DEMOGRAPHIC RESEARCH
A peer-reviewed, open-access journal of population sciences

DEMOGRAPHIC RESEARCH

VOLUME 54, ARTICLE 27, PAGES 835–876
PUBLISHED 22 APRIL 2026
https://www.demographic-research.org/Volumes/Vol54/27/
DOI: 10.4054/DemRes.2026.54.27

Research Article

Spatial perspective on environmental migration: Empirical insights from a spatiotemporal approach in the United States, 1970–2010

Shuai Zhou

Guangqing Chi

Chuan Liao

Contents

Demographic Research: Volume 54, Article 27
Research Article

Spatial perspective on environmental migration: Empirical insights from a spatiotemporal approach in the United States, 1970–2010

Shuai Zhou[1]

Guangqing Chi[2]

Chuan Liao[3]

Abstract

BACKGROUND
Despite the growth of environmental migration studies in recent decades, spatial analyses examining the impact of climate variability on migration within the United States at a finer geographical scale remain limited.

OBJECTIVE
This study aims to investigate the environmental aspects of migration and explore the heterogeneous impacts of the environment on age- and place-specific migration patterns at the county level in the United States using spatial methods.

METHODS
We employed spatial techniques to investigate the impacts of temperature and precipitation variability on county-level net migration rates (NMRs) across age groups and rural/urban counties in the United States.

RESULTS
As temperature anomalies increase, nonmetropolitan counties experience a greater decline in NMRs compared to metropolitan counties, indicating that nonmetropolitan areas may be more sensitive to rising temperatures in terms of population change. The age-specific models revealed distinct migration patterns among working-age and older adults, with the NMRs of working-age adults showing a decreasing trend as temperature

[1] Corresponding author. Department of Sociology, Anthropology, and Social Work; Stokes School of Marine and Environmental Sciences, University of South Alabama, Mobile, AL, USA. ORCID: 0000-0001-6555-4088. Email: szhou@southalabama.edu.
[2] Environmental Demography Network, Department of Geography, Indiana University, Bloomington, IN, USA. ORCID: 0000-0003-0888-7964. Email: chig@iu.edu.
[3] Department of Global Development, Cornell University, Ithaca, NY, USA. ORCID: 0000-0001-5468-6894. Email: cl824@psu.edu.

anomalies increase. In contrast, the NMRs of older adults show an increasing trend primarily in counties with historically cool climates.

CONCLUSIONS
This study reveals that environmental factors, particularly temperature anomalies, influence migration patterns in the United States, with older adults exhibiting greater net migration in warmer and rural counties while working-age adults experience less net migration as temperature anomalies increase.

CONTRIBUTION
This study contributes to the environmental migration literature by employing spatial analysis to explore heterogeneous environmental impacts across age groups and locations in the United States at a finer geographic scale.

1. Introduction

Climate change has profoundly affected migration processes (Hoffmann et al. 2020; Zhou and Chi 2024). Globally, rising temperatures, irregular precipitation, and more frequent environmental disasters have triggered large-scale internal and international migration. Looking ahead, researchers estimate that by 2050, climate-related migration could involve hundreds of millions of people (Hauer, Jacobs, and Kulp 2024; Kaczan and Orgill-Meyer 2020). The rapidly changing climate and its implications for migration have fueled a growing body of literature on climate-induced mobility. Since 2000, the number of annual publications on environmental migration has increased dramatically (Zhou and Chi 2024).

Although consensus regarding environmental impacts on migration has not been achieved, theoretical and empirical research have advanced our understanding of climate-related migration. Mainstream migration studies have moved beyond classical push-pull theory and economic perspectives such as neoclassical migration theory and the new economics of labor migration. Recent approaches have incorporated volition, aspiration, and capability frameworks into migration theory (Fussell 2012; Schewel 2020; de Sherbinin et al. 2022; Zickgraf 2021). Rather than assuming that environmental stress increases migration, these theoretical frameworks emphasize that socioeconomically vulnerable populations may be least able to migrate, even when exposed to adverse climatic conditions. Consequently, environmental change can simultaneously lead to mobility, immobility, and differential migration responses across social groups.

Empirical evidence from various contexts has also demonstrated that environmental factors influence migration, with such impacts varying across time, place, and demographic groups. For instance, while environmental disasters such as hurricanes often propel migration out of affected areas, migration may occur only after in situ adaptive strategies have been exhausted, resulting in a lagged or delayed response (Nawrotzki and DeWaard 2016). Rapid-onset environmental disasters can also quickly deplete the financial and social resources necessary for migration among socially vulnerable populations, leaving many people trapped or immobile (Nawrotzki and DeWaard 2018). Studies have shown that in some developing countries, the association between adverse climate conditions and migration is positive only for wealthier households that can afford to move (Nawrotzki and DeWaard 2018). Similar patterns were observed during Hurricane Katrina, when socially vulnerable groups such as Black and low-educated residents were less likely to participate in evacuation (Thiede and Brown 2013). Gendered disparities and age-specific migration patterns under environmental change are also well documented in the literature (Chi et al. 2024; Johnson, Winkler, and Rogers 2013; Johnson and Winkler 2015).

However, several gaps remain in the current environmental migration literature. First, previous theoretical frameworks and empirical studies often overlooked the spatial dimension of environmental migration. In reality, environmental factors such as temperature and precipitation rarely adhere to administrative boundaries, influencing entire regions rather than isolated areas. Spatial models can account for this interconnectedness, revealing how regional clusters of environmental conditions and socioeconomic factors jointly shape migration outcomes. In the United States, several studies have employed spatial methods to examine the impacts of climate variability on migration. Many of these studies have emphasized the role of natural amenities as pull factors attracting in-migrants (Chi and Marcouiller 2013; Winkler and Rouleau 2021) or analyzed migration patterns at broader geographic scales, such as regions (Feng, Oppenheimer, and Schlenker 2012; Gutmann et al. 2005) and states (Poston et al. 2009). Second, environmental migration is selective by age. A salient example of age disparity in environmental migration is the snowbird phenomenon, in which southbound migration during winter primarily involves retirees and other older adults drawn to warmer climates in the southern United States (Johnson et al. 2005; McLeman and Hunter 2010). Building on previous approaches and foundational literature, this study addresses these gaps by investigating the environmental dimensions of migration and examining the heterogeneous effects of environmental factors on age- and place-specific migration patterns at the county level in the United States using spatial analytical methods. This study contributes to the environmental migration literature by applying spatial analysis to explore heterogeneous environmental impacts across age groups and locations at a finer geographic scale. The findings provide valuable insights into the complex relationship between environmental change and migration, informing the development of targeted policies and interventions for vulnerable demographic groups and areas experiencing both gradual and rapid environmental changes.

This paper is organized as follows: First we review the spatial dimensions of environmental migration in existing environmental migration studies, with a focus on research in the United States. We then introduce the analytical approach, followed by descriptive statistics and an exploratory spatial data analysis (ESDA). Next we fit aspatial and spatial models to the data and interpret the results. Finally we discuss the findings and their implications for policy and future studies.

2. Environmental change and migration

Migration has been a central theme in demographic and sociological research for decades, during which a series of theoretical frameworks have been developed to explain the migration decision-making process. For instance, during the formative era of migration studies, the classic push-pull theory was developed to account for push and pull factors at the origin and destination as well as obstacles between the two ends (Lee 1966). The 20th century witnessed the dominance of economic explanations for migration. Frameworks such as neoclassical economics (Todaro 1969; Todaro and Maruszko 1987), the new economics of labor migration (Stark and Levhari 1982), the dual labor market model (Müller 2003), and the world system theory (Wallerstein 1983) emphasized the economic benefits migration can bring to individuals and households. In the meantime, migration system (Curtis, Fussell, and DeWaard 2015; Hauer, Holloway, and Oda 2020) and migration network (Hunter, Murray, and Riosmena 2013; Mahajan and Yang 2020) theory emerged, highlighting system-level and social network perspectives on migration dynamics. In recent years, theoretical explanations have increasingly turned toward volition and capability frameworks to understand migration under environmental stress. The volition or capabilities perspective emphasizes migrants' agency in decision-making while recognizing that, despite the intention to move, socioeconomically vulnerable populations may lack the means to do so under environmental pressure (Fussell 2012; Schewel 2020; de Sherbinin et al. 2022). This theoretical shift has also led to growing scholarly attention on immobility within the field of migration research.

Despite the flourishing of theoretical explanations, a consensus on the environmental impacts of migration remains elusive within the scientific community, on social media, and among the general public. This is evident in the fact that two contentious perspectives – environmental determinism and environmental indeterminism – continue to characterize discourse surrounding the environment–migration relationship (Hunter and Simon 2023). Recent evidence revealed in the IPCC (2021) report and other empirical studies across the globe tends to support the idea that environmental change influences migration, although effects may depend on specific environmental factors, place, population characteristics, and preexisting nonenvironmental impacts (Fussell, Hunter, and Gray 2014; Hoffmann et al. 2020; Zhou et al. 2024; Zhou and Chi 2024).

Empirical research has shown that environmental change primarily influences migration by affecting livelihoods and economic prospects in impacted areas. Studies have demonstrated that environmental change negatively affects agriculture and economic growth, particularly in less developed countries across sub-Saharan Africa and Latin America (Barrios, Bertinelli, and Strobl 2018; Dell, Jones, and Olken 2009). These environmental disruptions to economic productivity contribute to widening income disparities between affected and less-impacted regions, thereby driving migration flows. For instance, research has revealed that weather anomalies reduce agricultural output and rural incomes, prompting migration from rural areas to urban centers in Africa (Marchiori, Maystadt, and Schumacher 2012) and India (Viswanathan and Kumar 2015). Environmental change may also trigger international migration, particularly to geographically close areas. Hunter, Murray, and Riosmena (2013) examined the impact of rainfall patterns on migration to the United States from rural Mexico using data from the Mexican Migration Project. They discovered that communities experiencing drought two years prior were more inclined to send migrants to the United States.

Another pathway through which environmental change can lead to migration is by shaping the composition of the labor market. Despite the devastation caused by environmental disasters, such events can create opportunities for new migration flows, particularly in industries related to construction and post-disaster recovery (Fussell, Curtis, and DeWaard 2014). A notable example is Hurricane Katrina, one of the deadliest disasters in US history, which led to a substantial labor market in construction and recovery-related sectors, attracting a migration flow of workers to hurricane-damaged areas (Fussell 2009; Sisk and Bankston 2014).

The relationship between the environment and migration may also be mediated by preexisting socioeconomic and demographic characteristics, including age and wealth. Age is an important factor in migration decision-making in response to environmental change, as migration is not an age-neutral life transition, and migration patterns vary across age groups (Johnson, Winkler, and Rogers 2013). Johnson and Winkler (2015) found that younger individuals (in their 20s and 30s) are generally more mobile, often migrating to urban areas in search of work opportunities, while older individuals (60 and above) are more likely to move to rural areas for natural and environmental amenities. A well-documented example is the phenomenon commonly referred to as snowbird migration. In this migration pattern, retirees and other older adults migrate seasonally or permanently from colder northern states to warmer southern regions, such as Florida, Arizona, and Texas. These moves are often motivated by the desire for milder climates and associated outdoor recreation opportunities. Researchers have estimated that in the early 2000s, Arizona and Florida received more than 273,000 and 800,000 seasonal or permanent migrants, respectively (Happel and Hogan 2002; Smith and House 2006). Wealth also moderates environmental impacts on migration by enabling higher-income individuals to migrate while often restricting the mobility of poorer populations. Elliott and Pais (2006) identified income as the primary determinant of evacuation timing during Hurricane Katrina, with higher-income individuals evacuating earlier and lower-income individuals evacuating later or not at all.

The environmental migration literature has long focused on the positive impacts of environmental shocks on migration; however, environmental change may also suppress migration. In recent years, researchers have found that immobility often coexists with migration under environmental pressure (Zickgraf 2021). On the one hand, immobility can occur due to a strong sense of place. Place attachment or socioeconomic embeddedness can create powerful emotional and material ties to a place, discouraging migration even in the face of environmental risks (Schewel 2020). On the other hand, immobility can be involuntary, with individuals becoming trapped during environmental disasters. In such cases, environmental shocks exacerbate existing social and economic vulnerabilities, leaving certain groups disproportionately exposed to risk while limiting their ability to adapt through migration (Fussell 2012).

3. Spatial dimensions of environmental migration

Spatial analysis of migration has gained popularity in recent years (Johnson et al. 2005; Zhou and Chi 2024) owing to the development of spatial techniques, datasets, and computational power. Although spatial regressions use estimation methods similar to those used in aspatial models (e.g., maximum likelihood estimation), they can identify and account for important spatial effects embedded in migration processes, including spatial dependence and spatial heterogeneity (Chi and Zhu 2019). The term *spatial dependence* (or *spatial autocorrelation*) refers to the similarity or dissimilarity between two values of a geographically proximate attribute. Simply put, if positive spatial dependence exists, high values tend to cluster around other high values while low values cluster around other low values. Conversely, if negative spatial dependence exists, high values tend to cluster around low values while low values cluster around high values (Chi and Zhu 2008). The term *spatial heterogeneity* (which is often used interchangeably with the terms *spatial structure*, *nonstationarity*, and *large-scale global trends*) refers to differences in the average, variance, spatial covariance, and/or spatial autocorrelation across different spatial regions (Chi and Zhu 2019; LeSage 1999).

Existing studies have provided evidence of the presence of spatial dependence and/or spatial heterogeneity in environmental migration processes. In a study examining the association between environment and migration in Australia while controlling for spatial dependencies and temporal lags of environmental factors, Bakar and Jin (2018) found a strong link between migration and environmental factors such as temperature and temperature extremes, in addition to the influence of conventional socioeconomic factors. Similarly, a study using spatial autocorrelation models in Iran from 1996 through 2011 found that increases in temperature and decreases in precipitation led to higher migration (Shiva and Molana 2018). Ruyssen and Rayp (2014) employed spatial methods to explore bilateral migration between countries of origin and destination in the sub-Saharan Africa region, revealing that environmental factors such as natural disasters influenced bilateral migration patterns, although conventional socioeconomic factors and geographical proximity between countries played a primary role in interregional migration. The impacts of disasters on migration have also been observed within countries. Using spatial regressions, Saldaña-Zorrilla and Sandberg (2009) found that high frequencies of disasters increased out-migration at the municipal level in Mexico.

Because of its geolocation, the United States is susceptible to various environmental disasters, including sea level rise, hurricanes, and floods. These disasters have spatially shaped migration patterns throughout the country. Johnson et al. (2005) discovered spatial clusters of high net migration in the Southwest and Florida because of their favorable weather conditions. Chi and colleagues (e.g., Chi 2010; Chi and Marcouiller 2012; Chi and Ventura 2011) observed spatial heterogeneity and spatial dependence in environmental migration within the United States. Notably, in their investigation of the environment–migration relationship across the rural–urban continuum in Wisconsin, Chi and Marcouiller (2013) found that natural amenities such as water areas and forest coverage attracted in-migration into rural areas adjacent to metropolitan areas.

The consideration of spatial methods stems not only from the fact that migration is a spatial process but also from the spatiality of the environmental data. Many environmental factors, especially weather indicators such as precipitation- and temperature-related measures, are spatially correlated because of the interdependency of elements within the climatic system. The spatial dependence of environmental factors can also result from data generation and extrapolation processes (Auffhammer et al. 2013). For instance, weather indicators may originate from geographically close weather stations, and missing records may be filled with values from spatial interpolation using data from nearby weather stations. Without consideration of spatial dependence – for example, by employing ordinary least squares (OLS) to model the effects of environmental factors on migration – the error terms tend to be spatially correlated, violating the assumption of independently and identically distributed error terms. In this situation, OLS estimates of parameters can still be unbiased and normally distributed but are no longer efficient (Chi and Zhu 2019). In a worse scenario, if spatial effects exist, OLS yields both biased and inefficient estimates (Saldaña-Zorrilla and Sandberg 2009).

Therefore spatial regression modeling is crucial for environmental migration studies where the outcome and/or independent variables are spatially dependent.

However, it is essential to recognize the limitations of spatial models. One of the main challenges is that the underlying assumptions, such as the correct specification of the spatial weight matrix, are restrictive. The trade-off in using spatial models, though, lies in their ability to capture complex interdependencies between migration and environmental factors that are spatially correlated. Overall, while there is a risk of violating assumptions, the gains in more accurately representing spatial relationships often outweigh these costs, particularly in migration studies where spatial dependence is a prominent feature of both the data and the phenomenon.

4. Data and methods

The data come from four sources (Table A-1). The dependent variable – county-level net migration rates (NMRs) – is based on five-year, age-specific net migration estimates compiled by Winkler et al. (2013). Environmental factors, including anomalies and long-run averages in precipitation and temperature, are derived from PRISM (Parameter-elevation Regressions on Independent Slopes Model), a downscaled, model-based climate dataset that provides reliable high-resolution (0.04 degree; approximately 4 km) estimates of climatic conditions (Daly et al. 2008). Other county-level socioeconomic factors are obtained from decennial censuses conducted between 1970 and 2010. Rural/urban status is determined by USDA Rural-Urban Continuum Codes.

Specifically, we used county-level NMRs from 1970 to 2010 as the dependent variables in this study. The NMR data were developed by Winkler et al. (2013) using a multi-step approach. Initially, census population counts at the beginning of each decade underwent aging forward to the end of the decade, with subsequent subtraction of deaths and addition of births based on data from the National Center for Health Statistics, yielding the expected population by the decade's end. Subsequently, estimated net migrants were calculated by subtracting the expected population from the observed census population at the end of the decade. Finally, NMRs were calculated by dividing estimated net migrants by the expected population determined in the preceding steps. These high-quality migration estimates have been widely used in demographic studies exploring migration trends across various geographic areas and demographic cohorts (Johnson et al. 2005; Johnson and Winkler 2015). Following Winkler et al.'s (2013) approach and previous literature that delineates age groups by working status (Ghio, Goujon, and Natale 2022), we calculated both all-age and age-specific NMRs. Specifically, we derived NMRs by summing the estimated net migrants and dividing by the total expected population at the end of each decade for all ages, working-age adults (ages 15–64), and older adults (ages 65+). Positive NMRs denote an influx of individuals into a county, whereas negative NMRs signify a net loss of migrants. To provide context on county sizes, the average land area of counties in the contiguous United States is approximately 2,462 km^2, with the biggest county (San Bernardino, California) at 51,947 km^2 and the smallest county (Falls Church City, Virginia) at 5 km^2, based on 2010 census geography.

We measured environmental change using anomalies in precipitation and temperature. Following the meteorological and environmental literature, an anomaly is defined as the difference between a short-term average (in this case, a decadal average) and a 30-year long-run climatic average, divided by the long-run climatic standard deviation (McCright, Dunlap, and Xiao 2014). Here we use the period from 1940 through 1969 as the baseline for calculating the climatic average and standard deviation. For both the decadal and long-run climatic averages, instead of a simple mean, we utilized a 12-month moving average calculated from monthly average temperature and precipitation, since a moving average can mitigate seasonal fluctuations in climatic conditions, thereby offering a more consistent and precise depiction of long-run climatic trends and patterns (Emberson, Kirschbaum, and Stanley 2021). A positive anomaly signifies an increase compared to the long-run average, while a negative anomaly denotes a decrease compared to the long-run average. It should be noted that the precipitation values represent the monthly average rather than the total annual precipitation.

The empirical models also include socioeconomic factors known to affect migration. Those county-level contextual factors include household income, rent, employment rate, and homeownership, sourced from the decennial census. To adjust for inflation, household income, rent, and housing prices from 1970 through 2010 were recalibrated to represent their equivalent values in 2010 dollars using the Annual Average Consumer Price Index provided by the US Census Bureau (US Census Bureau 2023). We also used the Office of Management and Budget's delineation of rural and urban counties to determine a county's metropolitan status and derived a rural/urban classification using data compiled by the US Department of Agriculture. Although these classification codes were released in 1974, 1983, 1993, and 2003, they are based on data from the preceding decennial censuses (e.g., 1983 codes are derived from 1980 data; the 1993 codes are from 1990 data). Because the available classification years do not align exactly with our decadal migration data, we adopted the 1993 metropolitan/nonmetropolitan classification and treated it as a time-invariant variable throughout the research, as 1993 marks the approximate midpoint of the research period from 1970 through 2010. We acknowledge that nearly 25% of nonmetropolitan counties were reclassified as metropolitan between 1960 and 2017 (Johnson and Lichter 2020). While the use of the 1993 classification as a time-invariant variable may potentially influence the results, we ensured consistency in the operational definition of metro and nonmetro areas, enabling us to focus on long-term trends and spatial spillover effects without the confounding influence of reclassification. We used the terms *metropolitan* and *nonmetropolitan* interchangeably with *urban* and *rural*, respectively.

4.1 Analytic strategy

We employed spatial techniques to examine environmental impacts on migration while also incorporating aspatial analyses to test for spatial effects in the data and to compare the performance of aspatial and spatial models. We focused on the contiguous United States; we excluded Alaska, Hawaii, and other territories due to their distinct climatic conditions and geographic isolation, which would introduce discontinuities and potentially distort the spatial relationships central to our analysis.

To assess the spatial effects in the data, we began with an exploratory spatial data analysis (ESDA). We calculated a global Moran's *I* to detect overall spatial autocorrelation and conducted a local indicators of spatial autocorrelation (LISA) cluster analysis to examine spatial clustering patterns across counties in the contiguous United States. (See "Exploratory spatial data analysis" in the appendix.) Following this exploratory step, we estimated a series of cross-sectional aspatial OLS models by decade and assessed the residuals using Moran's *I* to detect spatial autocorrelation. To further evaluate whether spatial effects were characterized as a spatial lag or a spatial error process, we performed Lagrange multiplier (LM) tests. (See "Aspatial models" in the appendix.) LM-lag and LM-error tests are diagnostic tools that help determine whether spatial effects in residuals are due to spatially lagged variables or spatially correlated errors, respectively. A spatial lag is the dependence of a location's outcome on the outcomes of neighboring locations, suggesting that changes in one area can have impacts on nearby areas. A spatial error arises when spatial autocorrelation is present in the model's error terms, indicating that unobserved factors influencing the dependent variable are spatially correlated across neighboring areas (Chi and Zhu 2019; Saldaña-Zorrilla and Sandberg 2009; Voss et al. 2006).

We then compiled panel data by pooling the data from each decade together and employed maximum likelihood estimation to estimate the parameters of the panel data fixed effects spatial models to account for the spatial effects. We chose the fixed effects model because it is preferable when spatial units are located in an unbroken area (the contiguous United States in this study) (Elhorst 2014). The spatial lag model (SLM, Equation 1) and spatial error model (SEM, Equation 2) take the following general forms, respectively:

$$Y_{it} = X_{it}\beta + \rho W Y_{it} + \varepsilon_{it} \tag{1}$$

$$Y_{it} = X_{it}\beta + u_{it}, u_{it} = \rho W_{u_{it}} + \varepsilon_{it} \tag{2}$$

where Y_{it} is the NMR of county i at time t, X_{it} is a matrix of environmental and socioeconomic factors, β is the estimated coefficient, ρ is the spatial lag parameter, W is the spatial weight matrix, and ε_{it} and u_{it} are the error terms. To incorporate the spatial spillover effects of environmental factors, which are commonly discussed in the environmental migration literature (Millock 2015), we also included spatial lags of precipitation and temperature anomalies – the two primary variables of interest in this study – in both the spatial lag and spatial error models.

For the weight matrix, we used the first-order Queen's contiguity-based weight. Figure A-4 shows the structure and box plot of the neighbors under the selected weight matrix. The average number of neighbors in the United States is six, with a minimum of one neighbor (Nantucket County, Massachusetts, and 13 counties in Maryland) and a maximum of 14 neighbors (San Juan County, Utah).

Beyond the direct impact on migration, environmental effects may be moderated by historical climatic conditions. For example, a temperature anomaly might have a more pronounced effect in areas with historically cooler climates compared to regions accustomed to higher temperatures. Similarly, environmental impacts may differ between rural and urban counties. Rural and urban counties vary in their economic structures, infrastructure, and resource availability, which shape how populations experience and respond to environmental change. For example, urban areas often have more diversified economies, more accessible services, and greater resilience to certain environmental shocks. Rural areas, particularly those dependent on agriculture or natural resources, may be more severely affected by environmental change. Consequently, we included interaction terms between precipitation and temperature anomalies and long-term averages, as well as rural/urban status, in the models. At the same time, to control unobserved factors that may impact migration, such as environmental disasters and technological advancements during the study period, we included county and decade fixed effects in the analyses.

4.2 Descriptive statistics

We present the descriptive statistics of the data in Table 1. On average, the overall NMR was higher in urban counties (10.08) than in rural counties (4.30), with similar patterns observed for both working-age and older adults. Mean precipitation and temperature anomalies were 0.26 and –0.16, respectively, and these conditions varied by county type:

Urban counties experienced higher precipitation anomalies whereas rural counties exhibited slightly more negative temperature anomalies. Long-run average precipitation and temperature were 78.58 mm and 12.34°C, respectively, with urban counties having higher values for both measures. Socioeconomic disparities between rural and urban counties were pronounced. Urban counties exhibited higher household incomes, rents, and housing prices as well as higher employment rates. In contrast, homeownership rates were higher in rural counties than in urban counties. Finally, based on 1993 Office of Management and Budget metropolitan delineations, 27% of counties were classified as metropolitan counties.

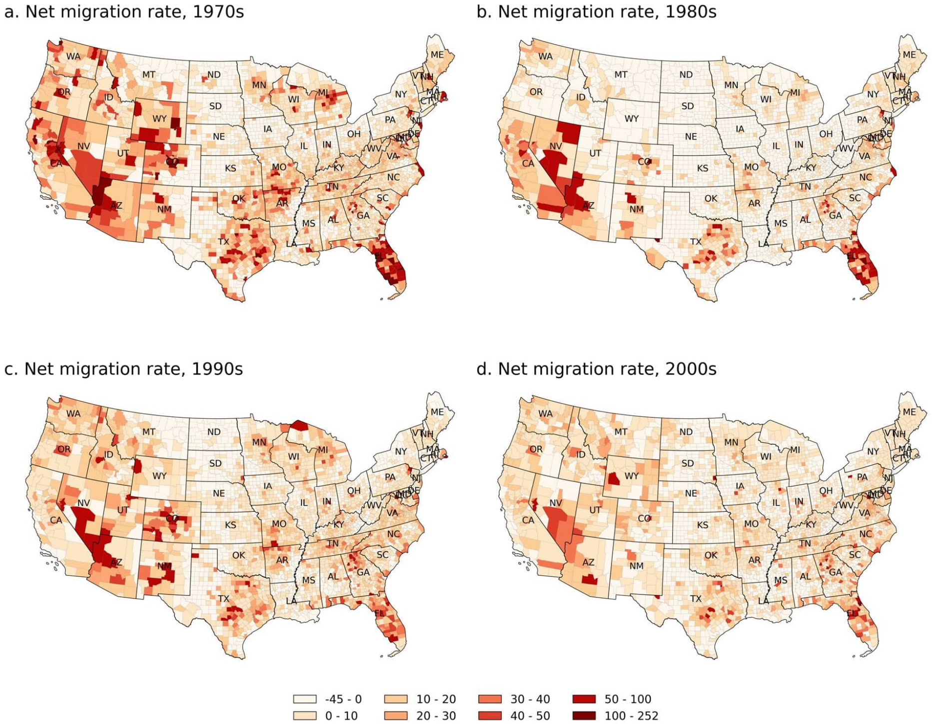
Table 1: Descriptive statistics of county-level NMRs and environmental and socioeconomic factors in the contiguous United States, 1970–2010

	All counties (N = 12,436)	Rural counties (N = 9,096)	Urban counties (N = 3,340)	*P*-value
NMR_{All}	5.85	4.30	10.08	2.98e-73
$NMR_{15–64}$	5.38	3.36	10.86	4.25e-88
NMR_{65+}	4.84	4.12	6.78	9.10e-19
Precipitation anomaly	0.26	0.24	0.31	1.02e-15
Temperature anomaly	–0.16	–0.18	–0.12	9.97e-29
Long-run precipitation average (mm)	78.58	76.37	84.61	1.20e-45
Long-run temperature average (℃)	12.34	12.06	13.10	4.26e-29
Household income ($1,000s)	43.60	40.11	53.08	0.00e+00
Rent ($1,000s)	0.49	0.44	0.61	0.00e+00
Housing price ($1,000s)	83.98	72.38	115.58	0.00e+00
Employment (%)	54.58	53.28	58.14	3.6e-237
Homeownership (%)	72.71	73.82	69.72	3.4e-150
Metropolitan county	0.27	0.00	1.00	—

Notes: Values are the mean. *P*-values from a two-sample *t*-test are reported to compare rural and urban counties. N is the county–year pair, with 3,109 unique counties between 1970 and 2010.

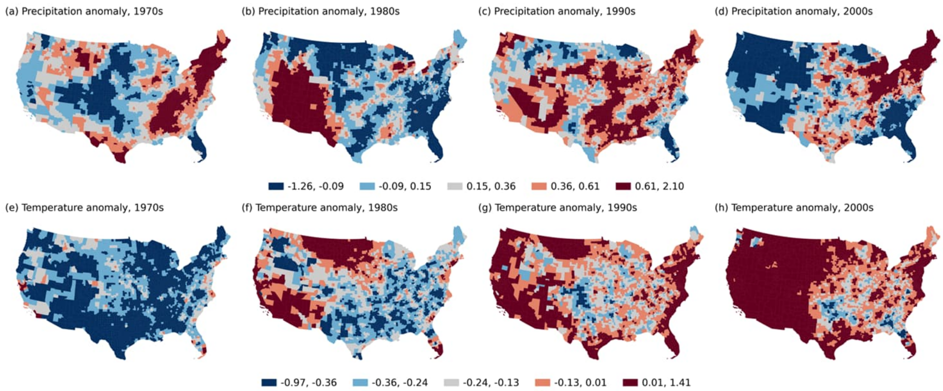
To demonstrate the spatial patterns, we plot NMRs from 1970 through 2010 in Figure 1. Throughout the study time frame, distinct migration patterns emerged. First, a majority of the West witnessed in-migration starting in the 1970s. However, over subsequent years, the migration rate shows a gradual decline, as evidenced by the shrinking cluster of high NMRs within that area. Second, the Great Plains, spanning from Montana and North Dakota in the north to New Mexico and parts of Texas in the south, consistently experienced out-migration. Nevertheless, metropolitan areas within this region, such as the Sioux Falls area in southeastern South Dakota and booming areas in Texas, experienced increased in-migration. Third, the East Coast, particularly major cities such as Boston, New York, Philadelphia, and Washington, DC, and most counties in Florida, experienced in-migration.

Figure 1: County-level NMRs per 100 people in the contiguous United States, 1970–2010



In addition to examining the spatial dimensions of the dependent variable, we plotted spatial distribution of county-level precipitation and temperature anomalies over the four decades from 1970 to 2010 (Figure 2). The precipitation anomaly maps show a noticeable shift in spatial patterns, with wetter anomalies concentrating in the Northeast and Midwest and drier conditions becoming more concentrated in the West and Southeast in the recent decade. In contrast, the temperature anomaly maps show a clear warming trend over time, with more regions experiencing warmer anomalies, particularly in the later decades. The spatial distributions of socioeconomic factors are illustrated in Figure A-5.

Figure 2: County-level precipitation and temperature anomalies in the contiguous United States, 1970–2010



5. Spatial models

5.1 Overall environmental effects

Recognizing that aspatial models are incapable of accounting for spatial dependence embedded in the data, we then conducted panel data fixed effects spatial lag and spatial error models (Table 2). The results suggest that increasing temperature anomalies tended to decrease NMRs after controlling for socioeconomic covariates. Meanwhile, the interaction terms between temperature anomaly and long-run temperature and a county's metropolitan status played an important role in affecting NMR_{All}.

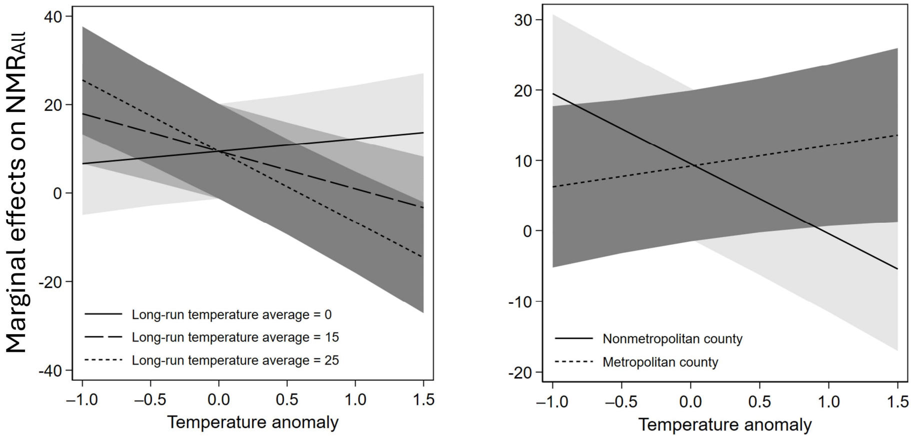
Table 2: Fixed effects SLMs and SEMs of all-age NMRs on environmental and socioeconomic factors in the contiguous United States, 1970–2010

	NMR_{All}	
	SLM	SEM
Climatic variables		
Prec anomaly	1.51	1.11
	(0.188)	(0.412)
Temp anomaly	–6.32	–2.72
	(0.002)	(0.246)
Climatic interactions		
Prec anomaly * long-run prec average	–0.00	0.00
	(0.971)	(0.903)
Temp anomaly * long-run temp average	–0.40	–0.66
	(0.000)	(0.000)
Prec anomaly * metropolitan status	–0.66	–0.70
	(0.211)	(0.239)
Temp anomaly * metropolitan status	6.85	6.53
	(0.000)	(0.000)
Control variables		
Household income ($1,000s)	–0.25	–0.32
	(0.000)	(0.000)
Rent ($1,000s)	–20.85	–26.28
	(0.000)	(0.000)
Housing price ($1,000s)	–0.00	–0.01
	(0.541)	(0.019)
Employment (%)	–0.02	–0.00
	(0.518)	(0.891)
Homeownership (%)	0.39	0.49
	(0.000)	(0.000)
Decade effect	Controlled	Controlled
County effect	Controlled	Controlled
Metropolitan status	Omitted	Omitted
Spatial effect		
W_{NMR}	0.47	0.50
	(0.000)	(0.000)
$W_{Prec\ anomaly}$	–1.87	–1.88
	(0.072)	(0.082)
$W_{Temp\ anomaly}$	5.98	2.45
	(0.003)	(0.272)
Observations	12,436	12,436
Number of counties	3,109	3,109
Log likelihood	–33,439	–33,402
AIC	66,915	66,839
BIC	67,049	66,973

Notes: *P*-values are in parentheses. Prec = precipitation. Temp = temperature. AIC = Akaike's information criterion. BIC = Schwartz's Bayesian information criterion.

Figure 3 shows the marginal effects of the interaction terms on the NMRs. The plots suggest that historically cooler counties and metropolitan counties experienced an increase in NMRs. In other words, as the temperature got warmer than the baseline from 1970 through 2010, historically warm and rural counties generally witnessed less net migration while historically cooler and urban counties were less affected by such changes in temperature and experienced more net migration.

Figure 3: Marginal effects of interactions between temperature anomaly and long-run temperature average and county metropolitan status on county-level NMRs



Meanwhile, we found evidence of spatial spillover effects in migration patterns, as indicated by positive spatial lag coefficients for NMR (W_{NMR}) and temperature anomalies ($W_{Temp\ anomaly}$). The coefficient for W_{NMR} in the SLM suggests that a 1-unit increase in net migration rates in neighboring counties is associated with a 0.47-unit increase in the NMR of a given county, even after controlling for local factors. Similarly, the coefficient for $W_{Temp\ anomaly}$ implies that higher temperature anomalies in surrounding counties are associated with increased net migration in a focal county. These findings highlight the regional interconnectedness of migration behavior, where migration decisions are influenced not only by local environmental conditions but also by broader climatic trends across adjacent counties.

5.2 Heterogeneous environmental effects across ages and metropolitan statuses

The NMR models, which included people of all ages, verified the influence of climate exposure on migration. However, as previously mentioned, different age groups may have distinct levels of climatic tolerance or different weather preferences when deciding on their migration destinations. Consequently, we stratified the dataset into age group 15–64 and age group 65+ and used the same estimation techniques for both groups to test for heterogeneous environmental effects. Table 3 shows the results of modeling $NMR_{15–}$

64 and NMR_{65+} over four decades (1970 through 2010) using SLMs and SEMs. Again, LM-lag and LM-error tests indicate the necessity of spatial models.

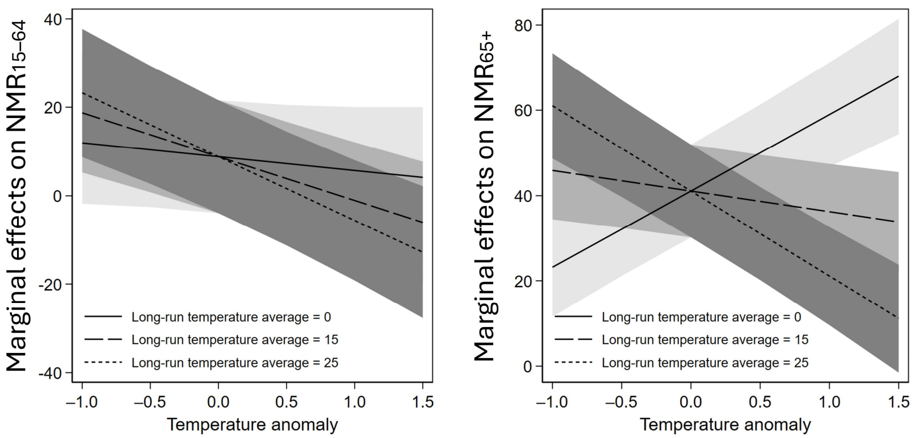
Table 3: Fixed effects SLMs and SEMs of age-specific NMRs on environmental and socioeconomic factors in the contiguous United States, 1970–2010

	$NMR_{15–64}$		NMR_{65+}	
	SLM	SEM	SLM	SEM
Climatic variables				
Prec anomaly	2.25	1.92	0.01	–0.32
	(0.099)	(0.234)	(0.989)	(0.805)
Temp anomaly	–10.13	–7.53	–0.34	6.02
	(0.000)	(0.007)	(0.859)	(0.007)
Climatic interactions				
Prec anomaly * long-run prec average	0.00	0.00	0.00	0.01
	(0.914)	(0.941)	(0.946)	(0.576)
Temp anomaly * long-run temp average	–0.24	–0.40	–0.76	–1.30
	(0.017)	(0.017)	(0.000)	(0.000)
Prec anomaly * metropolitan status	–0.47	–0.61	–0.07	0.02
	(0.451)	(0.392)	(0.880)	(0.972)
Temp anomaly * metropolitan status	8.34	7.73	1.77	2.65
	(0.000)	(0.000)	(0.050)	(0.010)
Control variables				
Household income ($1,000s)	–0.35	–0.45	–0.08	–0.09
	(0.000)	(0.000)	(0.001)	(0.001)
Rent ($1,000s)	–23.89	–30.56	0.48	1.98
	(0.000)	(0.000)	(0.811)	(0.389)
Housing price ($1,000s)	–0.00	–0.02	–0.01	–0.01
	(0.437)	(0.009)	(0.321)	(0.262)
Employment (%)	–0.01	0.01	0.06	0.07
	(0.826)	(0.808)	(0.043)	(0.035)
Homeownership (%)	0.46	0.58	0.30	0.36
	(0.000)	(0.000)	(0.000)	(0.000)
Decade effect	Controlled	Controlled	Controlled	Controlled
County effect	Controlled	Controlled	Controlled	Controlled
Metropolitan status	Omitted	Omitted	Omitted	Omitted
Spatial effect				
W_{NMR}	0.47	0.50	0.50	0.51
	(0.000)	(0.000)	(0.000)	(0.000)
$W_{Prec\ anomaly}$	–3.10	–3.19	0.36	0.30
	(0.012)	(0.013)	(0.716)	(0.769)
$W_{Temp\ anomaly}$	6.23	1.76	8.80	7.81
	(0.010)	(0.508)	(0.000)	(0.000)
Observations	12,436	12,436	12,436	12,436
Number of counties	3,109	3,109	3,109	3,109
Log-likelihood	–35,060	–35,009	–32,915	–32,909
AIC	70,156	70,054	65,867	65,853
BIC	70,290	70,187	66,000	65,987

Note: *P*-values are in parentheses. Prec = precipitation. Temp = temperature. AIC = Akaike's information criterion. BIC = Schwartz's Bayesian information criterion.

The age-specific model results demonstrate that environmental impacts on the NMRs were age-specific, as reflected in the heterogeneous impacts of temperature anomaly on the two groups' NMRs. Specifically, while temperature anomalies decreased the NMRs for the working-age adults, they tended to increase the NMRs for the older adults. In other words, warmer temperatures are not universally attractive; it is primarily older adults moving to warmer places. This is also reflected in the interaction terms between temperature anomaly and long-run temperature average (Figure 4). However, the result also suggests that cooler counties have an influence on the observed effect of temperature anomalies on migration patterns among older adults. Therefore the interpretation of the overall effect of temperature anomalies should be made with caution, as it is contingent on the long-run climatic contexts of counties, particularly in cooler regions. While working-age adults' NMRs decreased regardless of the historical temperature average, older adults tended to move to historically cool counties as temperature anomalies increased. In summary, the findings indicate distinct migration patterns among different age groups in response to increasing temperatures. NMRs for working-age adults tended to decrease as temperatures increased while NMRs for older adults increased with warmer temperatures, particularly in areas that were historically cooler.

Figure 4: Marginal effects of interactions between temperature anomaly and long-run temperature average on county-level age-specific NMRs



Although it's not the primary focus of this study, the results revealed an intriguing relationship between migration patterns and socioeconomic factors, particularly household income and housing rent. Specifically, net out-migration of individuals across all age groups was higher in counties with higher household incomes. This finding may suggest that wealthier areas, while attractive in many respects, may also experience higher costs of living or housing, potentially driving residents to seek more affordable regions. Additionally, the results indicated that net out-migration of working-age adults was associated with higher housing rents, suggesting that rising living costs in these areas may disproportionately affect them. In contrast, net in-migration of older adults was positively associated with higher average rent, indicating that older adults may be more willing or able to afford higher-rent areas, potentially seeking amenities, health care access, or climate preferences in such locations. These socioeconomic factors underscore the complexity of migration decisions and highlight the importance of considering both environmental and economic drivers in understanding population movements.

6. Nonlinearity and sensitivity analyses

So far we have explored environmental impacts on migration and their heterogeneous effects on working-age and older adults across rural and urban counties. It is important to note, however, that environmental factors may influence migration in complex, threshold-dependent ways. For instance, moderate anomalies might have negligible effects on migration while extreme anomalies could trigger migration due to severe economic disruptions. To this end, we included the square terms of precipitation and temperature terms in the age-specific models to explore the nonlinear relationship between environmental factors and migration (Table A-4). We found that environmental factors, particularly temperature anomalies, have a nonlinear effect on migration, with a threshold of –0.57 and 0.55 based on the SEM for working-age and older adults, respectively (Figure A-6). However, the nonlinear pattern for working-age adults is less pronounced. For older adults, the nonlinear relationship is much clearer, with NMRs increasing substantially under negative temperature anomalies and decreasing as temperatures become extremely warm relative to the baseline. This indicates that counties with moderate temperatures are more likely to attract older adults while extreme heat may have the opposite effect.

Another issue that could potentially bias the analysis is the crude classification of age, which categorizes individuals broadly into working-age and older adults. This approach may overlook critical differences in migration patterns between younger and middle-aged populations. In addition, the working-age category includes minors, who are unlikely to participate in the labor market independently and whose migration decisions are typically tied to those of their parents. To address this issue, we further subdivided the 15–64 age group into finer categories (20–29, 30–39, and 40–64) and conducted a sensitivity analysis (Table A-5). The results align with those presented in Table 3 and Table A-4, regardless of whether squared terms of anomalies are included in the models. This consistency is particularly evident in the effects of temperature anomalies and their interactions with metropolitan status, which are the primary research questions in this study. In sum, the sensitivity analysis provides evidence that the analyses and results are robust and that migration in response to environmental factors is heterogeneous across age groups and rural/urban status.

7. Discussion and conclusion

Utilizing NMRs, harmonized census data, and high-resolution climate data from 1970 through 2010, we sought to examine the spatial dimensions of environmental impacts on migration at the county level and their heterogeneous impacts on area- and age-specific migration decisions in the United States. The ESDA results showed that both the dependent and independent variables were spatially dependent. LM-lag and LM-error tests further confirmed the existence of spatial lag and spatial error effects, necessitating spatial techniques to account for such spatial features in the data. The spatial models demonstrated an environmental effect on migration decision-making in general, with temperature anomaly being an important contributor to NMRs while precipitation anomaly was not. Meanwhile, environmental effects were heterogeneous across a county's metropolitan status and age groups. On the one hand, as temperature anomaly increases, nonmetropolitan counties experience a sharp decrease in NMRs, indicating a higher rate of out-migration than in-migration. On the other hand, working-age adults displayed an overall decrease in NMRs as the temperature anomaly increased. In contrast, older adults exhibited a preference for counties with warmer temperatures, particularly when the warmer environment was coupled with historically cooler weather. In addition, we found spatial spillover effects in the environmental migration process, where migration decisions are shaped by both local factors and the migration patterns and climatic conditions of neighboring areas.

These findings underscore the intricate relationship between climate variability and migration in the United States. The differential impacts of temperature anomalies across places and age groups highlight the importance of considering spatial and demographic contexts when assessing environmental migration patterns. The vulnerability of rural areas to population loss under warming temperatures resonates with and complicates the existing rural exodus of the younger population (Johnson and Lichter 2019). Older adults' preference for warmer places echoes well-documented amenity migration patterns (Chi and Marcouiller 2012; Gosnell and Abrams 2011) and the snowbird phenomenon (e.g., Johnson et al. 2005; McLeman and Hunter 2010), where retirees and other older adults temporarily or permanently migrate to warmer regions.

The decreasing trend in NMRs in working-age adults under warming temperatures deserves further discussion. Unlike older adults, who seek natural and environmental amenities when choosing migration destinations, working-age adults prioritize building careers and following work opportunities. Higher temperatures harm economic growth

(Dell, Jones, and Olken 2012), particularly in rural settings, therefore offering fewer diverse employment opportunities in fields appealing to working-age adults. Furthermore, concerns about the long-term impacts of climate change, such as worsening heat waves, may deter working-age adults from choosing warmer regions. However, it is important to note that environmental factors are among many considerations in migration decisions and often show limited impacts globally (Zhou and Chi 2024) and within the US context (Chen, Kim, and Fouzia 2024). As reflected in the stepwise regression approach (Table A-3), where the inclusion of environmental factors accounted for only an additional 1% of the explained variance in migration, these results suggest that environmental factors alone are unlikely to serve as the sole or primary driver of migration. Instead, they appear to influence migration through their impact on broader economic dynamics, especially for the working-age adults. Thus, while the environment plays a role in shaping migration patterns, it should be viewed as one component within a complex web of factors, such as social, economic, demographic, and cultural influences.

This study contributes to the understanding of environmental impacts on migration and their heterogeneous effects across demographic groups and places in the United States. These findings have important implications for policymakers and stakeholders, providing critical guidance for the development of targeted interventions and strategic allocation of resources. Understanding age-specific differences in migration responses can inform policies aimed at supporting both the aging population in amenity-rich retirement destinations and working-age adults seeking economic opportunity in regions less vulnerable to climate variability. Recognizing the greater sensitivity of nonmetropolitan areas to temperature increases is vital for implementing proactive measures, including agricultural adaptation, economic diversification, and infrastructure investments supporting climate resilience.

Although spatial techniques seem rational for studying sociodemographic processes such as migration where spatial dimensions are evident, such methods come with limitations. In particular, spatial analyses inevitably encounter the modifiable areal unit problem (Torche and Corvalan 2018). Leyk et al. (2012) have shown that results from environmental migration at a finer scale are more reliable because finer-scale models capture a higher level of spatial details, such as heterogeneity and spatial autocorrelation in the data; this study's conclusions at the county level may not hold at other scales or at the individual level. Another concern arises from the adoption of the 1993 rural/urban classification as a time-invariant variable throughout the research period. While this approach streamlines the analysis, it prevents isolation of the effects of metropolitan status and its interaction with climatic conditions. This limitation arises because fixed effects models cannot estimate the impacts of time-invariant variables. Meanwhile, it may introduce some variation in the results, as the socioeconomic and demographic shifts associated with such reclassifications are not reflected in the static classification, potentially affecting the relationships analyzed. Meanwhile, alternative county classification schemes may also be relevant for understanding environmental migration dynamics. For example, the Economic Research Service identified recreation and retirement counties (Johnson and Beale 2002), both of which are known to exhibit distinctive migration patterns and may be particularly sensitive to climatic conditions that deserve further investigation. The choice of the spatial weighting matrix, which defines spatial relationships among units, can influence the results of spatial models. Different weighting matrices (e.g., contiguity-based or distance-based) may yield varying degrees of spatial dependence, potentially altering the interpretation of spatial effects. Additionally, this study adopts a decadal time scale to align with the availability of the NMR dataset. While this approach captures long-term trends, it may obscure intra-decade migration dynamics. Thus the findings reflect long-term associations rather than immediate behavioral responses to environmental change.

Future research can expand our understanding of environmental migration by taking several key directions. First, climatic processes such as temperature and precipitation variability often operate at finer spatial scales, and sub-county units may better capture localized environmental exposures and mitigate the modifiable areal unit problem. Future research could advance environmental migration research by integrating individual-level data or developing migration measures at finer geographic units, such as census tracts or blocks, to more precisely assess how localized environmental change shapes migration decisions. Second, rather than relying solely on a rural/urban classification, future studies could incorporate alternative county typologies, such as recreation and retirement county classifications, to better capture amenity-driven and climate-sensitive migration patterns that may be obscured by conventional rural/urban distinctions. Third, there is also a pressing need to develop robust measures of environmental change beyond conventional indicators such as disaster counts or average climatic conditions. Achieving this objective necessitates interdisciplinary collaboration among population scientists, environmental researchers, and meteorologists to utilize nontraditional datasets such as weather station records and downscaled climate data products to better understand the localized impacts of environmental changes and their connections to migration patterns. Fourth, apart from people who are willing or able to migrate in response to environmental change, some people may be unwilling to move from disaster-stricken areas (e.g., those strongly attached to a place) or may be trapped (e.g., those who lack the financial and human capital to migrate). More studies should be done on the driving forces and mechanisms behind immobility under adverse environmental change, and corresponding resolutions or policies should be developed to overcome environmental immobility and to promote population and property safety for those who voluntarily stay in places that are prone to environmental change. Finally, a crucial area for future research in the field of environmental migration lies in disentangling the specific contributions of environmental impacts from the influence of conventional socioeconomic and demographic factors. While numerous studies have explored the complex interplay between environmental change and migration, it remains challenging to isolate and quantify the distinct effects of environmental factors in the presence of various other drivers. To advance our understanding, it is necessary to employ rigorous research methodologies that can effectively separate the unique influence of environmental impacts from other established determinants of migration, such as income levels, education, and social networks. This entails utilizing advanced statistical models, longitudinal data, and innovative analytical techniques to tease apart the intricate connections between environmental change and migration outcomes.

8. Acknowledgments

This research was supported in part by the National Science Foundation (awards 1541136, 1823633, 1927827, 2032790, 2121909, 2207436, and 2552520), the USDA National Institute of Food and Agriculture Multistate Research Project PEN04623 (accession 1013257), and the Eunice Kennedy Shriver National Institute of Child Health and Human Development (award P2C HD041025). Shuai Zhou and Guangqing Chi conceptualized the study. Shuai Zhou conducted the data analysis and drafted the manuscript. Guangqing Chi and Chuan Liao reviewed and edited the manuscript. The authors declare no conflicts of interest.

References

Anselin, L., Sridharan, S., and Gholston, S. (2007). Using exploratory spatial data analysis to leverage social indicator databases: The discovery of interesting patterns. *Social Indicators Research* 82(2): 287–309. doi:10.1007/s11205-006-9034-x.

Auffhammer, M., Hsiang, S.M., Schlenker, W. and Sobel, A. (2013). Using weather data and climate model output in economic analyses of climate change. *Review of Environmental Economics and Policy* 7(2): 181–198. doi:10.1093/reep/ret016.

Bakar, K.S. and Jin, H. (2018). Spatio-temporal quantitative links between climatic extremes and population flows: A case study in the Murray–Darling Basin, Australia. *Climatic Change* 148(1–2): 139–153. doi:10.1007/s10584-018-2182-6.

Barrios, S., Bertinelli, L., and Strobl, E. (2018). Trends in rainfall and economic growth in Africa: A neglected cause of the growth tragedy. *The Review of Economics and Statistics* 92(2): 350–366. doi:10.1162/rest.2010.11212.

Beine, M. and Jeusette, L. (2021). A meta-analysis of the literature on climate change and migration. *Journal of Demographic Economics* 87: 293–344. doi:10.1017/dem.2019.22.

Chen, Y., Kim, M., and Fouzia, S. (2024). Climate-related disaster exposure and regional migration. *Annals of Regional Science* 73(2): 795–824. doi:10.1007/s00168-024-01276-z.

Chi, G. (2010). The impacts of highway expansion on population change: An integrated spatial approach. *Rural Sociology* 75(1): 58–89. doi:10.1111/j.1549-0831.2009.00003.x.

Chi, G., Zhou, S., Mucioki, M., Miller, J., Korkut, E., Howe, L., Yin, J., Holen, D., Randell, H., Akyildiz, A., Halvorsen, K.E., Fowler, L., Ford, J., and Tickamyer, A. (2024). Climate impacts on migration in the Arctic North America: Existing evidence and research recommendations. *Regional Environmental Change* 24(47). doi:10.1007/s10113-024-02212-9.

Chi, G. and Marcouiller, D.W. (2012). Recreational homes and migration to remote amenity-rich areas. *Journal of Regional Analysis and Policy* 42(1): 47–60. doi:10.22004/AG.ECON.143766.

Chi, G. and Marcouiller, D.W. (2013). Natural amenities and their effects on migration along the urban-rural continuum. *Annals of Regional Science* 50(3): 861–883. doi:10.1007/s00168-012-0524-2.

Chi, G. and Ventura, S.J. (2011). An integrated framework of population change: Influential factors, spatial dynamics, and temporal variation. *Growth and Change* 42(4): 549–570. doi:10.1111/j.1468-2257.2011.00567.x.

Chi, G. and Zhu, J. (2008). Spatial regression models for demographic analysis. *Population Research and Policy Review* 27(1): 17–42. doi:10.1007/s11113-007-9051-8.

Chi, G. and Zhu, J. (2019). *Spatial regression models for the social sciences*. Thousand Oaks, CA: SAGE Publications. doi:10.4135/9781544302096.

Curtis, K.J., Fussell, E., and DeWaard, J. (2015). Recovery migration after Hurricanes Katrina and Rita: Spatial concentration and intensification in the migration system. *Demography* 52(4): 1269–1293. doi:10.1007/s13524-015-0400-7.

Daly, C., Halbleib, M., Smith, J.I., Gibson, W.P., Doggett, M.K., Taylor, G.H., Curtis, J., and Pasteris, P.P. (2008). Physiographically sensitive mapping of climatological temperature and precipitation across the conterminous United States. *International Journal of Climatology* 28: 2031–2064. doi:10.1002/joc.1688.

Dell, M., Jones, B.F., and Olken, B.A. (2009). Temperature and income: Reconciling new cross-sectional and panel estimates. *American Economic Review* 99(2): 198–204. doi:10.1257/aer.99.2.198.

Dell, M., Jones, B.F., and Olken, B.A. (2012). Temperature shocks and economic growth: Evidence from the last half century. *American Economic Journal: Macroeconomics* 4(3): 66–95. doi:10.1257/mac.4.3.66.

Elhorst, J.P. (2014). *Spatial econometrics: From cross-sectional data to spatial panels*. Heidelberg: Springer. doi:10.1007/978-3-642-40340-8.

Elliott, J.R. and Pais, J. (2006). Race, class, and Hurricane Katrina: Social differences in human responses to disaster. *Social Science Research* 35(2): 295–321. doi:10.1016/j.ssresearch.2006.02.003.

Emberson, R., Kirschbaum, D., and Stanley, T. (2021). Global connections between El Nino and landslide impacts. *Nature Communications* 12: 2262. doi:10.1038/s41467-021-22398-4.

Feng, S., Oppenheimer, M., and Schlenker, W. (2012). Climate Change, Crop Yields, and Internal Migration in the United States. Cambridge, MA: National Bureau of Economic Research (NBER Working Paper 17734). doi:10.3386/w17734.

Fussell, E. (2009). Hurricane chasers in New Orleans: Latino immigrants as a source of a rapid response labor force. *Hispanic Journal of Behavioral Sciences* 31(3): 375–394. doi:10.1177/0739986309339735.

Fussell, E. (2012). Space, time, and volition: Dimensions of migration theory. In: Rosenblum, M.R. and Tichenor, D.J. (eds.). *Oxford handbook of the politics of international migration*. New York, NY: Oxford University Press: 25–52. doi:10.1093/oxfordhb/9780195337228.013.0002.

Fussell, E., Curtis, K.J., and DeWaard, J. (2014). Recovery migration to the City of New Orleans after Hurricane Katrina: A migration systems approach. *Population and Environment* 35(3): 305–322. doi:10.1007/s11111-014-0204-5.

Fussell, E., Hunter, L.M. and Gray, C.L. (2014). Measuring the environmental dimensions of human migration: The demographer's toolkit. *Global Environmental Change* 28(1): 182–191. doi:10.1016/j.gloenvcha.2014.07.001.

Ghio, D., Goujon, A., and Natale, F. (2022). Assessing the demographic impact of migration on the working-age population across European territories. *Demographic Research* 46(9): 261–272. doi:10.4054/DemRes.2022.46.9.

Gosnell, H. and Abrams, J. (2011). Amenity migration: Diverse conceptualizations of drivers, socioeconomic dimensions, and emerging challenges. *GeoJournal* 76(4): 303–322. doi:10.1007/s10708-009-9295-4.

Gutmann, M.P., Deane, G.D., Lauster, N., and Andrés Peri, A. (2005). Two population-environment regimes in the Great Plains of the United States, 1930–1990. *Population and Environment* 27(2): 191–225. doi:10.1007/s11111-006-0016-3.

Happel, S.K. and Hogan, T.D. (2002). Counting snowbirds: The importance of and the problems with estimating seasonal populations. *Population Research and Policy Review* 21(3): 227–240. doi:10.1023/A:1019560405310.

Hauer, M.E., Holloway, S.R., and Oda, T. (2020). Evacuees and migrants exhibit different migration systems after the great East Japan earthquake and tsunami. *Demography* 57(4): 1437–1457. doi:10.1007/s13524-020-00883-7.

Hauer, M.E., Jacobs, S.A., and Kulp, S.A. (2024). Climate migration amplifies demographic change and population aging. *Proceedings of the National Academy of Sciences of the United States of America* 121(3): e2206192119. doi:10.1073/pnas.2206192119.

Hoffmann, R., Dimitrova, A., Muttarak, R., Crespo Cuaresma, J., and Peisker, J. (2020). A meta-analysis of country-level studies on environmental change and migration. *Nature Climate Change* 10: 904–912. doi:10.1038/s41558-020-0898-6.

Hunter, L.M., Murray, S., and Riosmena, F. (2013). Rainfall patterns and U.S. migration from rural Mexico. *International Migration Review* 47(4): 874–909. doi:10.1111/imre.12051.

Hunter, L.M. and Simon, D.H. (2023). Time to mainstream the environment into migration theory? *International Migration Review* 57(1): 5–35. doi:10.1177/01979183221074343.

IPCC (2021). *Climate change 2021: The physical science basis*. Cambridge: Cambridge University Press. doi:10.1017/9781009157896.

Johnson, K.M. and Beale, C.L. (2002). Nonmetro recreation counties: Their identification and rapid growth. *Rural America* 17(4): 12–19. doi:10.22004/AG.ECON.289572.

Johnson, K.M. and Lichter, D.T. (2019). Rural depopulation: Growth and decline processes over the past century. *Rural Sociology* 84(1): 3–27. doi:10.1111/ruso.12266.

Johnson, K.M. and Lichter, D.T. (2020). Metropolitan reclassification and the urbanization of rural America. *Demography* 57(5): 1929–1950. doi:10.1007/s13524-020-00912-5.

Johnson, K.M., Voss; P.R., Hammer; R.B., Fuguitt; G.V., and McNiven, S. (2005). Temporal and spatial variation in age-specific net migration in the United States. *Demography* 42(4): 791–812. doi:10.1353/dem.2005.0033.

Johnson, K.M. and Winkler, R.L. (2015). Migration signatures across the decades: Net migration by age in U.S. counties, 1950–2010. *Demographic Research* 32(38): 1065–1080. doi:10.4054/DemRes.2015.32.38.

Johnson, K.M., Winkler, R., and Rogers, L.T. (2013). Age and lifecycle patterns driving US migration shifts. Durham, N.H.: Carsey Institute, University of New Hampshire (National Issue Brief 62). doi:10.34051/p/2020.192.

Kaczan, D.J. and Orgill-Meyer, J. (2020). The impact of climate change on migration: a synthesis of recent empirical insights. *Climatic Change* 158: 281–300. doi:10.1007/s10584-019-02560-0.

Lee, E. (1966). A theory of migration. *Demography* 3(1): 47–57. doi:10.1007/s13524-011-0049-9.

LeSage, J.P. (1999). A spatial econometric examination of china's economic growth. *Geographic Information Sciences* 5(2): 143–153. doi:10.1080/10824009909480523.

Leyk, S., Maclaurin, G.J., Hunter, L.M., Nawrotzki, R., Twine, W., Collinson, M., and Erasmus, B. (2012). Spatially and temporally varying associations between temporary outmigration and natural resource availability in resource-dependent rural communities in South Africa: A modeling framework. *Applied Geography*, 34: 559–568. doi:10.1016/j.apgeog.2012.02.009.

Mahajan, P. and Yang, D. (2020). Taken by storm: Hurricanes, migrant networks, and US immigration. *American Economic Journal: Applied Economics* 12(2): 250–277. doi:10.1257/app.20180438.

Marchiori, L., Maystadt, J.F., and Schumacher, I. (2012). The impact of weather anomalies on migration in sub-Saharan Africa. *Journal of Environmental Economics and Management* 63(3): 355–374. doi:10.1016/j.jeem.2012.02.001.

McCright, A.M., Dunlap, R.E., and Xiao, C. (2014). The impacts of temperature anomalies and political orientation on perceived winter warming. *Nature Climate Change* 4(12): 1077–1081. doi:10.1038/nclimate2443.

McLeman, R.A. and Hunter, L.M. (2010). Migration in the context of vulnerability and adaptation to climate change: Insights from analogues. *Wiley Interdisciplinary Reviews: Climate Change* 1(3): 450–461. doi:10.1002/wcc.51.

Millock, K. (2015). Migration and environment. *Annual Review of Resource Economics* 7(1): 35–60. doi:10.1146/annurev-resource-100814-125031.

Müller, T. (2003). Migration policy in a small open economy with a dual labor market. *Review of International Economics* 11(1): 130–143. doi:10.1111/1467-9396.00373.

Nawrotzki, R.J. and DeWaard, J. (2016). Climate shocks and the timing of migration from Mexico. *Population and Environment* 38(1): 72–100. doi:10.1007/s11111-016-0255-x.

Nawrotzki, R.J. and DeWaard, J. (2018). Putting trapped populations into place: climate change and inter-district migration flows in Zambia. *Regional Environmental Change* 18(2): 533–546. doi:10.1007/s10113-017-1224-3.

Poston, D.L., Zhang, L., Gotcher, D.J., and Gu, Y. (2009). The effect of climate on migration: United States, 1995–2000. *Social Science Research* 38(3): 743–753. doi:10.1016/j.ssresearch.2008.10.003.

Ruyssen, I. and Rayp, G. (2014). Determinants of intraregional migration in sub-Saharan Africa 1980–2000. *Journal of Development Studies* 50(3): 426–443. doi:10.1080/00220388.2013.866218.

Saldaña-Zorrilla, S.O. and Sandberg, K. (2009). Impact of climate-related disasters on human migration in Mexico: A spatial model. *Climatic Change* 96(1): 97–118. doi:10.1007/s10584-009-9577-3.

Schewel, K. (2020). Understanding immobility: Moving beyond the mobility bias in migration studies. *International Migration Review* 54(2): 328–355. doi:10.1177/0197918319831952.

de Sherbinin, A., Grace, K., McDermid, S., van der Geest, K., Puma, M.J., and Bell, A. (2022). Migration theory in climate mobility research. *Frontiers in Climate* 4: 882343. doi:10.3389/fclim.2022.882343.

Shiva, M. and Molana, H. (2018). Climate change induced inter-province migration in Iran. Aberdeen: University of Aberdeen (Discussion Papers in Economics and Finance).

Sisk, B. and Bankston, C.L. (2014). Hurricane Katrina, a construction boom, and a new labor force: Latino immigrants and the New Orleans construction industry, 2000 and 2006–2010. *Population Research and Policy Review* 33(3): 309–334. doi:10.1007/s11113-013-9311-8.

Smith, S.K. and House, M. (2006). Snowbirds, sunbirds, and stayers: Seasonal migration of elderly adults in Florida. *Journals of Gerontology – Series B Psychological Sciences and Social Sciences* 61(5): S232–S239. doi:10.1093/geronb/61.5.S232.

Stark, O. and Levhari, D. (1982). On migration and risk in LDCs. *Economic Development and Cultural Change* 31(1): 191–196. doi:10.1086/451312.

Thiede, B.C. and Brown, D.L. (2013). Hurricane Katrina: Who stayed and why?. *Population Research and Policy Review* 32(6): 803–824. doi:10.1007/s11113-013-9302-9.

Todaro, M. and Maruszko, L. (1987). Illegal migration and US immigration reform : A conceptual framework. *Population and Development Review* 13(1): 101–114. doi:10.2307/1972122.

Todaro, M.P. (1969). A model of labor migration and urban unemployment in less developed countries. *The American Economic Review* 59(1): 138–148. doi:10.2307/1811100.

Torche, F. and Corvalan, A. (2018). Estimating intergenerational mobility with grouped data: A critique of Clark's the Son Also Rises. *Sociological Methods and Research* 47(4): 787–811. doi:10.1177/0049124116661579.

US Census Bureau (2023). Current versus constant (or real) dollars [electronic resource]. Washington, D.C.: US Census Bureau. https://www.census.gov/topics/income-poverty/income/guidance/current-vs-constant-dollars.html.

Viswanathan, B. and Kumar, K.S.K. (2015). Weather, agriculture and rural migration: Evidence from state and district level migration in India. *Environment and Development Economics* 20(4): 469–492. doi:10.1017/S1355770X1500008X.

Voss, P.R., Long, D.D., Hammer, R.B., and Friedman, S. (2006). County child poverty rates in the US: A spatial regression approach. *Population Research and Policy Review* 25(4): 369–391. doi:10.1007/s11113-006-9007-4.

Wallerstein, I. (1983). *Historical capitalism with capitalist civilization*. London: Verso.

Winkler, R.L., Egan-Robertson, D., Curtis, K.J., Johnson, K.M., and Bourbeau, C. (2013). Age-specific net migration estimates for US counties, 1950–2010. Madison, WI: Applied Population Laboratory, University of Wisconsin-Madison. https://netmigration.wisc.edu/.

Winkler, R.L. and Rouleau, M.D. (2021). Amenities or disamenities? Estimating the impacts of extreme heat and wildfire on domestic US migration. *Population and Environment* 42(4): 622–648. doi:10.1007/s11111-020-00364-4.

Zhou, S. and Chi, G. (2024). How do environmental stressors influence migration? A meta-regression analysis of environmental migration literature. *Demographic Research* 50(2): 41–100. doi:10.4054/DemRes.2024.50.2.

Zhou, S. Chi, G., Qiu, H., Lei, Z., Smithwick, E..H., and Chen, J. (2024). Relocation preference and settlement: Lessons from the Poverty Alleviation Relocation Program in China. *PLOS One* 19(10): e0309534. doi:10.1371/journal.pone.0309534.

Zickgraf, C. (2021). Theorizing (im)mobility in the face of environmental change. *Regional Environmental Change* 21(4): 126. doi:10.1007/s10113-021-01839-2.

Appendix

Data sources

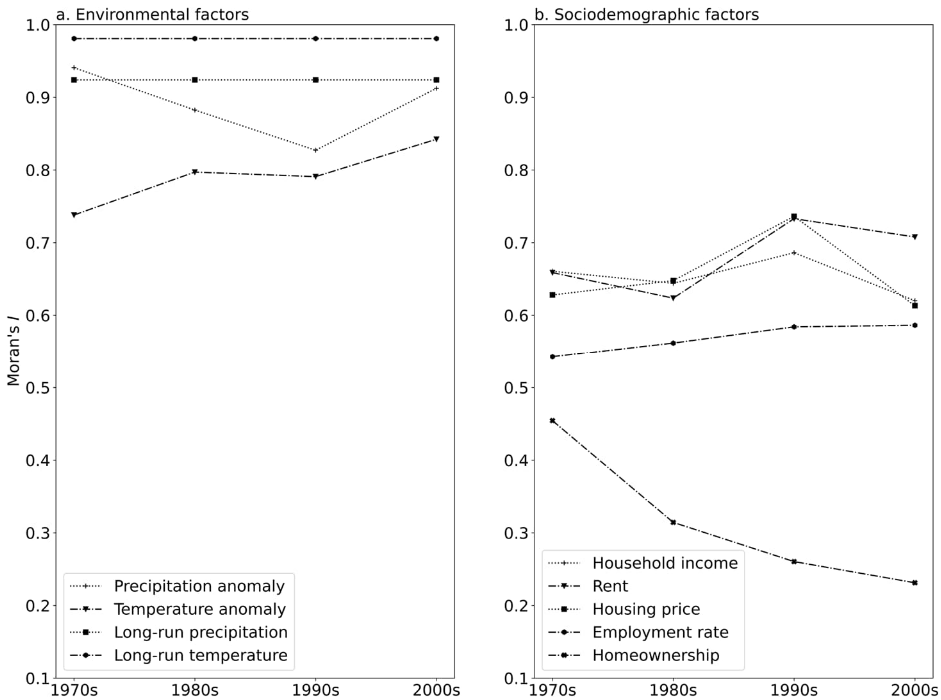
Table A-1: Data sources

Source	Variables	Year
County-level estimates of net migration rates	All-age and age-specific NMRs	1970–2010
PRISM	Environmental factors	1970–2010
US Census Bureau	Socioeconomic factors	1970–2010
US Department of Agriculture	Rural–urban continuum codes	1993

Exploratory spatial data analysis

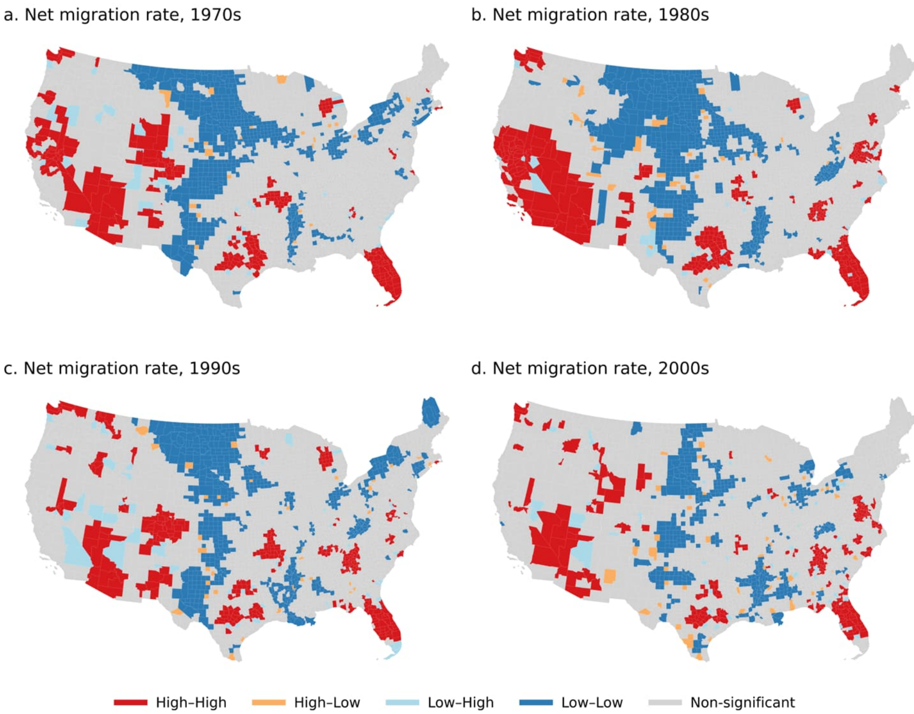
To explore the spatial characteristics of the data, we employed the ESDA, a common approach used to visualize and explore data from a spatial perspective. We first quantified the spatial patterns of the dependent and independent variables using Moran's *I*, a measure of spatial autocorrelation (Anselin, Sridharan, and Gholston 2007; Chi and Zhu 2008). The results indicated positive spatial autocorrelations for migration, with Moran's *I* values of 0.47, 0.49, 0.45, and 0.36 in the 1970s, 1980s, 1990s, and 2000s, respectively. Furthermore, the independent variables displayed varying levels of autocorrelation. Notably, environmental measures exhibited higher autocorrelation than socioeconomic factors, with Moran's *I* values exceeding 0.7 (Figure A-1).

Figure A-1: Moran's *I* for the independent variables



We then applied LISA cluster analysis to identify and visualize the spatial clustering of NMRs, as illustrated in Figure A-2. Consistent with the results shown in Figure 1, four primary clustering patterns emerged in terms of NMRs. First, some counties in the West and East experienced in-migration, with their neighboring counties also witnessing in-migration (high–high region, where counties with high NMRs are surrounded by counties with similarly high NMRs). Second, counties on the Great Plains constantly underwent out-migration along with neighboring counties (low–low region, where counties with low NMRs are surrounded by counties with similarly low NMRs). Some counties on the Great Plains sporadically experienced in-migration while their neighboring counties faced out-migration (high–low region, where counties with high NMRs are surrounded by counties with low NMRs). Last, certain counties, including in California, Nevada, and Arizona, experienced out-migration while their neighboring counties saw in-migration (low–high region, where counties with low NMRs are surrounded by counties with high NMRs).

Figure A-2: LISA cluster map of NMRs in the contiguous United States, 1970–2010



Aspatial models

We first fitted a series of aspatial models (Table A-2) by decade to evaluate the presence of spatial autocorrelation, as well as spatial lag and error effects, using Moran's *I* for the model residuals and LM-lag and LM-error tests, respectively. The results suggested that environmental factors influenced migration across the decades, with effects also mediated by long-term climatic averages and a county's metropolitan status, even after controlling for conventional socioeconomic factors known to affect migration.

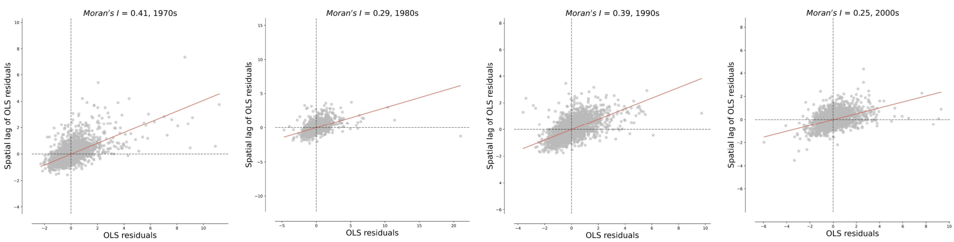
Table A-2: Decade-specific OLS models of all-age NMRs on environmental and socioeconomic factors in the contiguous United States, 1970–2010

	NMR_{All}			
	1970s	1980s	1990s	2000s
Climatic variables				
Prec anomaly	3.44	19.40	0.37	–5.89
	(0.221)	(0.000)	(0.815)	(0.000)
Temp anomaly	15.74	24.90	–20.40	1.40
	(0.000)	(0.000)	(0.000)	(0.531)
Climatic interactions				
Prec anomaly * long-run prec average	–0.13	–0.32	0.01	0.02
	(0.000)	(0.000)	(0.504)	(0.232)
Temp anomaly * long-run temp average	–1.97	–2.82	1.79	–0.16
	(0.000)	(0.000)	(0.000)	(0.360)
Prec anomaly * metropolitan status	–9.92	–3.59	–5.34	–2.85
	(0.000)	(0.015)	(0.002)	(0.000)
Temp anomaly * metropolitan status	4.28	5.70	–22.27	–7.73
	(0.439)	(0.032)	(0.000)	(0.000)
Control variables				
Household income ($1,000s)	–0.97	–0.81	–0.77	–0.14
	(0.000)	(0.000)	(0.000)	(0.000)
Rent ($1,000s)	7.51	56.85	64.89	38.90
	(0.268)	(0.000)	(0.000)	(0.000)
Housing price ($1,000s)	0.57	0.19	0.04	0.00
	(0.000)	(0.000)	(0.000)	(0.464)
Employment (%)	–0.40	–0.16	0.22	–0.01
	(0.000)	(0.000)	(0.000)	(0.803)
Homeownership (%)	0.81	0.58	0.63	0.39
	(0.000)	(0.000)	(0.000)	(0.000)
Metropolitan status	9.45	7.84	2.42	3.64
	(0.000)	(0.000)	(0.018)	(0.000)
Constant	–22.73	–52.87	–57.30	–37.20
	(0.000)	(0.000)	(0.000)	(0.000)
Observations	3,109	3,109	3,109	3,109
R^2	0.22	0.35	0.20	0.26
Log-likelihood	–13,429	–12,135	–12,193	–11,447
AIC	26,884	24,297	24,412	22,919
BIC	26,962	24,375	24,491	22,998
LM-lag	3.00	8.16	14.11	1.65
	(0.083)	(0.004)	(0.000)	(0.199)
LM-error	5.14	9.38	14.69	3.02
	(0.023)	(0.002)	(0.000)	(0.082)

Note: *P*-values are in parentheses. Prec = precipitation. Temp = temperature. AIC = Akaike's information criterion. BIC = Schwartz's Bayesian information criterion.

LM-lag and LM-error tests indicated that spatial lag and spatial error effects were present in the OLS models. Meanwhile, Moran's *I* for OLS model residuals (Figure A-3) demonstrated spatial autocorrelation in the data, indicating a violation of the OLS model's assumption of the independence of residuals. Taken together, these diagnostics suggest the presence of spatial dependence within the data, emphasizing the need for spatial models capable of capturing such autocorrelation; currently employed OLS models do not have this ability. As previously discussed, aspatial models may produce biased or inefficient estimates in the presence of spatial autocorrelation within the data. Additionally, cross-sectional data by decade cannot capture temporal dynamics, such as the evolution of migration responses over time, thereby offering less reliable insights. Consequently, the interpretation of aspatial models will not be the primary focus of this study.

Figure A-3: Moran's *I* for OLS model residuals



We then compiled the data into a panel format and employed aspatial models using a stepwise approach with county and decade fixed effects. This approach allowed for the systematic evaluation of how the inclusion of different sets of variables influenced the model's coefficients and overall fit (Table A-3). The results indicate that both socioeconomic and environmental factors influenced all-age migration patterns. Including environmental variables improved model fit, as demonstrated by an increase in R-squared values when climatic variables and their interaction terms were incorporated. However, R-squared increased by only 0.01 across the three model specifications, suggesting that environmental factors and their interactions account for only an additional 1% of the variance in migration patterns. The modest increase suggests that while environmental impacts are important, their independent contribution to migration is limited. This finding aligns with the literature emphasizing that environmental influences operate alongside a broader set of socioeconomic drivers rather than serving as dominating forces on their own (Beine and Jeusette 2021; Hoffmann et al. 2020; Zhou and Chi 2024).

Table A-3: Fixed effects aspatial models of all-age NMRs on environmental and socioeconomic factors in the contiguous United States

	NMR_{All}	NMR_{All}	NMR_{All}
Climatic interactions			
Prec anomaly * long-run prec average			0.01
			(0.461)
Temp anomaly * long-run temp average			–0.71
			(0.000)
Prec anomaly * metropolitan status			–1.18
			(0.041)
Temp anomaly * metropolitan status			10.19
			(0.000)
Climatic variables			
Prec anomaly		–1.25	–1.37
		(0.002)	(0.090)
Square term of prec anomaly		0.22	–0.02
		(0.609)	(0.958)
Temp anomaly		–7.21	–1.34
		(0.000)	(0.326)
Square term of temp anomaly		–5.20	–7.65
		(0.000)	(0.000)
Control variables			
Household income ($1,000s)	–0.25	–0.29	–0.29
	(0.000)	(0.000)	(0.000)
Rent ($1,000s)	–31.58	–31.92	–31.02
	(0.000)	(0.000)	(0.000)
Housing price ($1,000s)	–0.01	0.01	–0.01
	(0.045)	(0.368)	(0.255)
Employment (%)	0.03	0.04	–0.02
	(0.395)	(0.285)	(0.613)
Homeownership (%)	0.38	0.37	0.45
	(0.000)	(0.000)	(0.000)
Decade effect	Controlled	Controlled	Controlled
County effect	Controlled	Controlled	Controlled
Metropolitan status	Omitted	Omitted	Omitted
Constant	5.83	5.59	3.30
	(0.067)	(0.079)	(0.299)
Observations	12,436	12,436	12,436
Number of counties	3,109	3,109	3,109
R-squared	0.22	0.23	0.24
Log-likelihood	–43,769	–43,685	–43,602
AIC	87,555	87,396	87,239
BIC	87,622	87,493	87,365

Note: *P*-values are in parentheses. Prec = precipitation. Temp = temperature. AIC = Akaike's information criterion. BIC = Schwartz's Bayesian information criterion.

Spatial weight

The first-order Queen criterion defines neighbors as spatial units that share either a common edge or a common vertex, resulting in an average of six neighbors per county (Figure A-4). One issue worth noting is that some counties separated by large water bodies – most notably across the Great Lakes – are treated as neighbors. This occurs because lake surfaces are assigned to adjacent counties, resulting in shared boundaries across the lake. For example, counties in western Michigan and eastern Wisconsin may be considered contiguous despite being separated by Lake Michigan. These instances are limited in number and should not substantially affect the overall neighborhood structure or the estimated spatial effects. Nevertheless, future research could refine spatial proximity definitions by excluding water bodies or by employing distance-based spatial weights to avoid such situations.

Figure A-4: Neighbor structure of counties in the contiguous United States based on the first-order Queen's contiguity weight matrix

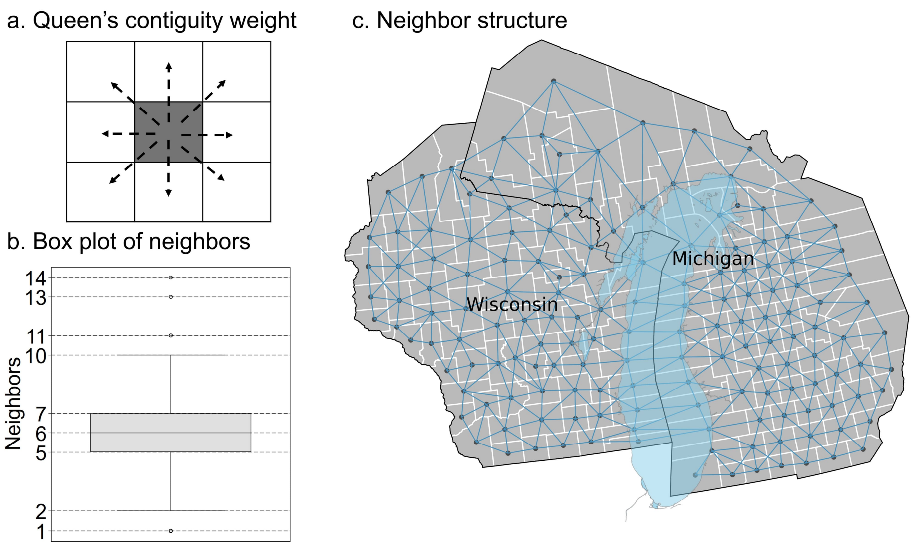
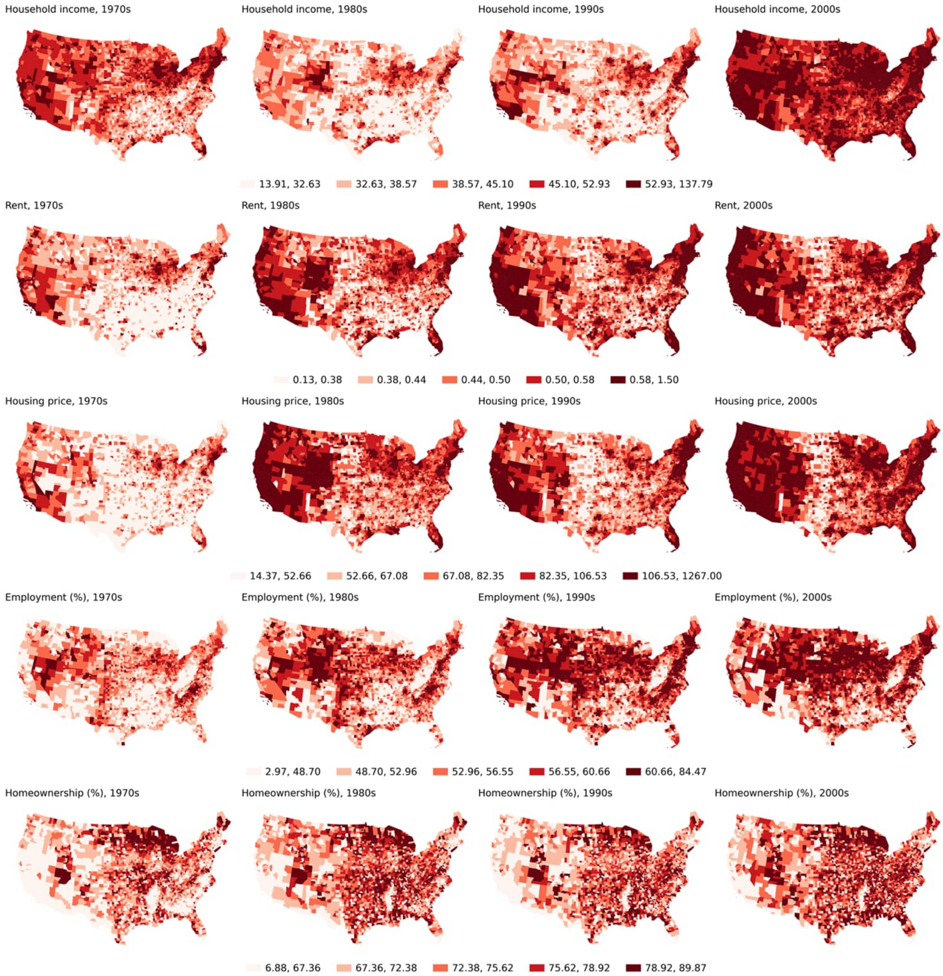


Figure A-5: Spatial distribution of county-level socioeconomic factors in the contiguous United States, 1970–2010



Nonlinearity and sensitivity analyses

Figure A-6: Nonlinear relationship between temperature anomalies and county-level age-specific NMR

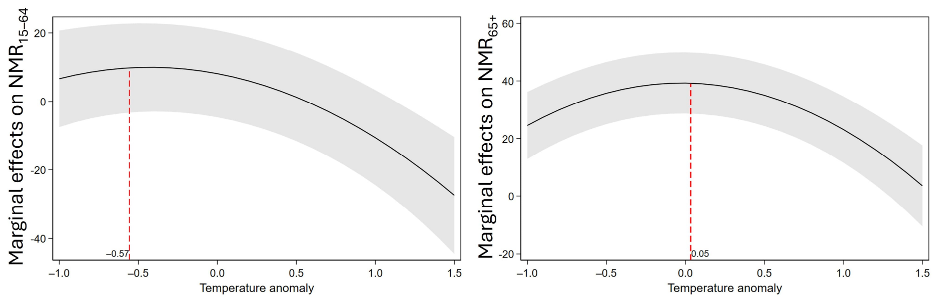


Table A-4: Fixed effects SLMs and SEMs of age-specific NMRs on environmental and socioeconomic factors with square terms in the contiguous United States, 1970–2010

	$NMR_{15–64}$		NMR_{65+}	
	SLM	SEM	SLM	SEM
Climatic variables				
Prec anomaly	2.23	1.86	0.29	–0.04
	(0.108)	(0.266)	(0.792)	(0.979)
Square term of prec anomaly	0.16	0.30	–0.32	–0.17
	(0.738)	(0.671)	(0.385)	(0.765)
Temp anomaly	–9.61	–6.81	0.74	7.26
	(0.000)	(0.015)	(0.703)	(0.001)
Square term of temp anomaly	–5.37	–5.93	–7.91	–8.92
	(0.000)	(0.000)	(0.000)	(0.000)
Climatic interactions				
Prec anomaly * long-run prec average	0.00	0.00	0.00	0.01
	(0.702)	(0.882)	(0.554)	(0.492)
Temp anomaly * long-run temp average	–0.29	–0.45	–0.85	–1.39
	(0.005)	(0.007)	(0.000)	(0.000)
Prec anomaly * metropolitan status	–0.60	–0.68	–0.19	–0.05
	(0.335)	(0.338)	(0.705)	(0.931)
Temp anomaly * metropolitan status	9.28	8.46	3.12	3.70
	(0.000)	(0.000)	(0.001)	(0.000)
Control variables				
Household income ($1,000s)	–0.36	–0.45	–0.09	–0.10
	(0.000)	(0.000)	(0.000)	(0.000)
Rent ($1,000s)	–24.23	–30.58	0.20	1.93
	(0.000)	(0.000)	(0.920)	(0.402)
Housing price ($1,000s)	–0.00	–0.02	0.00	–0.00
	(0.798)	(0.020)	(0.997)	(0.546)
Employment (%)	–0.01	0.01	0.05	0.07
	(0.747)	(0.847)	(0.072)	(0.044)
Homeownership (%)	0.47	0.59	0.32	0.36
	(0.000)	(0.000)	(0.000)	(0.000)
Decade effect	Controlled	Controlled	Controlled	Controlled
County effect	Controlled	Controlled	Controlled	Controlled
Metropolitan status	Omitted	Omitted	Omitted	Omitted
Spatial effect				
W_{NMR}	0.47	0.50	0.49	0.49
	(0.000)	(0.000)	(0.000)	(0.000)
$W_{Prec\ anomaly}$	–3.57	–3.60	–0.31	–0.30
	(0.004)	(0.005)	(0.753)	(0.770)
$W_{Temp\ anomaly}$	6.09	1.64	8.60	7.65
	(0.012)	(0.537)	(0.000)	(0.000)
Observations	12,436	12,436	12,436	12,436
Number of counties	3,109	3,109	3,109	3,109
Log-likelihood	–35,050	–35,003	–32,882	–32,887
AIC	70,140	70,045	65,803	65,814
BIC	70,289	70,194	65,952	65,963

Note: *P*-values are in parentheses. Prec = precipitation. Temp = temperature. AIC = Akaike's information criterion. BIC = Schwartz's Bayesian information criterion.

Table A-5: Fixed effects SLMs and SEMs of age-specific NMRs on environmental and socioeconomic factors with square terms in the contiguous United States, 1970–2010

	***NMR**$_{20–29}$*		***NMR**$_{30–39}$*		***NMR**$_{40–64}$*	
	SLM	SEM	SLM	SEM	SLM	SEM
Climatic variables						
Prec anomaly	0.92	0.54	1.90	1.11	2.99	2.80
	(0.635)	(0.815)	(0.408)	(0.682)	(0.035)	(0.099)
Square term of prec anomaly	0.15	0.26	0.70	1.04	–0.17	–0.00
	(0.822)	(0.790)	(0.367)	(0.362)	(0.725)	(0.996)
Temp anomaly	–20.21	–25.84	–21.10	–19.13	–1.39	6.14
	(0.000)	(0.000)	(0.000)	(0.000)	(0.577)	(0.031)
Square term of temp anomaly	–6.73	–8.33	–4.71	–5.26	–5.27	–4.95
	(0.000)	(0.000)	(0.018)	(0.053)	(0.000)	(0.004)
Climatic interactions						
Prec anomaly * long-run prec average	0.02	0.02	0.01	0.00	–0.00	–0.01
	(0.096)	(0.309)	(0.620)	(0.840)	(0.720)	(0.718)
Temp anomaly * long-run temp average	0.79	1.32	–0.07	–0.08	–0.90	–1.48
	(0.000)	(0.000)	(0.665)	(0.755)	(0.000)	(0.000)
Prec anomaly * metropolitan status	1.52	1.42	–2.12	–2.04	–1.02	–1.03
	(0.082)	(0.150)	(0.041)	(0.080)	(0.111)	(0.155)
Temp anomaly * metropolitan status	11.23	9.78	19.39	17.95	5.09	4.59
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)
Control variables						
Household income ($1,000s)	–0.43	–0.48	–0.46	–0.61	–0.33	–0.41
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Rent ($1,000s)	–7.50	–10.71	–53.88	–65.95	–23.81	–29.52
	(0.036)	(0.007)	(0.000)	(0.000)	(0.000)	(0.000)
Housing price ($1,000s)	–0.02	–0.04	–0.01	–0.04	0.01	–0.00
	(0.046)	(0.000)	(0.164)	(0.002)	(0.175)	(0.881)
Employment (%)	–0.26	–0.31	0.18	0.27	0.09	0.13
	(0.000)	(0.000)	(0.004)	(0.000)	(0.020)	(0.002)
Homeownership (%)	0.12	0.14	1.04	1.33	0.58	0.71
	(0.027)	(0.024)	(0.000)	(0.000)	(0.000)	(0.000)
Decade effect	Controlled	Controlled	Controlled	Controlled	Controlled	Controlled
County effect	Controlled	Controlled	Controlled	Controlled	Controlled	Controlled
Metropolitan status	Omitted	Omitted	Omitted	Omitted	Omitted	Omitted
Spatial effect						
W_{NMR}	0.44	0.01	0.42	0.47	0.46	0.48
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$W_{Prec\ anomaly}$	–5.39	–6.17	–4.86	–5.10	–2.69	–2.41
	(0.002)	(0.001)	(0.018)	(0.016)	(0.034)	(0.067)
$W_{Temp\ anomaly}$	–0.96	–6.65	9.03	1.36	9.61	7.59
	(0.776)	(0.068)	(0.024)	(0.753)	(0.000)	(0.005)
Observations	12,436	12,436	12,436	12,436	12,436	12,436
Number of counties	3,109	3,109	3,109	3,109	3,109	3,109
Log-likelihood	–38,100	–38,079	–39,691	–39,623	–35,233	–35,203
AIC	76,239	76,199	79,421	79,286	70,506	70,446
BIC	76,388	76,348	79,570	79,435	70,655	70,595

Note: P-values are in parentheses. Prec = precipitation. Temp = temperature. AIC = Akaike's information criterion. BIC = Schwartz's Bayesian information criterion.