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ORIGINAL PAPER

Sea-level rise and sub-county population projections in coastal Georgia

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Abstract It is increasingly apparent that stressors associated with anthropocentric climate change are likely to have dramatic effects on future human settlement patterns. Although sea-level rise is one of the best understood implications of climate change, geographically precise estimation of potential population displacement due to tidewater inundation has proven remarkably problematic. At least within the USA, these problems partially stem from methodological limitations of population projection methodology at sub-county scales. Using a case study of coastal Georgia, USA, this paper develops and demonstrates a new housing unit-based population projection method that is applied at the sub-county scale of Census Block Groups. These projections are then overlaid with spatiotemporally explicit assessments of future sea-level rise inundation provided through the Sea Level Affecting Marsh Model (SLAMM). We find that between 62,000 and 159,000 people are at risk of between 1 and 2 m of sea-level rise by 2100 in coastal Georgia.

Keywords Sea-level rise · Sub-county · Population projections · Hammer method · Housing unit method · Climate change

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Introduction

The interface of human–natural systems is important for understanding a host of ecological processes including wildfires (Syphard et al. 2007), forests (Hammer et al. 2009), land use, and sea-level rise (Grübler et al. 2007). Society's risks from any hazard are a function of both the likelihood and intensity of the event and the vulnerability of population to it (IPCC 2014). More broadly, vulnerability is composed of exposure to hazards as well as adaptive capacity (Adger et al. 2003). Our exposure to hazards is a function of both changes in the physical environment (manifested as heat waves, tropical cyclones, droughts, sea-level rise, etc.) as well as changes in a given population (growth, decline, age structure, etc.). While much research has focused on characterizing the potential changes in the frequency and magnitude of physical risks, increasingly, research is shifting to focus on the vulnerability of society to these hazards (McLeman and Hunter 2010; Hunt and Watkiss 2011; Parkinson and McCue 2011; Hassani-Mahmooei and Parris 2012; Cutter et al. 2013).

Population projections are an integral part of understanding a population's vulnerability to hazards and thus the future of society at large (Smith et al. 2001; Lutz 2013; United Nations 2013). They long have been used in planning, policy making, environmental investigations, and numerous other types of research (Glover and Prideaux 2008; Jenouvrier et al. 2009; Hansen 2010; Lutz and Samir 2010; Perkins 2014). Accordingly, there is growing recognition of the need to couple advanced understanding of local population dynamics with the future impacts of climate change (Hugo 2011).

Sea-level rise is one of the best understood and well-documented implications of future climate change (IPCC 2014). Detailed research has sought to identify specific locations and ecosystems at risk of impact from sea-level rise (Wu et al. 2002; Craft et al. 2009; Gesch 2009), and numerous publications have provided guidance and assessments for local adaptation to sea-level rise impacts (Lutsey and Sperling 2008; Titus et al. 2009). Although estimation of at-risk populations associated with future sea-level rise scenarios has also been of significant interest (Lutz et al. 2007; Rowley et al. 2007; Plyer et al. 2010), such research has typically used units of analysis (e.g., counties, regions, and even nations) that are geographically much larger than the sea-level rise hazard. For example, recent work by Curtis and Schneider (2011) presents a sea-level rise assessment conducted at a pixel size of less than one hectare, but then performs an overlay of at-risk population at a county level. While we acknowledge that such generalized risk allocations can inform and frame discussion of climate adaptation (McLeman 2013), development of population assessment methods that have more explicit spatiotemporal linkages with the local nature of the sea-level rise hazard is clearly warranted.

Lacking adequate data for projecting small areas, scholars resort to focus on national, regional, and county scale populations, assuming all populations in those geographies are at equal risk often left with projections of sea-level rise at the scale of 10 m by 10 m pixels (Curtis and Schneider 2011). This type of approach to modeling future population scenarios is quite problematic. The assumption that the total population in any given coastal county is at equal risk of sea-level rise inundation renders the point of utilizing sea-level rise modeling rather moot. Determining the areas at risk is rather redundant since it does not matter if 20 % of a county is at risk or 80 % of a county is at risk when the total projected county-level population is considered at risk regardless of the encroachment of the sea. If that is our working assumption, than a simple county-level population projection of coastal counties will suffice in estimating the populations at risk of sea-level rise inundation—no coastal modeling is required. Currently, 39 % of the US population resides in coastal areas. With just the working assumption that all coastal populations share equal risk of sea-level rise, we could easily deduce that 121 million people in the USA are currently at risk of sea-level rise. While inundation risk can be highly localized, other hazards that are the by-product of sea-level rise are potentially county-wide, including floodplains, storm surges, and changes in highest-high tides, among others (Nicholls and Cazenave 2010; Shepard et al. 2012), and we know that inundation risk is *not* equally shared across coastal populations.

It is well known that projection methodologies for small areal units (i.e., sub-county) tend to be less robust than projection methodologies with larger areal units (Swanson et al. 2010; Baker et al. 2013), particularly in terms of having less accuracy for long-range projections (Smith et al. 2001). Demographers, however, have proposed several projection methodologies for sub-county units that are thought to provide a generally suitable workaround. These include Hamilton–Perry (Swanson et al. 2010), the Share method (Zeng et al. 2014), and various extrapolation methodologies (Swanson and Tayman 2012). However, 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 (Cromley et al. 2009), referred to as the MAUP, thus effectively limiting the deployment of projections to areas in which geographic boundaries remain stable (Swanson et al. 2010). With projection accuracy increasing with more base periods (Smith et al. 2001), the mutability of sub-county units limits the base periods to just two. For the USA, the smallest geography that generally has stable boundaries across time are US Counties, making these previous approaches applicable to sub-county units that are the rare Census tract or block group whose boundaries remain stable between two decennial censuses. Tracts and block groups that have stable boundaries over time are generally typified by either population decline or very little population growth.

With these issues in mind, it is clear that better spatial understanding of future populations at risk of sea-level rise over the next fifty to one hundred years will require different approaches than those traditionally used by demographers. In this paper, we propose and demonstrate a novel approach to converting historic estimates of housing units to populations by combining a technique originally developed by Hammer et al. (2004) with the housing unit method (HU) for population estimation (Cai 2007). This method provides a mechanism for creating temporally contiguous sub-county boundaries over a 70-year base period from 1940 to 2010, which we then use to project populations at these same sub-county geographies at decadal intervals to the year 2100 through the use of two complex extrapolation techniques. We show how projections from this approach compare with a 2/3 forecast interval. We then present spatial overlays of future upland inundation predicted by Sea Level Affecting Marsh Modeling (SLAMM) to develop sub-county projections of populations at risk of being displaced by future tidewater flooding associated with sea-level rise.

Materials and methods

Projection methodologies share much in common with estimation methodologies. Many of the projection methodologies are also employed as estimation methodologies. The four main types of estimation methodologies—extrapolation, censal ratio, component, and statistical (Siegel 2002)—also describe the main types of projection methodologies. In fact, most estimation methods are simply projections for a short time period, generally $t + 1$, while most projections are for a longer time period, such as $t + 10$. The same basic demographic accounting equation used for population estimates is also the main equation used for the cohort-component method of population projection (Swanson et al. 2004).

The HU method is recognized as one of the most commonly used forms for estimating small-area populations (Smith 1986; Byerly 1990; Smith et al. 2002). It has been advocated before Congress for use by the Census Bureau for sub-county population estimates (Swanson 2006) and has been in practical use by state and local demographers since at least 1942 (Swanson 2010). Despite the recognized similarities between estimation and projection methodologies, the HU method has never been used in projection methodologies. While the HU method would be subject to the same bias and error as population estimates (Smith and Cody 1994), it would be able to convert any projection of housing units into projections of population.

Despite the fact that there are multiple proposed solutions to the MAUP (Martin et al. 2002; Norman et al. 2003), no current projection methodology can currently be used across national, state, county, and sub-county geographies as a standalone methodology because of the MAUP. Hammer et al. (2004) attempt to address this issue at the scale of sub-county boundaries by reverse forecasting estimates of housing units, Hammer's method, combined with the HU method, produces one ontologically coherent estimation and projection methodology for all geographies suitable for both forecasting and backcasting temporally contiguous areal units.

Population projections

Our new approach relies upon the similarities between population estimates and projections. The underlying relationship between a population estimate (Eq. 1) and projection (Eq. 2) is demonstrated with demographic accounting equation (Newbold 2010):

$$P_1 = P_0 + B - D + I - E \tag{1}$$

$$P_{t+1} = P_t + B - D + I - E \tag{2}$$

where B is the births, D is the deaths, I is immigration, and E is the emigration. The only significant difference between the two equations is in the definition of the time period. For an estimate, it is always time 1, i.e., the present year, and based on the population from $t-1$. For a projection, it is always time $t+1$ based on the population from time t. For all intents and purposes, most projection methodologies *are* estimation methodologies at their core, and the HU method is no different. It too is often referred to as a balancing equation (Smith and Cody 1994; Swanson 2010).

Equation 3 demonstrates the HU method (Cai and Spar 2008; Swanson 2010):

$$P = H * \mathrm{PPHU} + \mathrm{GQ} \tag{3}$$

where H is the number of housing units, PPHU is the persons per household, and GQ is the group quarters population—a count or estimate of populations in group living arrangements such as college dormitories, group homes, military barracks, correctional facilities, etc. Any error associated with the HU method is attributable to the quality of the inputs, as the HU method is considered a demographic identity (Siegel and Swanson 2008). Here, we use the HU method to convert projections of housing units to projections of populations. The HU method on its own could produce a population projection if all three variables are projected on their own, but the aforementioned Census boundary changes at sub-county scales lead to problems in forecasting any of the component inputs for sub-county geographies. The Hammer method, however, 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 (Hammer et al. 2004). 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 (Fig. 1).

We use a modified version of the Hammer method based on a proportional fitting algorithm (Deming and Stephan 1940) and build upon previous work (Hauer 2013). Hammer's method is essentially a combination of a growth allocation and proportional fitting approach, where the growth between time periods is allocated to

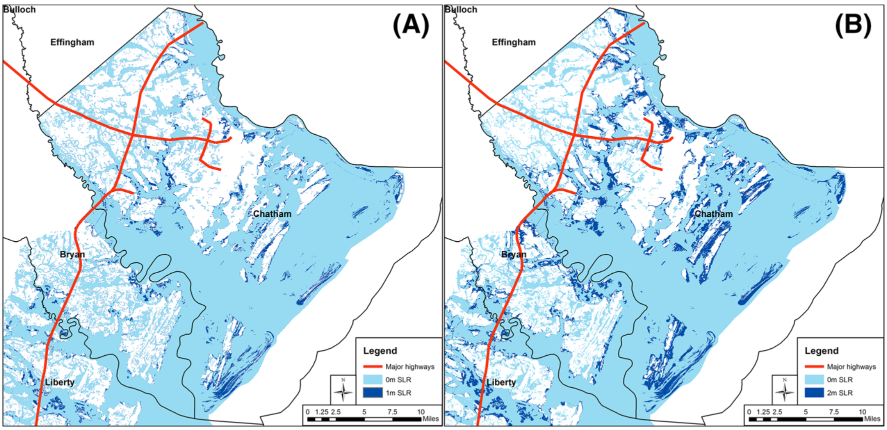

Fig. 1 Chatham County, Georgia, sea-level rise inundation maps for 1 m of sea-level rise (**a**) and for 2 m of sea-level rise (**b**) based on SLAMM results

each block group and proportionally fit to the marginals. This leads to estimates that can only increase over time and never decrease.[1] Instead, the approach proposed here does not use an allocation approach, but rather the simpler proportional fitting approach. The following set of equations demonstrates this proportional fitting approach.

$$\hat{H}_{ij}^{t} = \left(\frac{C_j^t}{\sum_{1939}^{t-1} H_j^t} \right) * \sum_{1939}^{t-1} H_{ij}^{t} \tag{4}$$

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, divided by the number of housing units at the county level in the ACS for the period 1939–1979, multiplied by the number of housing units observed in the ACS for the period 1939–1979 for block group i in county j. This process is iterated for each decade until the most recent time period, i.e., the 2010 Census. Figure 2 provides some examples of historic housing unit growth for various block groups in Chatham County, Georgia, for the period 1940–2010. Notice that simultaneous growth and decline within the county are now estimated. This modified approach will allow for more fluctuations in the estimated number of housing units between each Census and frees Hammer's approach from only estimating growth within each block group. 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 from Eq. 3.

$$\hat{P}_{ij}^{t+z} = \frown{H}_{ij}^{t+z} * PPHU_{ij}^{t} + GQ_{ij}^{t} \tag{5}$$

Equation 5 demonstrates the general approach employed here to utilize the HU method to convert a projection of housing units to a projection of *population*. While Eq. 4 allows us to recreate historic estimates of housing units, historic PPHU and GQ values are unknowable at the Census block group level due to the MAUP. Without CBG trend data of PPHU and GQ, we simply hold these values constant at time t. Equation 5 allows us to directly convert our unit of analysis from that of housing units to that of people. As such, $\frown{H}_{ij}^{t+z}$ is free to be projected using the family of share methods (constant, shift, and share of growth), simple and complex extrapolation approaches, ratio-correlation projections, ARIMA models, or any other extrapolation approach. We chose the use of a regression-based approach to

[1] For a more detailed explanation of the method, see Hammer et al. (2004).

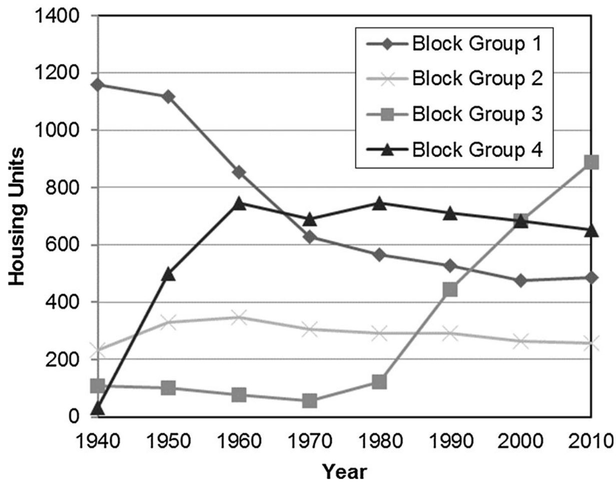

Fig. 2 Sample housing unit values for various block groups in Chatham County, Georgia. Notice the differential growth rates between the selective block groups

projecting our housing units using Eqs. 6 and 7 and use Eq. 5 to convert projections of $\widehat{H}_{ij}^{t+z}$ into $\hat{P}_{ij}^{t+z}$.

If the base housing stock is growing:

$$\widehat{H}_{ij}^{t+z} = (\alpha + \beta z) + [(H^t - (\alpha + \beta t)] \tag{6}$$

If the base housing stock is declining:

$$\widehat{H}_{ij}^{t+z} = e^{\beta} * z^{\alpha} + \left[H^t - (e^{\beta} * t^{\alpha})\right] \tag{7}$$

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 (Wilson 2014). 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 (Swanson and Tayman 2013).

The use of a regression-based extrapolation allows for the creation of 2/3 or 66 % forecast intervals. We follow a long line of inquiry in determining the credibility of population projections using forecast intervals (Cohen 1986; Swanson and Beck 1994; Swanson et al. 2000; Smith et al. 2001; Swanson et al. 2011; Swanson and Tayman 2015). Our analysis here differs markedly from this previous body of work: Here, we assess the credibility of small-area projections. These forecast intervals use the standard error of the estimate for the models and their sample sizes. Intervals were generated using Eqs. 4.1 and 4.2 from Hyndman and Athanasopoulos' *Forecasting: Principles and Practice* (2014).

It should be noted in the consideration of these inputs that the ACS data, though similar to decennial data, are subject to many types of error. While, all released ACS data have confidence limits above 90 % (Swanson and Tayman 2012), the "true" estimate from the "year structure built" question cannot be known. We have chosen to produce a set of three population projections for each block group, an upper, middle, and lower bound based on the published margins of error for the "year structure built" question. Thus, we produce a set of 942 projections—one for every block group in the study area ($n = 314$) as well as for the upper and lower bound.

Data

For this research, we conducted sub-county projections within the six counties of Georgia, USA, that abut the Atlantic Ocean: Bryan, Camden, Chatham, Glynn, Liberty, and McIntosh. These counties were chosen as a pilot area due to specific interest of the Georgia Sea Grant Program and Georgia Department of Natural Resources (GDNR) in assessing future risks of sea-level rise to local communities. These six counties account for 97.7 % of the estimated land area threatened by 1 m of sea-level rise and 98.01 % with 2 m of sea-level rise (Concannon et al. 2010). Because these six counties bear the overwhelming brunt of sea-level rise, we have chosen to assess only these six counties. Although the sub-county projection methodology can be readily applied at more national scales for assessing sea-level rise risks, the specific ability to utilize high-resolution land cover change outputs in coastal Georgia associated with prescribed sea-level rise using SLAMM outputs at 2050 and 2100 provides a unique opportunity and model for development of spatiotemporally consistent population risk projections.

Data for conducting the population projection come from two main sources. The first source of data comes from the American Community Survey 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. These data are available as digitized records from the Census Bureau's Web site.[2]

The Sea Levels Affecting Marshes Model (SLAMM) is the most commonly used ecological model for assessing changes in marsh area and habitat type under the

[2] 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.

influence of sea-level rise, incorporating the effects of inundation, erosion, accretion, salinity distribution, elevation, and feedbacks between accumulation and inundation. SLAMM utilizes a complex decision tree to represent transfers among coastal classes using raster cells with elevation, slope, aspect, estimated salinity, and wetland type. Most sea-level rise modeling employs three main approaches. These approaches, from most simple to most complex, are an elevation-based approach (Lam et al. 2009) where all cells under a specified threshold are considered inundated regardless of proximity to a water body, a 'bathtub' model (Murdukhayeva et al. 2013) where all cells under a specified threshold are considered inundated, but hydrological connectedness is now taken into account, and SLAMM. We chose to utilize SLAMM due to the availability of inputs for Georgia and because it accounts for six processes in coastal environments, potentially representing a more robust picture of inundation.

SLAMM (v. 6.0.1; Clough et al. 2010) was run for the six Georgia coastal counties using LiDAR elevation data, field-based estuarine salinity gradients, and distinct fresh, brackish, and salt marsh accumulation rates. Starting from a base year of 2007, predictions of wetland distribution (and thus areas that transitioned from upland to inundated intertidal) were made for 2025, 2050, 2075, and 2100, under a range of total sea-level rise scenarios. With sea levels expected to rise between 2 and 6 feet by 2100 (Vermeer and Rahmstorf 2009; Grinsted et al. 2010; Jevrejeva et al. 2012; Parris et al. 2012; Rahmstorf et al. 2012), here we analyze the results for the intermediate (1 m) and high (2 m) scenarios of sea-level rise. These two scenarios were chosen because Georgia's Department of Natural Resources recommends planning for 1 m by 2100 with the 2-m scenario for risk-averse decision makers. The Georgia Coastal Management Program, the Coastal Georgia Vulnerability Assessment, and the Georgia Disaster Recovery and Redevelopment Plan utilize these two scenarios for planning purposes also.

At-risk projected populations under prescribed sea-level rise scenarios were calculated using a spatial overlay workflow in ArcGIS 10.1. The first step in the analysis was to utilize a base land cover layer, which was derived from 2007 imagery and used as the initial condition for SLAMM, to calculate a base of dry upland area contained within the geographies of 2010 Census Block Groups in coastal Georgia. To assure completeness, only those Census Block Groups with geographies that were contained entirely within the geography of the SLAMM scenarios were included within the population analysis; Census Block Groups that had extents not covered by the SLAMM runs were excluded from the analysis. Non-developable uplands, which are defined as those held in public lands or with private conservation easements as mapped by State of Georgia (conservation lands file reference), were masked out of all upland calculations. The resulting calculation is therefore a total area of dry land currently available for human habitation within each Census Block Group geography (A_{2007}).

Projected populations for 2050 and 2100 in each Census Block Group were then divided by the available upland area provided by the 2007 land base, thus providing a projected population density per base habitable land area ($PopDens_{Year}$). The 2007 upland cover is used for this density calculation because these private lands currently provide the assumed habitable and buildable area for extant and future human populations, particularly if the sea-level rise hazard is not considered within the planning process.

The next step in the analysis was to calculate the area of uplands remaining in each Census Block Group area as projected under four different SLAMM outputs: (1) 2050 under the 1 M by 2100 curve; (2) 2050 under the 2 M by 2100 curve; (3) 1 m of SLR at 2100; and (4) 2 M of SLR at 2100. The difference in area between the 2007 upland cover and the upland cover identified in each of the SLAMM scenario runs was then calculated ($S_{SLAMMScenario}$). This area calculation represents the loss of uplands to sea-level rise under each given SLAMM scenario. The final step of the analysis is multiplication of $S_{SLAMMScenario}$ by $PopDens_{Year}$ for a given projection year. This calculation results in a Census Block Group level projection of human population displaced by sea-level rise due to inundation of current habitable uplands area—referred to from here on as the at-risk population.

Evaluation

Evaluating population projections typically involves comparing a projection launched from a historic period with population counts in more contemporary time periods (Murdock et al. 1991; Kanaroglou et al. 2009). This proves problematic, however, when looking to compare sub-county areas due to the changes in Census geography that would have occurred over any evaluation period. Even if the sub-county geographies were summed to the county level, evaluation of historic periods would be rather fruitless since the historic estimates are controlled to county-level totals from the historic Censuses. Additionally, virtually every projection is "wrong," but population projections still provide useful information for planning purposes (Swanson and Tayman 2013). The question then moves to the feasibility of a projection.

Forecast 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 % forecast interval to assess the degree of accuracy in a population projection (Swanson and Beck 1994; Tayman et al. 2007) representing empirical "low" and "high" scenarios from cohort-component projections (Stoto 1983). The use of a 2/3 interval is "neither so wide as to be meaningless nor too narrow to be overly restrictive" (Swanson and Tayman 2015). It should be noted that while this method of comparison does not utilize any of the typical demographic ex post facto evaluation statistics such as mean absolute percent error, mean algebraic percent error, or root mean squared error (Levinson 1946; Abraham and Ledolter 2009; Hauer et al. 2013), this comparison is more similar to a feasibility approach (Lutz et al. 1998; Tippett et al. 2013) in that this comparison determines whether these projections have a defensible amount of feasibility.

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 coastal Georgia. We produce projections based on the equations in the preceding section with base period 1940–2000. With such a limited set of data (1940–2010), longer range projection horizons are inadequate for this feasibility analysis. Each additional decade of the projection horizon automatically leads to one fewer decade in the base period. To assess a 20-year projection horizon, for instance, would require a 1940–1990 base period (50 years); a 40-year projection horizon would require a 1940–1970 base period (30 years). Given that both base period length and projection horizon length affect projection accuracy (Tayman et al. 2007), we cease to have an apples-to-apples comparison within this dataset and have chosen to simply assess the 1940–2000 base period with a 10-year projection horizon.

If less than 2/3 of the ACS estimates of housing units in 2010 fall 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 fall within the 2/3 forecast interval, then the results would suggest an ideal amount of accuracy in terms of long-range projections. Table 1 shows the number of ACS housing unit estimates that fall within the 2/3 forecast interval for the six coastal counties. Overall, 79 % of the 2010 estimates fell within the forecast echoing previous analyses of projection accuracy of simple extrapolation methods carried out on larger geographic bodies (Swanson and Beck 1994; Swanson and Tayman 2012, 2013). However, Bryan and McIntosh counties' forecast intervals—the two most rural counties in coastal Georgia—do not contain 2/3 of the 2010 values. In spite of this, the results from this assessment suggest this approach produces feasible population projections for small geographies.

Results

Table 2 shows the 2050 and 2100 projected populations and populations at risk of inundation for the six counties in Georgia. In total, we find approximately 60,000 people could be living in areas affected by 1 m of sea-level rise in 2100 and 160,000 people affected by 2 m representing between 8 and 17 % of the coastal population. Chatham and Glynn counties are poised to see the greatest numbers of population at risk, accounting for nearly 85 % of the total population at risk of sea-level rise. Clearly, both topography and population dynamics determine the level of risk in a given area as both of these counties are experiencing rapid population growth and are expected to see some of the most adverse effects of sea-level rise.

Table 1 Number of 2010 housing counts that fall within the 2/3 forecast interval

County	# in 2010 that fell within forecast interval	# of block groups	Percent
Bryan	5	8	63
Camden	22	24	92
Chatham	169	204	83
Glynn	39	54	72
Liberty	10	15	67
McIntosh	2	9	22
Total	247	314	79

Table 2 Projected populations at risk of being displaced by sea-level rise in coastal Georgia counties under 2050 and 2100 sea-level rise scenarios

Scenario	County						Total
	Bryan	Camden	Chatham	Glynn	Liberty	McIntosh	
1 m in 2050							
Lower limit	367	366	4,575	1,618	268	122	7,318
Projected	471	555	7,235	2,748	355	291	11,655
Upper limit	828	905	11,406	4,454	550	501	18,644
2 m in 2050							
Lower limit	727	833	9,593	3,864	521	305	15,844
Projected	929	1,274	15,304	6,944	695	680	25,826
Upper limit	1,634	2,078	24,126	11,322	1,080	1,152	41,392
1 m in 2100							
Lower limit	1,844	2,217	26,670	10,736	1,248	740	43,456
Projected	1,842	3,045	37,290	17,101	1,428	1,409	62,115
Upper limit	3,638	5,170	58,227	28,383	2,321	2,458	100,198
2 m in 2100							
Lower limit	5,013	7,426	65,986	27,794	2,923	1,587	110,729
Projected	5,115	10,235	93,776	44,444	3,380	2,887	159,838
Upper limit	10,459	17,558	141,756	73,191	5,509	5,245	253,718

The lower and upper limits are based on the margins of error in the American Community Survey 2008–2012 data

Additionally, threatened populations in 2050 can be as small as 11,000 under the 1 m in 2100 scenario or as large as 25,000 with 2 m in 2100 scenario. However, regardless of the sea-level rise scenario, it is clear that coastal Georgia should see some population displacement by 2050: a timeline that is nearly within the lifetime of a 30-year mortgage.

Figure 3 shows the total population at risk of sea-level rise by block group for all of coastal Georgia under the 2-m scenario in 2100, and Figs. 4 and 5 show more detailed maps of Chatham and Glynn counties under the same scenarios. The areas of these counties with the greatest concentration of block groups, indicative of downtown areas and also the old cities' urban cores, show the least risk of inundation. The populations at risk also do not follow a natural progression of risk inland, i.e., an area that is 5 miles inland could be at less risk than area that is 20 miles inland.

Discussion

Coastal Georgia and coastal South Carolina share many geophysical and population characteristics. The respective major cities in both states, Savannah and Charleston, are oftentimes lumped together in travel guides (Sullivan 2007), both coastal areas are home to Gullah populations (Pollitzer 2005), the system of barrier islands are

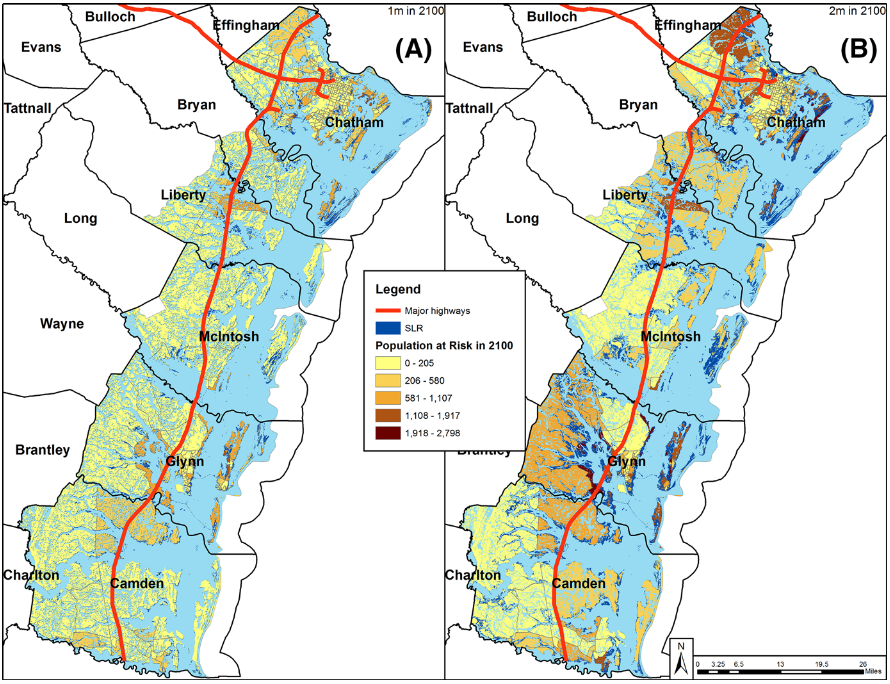

Fig. 3 Populations at risk of sea-level rise in coastal Georgia in 2100 at the Block Group Level under the 1-m scenario (**a**) and the 2-m scenario (**b**)

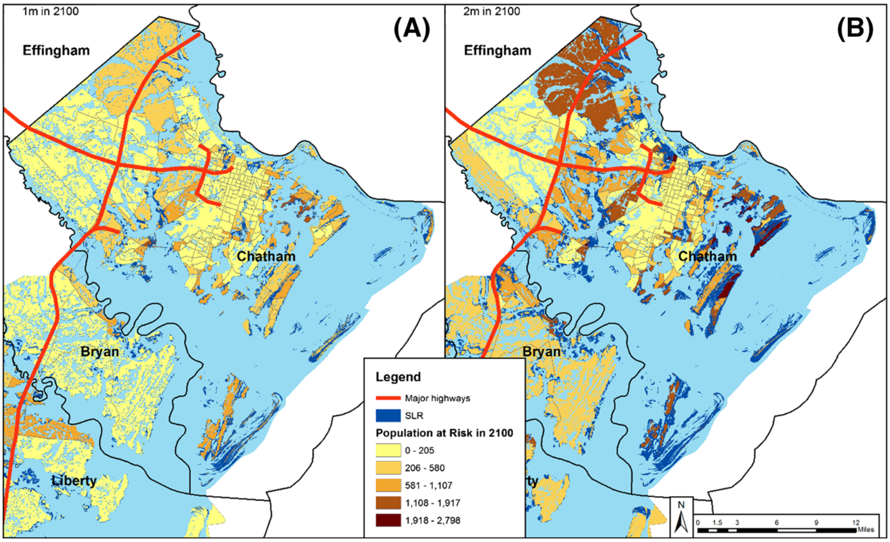

Fig. 4 Populations at risk of sea-level rise in Chatham County in 2100 at the Block Group Level under the 1-m scenario (**a**) and the 2-m scenario (**b**)

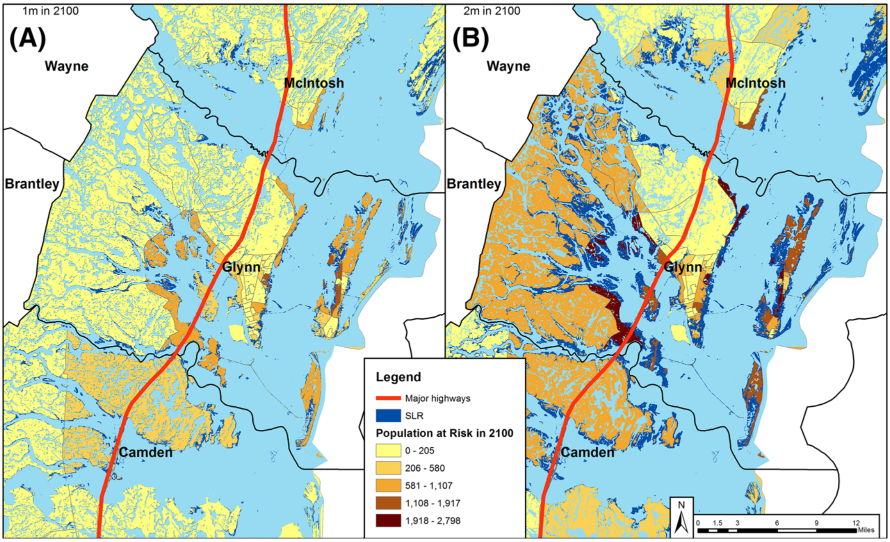

Fig. 5 Populations at risk of sea-level rise in Glynn County in 2100 at the Block Group. Level under the 1-m scenario (**a**) and the 2-m scenario (**b**)

both called sea islands (Jones-Jackson 2011), and both states share similar salt marsh estuaries (Odum 1988). Future projections also show similar population sizes with coastal South Carolina projected at 722,000 people by 2030 (Curtis and Schneider 2011) and Georgia with 816,000 people by 2050. Yet, the total projected populations at risk, despite these similarities, are markedly different. Previous projections for South Carolina find all 722,000 people at risk of inundation, while we find 160,000 people at risk in Georgia under 2 m of sea-level rise. Scale seems to play a decisive factor in these differences (Herod 2011), and specifically the scale at which population projections are undertaken. By better approximating the scale of sea-level rise with population projections, we are better able to project the future populations at risk of inundation.

The results show that the upper and lower limits of populations at risk from each sea-level rise scenario overlap. Put another way, the upper limit of populations vulnerable to displacement from 1 m of sea-level rise generally corresponds to the lower limit of 2 m of sea-level rise. This overlap suggests that populations that will be impacted are situated along a continuum comprised of both population growth and sea-level rise. By contrast, Curtis and Schneider's (2011) previous work assumes that all populations in a coastal area are at risk of sea-level rise. We find Curtis and Schneider's assumption to give results that lie in the extreme upper tail of future populations vulnerable to sea-level rise displacement.

The method presented here represents a methodological step forward for small-area population projections through the combination of the HU method with a modified Hammer method that unifies geographies across space and time and unifies projection and estimation methodologies. By using the Hammer method as the input into the HU method, spatially and temporally contiguous sub-county areal units are now unlocked for use in a host of simple population projections. Here, we used a linear/exponential regression-based approach, but logistic and polynomial extrapolations, the family of share methods (shift share, constant share, shifting growth share, etc.), and ARIMA models are unlocked for the use of demographers as well—methods that have previously been barred from use in such small geographies.

Given the strong assumptions regarding the PPHU variable and the variability of ACS estimates, the similarities between the proposed method and conventional projection methodologies speak to the strength and value of a method that can be employed across Census designated scales for both forecasting and backcasting. Despite these results, there are important limitations with this method regarding the components of projected populations. It is clear that this methodology can project total populations, but the ability to project components (age/sex/race) is left unexplored. Further refinements of this method to project the components of a population would be a fruitful endeavor in future demographic research. Previous scholars have questioned whether projected populations will remain in inundated areas (Curtis and Schneider 2011) and whether adaptation and mitigation policies will be employed, thus shaping future population scenarios along unknown future public policies (Wilson and Piper 2010; Gifford 2011). We share the same questions but recognize the need for baseline scenarios to both help shape these public policy decisions and craft ever better demographic scenarios. Much work is still to be done in understanding the demographic implications to environmental phenomena; this is but one piece in the puzzle.

It should also be noted that the analysis contained herein utilizes an enhanced bathtub model for sea-level rise that does not account for many hydrodynamic forces that affect relative sea-level rise rates at the local level, which raises questions about the accuracy usefulness of this data by ecologists and systems modelers (Parkinson and McCue 2011; Murdukhayeva et al. 2013). The authors of this paper share this critique and welcome future projections that can be utilized alongside a more comprehensive set of sea-level scenarios. However, with regard to population projections, more complicated methodologies do not always yield more accurate results (Smith et al. 2001; Swanson and Tayman 2012). The results contained herein should not necessarily be dismissed due to the simplified approach to sea-level rise modeling.

While the six counties in this study area account for the overwhelming land area threatened by sea-level rise, some parts of the five immediate inland counties in coastal Georgia (Brantley, Charlton, Effingham, Long, and Wayne) could see populations impacted by sea-level rise as well suggesting that the estimates of populations at risk of inundation could underestimate the actual populations at risk. However, these counties are both smaller in population at just one-third of the population of the six coastal counties and collectively account for just 2 % of the land area in Georgia threatened by sea-level rise.

Climate change and sea-level rise are global issues that will affect us all, but the methods available to researchers across for assessing potential at-risk populations are limited by local data and local capabilities. The housing unit method can likely be applied in both developed and developing countries, but the availability of data from the "year structure built" question in other countries' Census products would be the bedrock for applying these approaches in areas outside of the USA. Additionally, high-resolution LiDAR, localized information on sea-level rise, uplift/subsidence, tidal ranges, height of saltwater, over wash information, and accretion and erosion rates would be required for conducting SLAMM in other countries.

Despite these limitations, the authors of this paper see the successful application of this projection method as quite promising for a number of areas of scholarly inquiry—not just for sea-level rise. Future populations residing in flood plains, hurricane tracks, tornado or earthquake prone areas, and so on have the potential to be modeled and understood. Additionally, past population trends of sub-county areas are now possible to be understood at a level of detail that has been unheard of in the demographic literature.

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