nature climate change

LETTERS

PUBLISHED ONLINE: 14 MARCH 2016 | DOI: 10.1038/NCLIMATE2961

Millions projected to be at risk from sea-level rise in the continental United States

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Sea-level rise (SLR) is one of the most apparent climate change stressors facing human society[1]. Although it is known that many people at present inhabit areas vulnerable to SLR[2,3], few studies have accounted for ongoing population growth when assessing the potential magnitude of future impacts[4]. Here we address this issue by coupling a small-area population projection with a SLR vulnerability assessment across all United States coastal counties. We find that a 2100 SLR of 0.9 m places a land area projected to house 4.2 million people at risk of inundation, whereas 1.8 m affects 13.1 million people—approximately two times larger than indicated by current populations. These results suggest that the absence of protective measures could lead to US population movements of a magnitude similar to the twentieth century Great Migration of southern African-Americans[5]. Furthermore, our population projection approach can be readily adapted to assess other hazards or to model future per capita economic impacts.

Sea-level rise is widely recognized as one of the most likely and socially disruptive consequences of future climate change[2]. Scenarios of future SLR at the year 2100 range from a low of 0.3 m to a high scenario of 2.0 m associated with collapse of polar ice sheets[3]. Understanding the specific locations at risk of SLR impacts is a high priority in climate change research[6] and adaptation planning[7,8].

Although there is growing worry and debate that climate change could cause widespread human migration over the next century[2,9,10], relatively few studies have attempted to merge climate change scenarios with population growth trends and projections in high-risk areas (however, see ref. 11). Notably, several previous studies have estimated the populations at risk of future SLR inundation through the use of current population data[12]. Given the rapid growth of population in coastal areas[13], such temporal mismatch of data sets (that is, present population and future SLR) seems likely to underestimate the impacts SLR will have on future populations. Other research has tied small-area flood inundation risk to populations at a county scale[14]. Such spatial mismatch is likely to overestimate the future populations at risk of SLR, as populations located on higher ground within a coastal county may be erroneously assumed to flood.

The mutability of many sub-county geographic units (for example, Census Tracts and Census Block Groups) at each decennial Census cycle is a classic example of the modifiable areal unit problem[15], and generally limits the development of long-range projections to areas in which geographic boundaries remain stable[16]. Using a novel approach, we overcome the methodological issues related to spatial and temporal mismatch and the mutability of sub-county units[17] by synthesizing spatially explicit environmental data (that is, elevation and associated flood risk) with small-area population projections developed with a modified version of the Hammer method[17,18] in a dynamic flood hazard model. By spatially and temporally aligning small-area population projections from coastal states in the continental United States (US) to 2100, we are able to assess who could be at risk from future SLR.

This approach addresses two fundamental questions concerning the vulnerability of future coastal populations in the United States: How many people are potentially at risk of impact from SLR? and What areas in the US are likely to experience the greatest population exposure to SLR? 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) 0 m through 1.8 m (6 feet) SLR data sets for twenty-two coastal states and the District of Columbia[19]. These data sets 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 was not included in the data set at the time of analysis owing to local hydrologic complexities associated with coastal levees and accelerated land subsidence; however, we have recreated NOAA's hydrologic connectedness approach for Louisiana using USGS's National Elevation Dataset (NED) (Methods).

We used a linear/exponential extrapolation approach for projecting Census Block Groups (CBGs) from 2010 to 2100. We included only CBGs ($n = 72{,}664$) located in counties ($n = 319$) expected to experience impact under the 1.8 m scenario. A detailed technical description is available in Methods. Detailed projections of exposure for all 319 coastal counties are also found in Supplementary Fig. 1 and Supplementary Tables 1 and 2. The population at risk of SLR is dynamically assessed as the proportion of the CBG underwater when SLR is expected to exceed 0.3 m intervals under the 0.9 m and 1.8 m scenarios. With a recreation of NOAA's hydrologic connectedness approach for Louisiana at 0 m, 0.9 m, and 1.8 m, we assessed Louisiana's population at 0.9 m intervals rather than 0.3 m intervals. As populations become exposed under each SLR scenario in each block group, projected populations are dynamically adjusted to account for this exposure to ensure no persons are double counted.

We find that in the continental US approximately 13.1 million people are at risk under the 1.8 m scenario (Fig. 1). The projected number for the US is double the current population estimates

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NATURE CLIMATE CHANGE DOI: 10.1038/NCLIMATE2961

Table 1 | Projected populations at risk of sea-level rise by 2100.

State	Current populations		Projected populations			
	0.9 m SLR in 2100	1.8 m SLR in 2100	0.9 m SLR in 2100	±	1.8 m SLR in 2100	±
AL	20,914	32,775	38,238	7,801	57,303	11,584
CA	227,677	504,595	472,248	98,343	1,046,757	208,343
CT	34,980	82,922	53,566	7,189	128,048	17,947
DC	1,391	3,167	2,005	410	4,629	948
DE	24,251	43,262	44,597	7,708	76,836	14,061
FL	593,207	2,743,086	1,221,837	236,103	6,057,419	1,216,806
GA	50,837	96,727	93,036	18,683	178,787	37,263
LA	412,648	678,151	846,203	263,827	1,361,792	292,676
MA	67,540	303,649	103,552	13,329	427,549	57,669
MD	54,226	110,009	92,584	14,730	188,624	31,624
ME	9,085	18,492	15,230	1,848	29,028	3,574
MS	25,974	41,469	50,385	10,254	76,901	16,721
NC	90,538	165,760	163,260	27,210	297,917	52,013
NH	4,795	8,948	8,670	1,131	15,432	2,024
NJ	174,822	482,180	308,662	47,436	827,449	137,272
NY	110,865	505,359	198,257	32,543	901,366	159,124
OR	7,425	15,499	12,754	1,903	25,614	4,163
PA	5,692	16,593	9,939	1,858	27,427	5,659
RI	9,171	23,429	14,875	1,646	36,546	3,977
SC	91,394	204,039	163,492	38,527	374,395	86,058
TX	93,092	214,364	173,025	45,306	405,423	106,301
VA	96,622	248,600	181,130	38,072	475,871	102,952
WA	22,753	53,279	43,436	7,229	94,139	16,040
Tot	2,229,898	6,596,356	4,310,981	923,086	13,115,252	2,584,797

We considered only census block groups and counties expected to experience any inundation under 1.8 m of sea-level rise in 2100. ± values are the 90th percentile from the projection values.

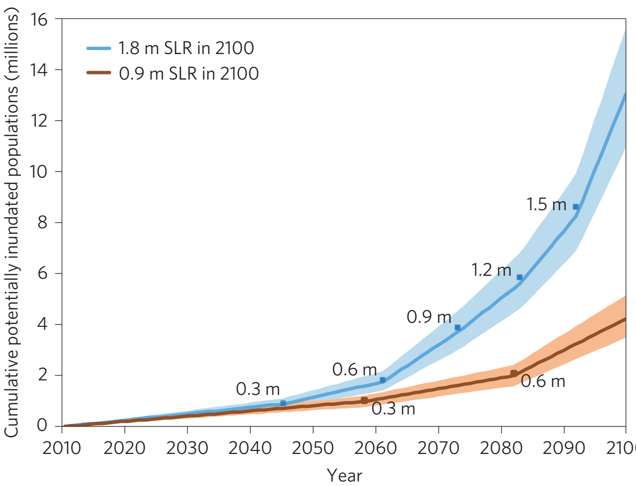

Figure 1 | Cumulative projected at-risk populations for the continental United States, 2010–2100. Projections reflect assumed growth/decline rates for 72,664 census block groups in 319 coastal counties. The shading indicates the 90% confidence interval of the projection models.

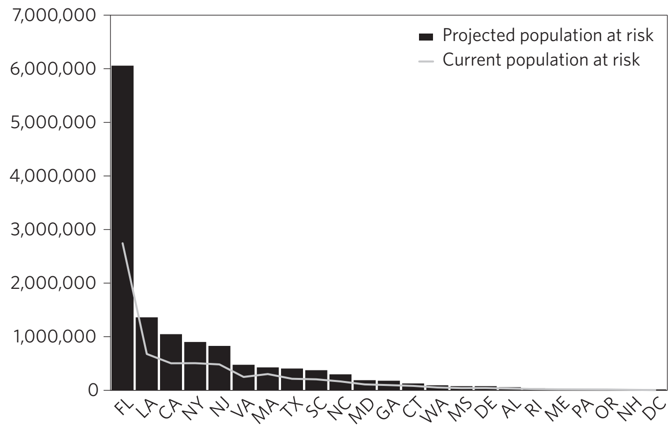

Figure 2 | Projected cumulative populations at risk of sea-level rise in 2100 under the 1.8 m scenario. We considered 22 states and the District of Columbia. Black bars are the projected population at risk and the grey line is the current population at risk based on Census 2010.

for 2010 in these areas (Fig. 2 and Table 1), suggesting an underestimation of risk when using current population estimates. Florida accounts for nearly half of the total at-risk population. Whereas other southeastern states have substantially fewer people at risk, states such as Georgia, South Carolina, and Louisiana have over 10% of future coastal populations at risk under the 1.8 m scenario. The southeastern US alone represents nearly 70% of the entire projected populations at risk, suggesting the impacts of SLR will be highly regionalized in nature.

Our results also suggest a hyperlocalized impact from SLR (Fig. 3 and Supplementary Table 2). Although the median percentage of the population subject to SLR impact across all 319 coastal counties is just 3.5% under the 1.8 m scenario, several low-lying counties would be likely to experience extreme exposure. Three counties in particular—Tyrrell, North Carolina (94% of the projected population located in land area at risk of inundation), Monroe, Florida (88%), and Hyde, North Carolina (82%)—could see catastrophic impacts with 1.8 m SLR. Broward, Miami-Dade and Pinellas, Florida; San Mateo, California; and Jefferson and Orleans, Louisiana are projected to see more than 100,000 residents potentially impacted with a 0.9 m SLR. An additional 25 counties would have more than 100,000 impacted persons with a 1.8 m SLR. Miami-Dade and Broward counties in Florida alone account for more than a quarter of the people impacted under the 1.8 m

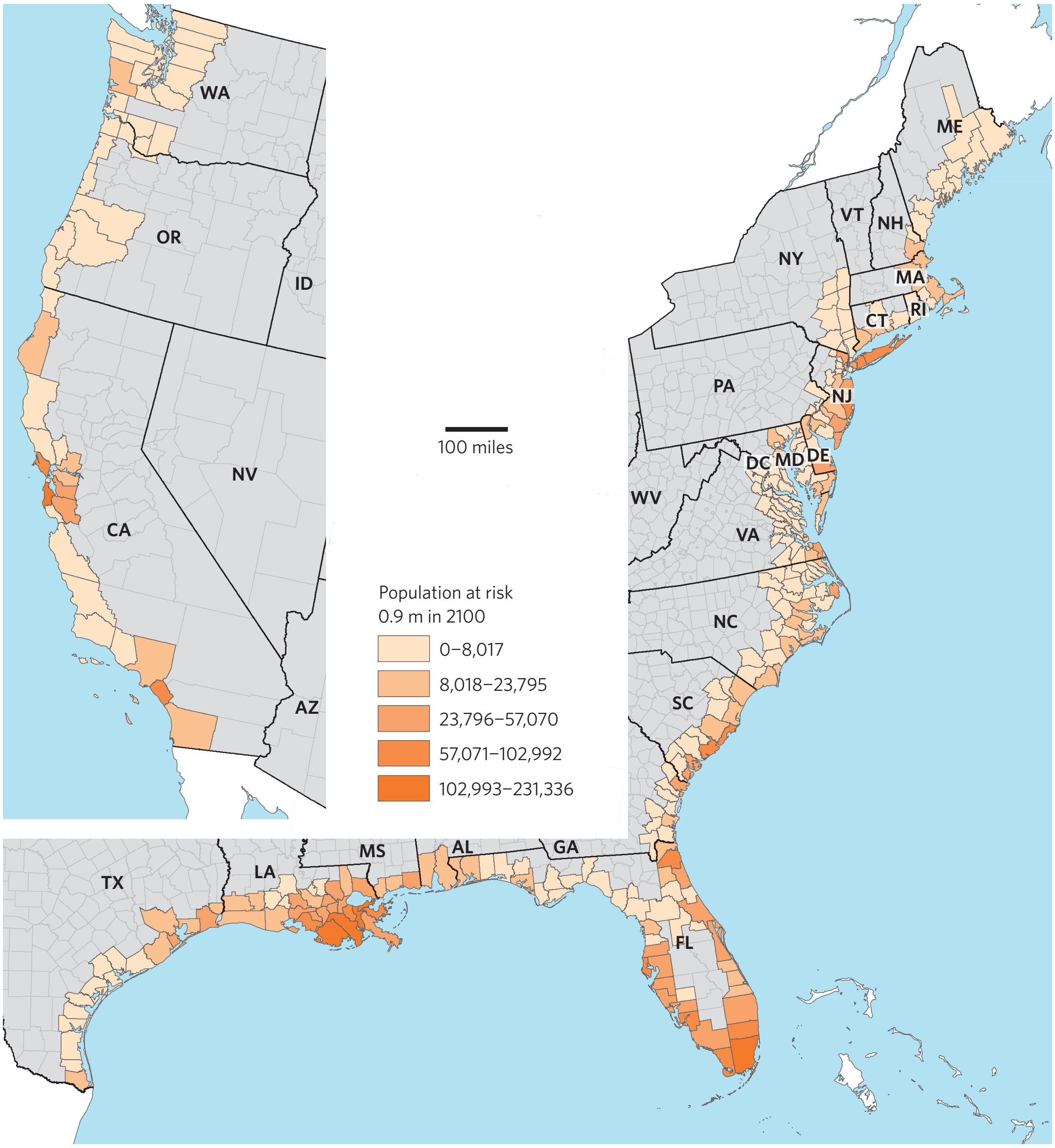

Figure 3 | Cumulative projected populations at risk of SLR under the 0.9 m scenario by 2100 for US counties. Counties not included in the study are coloured in grey.

scenario. Expanded results for all 319 counties can be found in Supplementary Table 2.

Cities such as Tampa–St Petersburg, Florida; Charleston, South Carolina; Poquoson, Virginia; and Cape May, New Jersey may experience serious levels of population impact 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 impact from SLR. Owing to geographic variability, one-size-fits-all national approaches for tackling SLR, such as recent changes to the US federal government's National Flood Insurance Program[20], could prove problematic or inadequate as adaptation strategies alone.

Adaptation strategies for SLR rely on accurate information about the geographies, timescales, economies and populations at risk. Recent estimates of annual global costs for adapting coastal flood protection infrastructure to a 2100 SLR of 2.0 m are approximately US$421 billion (2014 values) per year[21]. Although such cost inventories[22] are helpful, they do not take into account expansions in population and infrastructure that are likely to take place before inundation occurs. Our work indicates that existing estimates of future adaptation cost may, in fact, be deceptively low if future population growth is not taken into account.

Similarly, proposed managed retreat solutions could also prove troublesome if population projections are left out of the equation. So far, managed retreats have tended to involve small populations and areas[23,24], but future action could be needed in areas with areas with much larger and 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 US$1 million per resident in some small Alaskan villages[25], each decade both increases that population's exposure to SLR 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 towards 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 past decade[26] in spite of widely documented tidal flooding from both land subsidence and SLR, suggesting a complicated relationship between population dynamics and SLR. Furthermore, adaptation and mitigation strategies are likely to be employed, shaping future population scenarios through unknown future public policies. Our projections of inundated populations could be biased upwards 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[27]. By using the longest possible base period, we do find acceptable accuracy for these projections, with approximately half of the coastal states exceeding accuracy expectations. There were notable exceptions, however, as four states fell far below accuracy expectations—Massachusetts, Maine, Mississippi, and Rhode Island—with another eight states falling just below expectations (Supplementary Table 1). In spite of these issues, our out-of-sample validation found the projections to be reasonably calibrated, as four of the top six most affected states exceed expectations.

Past trends do not guarantee future trends. Local growth ordinances and population saturation points could improve future population projections. Furthermore, vertical land movement will exacerbate the impacts of SLR, specifically in southeast Louisiana and the Chesapeake Bay areas[12,28]. Although we do not model vertical land movement, our results could be considered conservative in the aforementioned areas expected to see the greatest land subsidence, as it is the combination of SLR and vertical land movement that can prove the most destructive.

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 used by decision makers and researchers. For example, other by-products of SLR, such as loss of coastal wetlands, saltwater intrusion, and higher storm surges from tropical cyclones[29–31] could also be modelled, as well as economic impacts from these hazards. For instance, using the example of the cost for relocating some Alaskan coastal villages[25] of US$1 million per resident, the cost of relocation could exceed US$14.0 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 modelling. We note, however, that our small-area projection method requires detailed demographic information on the age of housing stock, thus limiting the applicability of the approach to nations and jurisdictions where such data are regularly collected and available.

Methods

Methods and any associated references are available in the online version of the paper.

Received 4 April 2015; accepted 15 February 2016; published online 14 March 2016; corrected online 21 March 2016 and 22 April 2016

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Acknowledgements
Publication supported in part by an Institutional Grant (NA10OAR4170098) to the Georgia Sea Grant College Program from the National Sea Grant Office, National Oceanic and Atmospheric Administration, US Department of Commerce. Data reported in the paper are available in the Supplementary Methods. The authors are grateful for the assistance and constructive comments from K. Devivo, C. Hopkinson, J. M. Shepherd, S. Holloway, T. Mote, J. Baker and W. Anderson.

Author contributions
M.E.H. produced the small-area population projections and the projections of inundation, contributed to the methodological design, wrote the paper, and is the corresponding author to whom requests for materials should be addressed. J.M.E. contributed significantly to the methodological design, conceptual framing, and editing of the paper. D.R.M. produced the inundation modelling for Louisiana and contributed to the editing of the paper.

Additional information
Supplementary information is available in the online version of the paper. Reprints and permissions information is available online at www.nature.com/reprints. Correspondence and requests for materials should be addressed to M.E.H.

Competing financial interests
The authors declare no competing financial interests.

NATURE CLIMATE CHANGE DOI: 10.1038/NCLIMATE2961

Methods

The methodology for overlaying projected small-area population with sea-level rise (SLR) inundation layers is outlined in this section. First, we describe the data sets and basic methodology behind SLR inundation layers. Second, the methodology to historically estimate housing units is introduced. Third, the methodology to convert housing units to population is reviewed. Fourth, the extrapolation approach undertaken to produce population projections is reviewed. Next, the determination of at-risk populations through intersection with SLR curves and inundation models is described. Last, we evaluate the accuracy of our population projections.

Data. Many assessments of the populations at risk from SLR have used an elevation based 'bath-tub' approach for inundation modelling[12,14,32], whereby all areas under a given threshold (usually 1 m, 2 m, 3 m, or 6 m) are flooded without explicit consideration of hydrological connectedness. A known limitation of the simple bath-tub approach is that areas protected from inundation by dykes or levees will be shown as inundated. For example, much of New Orleans, Louisiana is located at an elevation well below local mean sea level. Under a simple bath-tub approach, all areas of New Orleans located below sea level, including those protected from floodwaters by dykes and levees, would be shown as inundated under even an initial condition (0 m) SLR model.

For this research, we used SLR inundation data sets developed by the National Oceanographic and Atmospheric Administration (NOAA) as the basis for simulating future SLR impacts on human populations in the coastal United States (US)[19,33]. The NOAA data sets are based on a 1/3 arcsecond (10m) resolution digital elevation model (DEM), which is then used to simulate expected 0.3 m increment (1 foot) changes in the mean higher high water (MHHW) mark, up to a maximum scenario of 1.8 m (6 feet), on areas of the continental US that are hydrologically connected to the coastal zone. The low SLR value of 0.3 m and the high SLR value of 1.8 m in the NOAA data sets generally represent the range of low to high SLR scenarios defined by the most current US National Climate Assessment[3]. The underlying 1/3 arcsecond DEM is used by the US federal government for development of floodplain contours, rated as ± 0.3 m at the 85% confidence interval[34]. Because such floodplain contour maps are used to set flood insurance rates at the parcel-scale, there is confidence in applying a similar 0.3 m interval assessment of SLR as generalized across much larger geographic areas (for example, counties and Census boundaries). However, we also note that the NOAA SLR data set does not take into account additional land loss caused by other natural factors such as erosion, subsidence, or future construction, and are provided 'as is' without warranty to their performance.

We used the 1/9 arcsecond (3 m) NED data to develop the SLR projection model for Louisiana. A 3 m MHHW surface was created using NOAA's vertical datum conversion software, VDatum (http://vdatum.noaa.gov) and a triangulated irregular network (TIN) was created and used for hydrologic connectivity mapping for the 0 m depth grid (current condition). A linear superposition method was used by adding 0.9 m (3 ft) and 1.8 m (6 ft) to the 0 m depth grid to map SLR scenarios.

A small-area housing unit projection method was used to produce sub-county population projections for all US coastal counties expected to have direct impacts from the 1.8 m SLR scenario ($n=319$). The sub-county unit for these projections was Census Block Groups (CBGs), with geographies defined by the 2010 US Census. Data for conducting the population projections come from three 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 2010 boundaries for CBGs. The second piece of data is the actual historic count of housing units (HU) and population for each county. This data is available as digitized records from the Census Bureau's website. 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. Finally, our Group Quarters (GQ) population data come from the 2010 Census. It should be noted that the ACS data, although similar to decennial data, is subject to sampling error, but all released ACS data have confidence limits above 90% (ref. 35). Furthermore, GQ tends to be the most volatile aspect of the Census Bureau's Estimates Program and ACS (ref. 36), but is an important aspect of the HU method.

Estimates of historic housing units. Demographic projections of small-areal units (that is, sub-county units) tend to be less robust than projection methodologies at larger scales[16,37]. The changeability of many sub-county boundaries (for example, Census Tracts and CBGs) at each decennial Census cycle provides a classic example of the modifiable areal unit problem (MAUP), thus effectively limiting the development of more long-range projections to areas in which geographic boundaries remain stable[16]. In the US, counties are the smallest geographies with boundaries that tend to remain stable over time.

We use a modified version of the Hammer method[17,18] based on a proportional fitting algorithm to project sub-county populations[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 fitted 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 and 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, that is, 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 make use of the Housing Unit (HU) method to convert an estimate of Housing Units to an estimate of population.

$$P_t = H * \mathrm{PPHU} + \mathrm{GQ} \tag{2}$$

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[39], 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). Whereas Census-designated boundaries may change, housing units typically do not move[18]. Based on the 'year structure built' question in Census data, the method produces proportionally adjusted housing unit estimates at the sub-county CBG, which is the smallest geography possible for such projections using US Census data.

Equation (3) demonstrates the approach employed here to use 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[40–43].

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

Projection approach. We employed 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 used a linear regression whereas geographies that have experienced decline use an exponential regression. A LIN/EXP model is used to ensure that long-range linear projections of decline do not project negative populations, and 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[44]. Included within the regression formulae 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 projection intervals.

If the base housing stock is growing:

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

If the base housing stock is declining:

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

The use of a regression-based extrapolation allows for the creation of projection intervals. We follow a long line of inquiry in determining the credibility of population projections using projection intervals[45–50]. These projection 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*[51]. 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% projection interval. Thus we produce a set of 210,942 projections—one for every block group in the study area ($n=72,664$) as well as for the upper and lower bound.

Assessing at-risk populations. At-risk projected populations of sea-level rise under prescribed SLR scenarios were calculated using equation (6).

$$\mathrm{PR}_{ij}^{t}=\sum_{PR_{ij}^{t-1}}+\left(\left(P_{ij}^{t}-\sum_{PR_{ij}^{t-1}}\right)*A_{ij}^{t}\right) \quad (6)$$

where the population at risk of sea-level rise (PR^t) is equal to the population projected at time t (P^t) minus the sum of the previously impacted populations (PR^{t-1}) multiplied by the land lost due to SLR (A^t). We subtract out previously impacted populations to ensure populations are not double counted. We consider this approach a first-order, one-way interaction between population dynamics and inundation modelling. Supplementary Fig. 1 demonstrates this first-order, one-way interaction between population dynamics and SLR in four select counties.

Land lost due to SLR is calculated with a spatial overlay workflow in ArcGIS 10.1 as one minus the percentage of land lost under the preceding amount of SLR, that is, 0.3 m divided by 0 m, 0.6 m divided by 0.3 m, and so on. The first step in the analysis was to use a base, 0 m MHHW layer, which was derived from NOAA's 0 m scenario, and used as the initial condition to calculate a base of dry land area contained within the geographies of 2010 CBGs. The resulting calculation is therefore a total area of dry land, without any distinction between habitable and uninhabitable dry land, available at present for human habitation within each CBG geography. Each subsequent scenario is expressed as the ratio of each scenario to the previous scenario.

Next, we used the method developed for the US National Climate Assessment[4] to determine the years SLR could be expected to exceed 0.3 m intervals. The following quadratic equation was used as the basis for calculating deterministic curves for high (1.8 m) and medium (0.9 m) SLR scenarios at 2100:

$$E(t)=at+bt^2 \quad (7)$$

where $E(t)=$ eustatic SLR, in metres, at time t; $a=$ global linear trend SLR constant of 0.0033 m yr^{-1}; $t=$ years since 2010; $b=$SLR acceleration coefficient (units of m yr^{-2}), with $b_{\mathrm{high}}=1.86\times10^{-4}$; $b_{\mathrm{medium}}=7.44\,E\times10^{-5}$.

These curves were then used to find the years when SLR would exceed 0.3 m increments under the high (1.8 m) and medium (0.9 m) curves. These correspond to 2058, 2082 and 2100 for the medium curve (0.9 m) and 2045, 2061, 2073, 2083, 2092 and 2100 for the high curve (1.8 m). With a recreation of NOAA's hydrologic connectedness approach for Louisiana at 0 m, 0.9 m and 1.8 m, we assessed Louisiana's population at 0.9 m intervals rather than 0.3 m intervals. This corresponds to the years 2100 for the 0.9 m curve and 2073 and 2100 for the 1.8 m curve.

We explicitly do not migrate those who are projected to be at risk from SLR. Our current understanding of the human migratory response to environmental events is not robust enough to model where these inundated persons will potentially move, or if they will move at all. There are several hypotheses on human migration and climate change, mostly drawing from environmental events in the twentieth century[14,52–55]. These hypotheses, however, result in empirical migration effects that are highly dependent on the type of environmental pressure. Drought, flooding, tropical cyclones, and tsunamis all exhibit differing migration patterns[56–58], with very little research suggesting the effect of SLR on human migration systems[14]. Furthermore, very little research has been undertaken that would be the bedrock of modelling who moves, where, and in what proportion[55]. Will impacted populations migrate landwards? 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, our approach is strictly a model of the confluence between two processes, SLR and population growth. Although this confluence implies a high level of societal impact (for example, coastal flood protection, architectural adaptation, migration, and so on) in the most general sense, our approach here makes no prediction as to what the specific impacts will be in any particular location.

Evaluation of projections. Projection intervals, produced through the use of a regression-based projection, allow us to determine the degree of feasibility in a projection. Previous analyses have used the 2/3 (or 66%) projection interval to assess the degree of accuracy in a population projection[27,46] representing empirical 'low' and 'high' scenarios from cohort-component projections[59]. The use of a 2/3 interval is "neither so wide as to be meaningless nor too narrow to be overly restrictive"[50].

To assess the degree of feasibility, we assess all intervals on the 2008–2012 ACS estimate of HU for each CBG 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 HU in 2010 falls within the 2/3 projection 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 HU falls within the 2/3 projection interval, then the results would suggest an ideal amount of accuracy in terms of long-range projections. It should be noted in the consideration of these inputs that the ACS data, although similar to decennial data, is subject to many types of error. Although all released ACS data have confidence limits above 90% (ref. 60), the 'true' estimate from the 'year structure built' question cannot be known. Our evaluation should be considered in lieu of the limitations of ACS accuracy.

Supplementary Table 1 shows the number of ACS housing unit projections that fall within the 2/3 projection interval. Overall, 68.1% of the 2010 estimates fell within the projection interval, suggesting an adequate degree of feasibility associated with these projections in the aggregate. Seven states greatly exceed the target 2/3 projection interval. Four states, however, fell far below the target 2/3 projection interval—Massachusetts, Maine, Mississippi, and Rhode Island—with another eight states falling just below the target.

Projections inherently rely on historic trend data, and therefore performance tends to suffer when growth deviates the greatest from historical patterns. State-level aggregation might hide underlying geographic variability, and the variation in the projected exposure to SLR is heavily influenced by areas with the greatest deviation in past population growth. To assess these patterns, we considered the block-group-specific coefficient of variation. Panel A in Supplementary Fig. 2 demonstrates the coefficient of variation for each block group's population projection model. We find that overall variation in projected populations is generally relatively low, with the greatest variation occurring in parts of Louisiana, southern Texas, and inland North Carolina and Virginia. The Pacific Coast also tends to have lower overall variation compared to the Gulf and Atlantic coasts. By comparison, if we assess the overall contribution to uncertainty in projected populations in panel B of Supplementary Fig. 2 (the standard error), we find most uncertainty in the Gulf Coast region, specifically from Mississippi through South Florida. Three of the four states with greatest observed downward deviation in accuracy from the 66% interval show some of the lowest standard errors, with Mississippi being the exception. The northeast states, including those that fall under the 66% threshold, nevertheless show low coefficients of variation. These results provide confidence that our overall small-area projections meet or exceed accepted feasibility standards for more standard projection geographies, and thus are well-suited for finer-grain assessments of future human hazard exposure.

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Corrigendum: Millions projected to be at risk from sea-level rise in the continental United States

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Nature Climate Change http://dx.doi.org/10.1038/nclimate2961 (2016); published online 14 March 2016; corrected online 21 March 2016.

In the version of this Letter originally published online, the data in columns 2, 3, 4 and 6 in Table 1 was found to be incorrect for the state of Louisiana. The data and their corresponding totals have been amended in Table 1 and Figure 2. This has been corrected in all versions of the Letter.

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In the version of the Letter originally published, the values for current estimates of populations at risk of 3 ft and 6 ft of sea-level rise were incorrect, affecting data in Table 1 and Fig. 2, as well as two sentences in the main text. These have all been corrected in all versions of the Letter.

The authors of the Letter are grateful to Scott Kulp and Ben Strauss of Climate Central for their assistance in identifying the error.