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Migration induced by sea-level rise could reshape the US population landscape

Mathew E. Hauer

Many sea-level rise (SLR) assessments focus on populations presently inhabiting vulnerable coastal communities[1-3], but to date no studies have attempted to model the destinations of these potentially displaced persons. With millions of potential future migrants in heavily populated coastal communities, SLR scholarship focusing solely on coastal communities characterizes SLR as primarily a coastal issue, obscuring the potential impacts in landlocked communities created by SLR-induced displacement. Here I address this issue by merging projected populations at risk of SLR[1] with migration systems simulations to project future destinations of SLR migrants in the United States. I find that unmitigated SLR is expected to reshape the US population distribution, potentially stressing landlocked areas unprepared to accommodate this wave of coastal migrants—even after accounting for potential adaptation. These results provide the first glimpse of how climate change will reshape future population distributions and establish a new foundation for modelling potential migration destinations from climate stressors in an era of global environmental change.

It is generally understood that sea-level rise (SLR) of 1–2 m (refs 4–6) could lead to widespread human migration[2,7] as residents of highly vulnerable coastal communities look to escape rising water levels. With up to 180 million people directly at risk to SLR in the world and over 1 billion living in the lower-elevation coastal zone[8,9], understanding the ramifications of these potential migrants on destination communities is a priority for climate change research[10–13].

SLR assessments, identifying both the number and locations of potentially displaced persons, fill the literature[1,2,14] and are useful for the deployment of critical infrastructure in coastal areas. Yet questions of where the millions of potentially displaced persons will go remain unanswered despite a general understanding that SLR displaced persons are likely to have profound effects on future population landscapes[11,14]. Only a few studies have put forth general hypotheses regarding SLR migration[11,15], and this void has prompted recent calls for additional migration modelling[16,17]. To date, no studies modelling precisely how SLR-induced migration will affect the population distribution exist. By focusing solely on coastal communities without directly addressing SLR-induced migration, we probably underestimate the scale and magnitude of these impacts.

Relationships between environmental stressors and migration are highly complex as press and pulse events trigger migration responses that range from short-distance temporary migration to permanent long-distance migration; some will move and others will not[18–23]. SLR is unique among environmental stressors as the conversion of habitable land to uninhabitable water is expected to lead to widespread human migration without the deployment of costly protective infrastructure[2,7,11,15]. It is unclear, however, what will actually trigger future climate migrants: press events, such as drought or SLR, or pulse events, such as tropical cyclones. When climate effects are integrated over long periods of time, it is likely that a combination of press and pulse events will spur migration[24] across pre-existing migration pathways[19,21], leveraging established networks of social capital and kin networks in destination decisions[25]. This is because press and pulse events that spur migration operate mostly independently of the kin networks and social capital that drive destination decisions[10]. Thus, climate migrants resulting from press stressors will probably constitute ‘enhanced’, or extra, normal out-migration.

I combine estimates of the populations at risk to SLR[1] within a migration systems simulation to estimate both the number and destinations of potential SLR migrants in the United States (US) over the coming century. By focusing on the destinations of SLR migrants I am able to more holistically describe the impacts of SLR. This study aims to answer one fundamental question regarding SLR-induced migration: What areas are likely to see the greatest in-migration due to SLR? Local officials in landlocked communities can use these results to plan for potential infrastructure required to accommodate an influx of coastal migrants and could shift the conceptualization of SLR from a coastal issue to a more ubiquitous issue.

To answer these questions, first I use published estimates of county-level projected populations at risk to SLR for the years 2010 through 2100[1] under the 1.8 m SLR scenario for 319 coastal US counties. Hauer *et al.*[1] simulated expected changes in the mean higher high water (MHHW) mark on areas that are hydrologically connected to coastal areas without taking into account additional land loss caused by other natural factors such as erosion or land subsidence. They then projected the populations exposed to SLR over the coming century in a dynamically assessed, spatially explicit small-area population-environment projection model, based on growth in the period 1940–2010, where populations under the projected MHHW mark are assumed to be at risk of displacement. They estimated a potential 13.1 million persons could be at risk of migrating due to a SLR of 1.8 m by 2100. These data provide the number of persons likely to migrate, but not the migration destinations.

I then integrated the projected populations within a projected migration system for all coastal counties affected by SLR ($n = 319$) and possible destinations ($n = 3{,}113$) based on the Internal Revenue Services’ annual series of county-to-county migration flow data for the years 1990–2013[26]. This is the largest dataset of county-to-county migration in the US and includes data for 95 to 98 per cent of tax filers and their dependents. To capture the temporal variability of the county-to-county migration flows I used unobserved component modelling (UCM)[27] for each individual dyad origin–destination pair ($n = 46{,}203$) to project shifts and changes in the migration system over the coming century. Populations are migrated based on the proportion of total outflows from the originating county in the projected system.

Department of Geography, University of Georgia, Athens, Georgia 30602, USA. e-mail: hauer@uga.edu

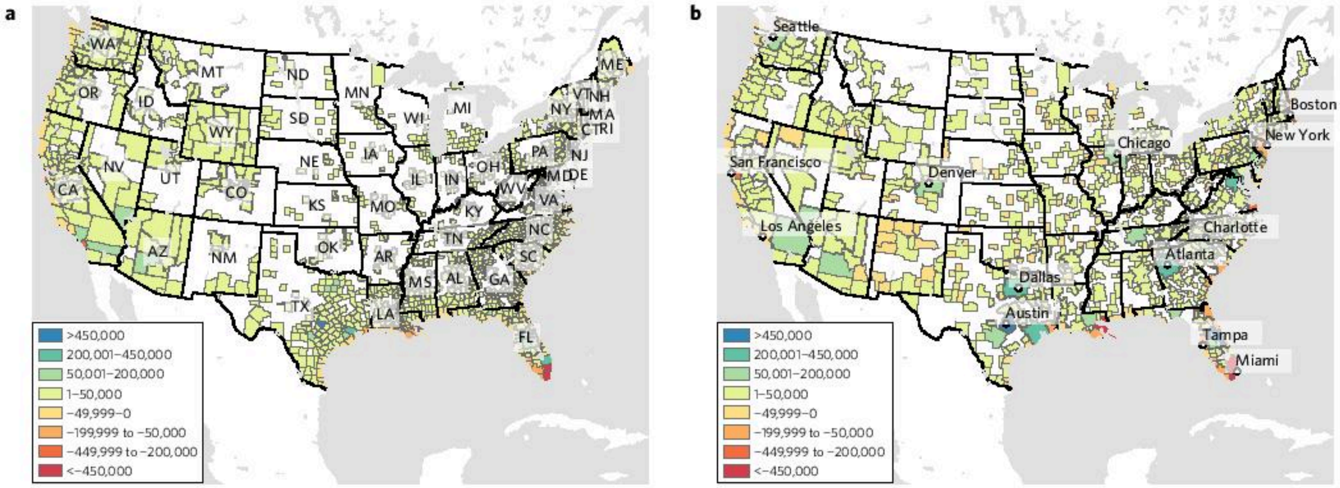

Figure 1 | Estimated SLR net migrants (in-migrants minus out-migrants) for counties and core based statistical areas under the 1.8 m scenario and no adaptation. a, US counties. **b**, Core based statistical areas. For **b**, I considered only counties located in CBSAs. Counties and CBSAs without expected SLR in-migration are in white. States are abbreviated to standard two-letter codes.

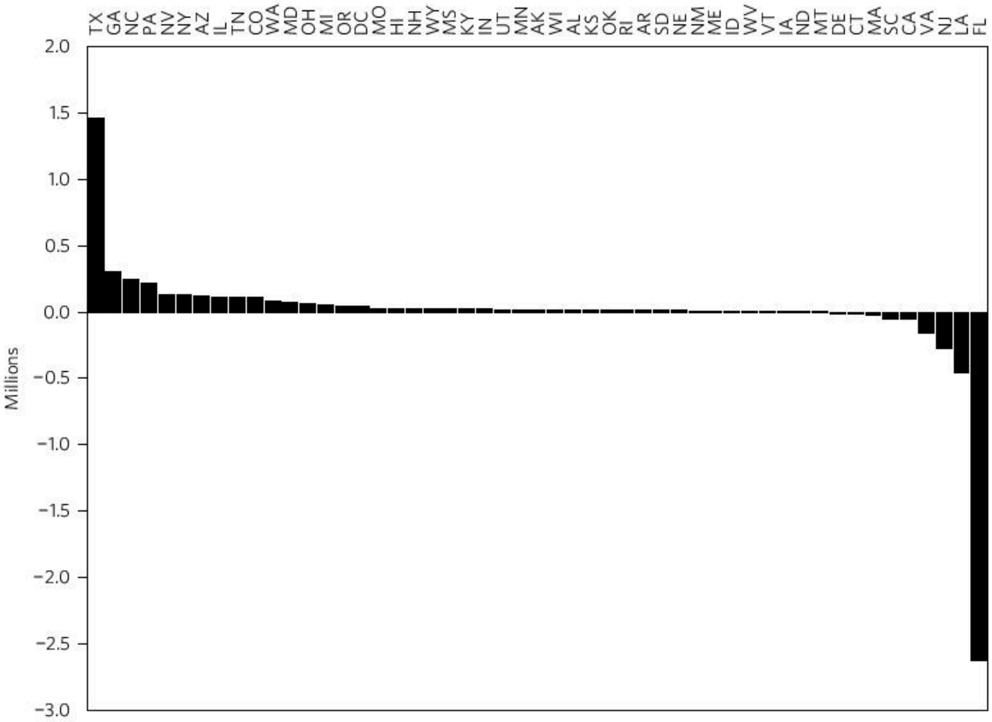

Figure 2 | Net change in population due to sea-level rise under the 1.8 m scenario and no adaptation. I considered migration destinations for all 50 states and the District of Columbia (DC) and migration origins for 22 states and the District of Columbia. These are the net changes in population due to both in- and out-migration due to sea-level rise. States are abbreviated to standard two-letter codes.

It is possible that populations escaping SLR might migrate to inland areas completely unaffected by SLR, as hypotheses suggest[11,15]. However, not all coastal counties will be completely inundated and many areas will still be suitable for human settlement even with 1.8 m of SLR. To capture these possibilities, projected migrants to each possible destination county are dynamically adjusted based on the unaffected populations remaining in each coastal county. In this way I model both migrations to inland areas completely unaffected by SLR and migrations to coastal areas still suitable for habitation. A detailed technical description is available in the Methods.

It is likely that many communities will deploy a wide variety of adaptation measures, including sea walls, beach and marsh nourishment, pumps, or elevate homes and roads to protect both people and property, and IPCC reports have increasingly emphasized adaptation when discussing SLR[28]. Global estimates of adaptive infrastructure for SLR could reach US$421 billion (2014 values) per year[8] and could cost upwards of US$1.1 trillion in the US[29]. However, the deployment of adaptation measures is driven by wealth for both cities[30] and individuals[10,31]. To approximate this dynamic, I assume that households earning greater than US$100,000 per year are likely to adapt to SLR in some manner, and thus unlikely to migrate. This income threshold represents approximately the top quartile and double the US median household income, and is neither too restrictive nor too broad to capture the range of individual adaptive measures. Detailed projections of SLR

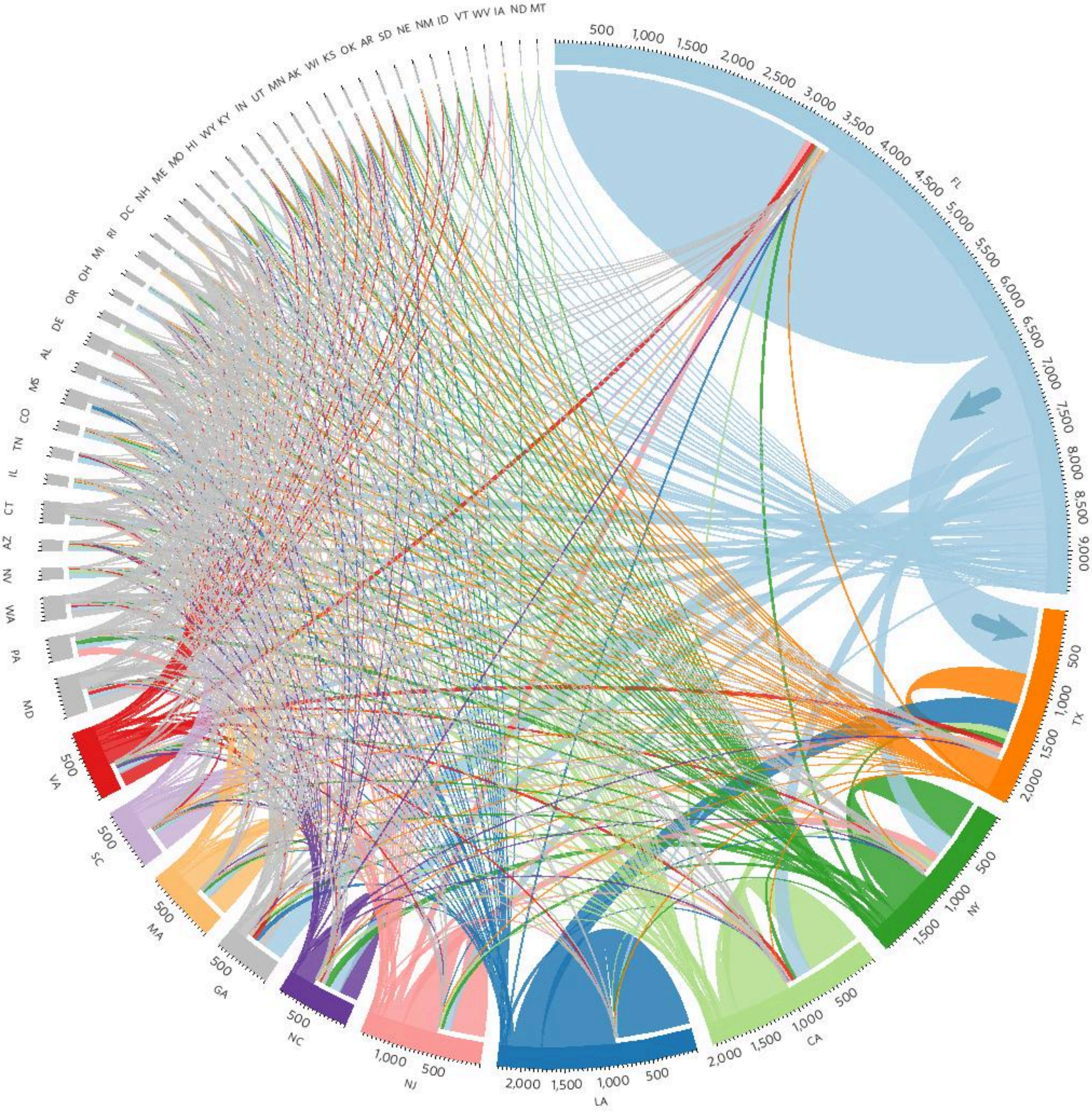

Figure 3 | Circular plot of bi-lateral SLR migration flows for US States under the 1.8 m scenario and no adaptation. Tick marks show the number of migrants (inflows and outflows) in thousands. States are ordered clockwise by the size of inflows. The top ten outflow states are coloured; all other states are in grey. States are abbreviated to standard two-letter codes.

migrants for all destination counties under both a 'no adaptation' scenario and a wealth-based adaptation scenario are also found in the Supplementary Dataset.

I find that in the US, every state, 86% of US Core Based Statistical Areas (CBSAs) (791 out of 915), and 56% of counties (1,735 out of 3,113) could be affected in some way by net migration (in-migration minus out-migration) associated with 1.8 m of SLR (Fig. 1). Florida could lose more than 2.5 million residents due to 1.8 m of SLR, while Texas could see nearly 1.5 million additional residents (Fig. 2). Additionally, nine states could see net losses in their populations due to SLR. Figure 3 demonstrates all origin–destination flows at the US state level, demonstrating that the sheer magnitude of places affected could alter the US population landscape. SLR migrants are expected to comprise both intra- and inter-state migrations, and no state is left untouched by SLR migration. Even accounting for the deployment of adaptive infrastructure, millions of people could still migrate (Table 1 and Supplementary Dataset).

My results also suggest that CBSAs such as Austin Texas, Orlando Florida, Atlanta Georgia, and Houston Texas could see more than 250,000 previously unforeseen future SLR net migrants each (Table 1 and Supplementary Dataset). Thirteen CBSAs could see more than 100,000 SLR net migrants by 2100 with 1.8 m of SLR. Conversely, ten CBSAs could lose more than 100,000 residents due to SLR, with Miami Florida losing over 2.5 million residents. Even accounting for those who could adapt in place, many inland communities could see tens of thousands of SLR in migrants, and many coastal communities could lose tens of thousands of residents. Extended results for all

Table 1 | Select core based statistical area (CBSA) destinations of SLR net migration (in-migration minus out-migration) in 2100 with and without adaptation under the 1.8 m scenario.

CBSA	No adaptation			With adaptation		
	Net migration	+/−	Rank	Net migration	+/−	Rank
Austin-Round Rock, TX	818,938	243,821	1	625,627	179,186	1
Orlando-Kissimmee-Sanford, FL	461,411	62,665	2	369,120	38,834	2
Atlanta-Sandy Springs-Roswell, GA	320,937	131,984	3	248,684	68,868	3
Phoenix-Mesa-Scottsdale, AZ	100,524	12,851	13	73,935	1,949	13
Myrtle Beach-Conway-N Myrtle Beach, SC-NC	12,146	13,855	78	3,142	9,389	141
North Port-Sarasota-Bradenton, FL	−208	25,057	727	2,128	21,717	168
Los Angeles-Long Beach-Anaheim, CA	−3,140	51,590	737	13,181	22,200	61
New York-Newark-Jersey City, NY-NJ-PA	−50,804	494,625	775	15,808	194,047	50
New Orleans-Metairie, LA	−500,011	24,053	795	−373,283	10,733	795
Miami-Fort Lauderdale-West Palm Beach, FL	−2,509,978	155,119	796	−2,009,263	95,845	796

+/− represents the 80th confidence interval. States are abbreviated to standard two-letter codes.

counties and CBSAs are available in the Supplementary Methods (Supplementary Dataset).

With many projected migrants remaining in coastal communities (Table 1 and Supplementary Dataset), SLR could generate millions of 'trapped' people[32]. Trapped populations are sometimes discussed through the concept of involuntary immobility[32], but there is also those who do not desire to move and thus constitute voluntary immobility. These results suggest that many people displaced by SLR could find themselves or their descendants exposed to SLR, even with migration as an adaptation, as sea levels continue to rise past the year 2100 with migration that constitutes relocation to presently safe, but ultimately vulnerable, coastal communities.

Additionally, infrastructure challenges required to protect coastal communities are well documented[1,2], but the infrastructure challenges of accommodating millions of SLR migrants in largely unprepared inland municipalities is virtually unexplored. For many destinations, such as Riverside California, Phoenix Arizona, Las Vegas Nevada, and Atlanta Georgia, already experiencing water management and growth management challenges, the SLR migrants who wash across the landscape over the coming century could place undue burden in these places if accommodation strategies are left unplanned. Studies of migration impacts do not solve the challenges in these areas, but rather reveal a more holistic understanding of SLR impacts and needed interventions.

SLR has been broadly conceptualized as a coastal issue or hazard, as assessments have focused on the effects in coastal communities[1,2,8,9]. With millions of potential future migrants in heavily populated coastal communities, SLR scholarship focusing solely on coastal communities endorses a narrative that characterizes SLR as primarily a coastal issue, obscuring the potential impacts in landlocked communities created by SLR-driven migration. My work shows that this coastal conceptualization of SLR creates a deceptively small area of affect if relocation is left unaccounted. This work offers the first glimpse of how SLR could alter the population distribution of the US as both coastal and landlocked communities are likely to be affected by SLR: directly in coastal areas due to SLR itself and indirectly in landlocked areas through the influx of people escaping SLR.

Furthermore, the migration approach for examining destinations associated with climate change shown here allows for modelling migration destinations of other climate change stressors. For instance, it has been estimated that parts of the Middle East and North Africa (MENA) could become uninhabitable by the end of the century, potentially spurring an exodus of 500 million people[3]. Future scholars could employ my approach to model the destinations of these potential MENA migrants. There is tremendous potential in coupling migration systems information with climate change models to examine the implications of climate-change-induced migration. This type of modelling requires detailed origin–destination migration information, limiting the areas where this approach could be used to those where data are available.

Migration models are only as good as the data underlying them. The suppression of IRS migration data of flows with fewer than 10 migrants could systematically bias my results against rural areas far from coastal communities, and the modelling approach undertaken does not allow for new unforeseen migration pairs to emerge in the future. However, the destination counties cover 93.6% of the US population and over 250 destination counties are outside of CBSAs (the typical distinction of urban/rural), limiting the scope of the rural bias to mainly sparsely populated communities far from coastal areas. New destinations for SLR migrants could still emerge in rural areas, and if they do, my results of the geographic spread of SLR migrants could be considered conservative. Environmental migration scholars could further investigate the likelihood of emerging rural destinations related to climate change migration to better inform future modelling efforts.

Previous trends are not always indicative of future results. Societal and economic shifts, population ceilings, local growth ordinances, adaptive behaviour, and climate change itself could all change future migrant destinations. Although I model the potential destinations of SLR migrants, I do not precisely model how other climate stressors or other factors might influence the future migration systems. Our current understanding of the location decisions of environmental migrants is still limited, and there have been recent calls to better understand migration flows[16]. My approach builds on the growing literature concerning migrant destinations and environmental change[10,11,15,25,33–35], and accounts for potential future migration systems.

High potential exists for development of deeper and more integrated examinations of the role of adaptation and other climate stressors on SLR migration. Neglecting to account for adaptive behaviour could lead to an overestimation of either flood risk[36] or migration[37]. Future studies could examine varying adaptation scenarios related to the 100-year flood plain or the lower-elevation coastal zone creating differing scenarios of 'stayers.'

If future migration pathways mimic past pathways, SLR is expected to reshape the US population distribution and could stress some landlocked areas unprepared for these migrations while revitalizing others. SLR is currently framed as a coastal hazard, but the migratory effects could ripple far inland. My results show the importance of accounting for future migrations associated with climate change in long-range planning processes for disaster management, transportation infrastructure, land-use decisions, and so on.

Methods

Methods, including statements of data availability and any associated accession codes and references, are available in the online version of this paper.

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Additional information

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Competing financial interests

The author declares no competing financial interests.

Methods

The methodology for projecting sea-level rise (SLR) migrant destinations is outlined in this section. First, I describe the datasets and basic methodology for creating my migration matrices. Second, the methodology for capturing migration system uncertainty is discussed.

Data. I utilize two primary sources of data concerning the magnitude of flows in the migration system and the migration system itself. The first, the magnitude of flows, comes from published populations projected to be at risk to SLR[1]. Hauer *et al.*[1] used the National Oceanic and Atmospheric Administration's (NOAA) 0 m, 0.9 m (3 feet) and 1.8 m (6 feet) SLR datasets for twenty-two coastal states and the District of Columbia. These datasets simulate expected changes in the mean higher high water (MHHW) mark on areas that are hydrologically connected to coastal areas without taking into account additional land loss caused by other natural factors such as erosion. They projected populations using a modified Hammer Method[38] combined with the Housing Unit Method[39] for population estimation to create temporally contiguous sub-county boundaries over a 70-year base period from 1940 to 2010, which were then used to project populations at these same sub-county geographies through the use of a linear/exponential extrapolation approach for projecting census block groups (CBG) from 2010 to 2100. The populations at risk to SLR, aggregated to the US county and available in their Supplementary Table 2[1], provide the magnitude of out-migrants from 319 coastal counties.

For this research, I used the annual series of county-to-county migration datasets[26], produced by the Internal Revenue Service (IRS) in conjunction with the US Census Bureau, as the basis for the migration system. The IRS datasets utilize the IRS Individual Master File containing every Form 1040, 1040A and 1040EZ processed by the IRS, and includes 95 to 98 percent of all individual tax filers and their dependents. The Census Bureau identifies migrants when a current filing years' return is from a different location than the matched preceding years' return. These data capture only the tax-filing universe, but the spatio-temporal stability[40–42] coupled with the very large administrative sample make them attractive for modelling large-scale migration patterns. The IRS does suppress migration flows comprising fewer than 10 individual migrants, systemically suppressing small rural migration flows. However, the long-term trend of rural out-migration to urban areas[43] is expected to continue in this century[44].

Migration systems theory (MST) has been tied to environmental migration in recent years[45–47]. MST is a branch of migration research that holistically examines migration options by studying all origin–destination combinations rather than any single origin–destination combination[45,46,48]. Migration decisions—not just the decision to migrate, but also decisions on where to migrate—are often driven by kin networks, employment opportunities, amenities, both natural and economic, economic vitality, and so forth[10,22,46,49–51]. This network of 'pull' factors embedded within the migration system tends to drive locational decision-making due to environmental, or other, 'push' factors[10,13,17,18,25,52,53].

To describe the complete migration system in the United States, let matrix $M(x)$ represent all possible county-level origin–destination combinations. The sum of any given column and row in the matrix will equal the total number of migrants into or out of any given county. For this analysis I am concerned only with the 319 coastal counties expected to experience some form of SLR inundation under the 1.8 m scenario and their connections to the other 3,113 US counties ($n=993{,}047$ matrix cells). I created these matrices for each year of the IRS migration data between 1990 and 2013. Supplementary Fig. 1 shows examples of these systems into and out of three sample counties.

$$M(x)=\begin{bmatrix} m_{1,1} & \cdots & m_{1,3113} \\ \vdots & \ddots & \vdots \\ m_{319,1} & \cdots & m_{319,3113} \end{bmatrix}=[m^{x}_{od}] \tag{1}$$

where

$$o\in\{1,\dots,319\}$$

$$d\in\{1,\dots,3113\}$$

Migration system projection approach. I employed the use of an unobserved components model (UCM) for forecasting equally spaced univariate time series data[27]. UCMs decompose a time series into components such as trends, seasons, cycles and regression effects, and are designed to capture the features of the series that explain and predict its behaviour. UCMs are similar to dynamic models in Bayesian time series forecasting[54]. All projections were undertaken in SAS 9.4 using the PROC UCM procedure.

The basic structural model (BSM) is the sum of its stochastic components. Here I use a trend component μ_t and a random error componentε_t, and it can be described as:

$$y_t=\mu_t+\varepsilon_t \tag{2}$$

Each of the model components are modelled separately with the random error ε_t modelled as a sequence of independent, identically distributed zero-mean Gaussian random variables. The trend component is modelled using the following equations:

$$\begin{aligned} \mu_t &= \mu_{t-1}+\beta_{t-1}+\eta_t \\ \beta_t &= \beta_{t-1}+\xi_t \\ \eta_t &\sim N(0,\sigma^2_\eta) \\ \xi_t &\sim N(0,\sigma^2_\xi) \end{aligned} \tag{3}$$

These equations specify a trend where the level μ_t and the slope β_t vary over time, governed by the variance of the disturbance terms η_t and ξ_t in their equations. Here all origin–destination dyadic pairs containing any migration information over the series were modelled ($n=46{,}203$) in individual UCM models.

This approach allows for the projected evolution of the migration system as dyadic pairs either strengthen or weaken over time, allowing for migration links to wax or wane over the projection horizon. Empirical simulations of environmental migration have proven very fruitful in the modelling of climate-change-induced migration[15,55,56], and here I build upon those efforts by projecting future climate migration.

Our current understanding of the migratory response to sea-level rise is still underdeveloped. Will displaced coastal populations relocate into the parts of coastal communities unaffected by sea-level rise? Or will displaced persons migrate to more inland areas free from the challenges of sea-level rise[11,15]? Many areas in threatened coastal communities are still eligible for human settlement and could be possible destinations for future SLR migrants. To capture both possibilities, I employ a raking procedure to proportionally adjust in-migrants based on the inverse of the proportion of the population affected by SLR and a redistribution of those migrants to unaffected counties.

$$\hat{M}^t_{od}=M^t_{od}*(1-D^t_d/P^t_d) \tag{4}$$

The adjusted number of in-migrants M to destination county d from origin county o at time t is equal to the number of migrants multiplied by one minus the proportion of the population impacted by SLR in the destination county at time t. For inland counties, the right-hand side of the equation equals one, yielding no adjustment.

$$\hat{M}^t_{od[i=U]}=\left(\sum M^t_o-\sum \hat{M}^t_o\right)*\left(\frac{\hat{M}^t_{od[i=U]}}{\sum \hat{M}^t_{o[i=U]}}\right) \tag{5}$$

However, the out-migrants from each affected coastal county must be raked to equal the total population at risk to SLR expected to be displaced. This is accomplished by redistributing the difference of the unadjusted migrants M^t_o from origin o from the adjusted migrants from origin o and multiplying it by the proportion of adjusted migrants from origin o to destination d to the unaffected counties ($i=U$) from the total adjusted migrants from origin o. In this way, the underlying migration system from each individual origin is preserved in the raking procedure.

To assess how adaptation might impact future migration streams, the proportion of the population in households earning greater than $100,000 per year in the 2011–2015 American Community Survey data were assumed to be non-migrants.

Projection uncertainty. *Evaluation of migration system projection.* Projection intervals allow us to examine the feasibility of the future projected migration systems and are typically employed in the evaluation of population projections[57]. Demographers have typically used the 2/3 or 66% projection interval to assess the accuracy of a population projection[58,59], representing 'low' and 'high' scenarios that are 'neither so wide as to be meaningless nor too narrow to be overly-restrictive'[60].

To examine the feasibility of the migration system projections, I produce projections based on the equations in the preceding section with the base period 1990–2003 and an evaluation period of 2004–2013. If less than 2/3 of the IRS migration counts fall within the 2/3 projection interval then the results would suggest less than ideal accuracy. However, if more than 2/3 of the IRS migration counts fall within the 2/3 projection interval, it would suggest an ideal amount of accuracy. I assessed the 2/3 interval for 10 years of projections for an evaluation of base period 1990–2003 and a projection period of 2004–2013.

Supplementary Table 1 shows the overall number of IRS migration counts that fall within the 2/3 projection interval for each year of the evaluation period. Overall, the UCMs produce robust projections, as all projection years are above the 2/3 projection interval.

Data availability. The data that support the findings of this study have been deposited in openICPSR (http://dx.doi.org/10.3886/E100413V3)[61].

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