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Title: Millions projected at risk of displacement from sea level rise in the Continental United States

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Abstract:

Nearly 40%[1] of the US population resides in coastal areas experiencing rapid growth likely to exacerbate long-term exposure to flood risks. Previous estimates of the populations at risk of sea level rise inundation for the US are limited in the sense that they do not account for future population growth in at-risk coastal areas[2-4]. Applying a novel small area population projection methodology that accounts for dynamic interactions between population change and sea level rise, we find that approximately 1.3 million, 3.4 million, and 11.7 million people in the continental United States could be at risk of inundation-related displacement under scenarios of 0.3m, 0.9m, and 1.8m sea level rise by 2100. Importantly, these displacement figures are approximately three times larger than those based solely upon current populations. The southeastern United States accounts for 70% of the projected displaced US population. The magnitude of populations displaced from sea level rise could mirror the Great Migration of southern African-Americans during the 20th century and radically alter the future distribution of the US population[5]. It could cost up to $US11.7 trillion to relocate these displaced populations, based on costs associated with managed retreats[6]. Thus, a one-size-fits-all national approach for tackling SLR could prove problematic.

Main Text:

Sea level rise (SLR) is widely recognized as one of the most likely and socially disruptive consequences of future climate change [6]. Scenarios of future SLR at the year 2100 range from a low of 0.3 meters to a high scenario of 2.0 meters associated with collapse of polar ice sheets [7]. Understanding the specific locations and ecosystems at risk of SLR impacts is a high priority in climate change research [8-10] and adaptation planning [11,12] yet no complete estimates exist of the potential magnitude of displacement from SLR.

Although there is growing worry that climate change is likely to cause widespread human migration over the next century [6], relatively few studies have attempted to merge climate change scenarios with population growth trends and projections in high-risk areas see, however, [13,14]. The few that have suffer from methodological shortcomings related to both spatial and temporal mismatch. For example, previous estimates of the populations at-risk of future SLR inundation have been based solely on current population data [15]. Given the rapid growth of population in coastal areas [16], such temporal mismatch of datasets (i.e., present population and future SLR) appears likely to underestimate the impacts that SLR will have on future populations. Other research has coupled county-scale populations with small-area flood inundation risk [2]. Such spatial mismatch is likely to overestimate the future populations at risk of SLR, as no accounting is provided for populations located on higher ground within a county.

The mutability of many sub-county geographic units (e.g., Census Tracts and Census Block Groups) at each decennial Census cycle is a classic example of the modifiable areal unit problem [17], and generally limits the development of long-range forecasts to areas in which geographic boundaries remain stable [18]. Using a novel approach, we overcome the methodological issues related to spatial and temporal mismatch and the mutability of sub-county units [1] by synthesizing spatially explicit environmental data (i.e., elevation and associated flood risk) with small-area population projections developed with a modified version of the Hammer Method [1,19] in a dynamic flood hazard model. By spatially and temporally aligning small area population projections from coastal states in the continental United States to 2100, we are able to assess who will be at risk of inundation from future SLR.

This approach addresses two fundamental questions concerning the vulnerability of future coastal populations in the United States: 1) How many people are potentially at risk of displacement from SLR? and 2) What areas in the United States will likely experience the greatest population displacement from inundation? Accordingly, our results can be used to inform local adaptation infrastructure and growth management strategies, alerting officials to the areas where interventions and policies are most needed.

We assess the populations at risk of SLR by using the National Oceanic and Atmospheric Administration's (NOAA) 0m, 0.3m (1ft), 0.9m (3 feet), and 1.8m (6 feet) SLR datasets [20] for twenty-one 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. Notably, the State of Louisiana is currently excluded from the NOAA SLR dataset due to complexities with accurate simulation of the coastal levee system and high local land subsidence in relation to future SLR. Although we recognize that Louisiana has high vulnerability to SLR, we follow NOAA by excluding Louisiana from our present analysis.

We utilize a linear/exponential extrapolation approach for projecting Census Block Groups from 2010 to 2100. We included only Census Block Groups (n=70,314) located in counties (n=292) expected to experience any inundation under the 1.8 m scenario. A detailed technical description is available in the Supplementary Information. Detailed projections of displacement for all 292 coastal counties are also found in figure S1 and tables S1 and S2. The population at risk of SLR is dynamically assessed as the proportion of the census block group underwater when SLR is expected to exceed 0.3m intervals under the 0.3m, 0.9m, and 1.8m scenarios. As populations become displaced under each SLR scenario in each block group, projected populations are dynamically adjusted to account for this displacement.

We find that in the continental United States approximately 11.7 million people are at risk under the 1.8m scenario (Figure 1), with Florida accounting for over half of this total. The projected number for the US is nearly triple what the current population estimates for 2010 suggest (Figure 2 and Table 1). Florida accounts for over half of the total at risk population and while other southeastern states have substantially fewer people at risk, states such as Georgia and South Carolina have over 10% of future coastal populations at risk of displacement under the 1.8m scenario. The southeastern United States alone represents nearly 70% of the entire projected populations at risk of displacement, suggesting the impacts of SLR will be highly regionalized nature.

Our results also suggest a hyperlocalized impact of inundation from SLR (Figure 3 and table S2). While the median percentage of the population subject to inundation across all 292 coastal counties is just 3.5%, several counties would likely experience displacement far in excess of 3%. Three counties in particular—Tyrrell, North Carolina (94% of the projected population at risk of inundation), Monroe, Florida (88%), and Hyde, North Carolina (82%)—should experience population inundation that is catastrophic in nature with 1.8m SLR. Broward, Miami-Dade, Pinellas, and San Mateo counties are projected to see more than 100,000 residents potentially displaced with a 0.9m SLR, and an additional 23 counties would have more than 100,000 potentially displaced persons with a 1.8m SLR. Miami-Dade and Broward counties in Florida alone account for more than a quarter of the people expected to be displaced under the 1.8 m scenario.

Cities such as Tampa–St. Petersburg, Florida; Charleston, South Carolina; Poquoson, Virginia; and Cape May, New Jersey may experience dramatic levels of population displacement under the 1.8 m SLR scenario. Other areas such as Hartford, Connecticut; Fairfax, Virginia; and San Diego California, by contrast, may expect to see very little displacement from sea level rise. Due to geographic variability, a one-size-fits-all national approach for tackling SLR could prove problematic.

Adaptation strategies for SLR rely on accurate information about the geographies, time scales, economies, and populations at risk. With annual global infrastructure costs estimated as high as US$421 billion (2014 values) [21], underestimating the potential populations at risk of inundation is likely to result in concomitant underestimation of future adaptation costs. This is because cost analyses for future climate change impacts have typically been based around current population estimates [22]. For instance, a 2011 study calculated that currently 137 schools, 55 health care facilities, and US$99 billion worth of property located in California are at risk of 1.4m of inundation [23]. While such an "inventory" is helpful, it does not take into account expansions in California's population and infrastructure that are likely to take place before inundation occurs.

Similarly, proposed managed retreat solutions could also prove troublesome if population projections are left out of the equation. To date, managed retreats have tended to involve small populations and areas [24,25], but in the future, action could be needed in areas with currently small but growing populations. Not only could the costs of relocating a community be greatly underestimated if that population is growing, but the challenge of finding suitable areas for relocation could be problematic as well. With current estimates as high as $US1 million per resident in some small Alaskan villages [4], each decade both increases that population's exposure to sea level rise and increases their vulnerability to the economic costs of inaction. Potential growth management strategies in high risk areas experiencing rapid population growth could also prove more effective than relocation. Population projections are not a panacea for these problems, but they move us toward evaluating the potential SLR impacts on future, rather than current, populations.

Research indicating how populations might adapt to SLR is still in its infancy, thus limiting our ability to model how future populations might organically adapt to rising seas and the loss of both current and future coastal human habitat. For instance, Venice, Italy has seen its population remain stable over the last decade in spite of widely documented tidal flooding from both land subsidence and SLR suggesting population dynamics and SLR have a complicated relationship. Our projections of displaced populations could be biased upward by the limited interaction between SLR and population growth.

Uncertainty in our projections result from the sensitivity of long-term population to both the selection of base period length and projection horizon length [26]. By using the longest possible base period, we do find acceptable accuracy for these projections (supplementary materials); however, past trends do not guarantee future trends. Local growth ordinances and population saturation points could improve future population projections.

The approach demonstrated in this paper allows for spatially and temporally aligning population data with any type of hazard modelling requiring small area spatio-temporal population projections that can be readily utilized by decision makers and researchers. For example, other byproducts of SLR, such as relative sea level rise, loss of coastal wetlands, intrusion of saltwater into both surface and ground water, and higher storm surges from tropical cyclones [27-29] could also be modeled as well as economic impacts from these hazards. For instance, using the example of the cost for relocating some Alaskan coastal villages [4] of US$1 million per resident, the cost of relocation could exceed $US11.7 trillion (2014 values). More precise cost estimates could incorporate our approach. There is high potential for coupling population projections in dynamic systems simulations that incorporate such stressors into multivariate scenario modeling.

Methods

We assess the populations at risk of MSLR by using NOAA's 0m, 0.3m (1ft), 0.9m (3 feet), and 1.8m (6 feet) MSLR datasets for the continental United States. 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 and represent the middle and high end scenarios expected by 2100 [7]. Twenty-two states and the District of Columbia are expected to experience some form of MSLR by 2100. We assess the populations at risk for MSLR for all states and DC with the exception of Louisiana. Unfortunately, Louisiana currently lacks recent, accurate coastal elevation data, is experiencing land subsidence, and has a complex levee system. To date, Louisiana is the only state completely missing from NOAA's MSLR database and was thus excluded from this analysis.

We utilize a linear/exponential extrapolation for all geographies and use a modified Hammer Method [30] for projecting CBGs from 2010-2100. We included only census block groups (n=70,314) located in counties (n=292) expected to experience any inundation under the 1.8m scenario. The population at risk of MSLR is assessed as the proportion of the CBG underwater at the 0.3m, 0.9m, and 1.8m scenarios. The proportion of each CBG inundated is then applied to its projected population when sea level rise is expected to exceed 0.3m intervals to assess the populations at risk of inundation. We explicitly account for population-environment feedback interactions allowing for dynamic growth rates as each block group becomes inundated over time. A detailed technical description is available in the Supplementary Information. Additional information is also found in Supplementary Figure 1 and Supplementary Tables 1 and 2.

Acknowledgements
Data reported in the paper are available in the Supplementary Materials.

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Table 1. Projected Populations at Risk of Sea Level Rise by 2100. ST, state; Pop. 2010, population in 2010; Pop. 2100, projected population in 2100. Only census block groups and counties expected to experience any inundation under 1.8m of sea level rise in 2100 and had inundation data were included. Areas not included are denoted with a dash.

			Current Populations			Projected Populations		
ST	**Pop. 2010**	**Pop. 2100**	**0.3m SLR in 2100**	**0.9m SLR in 2100**	**1.8m SLR in 2100**	**0.3m SLR in 2100**	**0.9m SLR in 2100**	**1.8m SLR in 2100**
AL	661,739	1,253,337	8,002	14,648	25,326	16,408	38,238	57,303
CA	26,934,343	53,301,543	95,004	94,217	216,174	222,757	472,248	1,046,757
CT	3,113,051	5,865,392	12,981	17,249	39,482	22,558	53,566	128,048
DC	601,723	867,172	418	545	1,257	645	2,005	4,629
DE	897,934	1,829,353	9,865	19,782	35,811	20,192	44,597	76,836
FL	17,099,967	34,979,118	173,291	385,436	1,499,509	394,531	1,221,837	6,057,419
GA	645,274	1,256,874	26,266	25,061	48,426	55,608	93,036	178,787
LA	-	-	-	-	-	-	-	-
MA	4,924,916	8,627,489	21,792	38,232	155,335	38,316	103,552	427,549
MD	5,120,419	7,861,926	18,176	30,300	68,667	34,291	92,584	188,624
ME	1,098,127	1,849,668	3,815	6,849	13,233	7,437	15,230	29,028
MS	449,114	814,600	9,879	12,379	20,075	22,006	50,385	76,901
NC	1,919,209	3,047,125	38,836	59,884	109,756	77,886	163,260	297,917
NH	418,366	881,189	2,125	3,299	6,211	4,373	8,670	15,432
NJ	7,913,312	14,646,202	55,424	117,553	300,923	108,555	308,662	827,449
NY	13,797,269	22,976,871	22,816	48,933	221,056	45,376	198,257	901,366
OR	1,813,789	2,750,665	2,375	4,374	8,985	4,352	12,754	25,614
PA	4,008,994	4,472,968	1,137	2,537	7,288	2,116	9,939	27,427
RI	1,052,567	1,830,090	3,265	5,188	13,150	6,050	14,875	36,546
SC	1,512,451	2,979,159	35,091	52,443	126,498	72,562	163,492	374,395
TX	6,307,493	13,241,311	28,017	52,600	114,797	54,490	173,025	405,423
VA	4,036,764	8,603,821	37,043	45,521	109,507	78,065	181,130	475,871
WA	4,440,696	10,745,057	7,332	11,178	26,597	13,567	43,436	94,139
Tot	**108,767,517**	**204,680,930**	**612,950**	**1,048,211**	**3,168,064**	**1,302,141**	**3,464,778**	**11,753,459**

Figures

Figure 1. Cumulative Displaced Populations for the Continental United States, 2010-2100. Projections reflect assumed growth/decline rates for 70,314 census block groups in 292 coastal counties. Error bars were generated as the 90% confidence interval from the projection models.

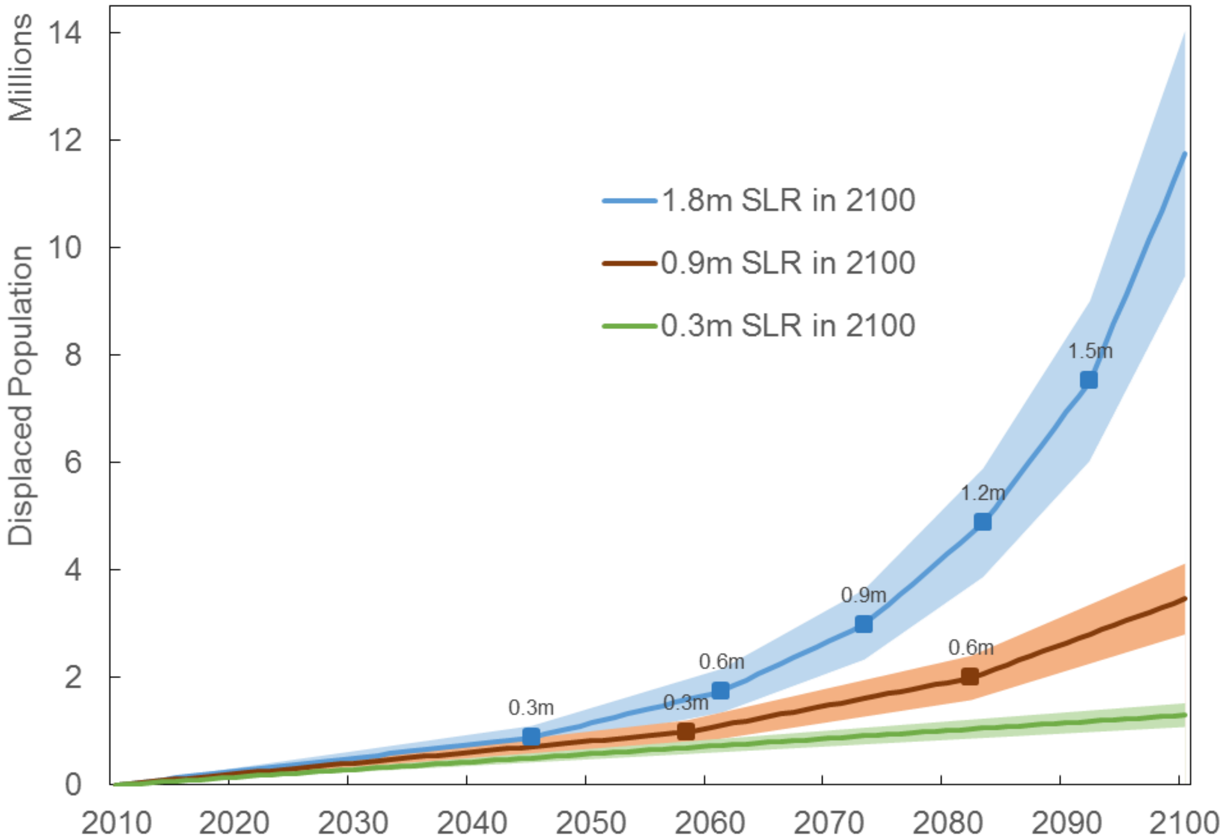


Figure 2. Projected Cumulative Populations at Risk of Sea Level Rise in 2100 under the 1.8m scenario. We considered 22 states and the District of Columbia. Louisiana was excluded from this analysis due to severe data limitations. Current populations are based on Census 2010.

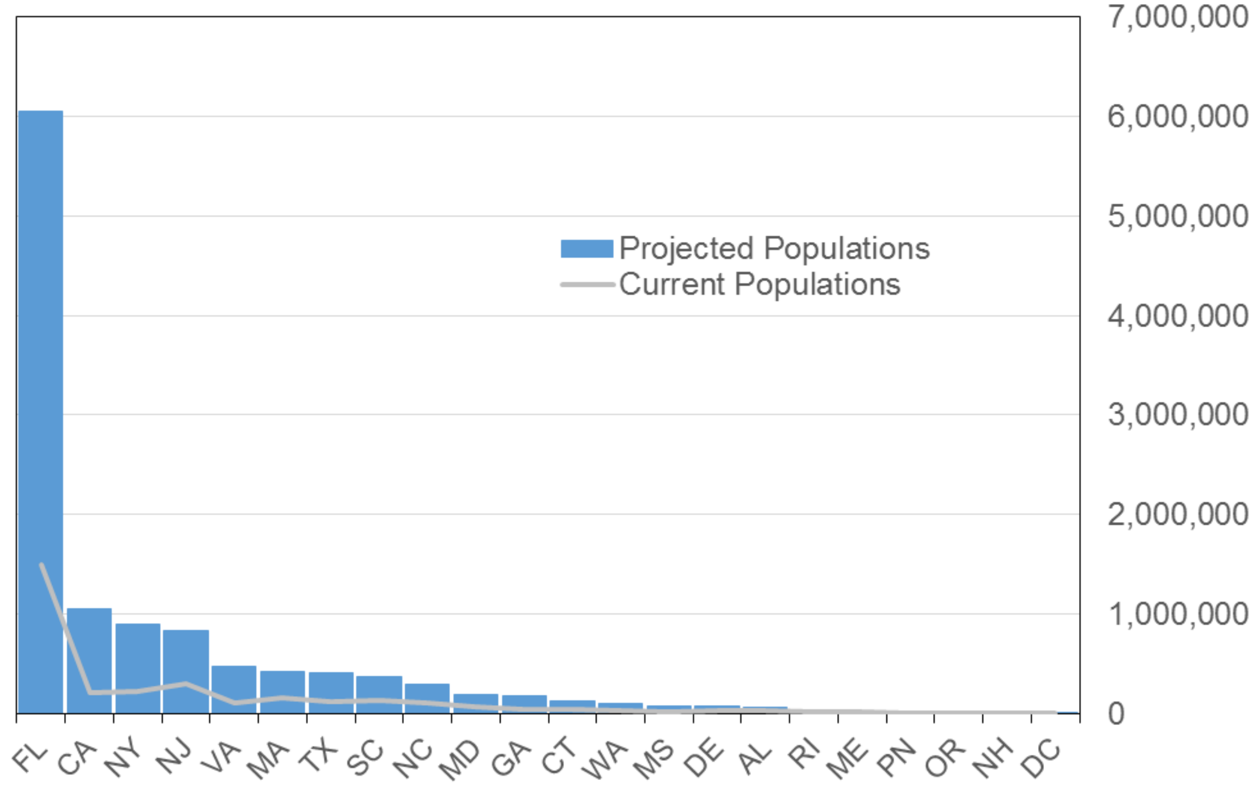
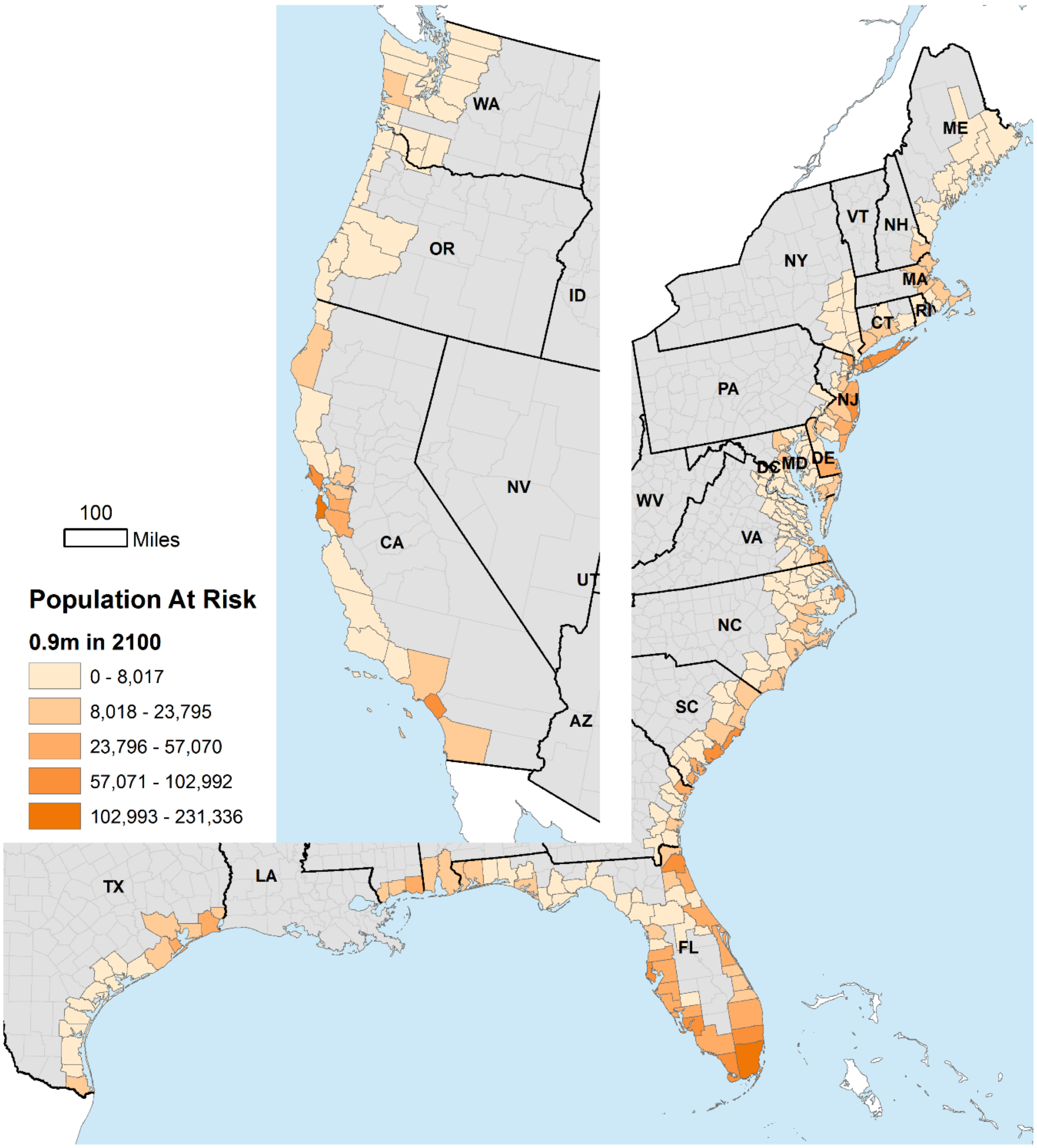


Figure 3. Cumulative Projected Populations at risk of Displacement under the 0.9m Scenario by 2100. Counties not included in the study are colored in gray.



Supplementary Materials:

Materials and Methods

Figures S1-S2

Tables S1-S2

References (*29*-*60*)

Supplementary Materials:
Materials and Methods

The methodology for projecting small-areas is outlined in this section. First, the methodology to historically estimate housing units is introduced. Second, the methodology to convert housing units to population is reviewed. Third, the extrapolation approach undertaken to produce population projections are reviewed. Fourth, the determination of populations at risk of inundation through intersection with sea level rise curves is described.

Data. Previous assessments of the populations at risk of sea level rise typically utilize an elevation based approach for inundation modelling [3,4,17] whereby all areas under a given threshold (usually 1m, 2m, 3m, or 6m) are flooded without consideration of hydrological connectedness. Without this crucial consideration in tidewater inundation modelling, areas that are currently protected from inundation due to dykes or levees will be inundated under this approach. Notable locations such as New Orleans, LA would be considered flooded even with a 0m scenario since New Orleans currently sits below sea level. For this research, we chose to use the National Oceanographic and Atmospheric Administration's (NOAA) sea level rise databases. These datasets simulate expected changes in the mean higher high water (MHHW) mark on areas that are hydrologically connected to coastal areas and represent the middle and high end scenarios expected by 2100 [8]. This dataset does not take into account additional land loss caused by other natural factors such as erosion, subsidence, or future construction and NOAA provides these data "as is" without warranty to their performance. The state of Louisiana is not included in the dataset due to local hydrologic complexities associated with coastal levees and accelerated land subsidence. Only coastal counties expected to have direct effects from sea level rise under the 1.8m scenario from were selected to be projected and assessed (n=292). Figure S1 comprises the study area.

Data for conducting the population projections come from two main sources. The first source of data comes from the American Community Survey (ACS) 2008-2012 estimates. The ACS provides the "year structure built" data, and the contemporary census boundaries for block groups. The second piece of data is the actual historic count of housing units and population for each county, and with regard to the 2010 Census provides us with counts of the Group Quarters Population. This data is available as digitized records from the Census Bureau's website[1]. It should be noted in the consideration of these inputs that the ACS data, though similar to decennial data, is subject to many types of error. However, all released ACS data have confidence limits above 90% [33]. Additionally, GQ tends to be the most volatile aspect of the Census Bureau's Estimates Program and American Community Survey [34-36], but is an important aspect of the HU method.

[1] For 1940 to 1990, data can be found at http://www.census.gov/prod/cen1990/cph2/cph-2-1-1.pdf. Census 2000 data can be downloaded through American FactFinder.

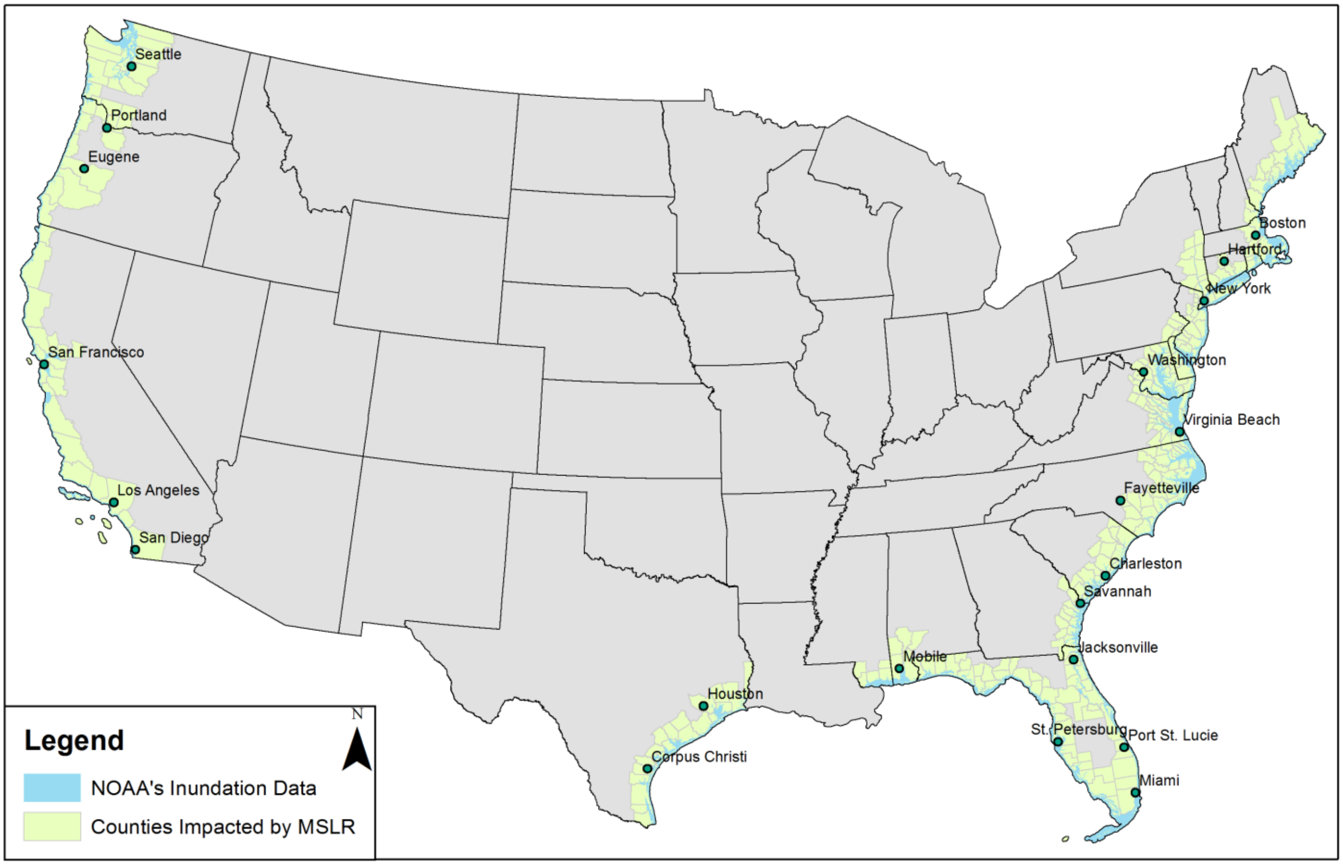


Figure S1. Study Area. Each of these counties experiences some form of SLR under the 1.8m scenario. Note the lack of data for Louisiana.

Estimates of Historic Housing Units. Demographic projections of small-areal units (i.e. sub-county units) tend to be less robust than projection methodologies at bigger scales [20,37]. The changeability of many sub-county boundaries (e.g., Census Tracts and Census Block Groups) at each decennial Census cycle provides a classic example of the modifiable areal unit problem referred to as the MAUP, thus effectively limiting the development of more long-range forecasts to areas in which geographic boundaries remain stable [20]. Notably, the smallest geographies with boundaries that tend to remain stable are US counties.

We use a modified version of the Hammer Method [2,21] based on a proportional fitting algorithm [38]. Hammer's Method is essentially a combination of a growth-allocation and proportional fitting approach, where the growth between time-periods is allocated to each block-group and proportionally fit to the marginals. Equation 1 demonstrates this proportional fitting approach.

$$\hat{H}_{ij}^{t} = \left(\frac{C_j^t}{\sum_{i=1939}^{t-1} H_j^t} \right) * \sum_{i=1939}^{t-1} H_{ij}^{t} \tag{1}$$

The number of housing units in county *j* as counted in the census taken in time *t* is denoted as C_j^t while the number of housing units in block group *i* in county *j* based on the "year structure built" question in the ACS is denoted as H_{ij}^t. Thus, any estimate of housing units in any given block group in county *j* is given as a proportionally adjusted estimate based on the ratio of the total number of housing units as counted in the Census to a county's estimated housing units from the ACS for *t*-1. For instance, an estimate of the number of housing units for block group *i* in county *j* for the year 1980 would be equal to the number counted at the county level according to the 1980 census, C_j^{1980},divided by the number of housing units at the county level in the ACS for the period 1939-1979, $\sum_{i=1939}^{1979} H_j^{1980}$, multiplied by the number of housing units observed in the ACS for the period 1939-1979 for block group *i* in county *j*, $\sum_{i=1939}^{1979} H_{ij}^{1980}$. This process is iterated for each decade until the most recent time period, i.e. the 2010 census. These estimates of housing units for each block group in each county provide the key input needed to convert an estimate of housing units into an estimate of total population.

Housing Units to Population. Equation 2 demonstrates the approach employed here to utilize the Housing Unit (HU) method to convert an estimate of Housing Units to an estimate of population [39,40].

$$(2)\quad P_t = H * \mathrm{PPHU} + \mathrm{GQ}$$

Where *H* is the number of housing units, *PPHU* is the persons per household, and *GQ* is the group quarters population. Any error associated with the HU method is attributable to the quality of the inputs [41] as the HU method is considered a demographic identity. The Hammer method, outlined above, can provide a long-range back cast of housing units for normalized boundaries in any given census geography (whether its 1990, 2000, or 2010 geographies). While Census designated boundaries may change, housing units typically do not move [21]. Based on the "year structure built" question in Census data, the method produces proportionally adjusted housing unit estimates at the smallest census geography possible – the block group.

Equation 3 demonstrates the approach employed here to utilize the HU method to project a population. While PPHU and GQ are held constant, $\widehat{H}_{ij}^{t+1}$ can be projected though any set of extrapolation methods [40,42-45].

$$(3)\quad P_{t+1} = \widehat{H}_{ij}^{t+1} * \mathrm{PPHU}_{ij}^{t} + \mathrm{GQ}_{ij}^{t}$$

Projection Approach. We explicitly do not migrate those who are projected to be inundated. Our current understanding of the human migratory response to environmental events is not robust enough to model where these inundated persons will potentially move. There are quite a few hypotheses on human migration and climate change, mostly drawing from environmental events in the 20th century[3,46-49]. These hypotheses, however, result in empirical migration effects that are highly dependent upon the type of environmental pressure. Drought, flooding, tropical cyclones, and tsunamis all exhibit differing migration patterns [50-52] with very little research suggesting the effect of sea level rise on human migration systems [3]. Furthermore, very little research has been undertaken that would be the bedrock of modeling who moves, where, and in what proportion[49]. Will impacted populations migrate landward? Could future coastal cities resemble Venice, Italy, complete with populations still adapting to rising sea levels? Or will populations move to more land-locked cities for protection? These questions still remain unanswered. For these reasons, we have chosen to simply model the confluence of two converging processes: coastal sea level rise and coastal population growth.

We employ a linear/exponential (LIN/EXP), regression-based extrapolation based on the past 70-years of population change for 1940-2010. Geographies that have experienced growth will utilize a linear regression while geographies that have experienced decline will utilize an exponential regression. A LIN/EXP model is used to ensure that 1) long range linear projections of decline do not project negative populations and 2) that long range exponential projections of growth do not produce extreme values of runaway growth. Recent research suggests that a LIN/EXP model outperforms both a linear and an exponential model, respectively [53]. Included within the regression formulas is an adjustment factor allowing for the projected and observed populations at launch year to be identical. This is computed by adding the residual of the estimate at time *t* back into the regressed estimate of time *t*. This allows the projection to go through the launch year population. The small data requirements make these extrapolation methods ideal for small-area projections and the use of a regression-based extrapolation allows for estimates of forecast intervals [54].

If the base housing stock is growing:

$$(4) \qquad \widehat{H}_{ij}^{t+z} = (\alpha + \beta z) + \left[(H^{t} - (\alpha + \beta t) \right]$$

If the base housing stock is declining:

$$(5) \qquad \widehat{H}_{ij}^{t+z} = e^{\beta} * z^{\alpha} + \left[H^{t} - (e^{\beta} * t^{\alpha}) \right]$$

The use of a regression-based extrapolation allows for the creation of forecast intervals. We follow a long line of inquiry in determining the credibility of population projections using forecast intervals[55-60]. These forecast intervals use the standard error of the estimate for the models and their sample sizes. Intervals were generated using equations 4.1 and 4.2 from Hyndman & Athanasopoulos' *Forecasting: Principles and Practice* [61]. We have chosen to produce a set of three population projections for each block group, an upper, middle, and lower bound based on the 90% forecast interval. Thus we produce a set of 210,942 projections – one for every block group in the study area (n=70,314) as well as for the upper and lower bound.

Evaluation of Projections. Forecast intervals, produced through the use of a regression-based projection, allow us to determine the degree of feasibility in a projection. Previous analyzes have used the 2/3 or 66% forecast interval to assess the degree of accuracy in a population projection [28,56] representing empirical "low" and "high" scenarios from cohort-component projections [62].

The use of a 2/3 interval is “neither so wide as to be meaningless nor too narrow to be overly-restrictive” [60].

To assess the degree of feasibility, we assess all intervals on the 2008-2012 ACS estimate of housing units for each census block group in the study area. We produce projections based on the equations in the preceding section with base period 1940-2000. If less than 2/3 of the ACS estimates of housing units in 2010 falls within the 2/3 forecast interval, then the results would suggest less than ideal accuracy in terms of long-range projections. Alternatively, if greater than 2/3 of the ACS estimates of housing units falls within the 2/3 forecast interval, then the results would suggest an ideal amount of accuracy in terms of long-range projections. Table S1 shows the number of ACS housing unit projections that fall within the 2/3 forecast interval. Overall, 68.4% of the 2010 estimates fell within the forecast interval suggesting a great degree of feasibility associated with these projections.

Table S1. Number of 2010 Housing Counts that fall within the 2/3 Forecast Interval.

State	# when 2010 fell within forecast interval	# of block groups	Percent
Alabama	262	362	72.4%
California	11,808	16,336	72.3%
Connecticut	1,469	2,253	65.2%
District of Columbia	350	450	77.8%
Delaware	377	573	65.8%
Florida	7,048	9,880	71.3%
Georgia	267	400	66.8%
Massachusetts	2,054	3,775	54.4%
Maryland	1,919	2,684	71.5%
Maine	466	794	58.7%
Mississippi	159	270	58.9%
North Carolina	716	1,086	65.9%
New Hampshire	162	258	62.8%
New Jersey	3,897	5,747	67.8%
New York	6,873	10,705	64.2%
Oregon	729	1,086	67.1%
Pennsylvania	1,623	2,154	75.3%
Rhode Island	457	813	56.2%
South Carolina	605	942	64.2%
Texas	2,528	3,513	72.0%
Virginia	1,919	2,576	74.5%
Washington	2,399	3,657	65.6%
TOTAL	48,087	70,314	68.4%

Assessing At-Risk Populations. At-risk projected populations of displacement under prescribed sea level rise scenarios were calculated using equation 4.

4) $$PR_{ij}^{t} = \sum PR_{ij}^{t-1} + ((P_{ij}^{t} - \sum PR_{ij}^{t-1}) * \mathrm{A}_{ij}^{t})$$

Where the population at risk of displacement (PR^t) is equal to the population projected at time t (P^t) minus the sum of the previously displaced populations (PR^{t-1}) multiplied by the land lost due to sea level rise (A^t).

Land lost due to sea level rise is calculated with a spatial overlay workflow in ArcGIS 10.1 as one minus the percentage of land lost under the preceding amount of sea level rise, ie 1ft divided by 0ft, 2ft divided by 1ft, etc. The first step in the analysis was to utilize a base, 0m Mean Higher High Water (MHHW) layer, which was derived from NOAA's 0m scenario, and used as the initial condition to calculate a base of dry land area contained within the geographies of 2010 Census Block Groups. The resulting calculation is therefore a total area of dry land currently available for human habitation within each Census Block Group geography. Each subsequent scenario is expressed as the ratio of each scenario to the previous scenario. This was repeated for the 0ft through 6ft scenarios.

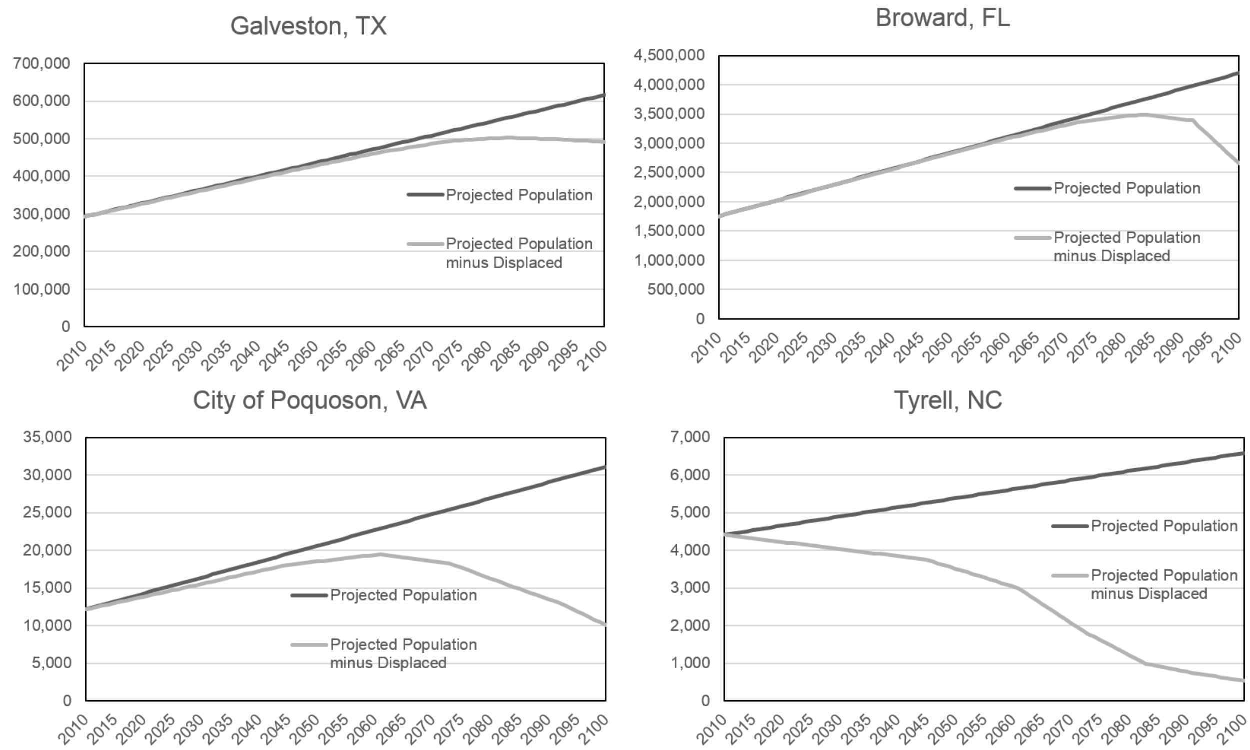


Figure S2. Accounting for Population Dynamics in the Inundation Model. These are the dynamic growth curves for four counties under the 1.8m scenario. All counties are exposed to dynamic population growth rates based on the amount of inundation. The greater the deviation from the Projected Population line, the greater the impact inundation has on a county's population growth.

Sea Level Rise Curves

Adapting methods developed for the US National Climate Assessment [63], the following quadratic equation was used as the basis for calculating deterministic curves for high (1.8m), medium (0.9m), and low (0.3m) sea level rise scenarios at 2100:

$E(t) = at + bt^2$; where

$E(t)$ = eustatic sea level rise, in meters, at time t;

a = global linear trend sea level rise constant of 0.0033 m/yr;

t = years since 2010;

b = sea level rise acceleration coefficient (units of m/yr^2), with b_{high} = 1.86E-04; b_{medium} = 7.44E-05; and b_{low} = 0