

Income strongly moderates climate-driven migration

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Understanding how climate change will reshape human migration remains an open empirical challenge. Migration decisions reflect a complex interplay of environmental and socioeconomic factors, yet existing data and models have struggled to capture this interaction at a global scale. To address this, we assemble spatially granular, long-panel migration data covering nearly the entire world and develop a statistical model that captures how both climate and income dynamics shape rural-to-urban migration responses. Using this new approach, we uncover a strong and globally robust dependence of climate-driven migration on income levels, as well as a nonlinear relationship between internal migration and climate. We then use these relationships, together with international migration data, to project how immigration pressures will be shaped by the interaction between warming and income growth. Our findings show that the magnitude and geography of climate-induced migration will depend critically on how quickly incomes rise across the world.

climate migration | income | adaptation | internal migration

Main Text:

Prospects for climate-driven human migration, while potentially of significant consequence for societies and policymakers, remain difficult to project (1, 2). This challenge stems both from the complexity of migration decisions (shaped jointly by environmental shocks and income opportunities) and from the lack of harmonized, spatially granular data tracking migration over time and across the globe (3–5). Climate change can alter migration patterns by reshaping local economic opportunities, agricultural productivity, and living conditions (6–8). Yet, there may be substantial heterogeneity in these responses across settings, reflecting variation in both climatic exposure and the capacity to adapt or move (9–12).

Prior research has documented nonlinearities in temperature–migration relationships (13, 14), income dependence in climate sensitivity (8, 15, 16), and larger responses in rural settings (17–19). Different lines of work have provided these insights through varying lenses: some analyzing specific countries or regions, others using coarser spatial units or shorter time horizons, and still others offering global correlations or projections (20, 21). Each of these perspectives sheds light on part of the overall relationship between climate and migration, yet these insights have typically been examined separately. Here we combine these elements in a comprehensive framework, assembling spatially granular migration data that span nearly the entire world and developing a long-run panel model that captures within-location variation over more than four decades. The analysis is conducted at the level of half-degree ($0.5^\circ \times 0.5^\circ$) grid cells intersected with first-level administrative regions, rather than only at national or large subnational scales. Our model focuses on internal, predominantly rural-to-urban migration, which serves as a key channel through which climate pressures manifest and accumulate within countries (15, 22). Given the heterogeneity in these responses across income levels and the structure of existing cross-border migration links, this framework provides a comprehensive global analysis that connects internal movements to international migration pressures and enables projections of how global migration pressures may evolve under warming and income-growth scenarios.

Recent data efforts have produced spatially resolved hindcasts of net migration in 5-year intervals using a combination of satellite and census data, yielding the most consistent and transparent global migration estimates to

Significance

Despite widespread interest in the topic, understanding how climate change will reshape human migration remains an open empirical challenge. Using a new model specification, we identify a globally robust, nonlinear dependence of climate-driven migration on income levels, as well as a nonlinear relationship between internal migration and climate. The pattern implies that climate-driven emigration peaks among middle-income populations. We present a framework that links these estimated internal migration responses to international mobility patterns. Applying these empirical relationships, together with international migration data, demonstrates that global climate-induced migration pressures will depend critically on how quickly incomes rise across the world.

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GK and KR conceived of the study and procured the funding. JSW conducted the climate data analysis. IG conducted the geospatial analysis, processing of population and migration data, constructed the sample, and did data validation checks. PP executed the primary econometric analyses, Monte Carlo analysis, and the projections. JL conducted the IPUMS analysis and developed the LASSO robustness tests. GK and KR supervised the research. All authors wrote the paper.

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date, validated against official statistics (5). For the following analysis, we carefully partition rural observations (see Materials and Methods), focusing on rural-to-urban migration for two reasons. First, the literature shows that rural communities are substantially more climate sensitive (8, 17, 23). Second, urbanization has been the dominant form of internal migration over the past century (24, 25), so even small climate-driven shifts in rural-to-urban flows translate into a large share of total climate-induced movement. Because this type of migration dwarfs other forms of internal migration at the global scale, it provides a natural starting point for quantifying overall climate-driven migration pressures. Our dependent variable, rural out-migration, is derived directly from net migration estimates. We interpret changes in net migration for rural locations as changes in rural outflows, an assumption justified by the overwhelming dominance of rural-to-urban moves relative to urban-to-rural or long-distance rural-to-rural moves across most of the world over the past half-century (24–26). Outside some supporting sensitivity analysis, we exclude all observations corresponding to urban areas from our primary analysis, thereby setting aside urban-to-urban mobility, the other major component of internal migration.

We develop a two-stage analytical framework to project future internal and international migration pressures (Fig. 1). First, we estimate income-dependent relationships between climate variations and rural-to-urban migration over 5-year intervals using panel data on historical grid-cell rural migration rates (5) and income measures (27), matched to grid-cell climate (28, 29). Panel data repeatedly observe the same grid-cell over time, allowing to compare within-cell changes across different periods. We then apply these estimated historical relationships to climate projections (30) for the coming decades to construct grid-cell level forecasts of climate-driven rural out-migration. Second, we use panel analysis of harmonized international survey data (31) to quantify how country-level internal migration patterns shape international emigration. These estimated linkages are embedded within a source–receptor model (32, 33) to project changes in international migration pressures under scenarios that both exclude and incorporate future income growth.

Income as the dominant moderator of climate-driven migration

Income can shape climate-driven migration through several channels. Low-income households often lack the liquidity to finance migration and can become “trapped” in place when adverse conditions intensify (10, 11). Middle-income households have both the resources to move and livelihoods that remain vulnerable to climatic shifts, making them the most responsive. High-income households, by contrast, tend to have better local opportunities, alternative adaptation strategies, and derive livelihoods less directly tied to climate-sensitive sectors (8, 9, 34), dampening their migration response. Consistent with the theoretical outcome of combining these competing moderating effects, we find a strong inverted-U-shaped income gradient in the relationship between climate variation and rural out-migration. This pattern implies that climate-driven emigration peaks among middle-

income populations. While prior studies on rural–urban migration (15), cross-border migration (35), and internal rural mobility (36) have each documented versions of this inverse-U pattern, these insights have largely emerged from specific national or regional contexts. Our analysis provides the first comprehensive and globally consistent evidence that this relationship is a universal feature of climate-driven migration.

In our analysis, income levels vary across grid cells, allowing us to examine how the climate–migration relationship changes across the income distribution. We identify the inverted-U-shaped income gradient in the historical relationships between both temperature and precipitation variations and rural out-migration (Fig. 2A–B). Accounting for these nonlinear interactions between climate and income is essential for identifying the climate effects on rural-to-urban migration. In contrast, models that include temperature and precipitation alone, or only linear interactions with income, yield effects that are neither consistent nor statistically significant ($p < 0.05$) (Table S2).

In the inverse-U-shaped relationship between temperature-induced rural out-migration and income (Fig. 2A), migration rates peak among middle-income groups that may have more financial resources to migrate and be economically exposed to rising temperatures. A similar pattern emerges for precipitation changes (Fig. 2B). We control for the underlying, climate-independent association between rural out-migration and income in our estimation, but omit it from the projections (see Methods), as the causal direction between income and migration is inherently ambiguous, and our objective is to isolate the climate-induced component of migration.

We project future changes to internal migration for several prominent countries in the temperature–income space (Fig. 2D), with arrows indicating projected changes under the SSP2-4.5 “middle-of-the-road” scenario. India, for example, currently experiences high temperatures and is middle-income; further warming is likely to increase rural emigration, and the amount of income growth expected over the next 25 years exacerbates this effect. In China, warming likewise increases emigration, but rising incomes expand adaptation options as China’s baseline income has already surpassed the income at which migration rate peaks. Unlike in India, rising incomes in China are therefore expected to reduce climate-driven rural out-migration. Rising incomes also dampen the sensitivity of rural out-migration to precipitation changes (Fig. 2E).

By contrast, and consistent with both the construction of the dataset and dominant migration patterns over the past four decades, climate-driven migration in urban areas follows an inverse, but statistically weaker relationship than in rural settings (Table S7, Fig. S4). Temperature-driven urban in-migration also reaches its minimum at middle incomes, reflecting urbanization as an adaptation response to rural climate shocks.

Climate’s signature in historical rural migration

After controlling for nonlinear income dependence, we find that – while sensitivities vary – warmer and drier conditions are associated with higher rural out-migration rates (Fig. S5). The effects of temperature and precipita-

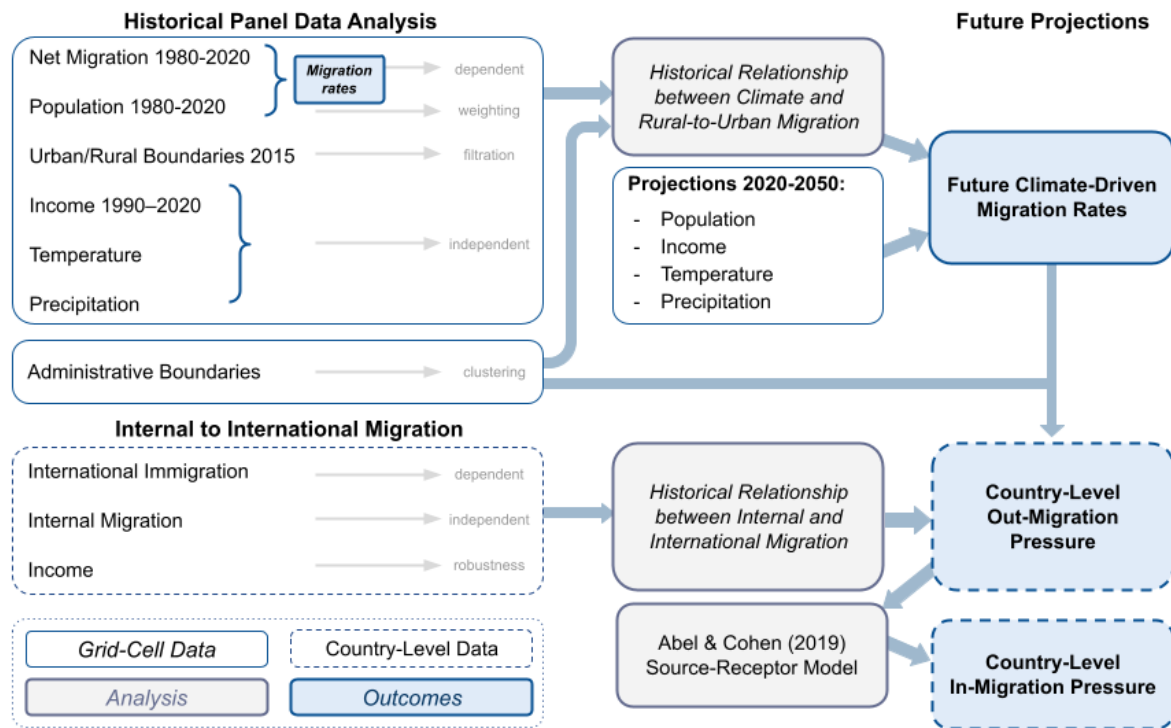


Fig. 1. Schematic of Data Processing & Analysis. We assemble a global grid-cell panel (1980–2020) with net migration, population, 2015 urban–rural boundaries, per-capita income (1990–2020), temperature, and precipitation, using administrative boundaries for clustering. We then combine these data with several sources of administrative boundaries to maximize global coverage of subnational units across countries to construct the panel data at the main unit of analysis: grid cell by administrative region. These data identify the historical relationship between climate and rural-to-urban migration via fixed-effects econometric models with income interactions (Materials and Methods). Fixed-effects models account for persistent differences across grid-cells, focusing on changes from a baseline outcome occurring within grid-cells over time. Using the estimated historical relationships from the econometric model and combining them with projections for 2020–2050 of population, income, temperature, and precipitation, we generate future climate-driven internal migration rates at the grid-cell level. In the lower part of the figure, we describe how an auxiliary specification links internal migration to international immigration using country-level data on immigration and income, and a source–receptor accounting of bilateral flows to translate grid-cell movements into country-level out-migration and in-migration pressure (based on Abel and Cohen flow matrices (32, 33)). White boxes denote data inputs (solid outlines for grid-cell data and dashed boxes for country-level data). Gray boxes denote analysis steps, and blue boxes denote derived model estimations and projection output. Blue arrows trace the flow of our empirical estimations and projections modeling: from historical estimations to capture the historical relationship between climate and migration to future projections, with additional analyses aggregating our grid-cell level data to country-level estimates. See Materials and Methods for data sources, variables, and the full model specifications.

tion on rural out-migration are highly significant ($p < 0.01$) (Table S2).

While in most places warmer temperatures drive higher emigration rates, the dependence is nonlinear. The marginal effect of additional warming varies substantially by income, with higher sensitivity for rich locations at high temperatures and poor locations at low temperatures (Fig. 2D, Fig. S5A). Contrary to the rest of the world, in the poorest, hottest places, each warmer five-year period dampens migration, possibly driven by the high damages of heat shocks in the most climate vulnerable societies (37), likely restricting households' ability to finance moves. We note that climate-driven migration in our 45-year study period has occurred in the context of a universally warming climate (Fig. 2C), making our findings challenging to disentangle from lower-frequency (multidecadal) variability.

Precipitation-driven rural out-migration likewise exhibits a robust nonlinear income dependence (Fig. S5B), but we do not identify any significant nonlinearity in the relationship between precipitation itself and migration. Drier conditions are associated with higher rural out-migration in both the highest and lowest income locations and a small but statistically insignificant decrease at middle incomes (Fig. 2E, Fig. S5). Unlike temperature, rural locations in the dataset experience a more heterogeneous

range of low-frequency changes to precipitation, both wetting and drying over the study period (Fig. 2F).

Because migration decisions often unfold over time and individuals may not relocate in response to a single short-lived shock, we view a five-year period as a reasonable interval of analysis. Moreover, globally consistent, spatially resolved migration data are typically unavailable at shorter timescales, making the five-year focus both practical and conceptually appropriate. Our main estimand is the relationship between plausibly exogenous climate variation and migration, conditional on grid-cell and time fixed effects, but we use distributed-lag exercises to test whether this relationship is materially altered when allowing for delayed climate responses. In order to investigate whether five-year mean temperature and precipitation are sufficient climate metrics for migration analysis, the explanatory power of additional measures of climate and climate change, as well as one-period lagged climate and migration variables, were tested in alternative model specifications (see Materials and Methods). Measures of the rate of temperature and precipitation change (i.e., trend) and the volatility of climate state (i.e., variability) were generated from the same environmental observations (28, 29) (Fig. S11). While we find that in some cases the rate of change or the higher-frequency variability to have a statistically significant relationship with rural

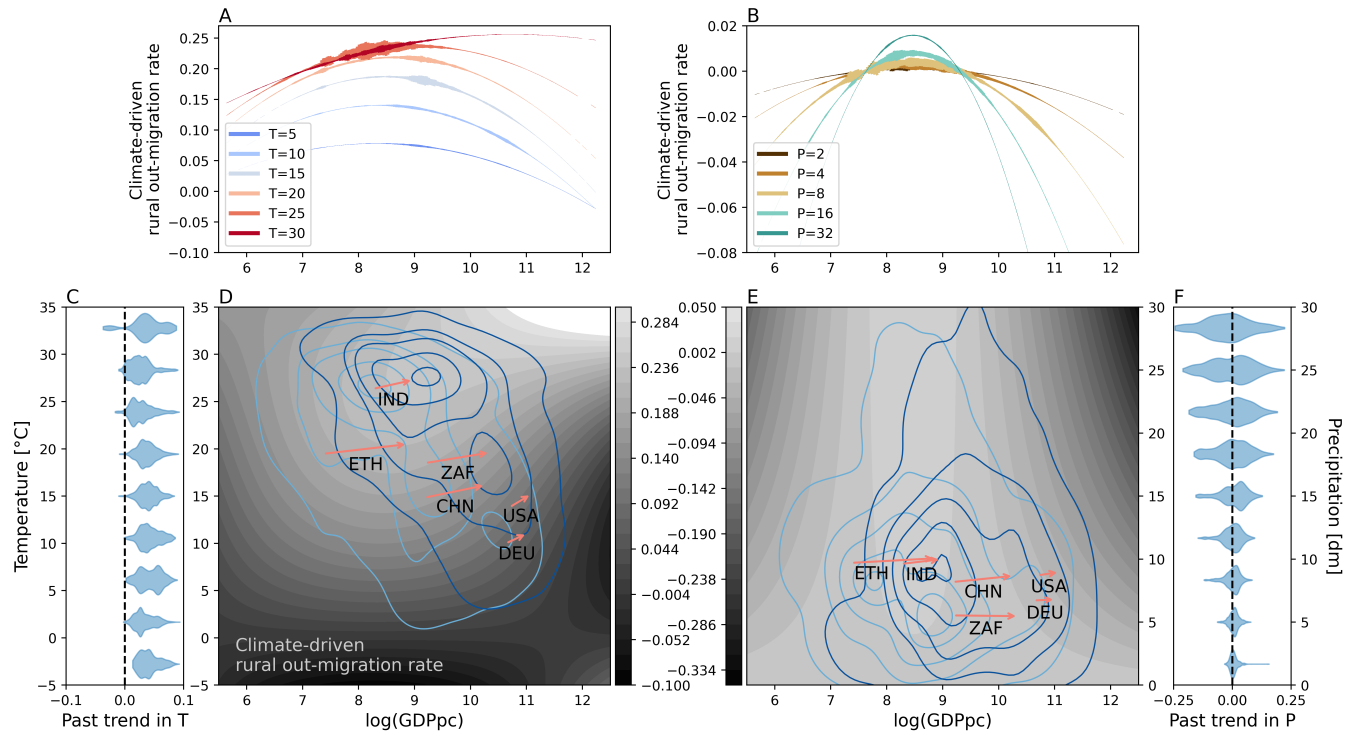


Fig. 2. Empirical characterization of climate-driven migration. Climate-driven rural out-migration rate shown as a function of log(GDPpc) and temperature (A) and precipitation (B) in color. Line width indicates the number of historical observations in the bin. Joint climate and log(GDPpc) results are shown in shaded contours for temperature (C) and precipitation (D), with the historical and 2050 projected (SSP2-4.5) distributions shown in contour lines. The arrows indicate the change from 2015 to 2050 of select countries (China, CHN; Ethiopia, ETH; Germany, DEU; India, IND; South Africa, ZAF; the United States, USA) for SSP2-4.5. Though the absolute values differ, the range of shading is the same in (D) and (E). Lastly, we include binned histograms of trends over the observational period of temperature (C) and precipitation (F).

out-migration (Fig. S9), the magnitude of the effect of changes to these variables on projected future rural out-migration is minimal compared to the effect of five-year mean temperature or precipitation.

To take an agnostic approach to variable selection in the face of extensive model specification options, we also applied a LASSO (Least Absolute Shrinkage and Selection Operator) variable-selection approach to select and test the implications of alternative model specifications. The LASSO helps identify the most relevant predictors from a large set of potential confounders while limiting the risk of overfitting (see Materials and Methods). We found that LASSO-generated models considering a wider selection of climate metrics and their linear combination did not provide additional power or substantially alter the projections relative to the more parsimonious and interpretable model we present here (Tab. S6). We test the global temperature relationship identified by our preferred specification at the grid-cell level (akin to (38)), and find that the global and local linear slopes are statistically indistinguishable for approximately 78% of grid cells (Fig. S6), and at least 72% of grid cells on all continents (Fig. S7).

Using our model of historical climate migration, climate model output, and gridded estimates of future income, we apply a Monte Carlo approach to project future climate-driven migration that accounts for empirical climate and statistical model uncertainties under four Shared Socioeconomic Pathways (SSP1-2.6, SSP2-4.5, SSP3-7.0, and SSP5-8.5). The results are shown in Fig. 3, and further details in the Methods section.

Projections using fixed 2015 income levels consistently show an increase in climate-driven rural out-migration nearly everywhere (Fig. 3, Fig. 3A) with the largest changes and uncertainty associated with the higher warming pathways (SSP3-7.0 and SSP5-8.5). However, including income growth reduces climate-induced rural migration in much of the world, because many locations are already near or beyond the income at which climate-driven migration is maximized (Fig. 4A, Fig. 4B, Fig. 3B). In this income-varying case, the largest changes and uncertainty associated with the high growth pathways (SSP1 and SSP5) illustrate the dominance of income in determining climate-driven rural migration pressures (Fig. 3B).

Robust increases in rural out-migration are concentrated in relatively few countries in parts of Africa and Asia (Fig. 4B). Most countries are projected to have substantial decreases in rural out-migration when both climate and income are allowed to vary. This includes wealthier regions — such as North America and Europe, but also parts of China, Indonesia, Latin America, and South Africa — which all experience lower out-migration as higher incomes facilitate alternative adaptation strategies. By contrast, sub-Saharan Africa, the Middle East, and Central Asia continue to exhibit high rates of rural-urban migration. In these regions, projected income growth from low to middle levels increases households' ability to finance migration while livelihoods remain highly climate-sensitive, thereby sustaining elevated migration flows (8). Consistent with our finding of income as the driving moderator of climate-driven migration, the

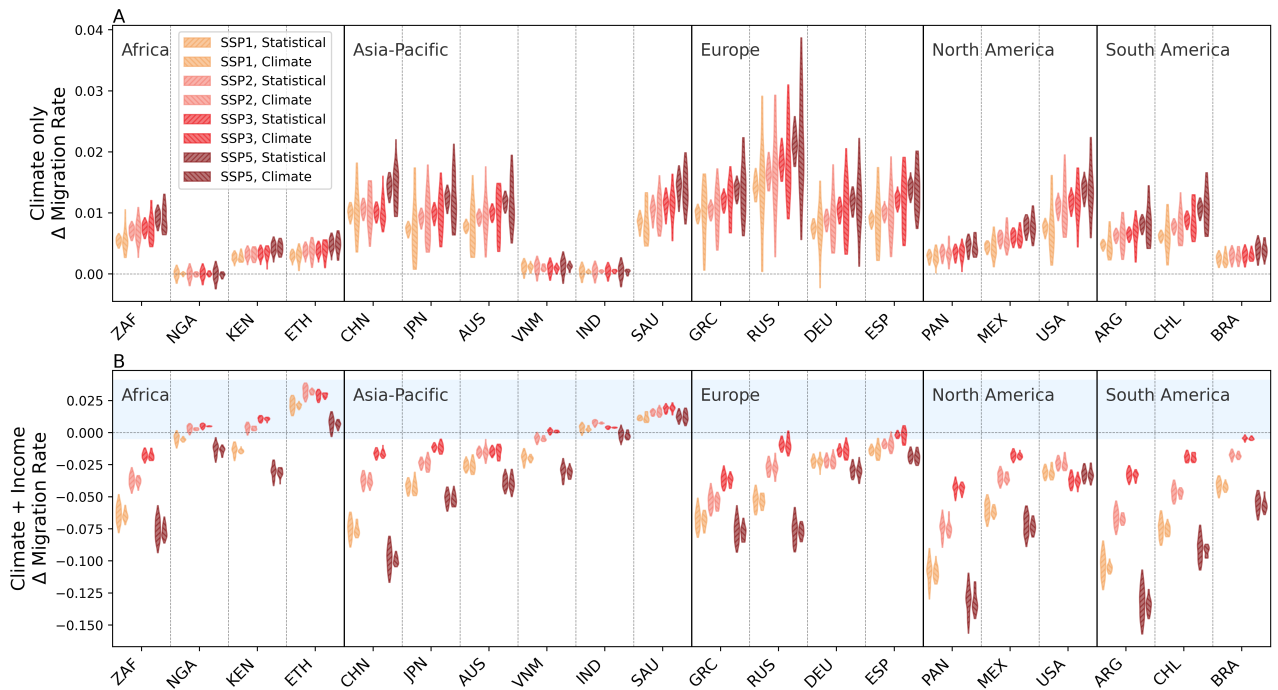


Fig. 3. Projected changes to climate-driven migration rates in 2050 relative to 2015 for select countries and for different SSPs, together with the associated uncertainties. Projections using a changing climate and fixed income are shown in (A), and projections using a changing climate and changing income are shown in (B). Shared Socioeconomic Pathways (SSP1-2.6, SSP2-4.5, SSP3-7.0, and SSP5-8.5) are designated by color. Countries are labeled with ISO 3166 codes. Uncertainty ranges are decomposed into statistical uncertainties that arise from errors associated with the regression and climate uncertainties that arise from differences between climate models (indicated in hatching).

magnitude of migration rate is generally much larger when using time-varying income projections. Since global and local economic growth vary by socioeconomic scenario, the timing and magnitude of projected changes is sensitive to the choice of SSP (Fig. 3B).

Cross-border migration pressures

Changes in rural–urban migration are also likely to generate migratory pressures across national borders. Increased internal mobility can exacerbate urban stresses, which in turn may spur greater emigration abroad. To examine these dynamics, we use the IPUMS International database (31), which harmonizes census and survey data from 43 countries over 1985–2017 (see Materials and Methods). Country-level internal migration is strongly and significantly associated with subsequent international migration pressures (Fig. S10). To project the likely destinations of these emigrants, we draw on historical bilateral migration patterns (32, 33). Combining these steps allows us to illustrate that the geographic distribution of future migratory pressures worldwide will depend strongly on economic development trajectories (Fig. 4C–F). We characterize our projected changes in international migrants and associated increases or decreases in migration “pressures,” recognizing that strong and adaptive policy constraints on international immigration mean that even where motivation to migrate exists, feasible pathways may not.

Keeping income levels constant, China emerges as a major sending country (due, in part, to its large population), with roughly 819,000 projected migrants over each 5-year period (Fig. 4C, Table S5). However,

when income growth is incorporated (Fig. 4D), China’s projected emigration declines sharply, consistent with the idea that rising incomes facilitate alternative adaptation strategies and reduce climate sensitivity. By contrast, out-migration pressures from India and several sub-Saharan African countries increase markedly, intensifying cross-border migration pressure. Under SSP2-4.5, in 2050, average income in rural India is projected to be close to those associated with peak climate-driven migration. We project that in 2050, in India alone, out-migration pressure increases by about one million migrants every five years.

Reflecting its historical role as a primary destination for migrants from Latin America and China, the United States shows the largest projected increases in inflow pressures when incomes are held constant (Fig. 4E), receiving roughly 432,000 climate migrants every 5 years. Yet when income growth is incorporated (Fig. 4F), U.S. border pressures are instead projected to decrease by 833,000 migrants every five years, as many key sending countries may adapt through non-migration strategies or experience reduced climate dependence. In contrast, intra-African migration pressures intensify, with several African countries projected to experience increased inflow pressures from neighboring states experiencing rising emigration rates.

Robustness. We subject our main results to a series of robustness checks that examine whether they depend on functional form, interaction structure, sampling variation, or specific modeling choices (details in Methods: Robustness Analyses). Across these exercises, the qualitative conclusions remain unchanged.

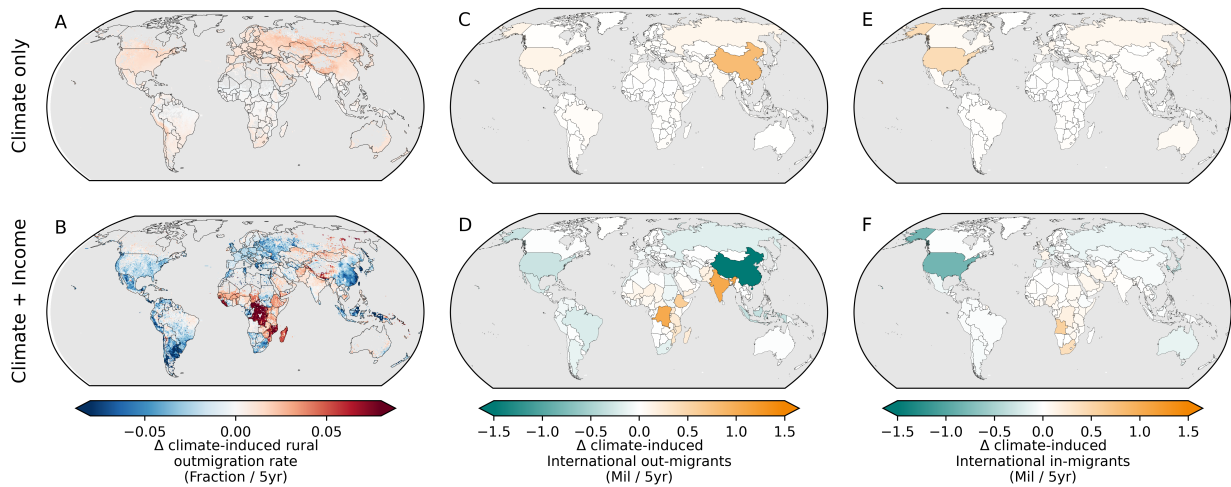


Fig. 4. Projections of climate-induced rural out-migration rates and international migration in 2050 relative to 2015. Change in climate-induced rural out-migration rate (**A**, **B**), change in climate-induced international in-migrant number (**C**, **D**), and change in climate-induced international out-migrant number (**E**, **F**). The top row (**A**, **C**, **E**) shows results for projections in which income is fixed at 2015 levels and only the climate is changed. The bottom row (**B**, **D**, **F**) shows results for projections in which both income and climate change.

We begin by comparing the global nonlinear specification to local linear relationships estimated separately at each rural grid cell. Approximately 78% of grid cells have local linear temperature coefficients whose 95% confidence intervals contain the marginal effect implied by the global model when evaluated at the corresponding covariate values (Fig. S6). These grid cells are geographically dispersed and do not cluster in particular regions of the world; in every continent, at least 72% of grid cells pass this test (Fig. S7). The results are insensitive to whether income enters linearly or quadratically and to the inclusion of precipitation as a control, indicating that the global nonlinear relationship is broadly consistent with locally estimated effects.

Next, we assess how results evolve as the specification is built up incrementally. When the model includes only climate variables and fixed effects (i.e. excluding income) temperature terms are not statistically significant, and only precipitation shows any statistical significance ($p < 0.05$ for precipitation, $p > 0.1$ for temperature terms; Table S2). Only when including both quadratic temperature with quadratic income interactions do the results become highly significant ($p < 0.01$). Adding a quadratic precipitation term eliminates statistical significance for precipitation entirely, which we interpret as overfitting; for this reason, we retain a parsimonious linear precipitation term in the preferred specification. Importantly, projection results are not materially affected by these modeling choices (Fig. S9, comparing specifications 1 and 0). Repeating the analysis with standard errors clustered at the country level yields larger p-values, as expected, but most terms remain statistically significant at conventional levels (Table S3).

We then turn to sampling uncertainty. Monte Carlo re-sampling exercises show that coefficient estimates remain stable even under highly conservative sampling schemes. As expected, sparser samples produce wider distributions of estimated coefficients (Fig. S12). Nevertheless, even when the sample is restricted to a single grid cell per administrative unit, all climate coefficients retain the same sign, and average magnitudes remain comparable

to those obtained using denser samples, and tend to be slightly larger under the most conservative sampling.

Finally, we examine a wide range of alternative specifications. Adding quadratic precipitation terms, temperature–precipitation interactions, climate trend and variability measures, lagged climate variables, or lagged migration does not materially affect the results (Fig. S9). Replacing the quadratic temperature term with an interaction between temperature and long-run mean temperature yields similar projections, indicating that the interpretation of the nonlinear temperature response does not rely on a specific functional form. Results are also robust to adopting a more conservative definition of rural areas that excludes any grid cell containing urban sub-cells. Coefficients for lagged specifications are shown in Table S4 and also yield largely consistent projections (Fig. S9).

While not easily partitioned from rural-to-urban migration within urban cells, urban-to-urban mobility is also likely to be an important component of climate-driven migration. When the analysis is restricted to urban locations, temperature effects remain statistically significant under administrative-unit clustering but weaken substantially under country clustering, while precipitation effects are generally insignificant (Table S7).

Further details on methods are in Methods: Robustness Analyses, and on alternative specifications are in SI Appendix.

Discussion

A wide range of regional, location-specific studies have documented a nonlinear relationship between climate, migration, and income. Our analysis demonstrates that this pattern is both robust and universally consistent, revealing income as a central moderator of climate-driven migration. Across the world, and in response to both thermal and hydrological stress, migration emerges as an adaptation strategy that individuals pursue when they have the means to do so, but tend to forgo once they become sufficiently affluent. Projected income growth

does not, however, imply that societies can simply grow out of climate-induced migration. Growth can be unevenly distributed, may leave vulnerable populations exposed, and can itself be linked to emissions and future climate damages. We interpret the income results as evidence that migration pressures depend on the interaction between warming, vulnerability, mobility constraints, and adaptation capacity, rather than as evidence that income growth alone can solve the problem of climate-driven migration.

Certain limitations of our empirical analysis warrant discussion. First, because precise localized migration flows are difficult to capture directly, our analysis relies on interpolated migration data. Consequently, there remains inherent uncertainty in the local net migration estimates, and our results should be interpreted as identifying broad global relationships rather than exact local population movements. Second, while the proposed mechanisms (e.g., agricultural distress) underpinning these relationships are plausible and well-supported by the existing literature, our empirical strategy does not separately identify or isolate each individual pathway within the analysis. Instead, we provide a reduced-form relationship between climate and migration without stressing any particular mechanism.

The global gridded migration dataset we examine is the product of high-resolution satellite observations of the built environment combined with national and subnational administrative unit census-based measurements (5). Unlike previous gridded migration datasets (3, 4, 39), the analytical approach applied in its construction was formulated with the goal of promoting the analysis of climate migration and urbanization at a high spatial resolution (5). Nonetheless, this imputed dataset is best suited for examining globally generalizable features of the relationship between migration patterns and climate, not for making precise local projections. The advantage of such a gridded global dataset, over more precise local or aggregate measures, is that it makes feasible an analysis that exploits the heterogeneous climate variability associated with the entirety of human settlements. In recognition of the potential limitation of using grid-cell-level migration data that rely on imputation methods, we conduct numerous robustness checks that provide confidence in our findings. For instance, even with standard errors clustered conservatively at the country level, the fundamental relationships identified between rural migration rates and temperature, precipitation, and income are robust (Table S3).

While we present a comprehensive framework for understanding the interdependencies between local, national, and international migration pressures, the estimates we present are incomplete. We do not account for other important types of climate migration, in particular, expected changes to forced migration from large disasters such as stronger tropical cyclones or floods. Urban-to-urban migration is also a major component of internal migration and not easily partitioned in the dataset we utilize, but likely to be influenced by climate change in ways which are distinct from rural-to-urban drivers. To the extent that evidence about and projections of these types of migration can be generalized, and established as independent from economically driven rural-to-urban migration, other forms of climate-driven migration can be readily incorporated into our larger framework to

understand how they may counteract or amplify each other.

Our estimates suggest that climate-driven international migration is likely to rise by several hundred thousand people a year – a relatively small share of global migration, but still meaningful for the regions where these pressures will concentrate. The pattern is regionally heterogeneous: as countries move from low to middle incomes, particularly in parts of Africa and Asia, they become more sensitive to climate stress, and contribute more to cross-border migratory pressures. Other countries may see pressures ease as incomes and adaptation capacity grow. Taken together, these projections show that the trajectory of climate-driven migration will depend as much on economic development as on warming itself. This underscores the need for policies that strengthen adaptation and reduce vulnerability, particularly in emerging economies, and that manage cross-border mobility proactively, including through viable legal pathways in places where climate pressures are expected to intensify.

Methods

Data Sources and Processing: Summary. Our analysis combines globally gridded data on population, migration, income, and climate, harmonized to a common spatial and temporal framework. This section provides a high-level overview; full source documentation, construction choices, and processing details are reported in SI Appendix.

Population and net migration. We use gridded population data from the Global Human Settlement Layer (GHSL), available at 1 km resolution in five-year intervals from 1975 to 2020 (40). Net migration at the same resolution and quinquennial frequency (1980–2020) is taken from the European Commission Joint Research Centre (JRC) framework (5, 39). These migration estimates are constructed using a demographic balancing identity in which cell-level population change equals natural increase (births minus deaths) plus net migration; births and deaths are downscaled from UN DESA World Population Prospects and spatially allocated by the JRC, and net migration is obtained as the residual (39, 41). We compute migration rates as net migrants divided by population and exclude clear outliers at the cell level. SI Appendix provides full details on the GHSL population surface and the JRC imputation procedure, including the treatment of vital rates across the urban–rural continuum. Further details about the data construction and validation against official statistics can be found in (5).

Rural sample and spatial aggregation. To focus on rural migration, we exclude urban areas using GHSL Functional Urban Area (FUA) boundaries (42). FUAs are treated as fixed over time to ensure a consistent rural sample. Grid cells fully inside FUAs are dropped, while partially intersecting cells are treated as border cells from which only the non-FUA portions are retained (see SI Figures S1 and S2). Because global processing at 1 km is computationally infeasible, we first aggregate population and migration inputs to a 5-arc-minute (≈9km) grid and then aggregate to the analysis resolution; the full step-by-step spatial processing algorithm and robustness checks are described in SI Appendix.

Administrative identifiers and analysis units. All demographic variables are ultimately aggregated to half-degree ($0.5^\circ \times 0.5^\circ$) grid cells intersected with first-level administrative regions (ADM1). We construct administrative identifiers by combining GADM v4.1 and World Bank subnational boundary layers (43, 44). This yields a panel of half-degree-by-ADM1 units that preserves within-country heterogeneity while aligning with the climate data resolution; additional details are in SI Appendix.

Income (GDP per capita). We use gridded GDP per capita as a proxy for local income. Historical GDP per capita (PPP, 2017 international USD) is taken from Kummu et al. (2025) (27), which harmonizes national and subnational accounts and downscales them to fine spatial resolution. We align these data to our working grid and (for consistency across outcomes) compute total GDP and GDP per capita using the same GHSL population counts used for migration (40). We then aggregate GDP and population to the half-degree-by-ADM1 units and compute per-capita GDP at that scale, applying the same rural/urban filtering described above. SI Appendix provides complete details on harmonization, aggregation, and consistency checks. For projections, we use SSP-based gridded GDP per capita data (45) and gridded population projections (46); to avoid discontinuities between historical and SSP series, we use SSP growth rates to extend the historical series (see SI Appendix). To verify that the relationship between and migration is not mechanical, residualized GDP per capita and rural outmigration rate observations are plotted against each other in Fig. S8.

Final sample restrictions. After aggregation, we begin with approximately 76,000 half-degree grid cells with population data. We drop cells with sparse underlying population support, cells with missing migration data, and cells with extremely low GDP per capita. We winsorize GDP per capita at an upper bound of \$200,000 and winsorize extreme migration rates by period. The resulting rural sample contains approximately 56,300 unique rural grid cells, of which about 55,000 have non-missing migration data. Exact thresholds and counts are reported in SI Appendix.

Temperature and precipitation. Historical monthly temperature and precipitation are obtained from station-based observational products interpolated to 0.5-degree resolution (28, 29). Future climate projections are drawn from CMIP6 Tier 1 experiments under multiple Shared Socioeconomic Pathways (30). We regrid model output to 0.5 degrees to match the historical climate data and bias-correct projections using monthly climatological means over a historical baseline; details on model coverage and bias correction are in SI Appendix. To align with quinquennial migration outcomes, we compute 5-year averages of temperature and precipitation, and we additionally construct metrics capturing the rate of change and variability over time; the full metric definitions and implementation details are provided in SI Appendix.

Internal and International Migration Data. We use two data sources to characterize the relationship between internal and international migration. First, we use IPUMS-International census microdata (31) to construct country-level internal and cross-border migration rates, which

allow us to construct an average measure of how internal migration leads to international migration. Second, we use global bilateral international migration flow estimates from (33), which report migration flows between all pairs of approximately 200 countries for five five-year periods from 1990 to 2015, constructed using demographic accounting methods applied to migrant stock data (47). Together, these datasets provide information on the relationship between internal migration, cross-border migration, and the global structure of migration corridors. Details are provided in SI Appendix, along with a full list of countries covered.

Historical Relationship Between Climate and Migration

Regression analysis. Following the broader climate-economy literature, which shows that climate affects aggregate economic productivity nonlinearly (38), we estimate reduced-form macro effects of climate conditions on migration, to be interpreted as the aggregate of nonlinear micro effects through multiple channels. Our preferred specification is a fixed-effects panel data model, which account for persistent differences across grid-cells and common changes over time, summarized by the following equation:

$$\text{mig}_{it} = \sum_{r=1}^R \sum_{k=1}^K \phi_{rk} \cdot \text{Climate}_{it}^r \cdot \text{Income}_{it}^k + \mu_i + \theta_t + \varepsilon_{it} \quad [1]$$

where mig_{it} represents the net outmigration rate for grid cell i at time t . $\text{Climate}_{it}^r = (T_{it}, T_{it}^2, P_{it})$ is a vector of r climate measures including temperature (T), temperature squared (T^2) and precipitation levels (P). The vector $\text{Income}_{it}^k = (1, (\text{Ln GDP pc})_{it}, (\text{Ln GDP pc})_{it}^2)$ contains k regressors, the log-transformed income in cell i and time t and its square. We population-weight when estimating the coefficients. We remove the upper and lower 0.1% of T , T^2 , and P values from the analysis to avoid outliers. This removes about 0.2% of the global population from the analysis. The measure of cell GDP is obtained from historical gridded per capita gross domestic product (details provided in the Data Sources and Processing section). Linear and quadratic income terms that are not interacted with climate terms are included as controls, but omitted from the projections. The model also includes cell (μ_i) and year (θ_t) level fixed effects. In our model, following standard practice for high-dimensional panel data, parameter estimation and inference depend on large-sample asymptotic theory rather than classical error distributional assumptions such as normality or homoscedasticity. Moreover, OLS provides the best linear approximation to the conditional expectation function regardless of whether the underlying data-generating process is strictly linear. Multicollinearity among controls or high-dimensional absorbed fixed effects affects only parameter precision rather than consistency, and exact collinearity is automatically handled by the estimation procedure. Finally, ε_{it} captures the idiosyncratic error term. Statistical inference relies on cluster-robust standard errors at the administrative 1 level to account for arbitrary heteroskedasticity and within-cluster error dependence. As a sensitivity test, aimed at assessing the susceptibility of our results to variations in assumptions

and analytical choices, we cluster standard errors by country. We also test versions of this equation without the quadratic income interactions, without any income terms, and with additional environmental variables in Climate_{it}^r .

Selection of regressors (LASSO). There are many plausible climatic variables that may impact individual migration choices, including mean climate over a short period, climatic variability, or longer-term climatic trends. The many possible permutations of climate metrics create a challenge in identifying the appropriate functional form for statistically modeling historical climate-induced migration. Therefore, we employ the LASSO shooting algorithm (48) under a rigorous penalization approach (49). The LASSO algorithm is a statistical method that selects the most relevant regressors from a large set of potential predictors by shrinking the estimated contributions of less informative variables toward zero. It allows us to understand whether alternative climate measures could help explain residual variation in the regression. The results are reported in Table S6 and the detailed methods are described in SI Appendix.

The LASSO selects only 2 of the 18 supplementary climate metrics, suggesting that the baseline climate variables already possess substantial explanatory power. It is important to emphasize that the LASSO imposes no prior structure on the nature of the regressors and, as such, provides no inherent rationale for including interaction or higher-order terms. We interpret these results as evidence that the category of climate metrics—specifically temperature trends and variance—may influence historical climate migration rates. We therefore include them, along with the respective income interactions, in some of our supplemental specifications as extensions and robustness checks. However, their influence on projections is small, and they are therefore not included in our preferred specification (Fig. S9).

Projections

We estimate future migration rates by taking the difference between projected migration rates for 2050 and subtracting modeled migration rates for 2015. We do this both for fixed and time-varying income

Internal Migration. In the time-varying income case, we use GDP_{pc} from (45) and climate model output for the climate variables. GDP_{pc} is bias-corrected to match our historical data, as described in the Data Sources and Processing section above. For our main projection, we use the average from all available climate models, though we also estimate climate uncertainty from individual climate models, as described in the Monte Carlo and Uncertainty section below. Importantly, we do not include the GDP_{pc} and GDP_{pc}^2 terms in the projections, as they are controls and do not constitute climate migration.

In the fixed-income case, we do not allow GDP_{pc} to change over time and instead fix it at 2015 levels. The treatment of climate and controls is the same as in the time-varying income case described above. We include this projection to demonstrate the impact of climate alone.

Cross-border Migration. Historically, increases in internal migration coincide with increases in international migration. To project country-level cross-border net migration,

we first multiply the projected grid-cell level migration rate by the grid-cell population. We then multiply this total number of migrants in a country by the fraction of people that migration internationally (a constant of 0.12, described below). We then apportion these international migrants to countries based on the matrix of between-country flows from (33). These steps are described in more detail below. Lastly, we sum the number of migrants by the destination country. This process is identical for the fixed-income and varying-income projections, except that the initial migration rates are taken from the fixed or varying income projections, respectively.

Using the IPUMS dataset, we construct a cross-sectional dataset of internal and international migration for 90 country-year observations from 43 countries between 1985 and 2017 (further detail in SI Appendix). Using the following regression, we derive the average relationship between internal and international migration with the estimating equation:

$$\text{MIG}_{it} = \alpha + \beta \text{mig}_{it} + \epsilon_{it} \quad [2]$$

where the outcome variable is the international out-migration flow from country i and time period t , and the main independent variable is the internal migration flow in the same country and period. The index t refers to a five-year period corresponding to the recall window from IPUMS measures. The parameter $\hat{\beta}$ captures the relationship between the two flows. Contemporaneity reflects the assumption that the migration pressures operating within a given period drive both internal relocation and cross-border emigration within that same window.

We plot this relationship in Fig. S10, and use the estimated coefficient $\hat{\beta} = 0.12$ when projecting cross-border pressures.

Next, we combine the data with the projected levels of internal migration to derive net migration levels in country j , according to the following equation:

$$\begin{aligned} \Delta \text{MIG}_{it} &= -\text{mig}_{it} \cdot \hat{\beta} + \sum_j \text{mig}_{jt} \cdot \hat{\beta} \cdot \frac{\text{MIG}_{ij}}{\sum_j \text{MIG}_j} \\ &= \hat{\beta} \left[\sum_j \text{mig}_{jt} \cdot \frac{\text{MIG}_{ij}}{\sum_j \text{MIG}_j} - \text{mig}_{it} \right] \end{aligned} \quad [3]$$

where $\text{mig}_{it} \cdot \hat{\beta}$ is the calculated outflow of international migrants leaving country i in time period t . The same stock in country j ($\text{mig}_{jt} \cdot \hat{\beta}$) constitutes an international inflow of migrants to country i , weighted by the existing bilateral migration relationships as per (33). The weight is computed using the ratio between the inflow of migrants to country i from country j (MIG_{ij}), and the total outflow of migrants from country j to all destinations ($\sum_j \text{MIG}_j$). As such, the equation redistributes a given volume of migrants across origins and destinations, with the common time index ensuring that a global adding-up constraint is met.

Climate uncertainty and statistical uncertainty. Future climate is available from many different climate models (see Temperature and Precipitation data section). Our main

analysis uses the model mean as the input, while we use each of the models individually to quantify the climate uncertainty.

To quantify the statistical uncertainty in the projections, we take a Monte-Carlo approach. We re-run the main estimating equation using only a subset of the panel dataset. In one case, we randomly sample a pre-specified fraction of the dataset (e.g., only use half the sample) and repeat this 100 times. This gives us a set of 100 estimates of the coefficients; each set is used for its own projections, which yields a range. Lastly, as a sensitivity test, we also sample by administrative unit 1 (e.g., states), rather than randomly sampling the whole dataset. In other words, we generate a set of estimated coefficients using only one random grid cell from each admin 1 unit, and repeat that test 100 times.

Robustness Analyses. We assess the robustness of our preferred specification using four complementary approaches: (1) validation of global nonlinear specification with local linear approaches, (2) sequentially including interaction terms and modifying the main specifications, (3) Monte Carlo resampling to test for coefficient stability, and (4) alternative specification tests.

Local-linear Validation of Global Nonlinear Specification. To assess whether the global nonlinear specification is consistent with local relationships observed in the data, we estimate a separate linear regression between migration rates and temperature at each rural grid cell. For each cell, we compare the estimated local linear temperature coefficient to the marginal effect implied by the global model, evaluated at that grid cell's covariate values. We then test whether the 95% confidence interval from the local linear regression contains the corresponding global marginal effect, following an approach similar to (38). We implement this exercise under several minor specification variants, including the use of linear versus quadratic income controls and the inclusion of precipitation as an additional control. The results of these tests are summarized in Fig. S6 and Fig. S7.

Sequential Inclusion of Higher-order and Interaction Terms in Main Specification. To clarify the role played by income interactions and higher-order climate terms, we estimate a sequence of specifications that build incrementally toward our preferred model. We begin with regressions that include only climate variables and fixed effects, excluding any interactions with income. We then introduce linear income interactions, followed by specifications that include quadratic temperature terms interacted with quadratic income terms. For each specification, we report standard errors clustered at the administrative unit level 1, and we repeat the analysis clustering at the country level to assess sensitivity to the choice of clustering unit. The corresponding coefficient estimates are reported in Table S2 and Table S3, with associated projections shown in Fig. S9.

Monte Carlo Resampling. We examine the stability of coefficient estimates under increasingly conservative sampling schemes using a Monte Carlo resampling approach. Specifically, we repeatedly draw subsamples from the panel and re-estimate the preferred specification using

(i) a random sample of 85% of grid cells, (ii) a random sample of 50% of grid cells, and (iii) a highly conservative sample consisting of one grid cell per administrative unit level 1. Each resampling procedure is repeated 100 times, generating distributions of estimated coefficients for comparison across sampling schemes. The resulting coefficient distributions are shown in Fig. S12.

Alternative Specifications and Definitions. We further test robustness by estimating a wide range of alternative specifications. These include adding quadratic precipitation terms; allowing for interactions between temperature and precipitation; incorporating climate trend and variability measures constructed using the LASSO procedure (see Methods above; and SI Appendix); replacing the quadratic temperature term with an interaction between temperature and long-run mean temperature; and including lagged climate variables. We also examine sensitivity to the definition of rural areas by restricting the sample to half-degree grid cells that contain no urban sub-cells at finer spatial resolution. Finally, we re-estimate the model using only urban locations to assess whether climate-migration relationships differ across rural and urban contexts. Results from these specification variants are reported in Fig. S9 and Table S7. Further detailed analyses and results are in SI Appendix.

1275	1. K Schewel, S Dickerson, B Madson, G Nagle Alverio, How well can we predict climate migration? A review of forecasting models. <i>Front. Clim.</i> 5 , 1189125 (2023).	1339
1276	2. RM Beyer, J Schewe, GJ Abel, Modeling climate migration: dead ends and new avenues. <i>Front. Clim.</i> 5 (2023).	1340
1277	3. A De Sherbinin, et al., Migration and risk: Net migration in marginal ecosystems and hazardous areas. <i>Environ. Res. Lett.</i> 7 (2012).	1341
1278	4. A De Sherbinin, et al., Global estimated net migration grids by decade: 1970–2000. <i>NASA Socioecon. Data Appl. Cent. (SEDAC) at http://sedac.ciesin.columbia.edu/data/set/popdynamics-global-est-net-migration-grids-1970-2000</i> (2015).	1342
1279	5. A Alessandrini, C Deuster, F Natale, Global estimates of net migration at high spatial resolution 1975–2020, (Publications Office of the European Union, Luxembourg), Technical Report JRC132876 (2023).	1343
1280	6. S Feng, AB Krueger, M Oppenheimer, Linkages among climate change, crop yields and Mexico–US cross-border migration. <i>Proc. Natl. Acad. Sci.</i> 107 , 14257–14262 (2010).	1344
1281	7. R Cai, S Feng, M Oppenheimer, M Pytkova, Climate variability and international migration: The importance of the agricultural linkage. <i>J. Environ. Econ. Manag.</i> 79 , 135–151 (2016) Publisher: Academic Press.	1345
1282	8. C Cattaneo, G Peri, The migration response to increasing temperatures. <i>J. Dev. Econ.</i> 122 , 127–146 (2016).	1346
1283	9. R Hoffmann, A Dimitrova, R Muttarak, J Crespo Cuaresma, J Peisker, A meta-analysis of country-level studies on environmental change and migration. <i>Nat. Clim. Chang.</i> 10 , 904–912 (2020).	1347
1284	10. IPCC, Climate change 2022: Impacts, adaptation and vulnerability (2022).	1348
1285	11. H Benveniste, M Oppenheimer, M Fleurbaey, Climate change increases resource-constrained international immobility. <i>Nat. Clim. Chang.</i> 12 , 634–641 (2022).	1349
1286	12. H Benveniste, P Huybers, J Proctor, Global climate migration is a story of who and not just how many. <i>Nat. Commun.</i> 16 , 7752 (2025).	1350
1287	13. P Bohra-Mishra, M Oppenheimer, SM Hsiang, Nonlinear permanent migration response to climatic variations but minimal response to disasters. <i>Proc. Natl. Acad. Sci. United States Am.</i> 111 , 9780–9785 (2014) Publisher: National Academy of Sciences.	1351
1288	14. A Missirian, W Schlenker, Asylum applications respond to temperature fluctuations. <i>Science</i> 358 , 1610–1614 (2017) Publisher: American Association for the Advancement of Science.	1352
1289	15. G Peri, A Sasahara, The impact of global warming on rural-urban migrations: Evidence from global big data. <i>Natl. Bureau Econ. Res.</i> (2019).	1353
1290	16. M Beine, CR Parsons, Climatic factors as determinants of international migration. <i>The Scand. J. Econ.</i> 119 , 593–630 (2017).	1354
1291	17. V Mueller, C Gray, K Kosec, Heat stress increases long-term human migration in rural Pakistan. <i>Nat. Clim. Chang.</i> 4 , 182–185 (2014).	1355
1292	18. C Gray, V Mueller, Drought and population mobility in rural ethiopia. <i>World Dev.</i> 40 , 134–145 (2012).	1356
1293	19. C Gray, V Mueller, Natural disasters and population mobility in bangladesh. <i>Proc. Natl. Acad. Sci.</i> 109 , 6000–6005 (2012).	1357
1294	20. KK Rigaud, B Jones, E Bergmann, et al., Groundswell: Preparing for internal climate migration, (World Bank), Technical report (2018).	1358
1295	21. M Burzyński, C Deuster, F Docquier, J De Melo, Climate Change, Inequality, and Human Migration. <i>J. Eur. Econ. Assoc.</i> 20 , 1145–1197 (2022).	1359
1296	22. C Cattaneo, et al., Human migration in the era of climate change. <i>Rev. Environ. Econ. Policy</i> 13 , 189–206 (2019).	1360
1297	23. R Hoffmann, G Abel, M Malpede, R Muttarak, M Percoco, Drought and aridity influence internal migration worldwide. <i>Nat. Clim. Chang.</i> 2024 14:12 14 , 1245–1253 (2024).	1361
1298	24. United Nations, <i>World Urbanization Prospects: The 2018 Revision</i> . (United Nations), (2019).	1362
1299	25. JV Henderson, A Storeygard, U Deichmann, 50 years of urbanization in africa : Examining the role of climate change. <i>World Bank Policy Res. Work. Pap.</i> (2014) Publisher: World Bank, Washington, DC.	1363
1300	26. AI Moreno-Monroy, M Schiavina, P Veneri, Metropolitan areas in the world. Delineation and population trends. <i>J. Urban Econ.</i> 125 , 103242 (2021).	1364
1301	27. M Kummu, M Kosonen, S Masoumzadeh Sayyar, Downscaled gridded global dataset for gross domestic product (gdp) per capita ppp over 1990–2022. <i>Sci. Data</i> 12 , 178 (2025).	1365
1302	28. Y Fan, H van den Dool, A global monthly land surface air temperature analysis for 1948–present. <i>J. Geophys. Res. Atmospheres</i> 113 (2008).	1366
1303	29. U Schneider, A Becker, P Finger, E Rustemeier, M Ziese, Gpcc full data monthly product version 2020 at 0.5°: Monthly land-surface precipitation from rain-gauges built on gts-based and historical data (2020).	1367
1304	30. V Eyring, et al., Overview of the coupled model intercomparison project phase 6 (cmip6) experimental design and organization. <i>Geosci. Model. Dev.</i> 9 , 1937–1958 (2016).	1368
1305	31. IPUMS, Ipums international: Version 7.4 (2023) Dataset.	1369
1306	32. GJ Abel, JE Cohen, Bilateral international migration flow estimates for 200 countries. <i>Sci. data</i> 6 , 82 (2019).	1370
1307	33. GJ Abel, JE Cohen, Bilateral international migration flow estimates updated and refined by sex. <i>Sci. Data</i> 9 , 173 (2022).	1371
1308	34. P Oliva, Migration and the environment: A look across perspectives. <i>Reg. Sci. Urban Econ.</i> 107 , 104005 (2024).	1372
1309	35. M Angelucci, Migration and financial constraints: Evidence from mexico. <i>The Rev. Econ. Stat.</i> 97 , 224–228 (2015).	1373
1310	36. S Bazzi, Wealth heterogeneity and the income elasticity of migration. <i>Am. Econ. Journal: Appl. Econ.</i> 9 , 219–55 (2017) Publisher: American Economic Association.	1374
1311	37. T Carleton, et al., Valuing the global mortality consequences of climate change accounting for adaptation costs and benefits. <i>The Q. J. Econ.</i> 137 , 2037–2105 (2022).	1375
1312	38. M Burke, SM Hsiang, E Miguel, Global non-linear effect of temperature on economic production. <i>Nature</i> 527 , 235–239 (2015).	1376
1313	39. A Alessandrini, D Ghio, S Migali, Estimating net migration at high spatial resolution, (Publications Office of the European Union, Luxembourg), Technical Report EUR 30261 EN (2020).	1377
1314	40. European Commission, Joint Research Centre (JRC), CIESIN, Ghs-pop r2023a: Global human settlement layer—population grid (1 km; 1975–2020) (2023) Gridded population counts derived from census and satellite data.	1378
1315	41. United Nations, Department of Economic and Social Affairs, Population Division, World population prospects 2022 (2022) Country-level births, deaths, and population totals.	1379
1316	42. Global Human Settlements Layer (GHS), Functional urban areas (fuas) 1km grid cells one-time urban area boundary representative of 2015 (2019) European Commission, Joint Research Centre (JRC).	1380
1317	43. GADM, Gadm 4.1: Database of global administrative areas (2023) Vector boundaries for ADM-0 and ADM-1 units.	1381
1318	44. World Bank, World bank official boundaries (2025) High-resolution Admin 0/1/2, NDLSA, and ocean mask; shapefile, GeoPackage, and GeoJSON. Metadata last updated 2025-09-16.	1382
1319	45. T Wang, F Sun, Global gridded gdp data set consistent with the shared socioeconomic pathways. <i>Sci. data</i> 9 , 221 (2022).	1383
1320	46. J Gao, Downscaling global spatial population projections from 1/8-degree to 1-km grid cells. <i>NCAR Tech. Note NCAR/TN-537+STR</i> (2017).	1384
1321	47. GJ Abel, Estimating global migration flow tables using place of birth data. <i>Demogr. Res.</i> 28 , 505–546 (2013).	1385
1322	48. R Tibshirani, Regression shrinkage and selection via the lasso. <i>J. Royal Stat. Soc. Ser. B (Methodological)</i> 58 , 267–288 (1996).	1386
1323	49. A Belloni, V Chernozhukov, C Hansen, Inference on treatment effects after selection among high-dimensional controls. <i>The Rev. Econ. Stud.</i> 81 , 608–650 (2014).	1387
1324	50. M Pesaresi, et al., Advances on the global human settlement layer by joint assessment of earth observation and population survey data. <i>Int. J. Digit. Earth</i> 17 , 2390454 (2024).	1388
1325	51. World Bank, World development indicators: Gdp per capita (constant 2015 us\$) (ny.gdp.pcap.kd) (2025) Accessed 2025-11-18; license CC BY 4.0.	1389
1326	52. MC Harding, C Lamarche, Small steps with big data: using machine learning in energy and environmental economics. <i>Annu. Rev. Resour. Econ.</i> 13 , 469–488 (2021).	1390
1327	53. D Hammami, TS Lee, TB Ouarda, J Lee, Predictor selection for downscaling gcm data with lasso. <i>J. Geophys. Res. Atmospheres</i> 117 (2012).	1391
1328	54. T Vandal, E Kodra, AR Ganguly, Intercomparison of machine learning methods for statistical downscaling: the case of daily and extreme precipitation. <i>Theor. Appl. Climatol.</i> 137 , 557–570 (2019).	1392
1329	55. F Iglesias-Suarez, et al., Causally-informed deep learning to improve climate models and projections. <i>J. Geophys. Res. Atmospheres</i> 129 , e2023JD039202 (2024).	1393
1330	56. A Ahrens, CB Hansen, ME Schaffer, lassopack: Model selection and prediction with regularized regression in stata. <i>The Stata J.</i> 20 , 176–235 (2020).	1394
1331	57. V Chernozhukov, C Hansen, M Spindler, Post-selection and post-regularization inference in linear models with many controls and instruments. <i>Am. Econ. Rev.</i> 105 , 486–490 (2015).	1395
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1433	prise: net-migration 5-year grids (1980–2020) from		1497
1434	the European Commission, Joint Research Centre		1498
1435	(JRC) estimation framework (5); gridded population		1499
1436	5-year counts (1975–2020) (GHSL POP R2023a) (50);		1500
1437	urban/rural boundaries defined by Functional Urban		1501
1438	Areas from the Global Human Settlement Layer (42);		1502
1439	and historical gridded income (GDP per capita) (27),		1503
1440	temperature (28), and precipitation (29) data. For		1504
1441	the internal–international migration linkage, we use		1505
1442	IPUMS International microdata (Version 7.4 from		1506
1443	2024) (31) together with national income from the		1507
1444	World Bank World Development Indicators (51).		1508
1445	Projection inputs are: gridded population (46), grid-		1509
1446	ded GDP per capita (45), and climate projections		1510
1447	from the CMIP6 Tier-1 ensemble (30). Bilateral		1511
1448	international migration flow matrices used to allocate		1512
1449	cross-border flows are available as a figshare collection		1513
1450	(32, 33). Persistent identifiers (DOIs) and access		1514
1451	URLs are provided here and/or in the References.		1515
1452			1516
1453	• Materials availability: Not applicable.		1517
1454			1518
1455	• Code availability		1519
1456	All code to replicate our main regres-		1520
1457	sions, projections and figures are at		1521
1458	https://github.com/ppolonik2/climate.income.migration .		1522
1459	To facilitate peer review, a data file containing the		1523
1460	main panel is attached as an auxiliary file.		1524
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1462	• Author contribution		1526
1463	GK and KR conceived of the study and procured the		1527
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1465	IG conducted the geospatial analysis, processing		1529
1466	of population and migration data, constructed the		1530