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Social vulnerability projections improve sea-level rise risk assessments

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ABSTRACT

Rising seas will impact millions of coastal residents in coming decades. The vulnerability of coastal populations exposed to inundation will be greater for some sub-populations due to differences in their socio-demographic characteristics. Many climate risk and vulnerability assessments, however, model current populations against future environments. We advance sea-level rise risk assessments by dynamically modeling environmental change *and* socio-demographic change. We project three scenarios of inundation exposure due to future sea-level rise in coastal Georgia from 2010 to 2050. We align the sea-level rise projections with five population projection scenarios of socially vulnerable sub-populations via the Hamilton-Perry method and the theory of demographic metabolism. Our combined fast sea-level rise and middle population scenarios project a near doubling of the population exposed, and a more than five-fold increase for those at risk (i.e., residing in a census tract with high social vulnerability) and most at risk (i.e., high social vulnerability and high exposure) compared to the same estimate based on 2010 population data. Of vulnerable sub-populations, women had the largest absolute increase in exposure for all scenario combinations. The Hispanic/Latinx population's exposure increased the largest proportionally under the fast and medium sea-level rise projections and elderly people's (65+) under the slow sea-level rise scenario. Our findings suggest that for coastal areas experiencing rapid growth (or declines) in more socially vulnerable sub-populations, estimates based on current population data are likely to underestimate (or overestimate) the proportion of such groups' risk to inundation from future sea-level rise.

1. Introduction

Global mean sea level is forecast to rise by as much as 2 m or more this century (DeConto & Pollard, 2016; Kopp et al., 2017, 2014; Sweet et al., 2017; Vermeer & Rahmstorf, 2009). By 2060, as much as 12% of the global population—1.4 billion people—could live in the low elevation coastal zone, many with the sustainability of their livelihoods linked to coastal environments (Neumann, Vafeidis, Zimmermann, & Nicholls, 2015). Under equal exposure to climate change hazards, however, the vulnerability of some coastal sub-populations will be much greater due to differences in their socio-economic characteristics (Gaillard et al., 2014; Jurgilevich, Räsänen, Groundstroem, & Juhola, 2017; Lutz and Muttarak 2017; Otto et al., 2017; Shepherd and KC 2015). Numerous case studies support the connections between increased vulnerability to environmental hazards and multiple socio-economic characteristics including non-white racial and non-Hispanic ethnic groups, women, people with low educational attainment or living in poverty, and both the young and elderly, as well as many other socio-economic factors (Bullard 1990; Bolin, Jackson, and Crist 1998; Ngo, 2001; Wisner, Blaikie, Cannon, & Davis, 2004; Bolin, 2007; Neumayer and Plümper 2007; Wailoo, 2010; Rufat, Tate, Burton, & Maroof, 2015; Shepherd and KC 2015). This suggests that assessing the risk of the most vulnerable coastal populations to inundation exposure from sea-level rise is increasingly important for improving coastal adaptation planning and policies. In this article, we define risk as a function of vulnerability, exposure, and hazard (see Jurgilevich et al., 2017).

Many climate risk and vulnerability assessments, however, model current populations against future environments (e.g., Emrich & Cutter, 2011; Frazier, Wood, Yarnal, & Bauer, 2010; Kopp et al., 2017; Kulp and Strauss 2017; Martinich, Neumann, Ludwig, & Jantarasami, 2013; Shepherd and Binita 2015; Spanger-Siegfried et al., 2017). This approach renders methods for assessing future climate risk as both static (population) and dynamic (environmental change). Only recently have studies of sea-level rise impacts started accounting for population change simultaneously with the associated environmental change expected from inundation (Neumann et al., 2015; Hauer, Evans, and Mishra 2016; Hauer 2017). These studies are limited to exposure assessments, however, quantifying the total future population expected to be impacted by sea-level rise inundation. They do not account for *who* that coastal population will be, in other words, its socio-demographic characteristics. Previous studies have compared future inundation

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exposure against either 1) current socially vulnerable populations, or 2) undifferentiated totals of future populations. Few, if any, have compared future inundation exposure against future projections of socially vulnerable sub-populations. Many of the previous studies have shown that a substantial portion of current coastal populations in the United States have sub-populations with increased levels of social vulnerability. Given this and the well-documented historical growth in US coastal populations (Crossett et al., 2013; Culliton et al., 2010) and its projected future growth (Hauer et al., 2016), such a temporal misalignment of comparing current social vulnerability against future inundation exposure will likely lead to incorrect estimates of the future risk of coastal populations.

The temporal misalignment in previous studies is due to limited methodological approaches for analyzing gradual environmental change in concert with multi-decadal socio-demographic change (Jurgilevich et al., 2017). Recent theoretical developments in demography, however, offer an approach for overcoming this shortcoming through a multi-dimensional predictive model of socio-demographic change called *demographic metabolism* (Lutz, 2013; Lutz and Muttarak 2017). Specifically designed for climate change research, demographic metabolism is a theoretical framework that argues that "the process of social change can be analytically captured through the process of younger cohorts replacing older ones" (Lutz, 2013, p. 284). The cohort aged 15–19 in 2015 becomes the 20–24 cohort in 2020 after adjusting for the components of population change: births, deaths, and migration. This approach creates reliable socio-demographic forecasts over decadal time scales for two key reasons: 1) many socio-demographic characteristics are either established at a young age (e.g., the proportion of people with a high school education aged 25–29 in 2015 is a good predictor of those aged 60–64 with a high school education in 2050) (Lutz and KC 2011), and 2) socio-demographic change is embedded within the age structure (e.g., life course analysis shows that earnings steadily increase after age 18, peaking around age 65, before declining through retirement) (Tamborini, Kim, and Sakamoto 2015).

In this article, we advance sea-level rise risk assessments by dynamically modeling environmental change *and* socio-demographic change of coastal populations. Specifically, we forecast inundation exposure due to future sea-level rise along with projections of the socio-demographic indicators of social vulnerability for populations in coastal Georgia. Given the high projections of US coastal population growth (Hauer et al., 2016), we examine the potential underestimation of previous estimates of social vulnerability to sea-level rise. We assess the total and proportional change in vulnerable sub-populations at risk to inundation by comparing estimates based on 2010 and 2050 population data. Our analysis allows us to capture the dynamic spatio-temporal relationship between shifts in socio-demographic indicators driving social vulnerability and increasing levels of inundation exposure from future sea-level rise.

2. Methods

2.1. Study area

We selected coastal Georgia in the United States as our study area given its rural-to-urban settings and diverse demographics including relatively high numbers of people with the characteristics that are indicated to increase social vulnerability (Fig. 1) (Cutter, Boruff, and Shirley 2003; Wisner et al., 2004). Of the greater than 500,000 people residing in the six coastal county region, roughly 227,000 (44%) are racial and/or ethnic minorities, approximately 87,000 (18%) are living in poverty, and over 38,000 (11%) of those 25 years and older have less than a high school equivalent educational attainment level (US Census 2012). Coastal Georgia's current population that could be exposed to inundation from sea-level rise of 0.9–1.8 m by the year 2100 is estimated to be between approximately 51,000 and 96,000, respectively (Hauer et al., 2016). The exposed population is expected to nearly double when accounting for Georgia's population growth to between approximately 93,000 and 179,000 people by the year 2100 (Hauer et al., 2016). Studies based on 2010 US Census population data estimate that there are approximately 5000 Georgia residents with high social vulnerability living within 0.9 m of the high tide line (Strauss et al., 2014). Taking into account the significant population growth projected for the region, however, it is likely that the socially vulnerable population of the future will be much greater. Moreover, being able to identify and quantify whom those socially vulnerable populations will be is of critical importance for targeting adaptation planning and policies at vulnerable sub-populations.

2.2. Population projections

One of the most well-accepted approaches for projecting populations is the cohort-component method, which uses migration, birth, and death rates to forecast population changes within an area (Smith, Tayman, & Swanson, 2001). Given the difficulty of obtaining these data for some areas and smaller geographies such as US Census tracts, a simpler approach was proposed, known as the Hamilton-Perry method, which uses cohort-change ratios (CCR) between the two most recent census counts to project populations by age and sex, and sometimes race or ethnicity (Hamilton & Perry, 1962; Swanson, Schlottmann, & Schmidt, 2010). Using the Hamilton-Perry method based on 2000–2010 US Census data and a series of controlling factors and limits, we projected populations by age, sex, race, and ethnicity in 10-year cohorts from 2010 to 2050 at both the county (n = 6) and census tract levels (n = 121) for the Georgia coast following:

$$ {}_{n}\mathrm{CCR}_{x} = \frac{{}_{n}P_{x+y,l}}{{}_{n}P_{x,b}}, \tag{1} $$

where n is the cohort interval, x is the starting age of the cohort, ${}_{n}P_{x+y,l}$ is the population aged $x + y$ to $x + y + n$ in the most recent census (l), ${}_{n}P_{x,b}$ is the population aged x to $x + n$ in the second most recent census (b), and y is the number of years between the two censuses ($l – b$) according to Smith et al. (2001).

Given the 10-year interval of most US Census data, the age cohort of 10–19 is the minimum for applying the CCR. Child-woman ratios (CWR) are used to project populations of the 0–9 age cohort. We made two adjustments to Smith et al.'s (2001) recommendation for assessing CWRs. First, we used 10-year age cohorts instead of five-year age cohorts because our projection interval was 10 years. Second, we assessed the combined CWR for the population of male and female children due to low counts for some groups. We calculated CWRs for the launch year's population by calculating the ratio of children aged 0–9 to women aged 15–49 following:

$$ \text{Children aged } 0-9\text{: } {}_{10}P_{0,t} = \frac{{}_{10}P_{0,l}}{{}_{35}P_{15,l}}, \tag{2} $$

We divided this combined CWR by two before calculating the projected target population of male and female children, which assumes an equal birth rate for the sexes. As we projected in 10-year age cohorts over 10-year periods, we used half of the 10–19 aged female population count to ascertain the number of women 15–19 to be included in the 35-year window in equation Eq. (2).

Two challenges emerge when projecting populations for sub-county geographies such as census tracts (Swanson et al., 2010). A common challenge is the frequent changes that occur with boundaries between census collection years. To overcome this first challenge, we applied the Longitudinal Tract Database's conversion tool (Logan, Xu, and Stults 2014) to each 2000 census tract data table to normalize the data to 2010 census tract boundaries. Another common challenge is specific to the Hamilton-Perry method, which can lead to forecast errors and upward bias in rapidly growing areas (Smith et al., 2001). This is due to small populations, particularly those that result in small denominators