (RP) and Air Quality Index (AQI) categories) and probabilities evaluated in creation of the expected value risk metric.

Hazard	Periods Evaluated	Associated Probabilities
Flood	5, 20, 100, 500 RP	0.2, 0.05, 0.01, 0.002
TC Winds	2, 5, 20, 100, 200 RP	0.5, 0.2, 0.05, 0.01, 0.005
Wildfire Smoke	Orange, Red, Purple, Maroon AQI	1, 0.5, 0.33, 0.25
Drought	2, 5, 10, 20, 100 RP	0.5, 0.2, 0.1, 0.05, 0.01
Wildfires	Burn Probability Pulled Directly from Wildfire Hazard Layer	
Extreme Heat	Probability of Heatwave Pulled Directly from Extreme-Heat Hazard Layer	

2.3. Measuring Population Change

The dependent variable of our models is the percentage block group population change, where the difference in population between 2020 and 2000 is divided by the population in 2000, as shown in Equation (2). These metrics produce a measure of the proportional difference in population over the time period. In order to calculate the dependent variable, the historical 2000 populations were crosswalked to the 2020 census block group boundaries [27]. Figure 1 depicts the historical relative change in population from years 2000 to 2020 based on census data. The formal specification of the population change variable is represented in Equation (2).

$$\text{block group change} = \frac{\text{Population}_{2020} - \text{Population}_{2000}}{\text{Population}_{2000}} \quad (2)$$

where

- *block group change* is the relative percentage change;
- *Population₂₀₂₀* is the population value at the census block group level in 2020;
- *Population₂₀₀₀* is the population value at the census block group level in 2000.

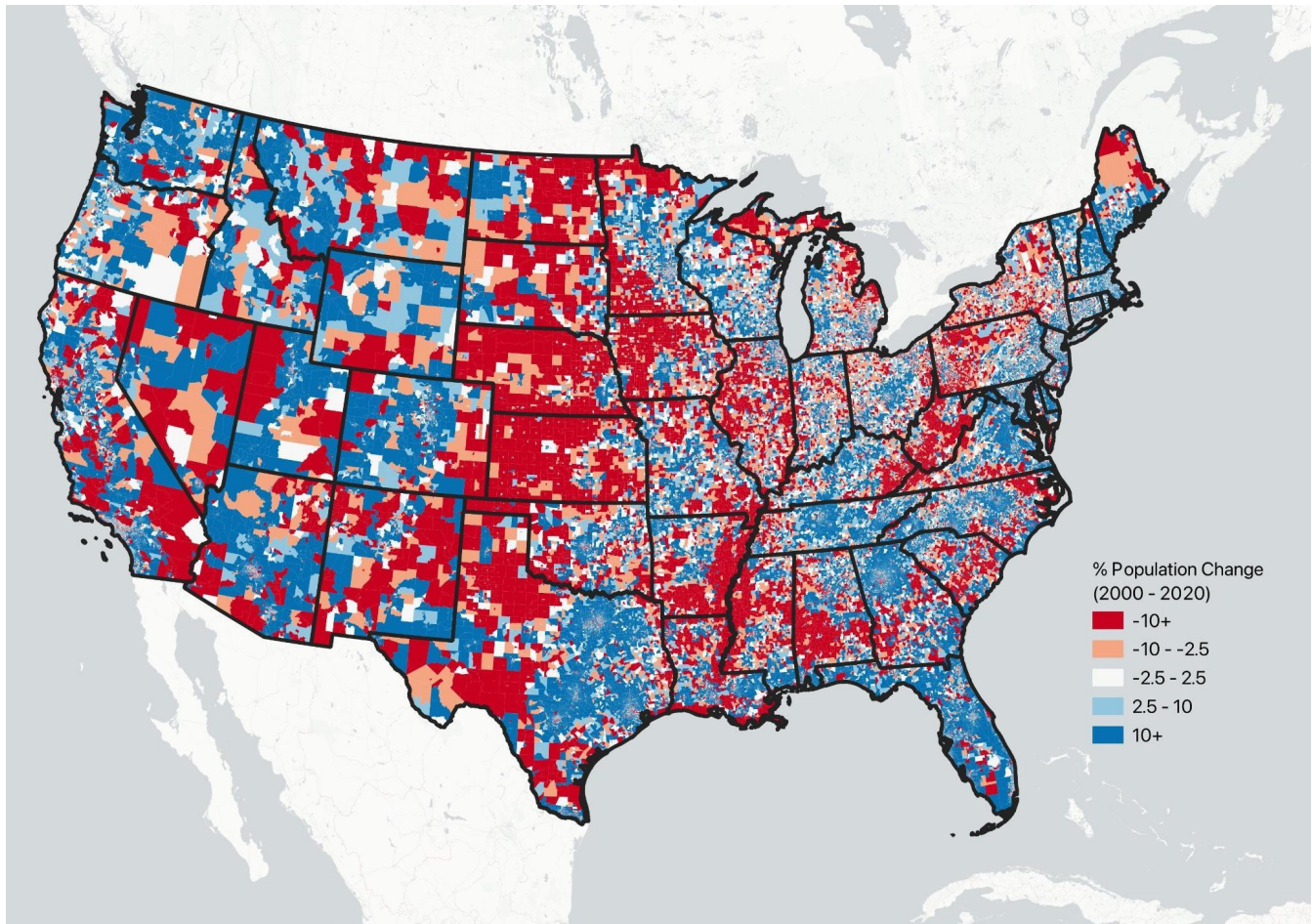


Figure 1. Census block group relative population change from years 2000 to 2020 (%).

2.4. Propensity Score Matching (PSM)

Before estimating the statistical models, the researchers identified control–treatment pairs using a propensity score matching (PSM) process. Initially, exposure thresholds for each climate hazard were established, and areas were classified based on whether they exceeded these thresholds (treatment group) or did not (potential control group). The identification of the thresholds documented below was based on a series of sensitivity analyses in which the impact of population change was maximized through the identification of thresholds operating as “tipping points”. Essentially, these tipping points ended up being the level of hazard exposure at which populations started to respond by leaving the area or growing more slowly than areas below the threshold. The defined thresholds for each climate hazard were as follows:

- **Flooding:** Areas where at least 1.6% of properties inundated in the 20-year return period (RP) or 4.2% in the 100-year RP are considered to be at high risk;
- **Tropical Cyclone Winds:** Areas experiencing wind speeds of 40 mph or higher in the 100-year RP are classified as high-risk;
- **Wildfire Smoke:** Areas with more than 7 days categorized as “Orange” or worse (indicating high levels of smoke) are deemed to be at high risk;

- Drought: Areas experiencing 29.5 or more weeks classified as D2+ (severe drought or worse) within a year are considered to be under significant drought stress;
- Wildfires: Areas with a probability of 0.01 or greater of wildfire occurrence are classified as high risk;
- Heatwaves: Areas with a probability of 0.54 or greater of experiencing heatwaves are considered to be at high risk.

The control and treatment groups were then matched based on a range of social, economic, and political characteristics to minimize the differences between them. The objective was to align areas as closely as possible on these characteristics while differing the climate hazard exposure. Key indicators used in this matching process included income, housing types, homeownership rates, occupation types, and access to natural and socioeconomic amenities, such as water bodies, jobs, schools, and hospitals. Propensity scores were computed for each area based on these indicators, and areas with similar scores were paired for the subsequent analysis.

2.5. Modeling the Impact of Climate Risk on Population Change

The full structure of the model used to estimate the impact of climate hazards is presented below in Equation (3).

$$bg\ change = b_0 + F + W + S + D + W + H + So + E + A + Sp + e \quad (3)$$

where

- The block group change (*bg change*) term is the percentage block group population change calculated in Equation (2);
- The Flood (*F*) term includes the expected value proportion of inundated properties at the block group level;
- The Wind (*W*) term includes the expected maximum observed wind speed over time;
- The Smoke (*S*) term includes the expected number of days at or above the Orange AQI level over time;
- The Drought (*D*) term includes the expected number of weeks in drought stage D2+;
- The Wildfire (*W*) term includes burn probability at the block group level;
- The Heatwaves (*H*) term includes the probability of a relatively hot heatwave;
- The Social (*So*) term captures a set of variables, including population density and homes occupied by single families;
- The Economic (*E*) term includes variables such as job opportunities and jobs tied to industries impacted by climate change;
- The Amenities (*A*) term includes an amenity rank, distance to natural amenities, such as proximity to coasts or rivers, and the number of fire stations, police stations, hospitals, and campsites;
- The Spatial (*Sp*) term includes the topography code, which classifies the geographic features of the land, such as elevation, slope, and terrain types.

Finally, the models were analyzed in both comprehensive and simplified versions. The comprehensive model included all available data, providing a holistic view of the relationship between climate hazards and population change. In contrast, the simplified versions were tailored to analyze specific subsets of data to uncover more nuanced insights. One simplified model focused on areas that experienced population growth during the study period, allowing us to examine how climate hazards interact with growing communities that may have greater resources and resilience. Another simplified model targeted areas that saw a decline in population, highlighting how these communities, which may already be facing challenges, such as economic hardship, job shortages, high crime rates, or subpar educational facilities, respond to climate risks. By isolating these subsets, we aimed to reveal how existing vulnerabilities in struggling communities could potentially amplify the negative effects of climate hazards, which might not be as evident in the more generalized comprehensive model. This approach helps in understanding whether and how factors,

like deteriorating economic conditions and inadequate infrastructure, might intersect with climate risks to influence residential mobility and settlement patterns in different ways.

The model selection process was optimized using a method called LASSO. LASSO, which stands for Least Absolute Shrinkage and Selection Operator, helps to choose the best model by efficiently narrowing down the features it uses.

LASSO applies a “penalty” to the size of the model’s parameters, which helps to simplify the model by shrinking some parameters to zero. This encourages the model to focus only on the most important features while ignoring less relevant ones. The penalty strength, often represented by a value called lambda (λ), is determined through a process called cross-validation, which tests different values to find the best balance between fitting the data well and keeping the model simple.

In the context of analyzing climate migration patterns, where many factors, such as environmental and socioeconomic indicators, might influence population changes, LASSO’s ability to automatically select the most relevant features makes the model more effective. This helps in understanding how specific climate hazards impact population movement, making the analysis clearer and more focused. For those interested in the technical details, the LASSO regression process is formally stated in Equation (4).

$$\min_{\beta} \left\{ \frac{1}{2n} \sum_{i=1}^n \left(y_i - \beta_0 - \sum_{j=1}^p x_{ij} \beta_j \right)^2 + \lambda \sum_{j=1}^p |\beta_j| \right\} \quad (4)$$

where

- $\min_{\beta}$: Minimization over the coefficients β of the estimated model;
- y_i : Observed population change value for each observation;
- x_{ij} : Value of predictor variables (including climate risk) for each observation;
- β_0 : Population change independent of the variables in the model;
- β_j : Coefficients for predictor variables (including climate risk) for each observation;
- λ : Penalty parameter controlling the strength of regularization.

Finally, the coefficient estimates extracted from the LASSO models were scaled in 10-year intervals to 2055 in order to estimate the climate penalty on future population projections based on future expectations of risk. The climate penalty was then added to the SSP population projections along all 5 SSP pathways at the block group level. The resulting application of the model results allowed for an understanding of both the historical relationships between observed climate exposure/risk and population change, as well as how the changing risk in the future is likely to impact populations in the near term (to 30 years).

2.6. Re-Distributing Climate Migrants

This model adjusts population projections to specific Shared Socioeconomic Pathways (SSPs) at the block group level and incorporates climate effects. This adjustment may lead to a national population decrease in our forecasts over time as all of the climate impacts in this analysis are deemed to be negative disamenities. However, the “lost” population should be expected to move to other areas. To ensure consistency in population levels across different time periods, we calibrated the climate-adjusted projections. This helped us focus exclusively on capturing population movements influenced by climate effects while minimizing interference from external factors. Conceptually, our approach is to rely on the population projection underlying drivers in the SSP scenarios, which directly integrate the larger social, economic, and political context and demographic makeup of the population [38]. Using well-established population forecasting techniques, these estimates were produced so that they are able to allocate populations to areas with strong “pull-factors” and create a demographic profile associated with a growing population.

Operationally, the process involves iterating through each SSP in each decade to compute baseline and climate-adjusted populations. The difference indicates the national population decline for each decade. For block groups that experience population growth in modeled decades driven, for instance, by SSP trends outweighing climate-related losses, they receive a portion of climate migrant populations limited to their historical population proportion. Equation (5) details the overall adjustment process. This ensures that populations are redistributed in a manner consistent with their current size and the expectations forecasted in the SSP projections. Essentially, this research relies on the expertise provided by Hauer [38] in order to understand what those parameters are. The Redistribution Process is formally stated in Equation (5).

$$\text{Population Redistribution}_{bg,year,ssp} = |NCE_{year,ssp}| \times HPP_{bg} \quad (5)$$

where

- $NCE_{year,ssp}$: National climate effect on population for a specific year and SSP scenario; HPP_{bg} : Historical proportion of the population for the block group.

3. Results

Each of the climate hazards was shown to have a negative impact on population estimates in both the full and reduced models. First, the impact of climate risk for both flooding and wildfire smoke was negatively related to population change in the full models (controlling for all other variables in the models). However, for wildfires, tropical cyclone winds, extreme heat, and drought, the full models showed no negative effect of climate risk on population change. For each of these hazards, reduced models were estimated to see if the context of the larger market played a role in the impact of climate. In all cases, the models showed that in communities with strong growth in populations over the 20-year study period, there was no negative effect of climate risk on population change. However, for communities that were seeing negative population change, there was a statistically significant negative effect of climate risk across all four of these hazards. These results indicate an amplification effect of climate risk as a “push-factor” in areas that already have a number of other factors pushing people out of the communities. The significant negative coefficients related to the impact of climate risk on observed historical population change patterns are presented in Table 2.

Table 2. Coefficient estimates from LASSO regression models in full and reduced form.

Climate Hazard	Coefficient Estimate (All Block Groups)	Coefficient Estimate (Gaining Block Groups)	Coefficient Estimate (Losing Block Groups)
Flood	−41.7487	NA	NA
Wildfire Smoke	−0.02593	NA	NA
Wildfires	No Effect	No Effect	−2.19871
TC Winds	No Effect	No Effect	−0.00027
Extreme Heat	No Effect	No Effect	−0.4163
Drought	No Effect	No Effect	−1.03611

Following the identification of the historical relationships between each of the climate hazards and historical population change, these coefficients were applied to future population projections along all five SSPs to the year 2055. The population projections were created through a series of demographic and statistical techniques aimed at distributing the global scale social, economic, and political relationships along the five scenarios to a higher resolution within the US context. For more information on both the techniques and framework for this downscaling, see the work by Hauer (2019), which details this process. The downscaling process for the application used in the current analysis was to the census block group level, and the application of the coefficients identified in the models’ results (Table 2) represents a climate correction to the downscaling framework

presented by Hauer [38]. In order to integrate the climate correction coefficients identified in the historical models into future population projections, expectations of climate risk were estimated at the block group level over a 30-year horizon (to 2055).

Once the future risk expectations were computed, the application of the climate correction coefficients (from Table 2) to the downscaled SSP scenario projections allowed for an estimation of the impact of climate risk on populations over that same period. A summary of the number of CONUS block groups that are negatively impacted to some level of risk by each climate hazard is shown in Table 3. The results in the table show that flood risk overwhelmingly has the highest percentage of future impact on the total number of block groups at 82.6%. This is followed by heatwaves at 47.4% coverage, drought at 46.6% coverage, wildfires at 32.7% coverage, wildfire smoke at 21.7% coverage, and tropical cyclone winds at 11.1% coverage.

Table 3. Count and percentage of block groups with a non-zero negative effect by climate hazard.

Climate Hazard	Block Groups Impacted by Timing (238,193 in Total)			
	Currently	2025–2035	2035–2045	2045–2055
Flood	193,961 (81.40%)	194,815 (81.80%)	195,878 (82.20%)	196,680 (82.60%)
Tropical Cyclone Winds	20,136 (8.50%)	21,936 (9.20%)	24,948 (10.50%)	26,556 (11.10%)
Wildfire Smoke	46,941 (19.70%)	48,710 (20.40%)	49,301 (20.70%)	51,684 (21.70%)
Drought	83,772 (35.20%)	92,386 (38.80%)	104,887 (44.00%)	111,007 (46.60%)
Extreme Heat	85,777 (36.00%)	93,936 (39.40%)	106,693 (44.80%)	112,896 (47.40%)
Wildfires	47,368 (19.90%)	66,551 (27.90%)	74,237 (31.20%)	77,952 (32.70%)

When exploring the spatial distribution of these losses, we found that the areas with the largest expected absolute person losses are in the major metropolitan areas of the country. From a very practical standpoint, this makes sense, given that these represent large population centers with the capacity to lose people at the rate reflected in the model. That being said, the patterns in the figure also underscore the critical intersection between environmental vulnerabilities and demographic trends. In particular, smaller communities grappling with a convergence of climate hazards, like tropical cyclones, floods, and wildfires, are expected to encounter more significant challenges in sustaining population growth and even maintaining current population levels. Figure 2 showcases the counties across CONUS and their associated population losses due to climate hazards in the next 30 years. The counties of Los Angeles and Miami-Dade, which are riddled with exposure to almost all of the climate hazards in some way, are those that can expect the greatest declines in population due to climate. In contrast, regions with lower exposure to these hazards may be better positioned to mitigate demographic declines and potentially foster more stable population dynamics, like counties such as Eureka, NV, Catron, NM, Harding, SD, to name a few. However, it is also important to point out that the map can be misleading in that the future projections of population growth often outpace the losses projected on the map. In order to fully understand the impact on community growth, population projections must be coupled with these negative impacts.

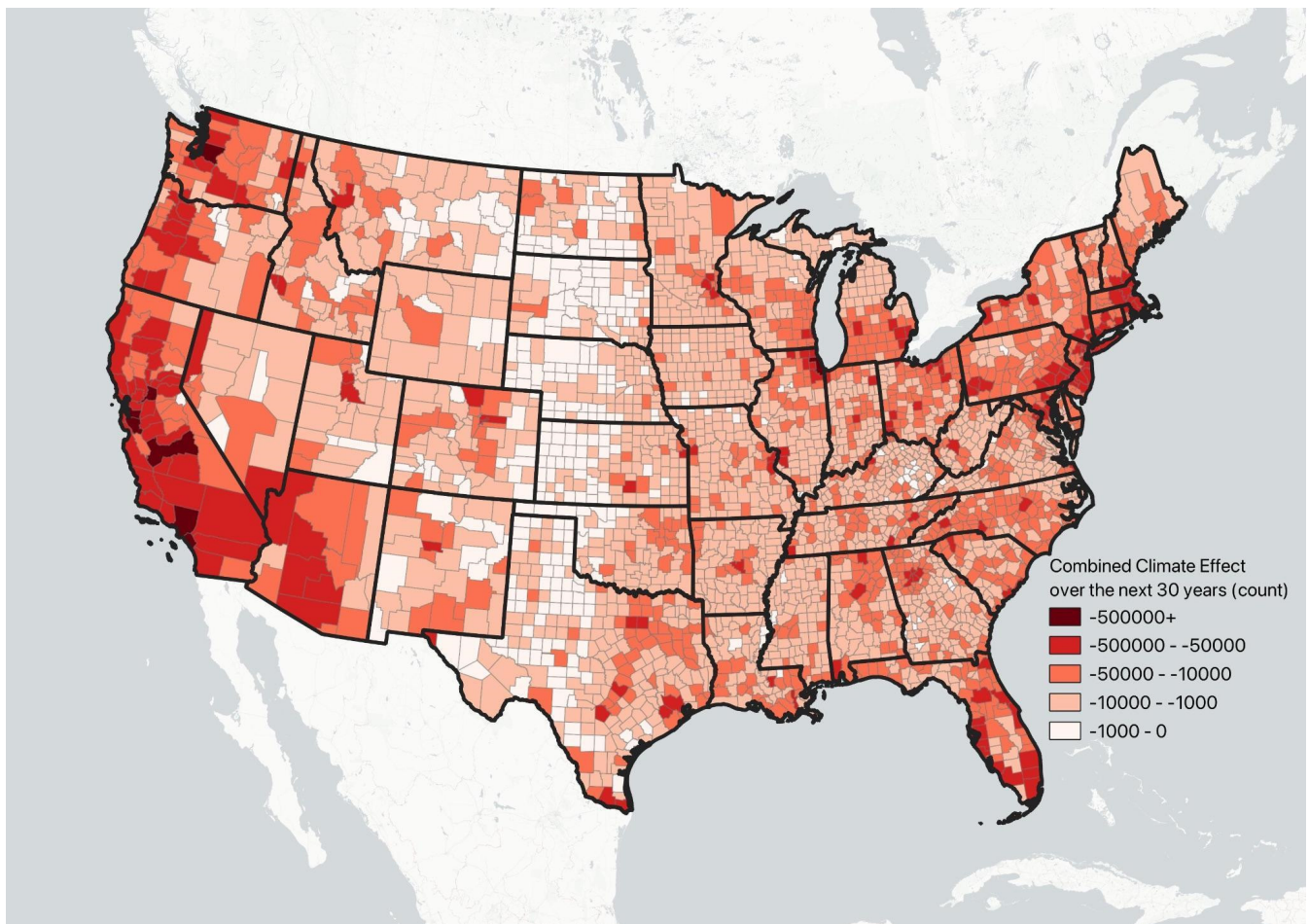


Figure 2. County-level projected population change resulting from the combined climate effect over the next 30 years.

Figure 3 illustrates the intersection of projected population trends under SSP2 with the integrated climate correction factor identified from the historical model presented above. This represents a more holistic approach to understanding the impact climate might have on future population levels as it fully integrates expectations around the social, economic, and political amenities of an area as competing drivers of population change due to climate risk. In many places with high levels of climate risk, these amenities will simply outweigh the disamenity of climate risk. This relationship should be understood as a balance in which fast-growing communities with large amounts of capital are able to allocate resources to adapt to the growing climate risk and continue to attract businesses and populations as a result. While there is no doubt that there is a drag on growth due to climate risk in these areas, that drag is overwhelmed by the influx of people and capital and represents a form of “risky growth”.

On the other hand, areas without these levels of capital are generally already seeing slowing growth rates or even negative population change and are more susceptible to the negative impacts of climate risk. These areas make up two distinct types of communities, one in which climate abandonment is simply another factor in the general abandonment of the community and one in which there continues to be risky growth in the area but at a rate slow enough to lead to a tipping point at which the community will become a net population loser in the future. The former group represents many areas in the Midwest and Northeast where out-migration due to other factors is helping to drive the amplification of the climate effect. More interesting are the areas that continue to grow in the near future but do not have enough forecasted growth due to other factors to keep up with the

negative impact of climate risk. These are the areas that can be projected to become climate abandonment areas in the next 30 years.

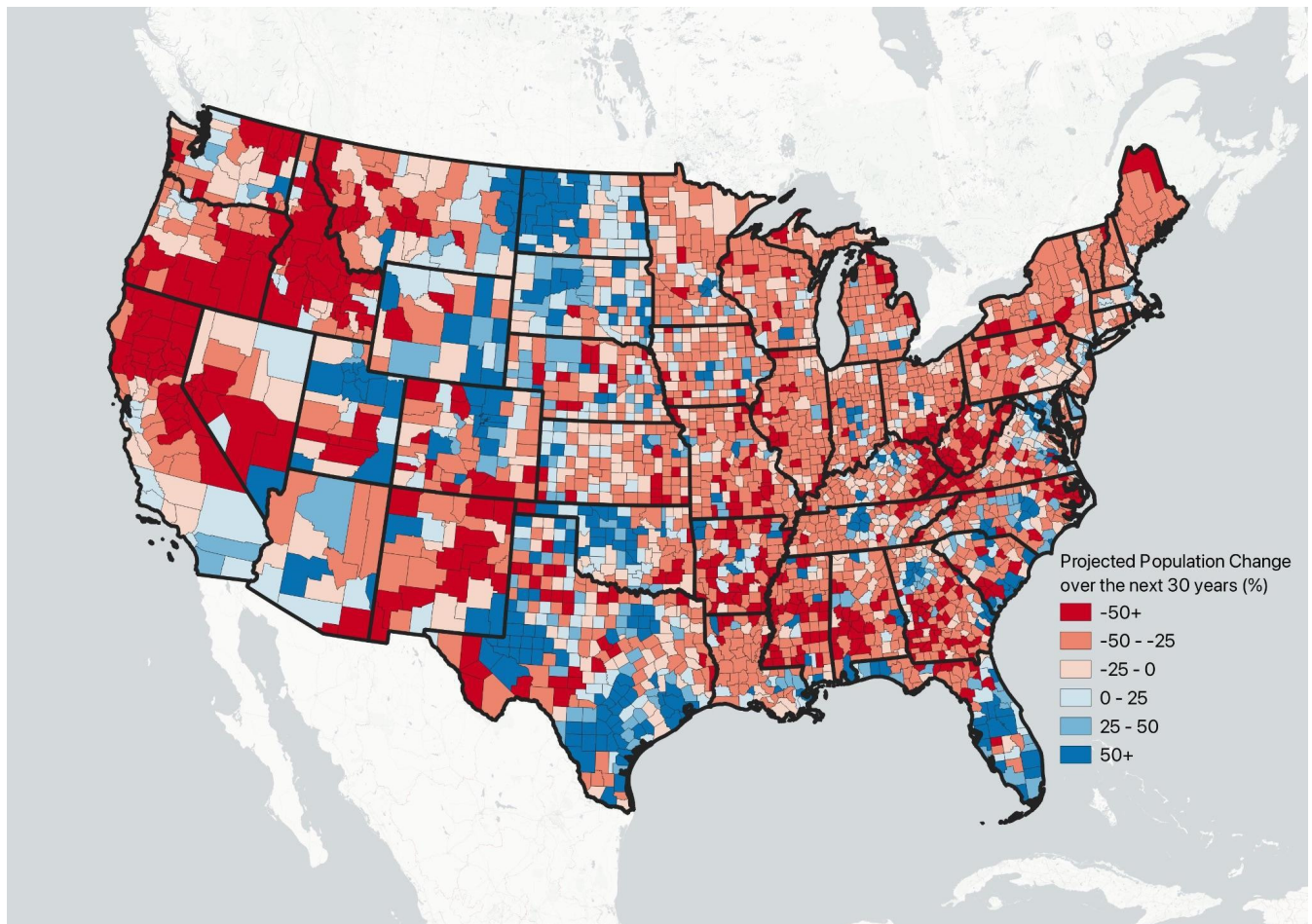


Figure 3. County-level projected population change (%) resulting from the combined climate effect, socioeconomic impact under SSP2, and population redistribution due to climate migration over the next 30 years.

While the county-level map in Figure 3 highlights some of the aggregate patterns in the data, it is hard to grasp the full utility of this method at that scale. In order to fully understand the insights that can be gained from coupling the high-resolution climate risk information with the high-resolution population projections, Figure 4 represents a focused investigation of three distinct neighborhoods within Miami-Dade County. For context, Figure 2 shows that Miami-Dade County will be an overall grower in population over the next 30 years, but if you disaggregate the data and view specific neighborhoods, one can see that all three of the neighborhood types mentioned in the previous paragraph exist within the county.

To illustrate this, Figure 4 reports the population change forecasts for three specific census block groups, which model the three trends of risky growth, declining growth with a quantifiable tipping point, and ongoing climate abandonment. In the figure, you can see the three distinct trends within the county, with the block group (120860056001) in the Flagler neighborhood representing an area of continued growth due to its positive population forecast and the relatively weak negative impact of climate in the area. On the other hand, the Sunny Isles Beach neighborhood (120860001071) represents an interesting case of an area that is currently growing due to the vast amount of amenities in the area (including being located directly on the coast) but is expected to hit a tipping point over the next two decades, in which the negative impact of climate will contribute to a decline in

population. Finally, the climate abandonment area located in the larger Doral neighborhood (120860090402) has seen out-migration in the historical dataset (2000–2020) and is expected to continue to see out-migration due, in part, to the climate risk in the area. The results presented in the figure highlight the need to investigate the process of population change and the impact of climate on a more granular level than the literature currently covers (which is generally at a county level).

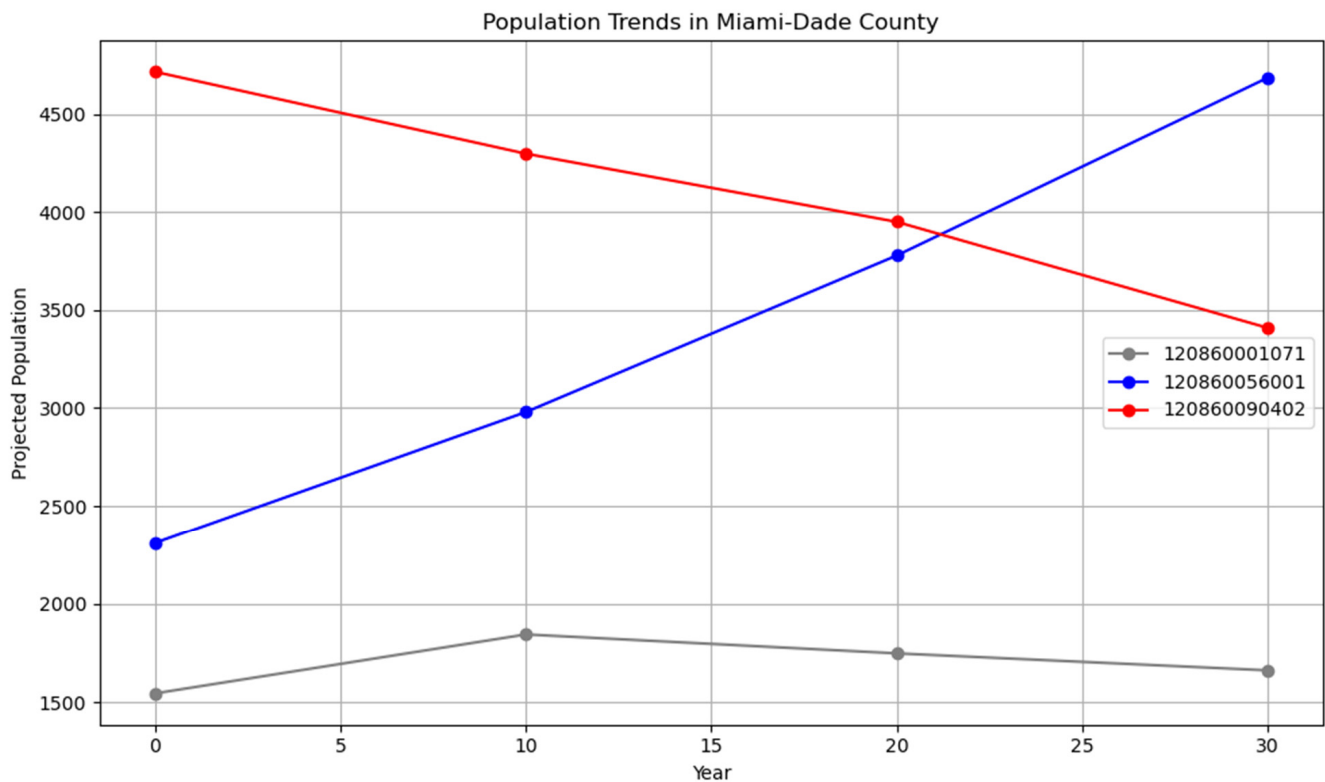


Figure 4. Population projection trends in Miami-Dade County neighborhoods for areas of continual growth (blue), risky growth with tipping points (gray), and climate abandonment (red).

The variation in the results is presented across all of Miami-Dade County, where the negative impacts of climate are represented in the left-hand figure, and the location of the three archetypes in Figure 4 is presented in the right-hand map of Figure 5. The results show that the largest negative impacts of climate risk are located along the coastal areas of Miami Beach (including the areas to the far northeast of the county), areas on mainland Miami-Dade along the coast (in the southeast part of the county), and areas along the everglades in the northwestern part of the county. These patterns underscore the impact of flood exposure in this area as these are also the communities with the highest levels of flood risk in the underlying climate risk models. In the right-hand map, it is clear that the inland part of the county has a high concentration of areas that are growing and continuing to grow, even with the higher-than-average risk across the county. In contrast, the coastal part of the county has a high proportion of areas that have lost population historically and are projected to continue to lose population into the future, in part, due to the high level of climate risk. Finally, perhaps the most interesting group exists in the coastal adjacent part of the county, where we can see a concentration of places that are currently growing but are expected to reach a tipping point in the next 30 years, which will result in declining populations in part due to the high level of climate risk in the area.

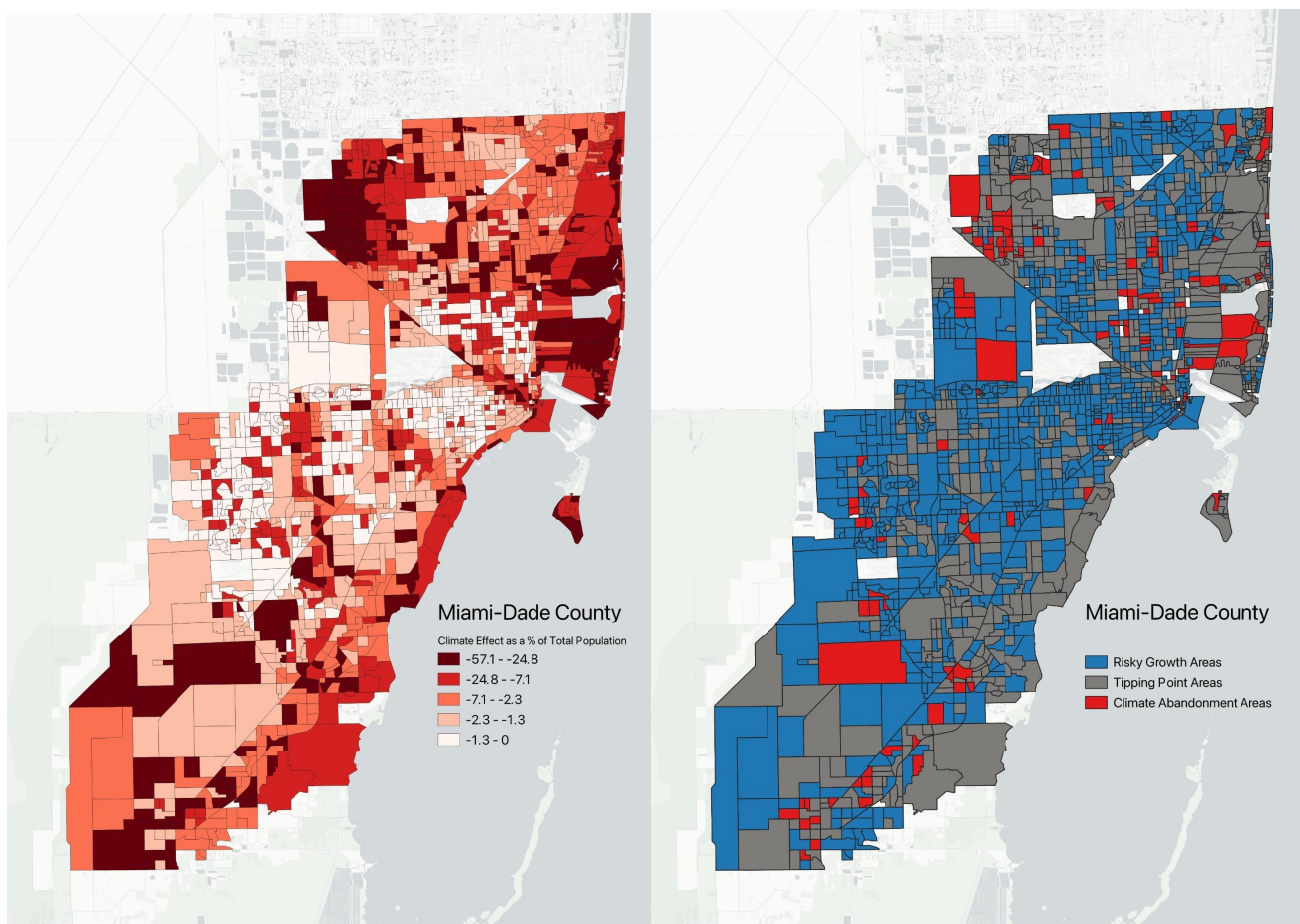


Figure 5. Miami-Dade County block groups’ combined climate effect and projected population trend designation (risky growth, tipping point, or climate abandonment area).

4. Conclusions

The impacts of climate change, including the increasing frequency and severity of climate hazards, are clear and profound. Extreme weather events, such as hurricanes, floods, wildfires, and heatwaves, have become more frequent and intense. These changes are driving significant socioeconomic consequences globally and within the United States, leading to escalating economic costs, the displacement of populations, and shifts in migration patterns. These movements are not merely responses to immediate disasters but reflect long-term environmental changes that impact the viability of living in certain regions.

Moreover, the research presented here highlights a nuanced interplay between socioeconomic amenities (such as job opportunities) and environmental disamenities (like flood and wildfire risks). Using propensity score matching and LASSO techniques, a sample was created in which we were able to model the relationship between historical population change and an expected value long-term risk metric for an individual climate hazard. It was shown that areas with desirable amenities historically attract population growth despite climate risks, but as these risks intensify, they can become significant factors in migration decisions. This dynamic creates complex patterns where areas facing climate risks may see population decline despite their initial attractiveness.

Our analysis uncovers three distinct patterns of climate-induced population change:

1. “Risky growth” areas where strong economic factors outweigh climate risks, leading to continued population growth despite increasing hazards;
2. Areas currently growing but projected to reach a “tipping point” where climate risks eventually drive population decline;

3. “Climate abandonment” areas where climate risks exacerbate existing out-migration trends.

These patterns are evident even within single counties, as demonstrated in our example case study of Miami-Dade County, highlighting the importance of granular, neighborhood-level analysis in understanding climate migration dynamics.

Similarly, our model results reveal that while flood and wildfire smoke risks showed consistent negative impacts on population change, the effects of wildfires, tropical cyclone winds, extreme heat, and drought were context-dependent, primarily affecting communities already experiencing population decline. Looking forward, our projections to 2055 across five Shared Socioeconomic Pathways (SSPs) suggest climate risks will increasingly influence US migration patterns. Flood risk is expected to affect the highest percentage of census block groups (82.6%), followed by heatwaves (47.4%), drought (46.6%), wildfires (32.7%), wildfire smoke (21.7%), and tropical cyclone winds (11.1%). Major metropolitan areas are projected to see the largest absolute population losses, but smaller communities facing multiple climate hazards may see larger portions of their populations impacted.

To effectively address the complexities of climate migration and mitigate its impacts, policymakers should consider a multifaceted approach that incorporates the following strategic recommendations:

- **Integrate Climate Risks into Urban Planning:** Develop adaptive urban planning strategies that account for the increasing risks of climate hazards. This includes strengthening building codes and investing in resilient infrastructure;
- **Promote Flexible Housing Policies:** Implement housing policies that facilitate mobility for those affected by climate risks. This could include incentives for relocation and support for housing affordability in less vulnerable areas;
- **Enhance Support for Vulnerable Communities:** Provide targeted support for communities at high risk of displacement, including financial assistance, relocation support, and access to social services. Ensure that adaptation measures are equitable and address the needs of the most vulnerable populations;
- **Foster Collaboration Across Sectors:** Encourage collaboration between government agencies, researchers, and community organizations to develop and implement effective climate adaptation and migration strategies.

As climate risks continue to increase and impacts on communities ensue, it will be crucial to understand the complex relationship between climate hazards and migration in order to develop effective policies to manage future population realignments and mitigate social inequalities exacerbated by climate change impacts. Although our study provides valuable insights into migration patterns driven by climate hazards, it does not include a detailed analysis of the specific socioeconomic impacts and demographic shifts occurring within vulnerable areas. Changes in population dynamics due to climate migration can significantly impact community well-being, local economies, and demographic compositions. Studies such as those by Hauer et al. [12], Hakovirta [39], Clark et al. [11], and Rikani et al. [40] offer valuable perspectives on these issues and highlight the need for further research, which should continue to focus on examining these broader socioeconomic consequences to aid in developing comprehensive policies and adaptation strategies.

Our study contributes to a growing body of literature on climate migration by providing a more comprehensive, high-resolution understanding of how various climate hazards influence residential mobility patterns in the United States within the larger economic context of local areas. This granular approach to analyzing and projecting climate migration is a building block to help inform policymakers, planners, and researchers as they consider adaptive strategies to mitigate future climate impacts.

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