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Supplementary material for this article is available [online](#)

## Abstract

The frequency of coastal floods around the United States has risen sharply over the last few decades, and rising seas point to further future acceleration. Residents of low-lying affordable housing, who tend to be low-income persons living in old and poor quality structures, are especially vulnerable. To elucidate the equity implications of sea level rise (SLR), we provide the first nationwide assessment of recent and future risks to affordable housing from SLR and coastal flooding in the United States. By using high-resolution building footprints and probability distributions for both local flood heights and SLR, we identify the coastal states and cities where affordable housing—both subsidized and market-driven—is most at risk of flooding. We provide estimates of both the expected number of affordable housing units exposed to extreme coastal water levels and of how often those units may be at risk of flooding. The number of affordable units exposed in the United States is projected to more than triple by 2050. New Jersey, New York, and Massachusetts have the largest number of units exposed to extreme water levels both in absolute terms and as a share of their affordable housing stock. Some top-ranked cities could experience numerous coastal floods reaching higher than affordable housing sites each year. As the top 20 cities account for 75% of overall exposure, limited, strategic and city-level efforts may be able to address most of the challenge of preserving coastal-area affordable housing stock.

## 1. Introduction

The frequency of coastal floods around the United States has risen sharply in recent decades, and rising seas point to further acceleration in both tidal (or ‘nuisance’) and extreme floods in the years ahead (Sweet *et al* 2017a, Sweet *et al* 2017b, Buchanan *et al* 2017, Vitousek *et al* 2017). For example, by 2050, with continued high carbon emissions, the flood level currently expected to occur approximately every 100 years (with an annual 1% chance of occurrence) could occur ~ 40 times more often on average at tide gauges along the contiguous United States (Buchanan *et al* 2017). By the same time, the frequency of tidal flooding, which generally occurs at least once a year,

may occur on a weekly basis in some places (Sweet and Park 2014, Sweet *et al* 2018). Together, these results indicate that more frequent flooding events will become a major concern for many U.S. coastal communities in the coming decades.

While people and assets in virtually all coastal areas face some degree of risk from coastal flooding, the exposure of low-lying affordable housing is of particular concern. Housing is conventionally considered affordable to low-income households if it costs no more than 30% of their gross household income (U.S. Census 2018b). Nationwide, affordable housing is an increasingly scarce resource. Median rents in the U.S. have increased by over 25% over the last decade while wages have remained largely stagnant (US Census

2007, Stone *et al* 2011). Unlike previous periods of price inflation, this rise in rents is not the result of increased incomes or improvements in housing quality (Desmond and Bell 2015). Nationwide, there are only an estimated 35 affordable rental units available for every 100 extremely low-income renters (those living in households with incomes  $\leq 30\%$  of the median income of their metropolitan area)—a national shortfall of over 7 million units that impacts all 50 largest metropolitan areas (NLIHC 2019). The result is that the majority of poor renting families today devote over half of their income to housing, and almost a quarter dedicate more than 70%, leaving little left over for basic needs such as food and health care and resulting in housing insecurity, including homelessness, multiple moves, or ‘doubling up’ with others (Desmond 2015). Moreover, affordable housing (the vast majority of which is in privately-owned buildings, even among subsidized units) tends to be older and of poorer quality than other housing (Vale *et al* 2014). Often built to older housing codes and prone to deferred maintenance, affordable housing tends to be far less structurally sound than general housing (Keenan *et al* 2018). Because of this, affordable housing structures are more physically vulnerable than the general housing stock to damage from flooding.

Residents of affordable housing also face high socioeconomic vulnerability due to the fact that they are predominately low-income and more likely to be disabled, single parents, seniors, minorities, and/or lacking stable employment than the general population (e.g. Brennan *et al* 2011, Desmond and Gershenson 2016, NLIHC 2019). Socially disadvantaged communities are more likely to be adversely impacted by natural hazards such as flooding because they have fewer financial resources, less political influence, and receive less information about financial aid to support recovery (Cutter *et al* 2009, Fussell *et al* 2010).

The combination of physical vulnerability of affordable housing infrastructure, socioeconomic vulnerability, and more frequent flooding due to sea level rise (SLR) presents a triple threat to residents of the country’s already scarce affordable housing. To help quantify these intersecting challenges and elucidate the equity implications of SLR, we provide the first nationwide assessment of the coastal flood risks facing affordable housing. To the best of our knowledge, this research advances upon previous methods for characterizing the impacts of coastal flooding and SLR in four important ways.

First, while past studies have used low-resolution data on the locations and numbers of people and structures, we base our analysis on a comprehensive geolocated inventory of individual building footprints across the United States. Prior studies have typically relied on density data at the relatively coarse scale of census tracts (e.g. Kirshen *et al* 2008, Clark *et al* 1998, Rygel *et al* 2006, Martinich *et al*

2013). Averaging  $\sim 4\,000$  inhabitants (1 200–8 000; US Census 2010), tract sizes vary widely depending on the density of settlement, and are often large enough to include substantial variation in both flood risk and socioeconomic conditions. Neumann *et al* (2015) used comparatively finer spatial data (150 m by 150 m, about the area of a New York City block); however, this scale still exceeds that of individual buildings. Others have used address-based points, which approximate the location of a house or building, but could misplace a structure in a nearby stream or on land with a different elevation (e.g. Torgersen *et al* 2017). Using building footprint data offers the advantage of being able to precisely locate the lowest ground elevation across a building’s footprint—a critical attribute for calculating flood risk. We combine this data with a comprehensive inventory of U.S. affordable housing buildings and units therein (both subsidized and market-driven).

Second, flood risk assessments have traditionally focused on a few particular storm surge water levels (e.g. Cooper *et al* 2008, San Francisco Bay Conservation and Development Commission 2011, Neumann *et al* 2015, Hallegatte *et al* 2013, Hinkel *et al* 2014, Diaz 2016). For example, San Francisco Bay Conservation and Development Commission (2011) and Houser *et al* (2015) showed the number of buildings and amount of land exposed to SLR plus the 100 yr flood. Here, we follow the approach of Kulp and Strauss (2017) using the full annual probability distribution of water levels above high tide, from minor to extreme flooding. This probability-weighted approach provides a more complete picture of flood hazard and could have a strong quantitative effect in calculating the threat posed by SLR.

Third, previous studies have estimated future flood risk by using a few particular projected amounts of SLR, either reflecting a scenario-based estimate of SLR (typically by 2100; e.g. Cooper *et al* 2008, Hallegatte *et al* 2013, Neumann *et al* 2015) or slices of a SLR probability distribution for a future year (e.g. the 50th or 95th percentiles; Diaz 2016, Houser *et al* 2015, Kulp and Strauss 2017). These approaches only provide a snapshot of potential future flood hazard, given the wide range of possible SLR values. Here, we integrate over the entire SLR distribution conditional on a selected greenhouse gas emissions scenario, extending the approach of Buchanan *et al* (2016) to incorporate the uncertainty in the SLR distribution into the calculation of future flood risk.

Finally, past studies have tended to focus on either the number of people and/or structures exposed or on average annual economic losses. Although a useful metric, calculation of average annual losses can be computationally intensive and thus is often done at relatively coarse scales (Hallegatte *et al* 2013, Neumann *et al* 2015) or with proprietary (Houser *et al* 2015) and limited information about the relationship between flood height and damage (Merz *et al* 2004).

We focus on exposure to projected extreme coastal water levels (driven by tides, storm surges, and SLR; Gregory *et al* 2019), or ‘flood-risk events’. Using a ‘bathtub’ model, a building is considered exposed if its ground elevation lies below projected water levels, accounting for hydrological connectivity. Accordingly, the probability of a structure being exposed in a given year is dependent on three factors: its elevation (adjusted to account for coastal defenses), local SLR projections by the year of interest, and local flood height exceedance probabilities. We note that bathtub models are generally known to overestimate coastal vulnerability to extreme flood levels, as they cannot capture water height attenuation over land with distance from the ocean (Vafeidis *et al* 2019). Hydrodynamic models do incorporate these physical interactions, but are computationally infeasible for the wide spatial scale we consider here.

We estimate *expected annual flood-risk events*, the number of times that a particular building may be exposed in a given year, as well as *expected annual exposure*, the average number of affordable housing buildings and units exposed in a typical year, which can be aggregated for an administrative region of interest (e.g. for a particular municipality, county, or state). Together, this information can provide an indication of not only *how many* buildings or units are at risk, but also of *how often* they are at risk. This provides counts of the number of times a place could potentially flood based on water and land elevations, not predictions of how many times a place will actually flood, dependent on floodplain features and on the nature of storms (Vafeidis *et al* 2019). This approach works best for milder (and thus more frequent) events and serves as an indicator of risk (Orton *et al* 2015, Seenath *et al* 2016).

By using high-resolution building footprints and integrating across both local flood and SLR distributions to calculate exposure, as described above, we aim to identify the coastal states and cities where affordable housing—both subsidized and market-driven—is most at risk. We also evaluate exposure of the general housing stock and identify the coastal states and cities where affordable housing is disproportionately exposed in comparison. This information may be particularly relevant for preserving the affordable housing stock, especially in places with strained public finance and dwindling affordable housing inventory.

## 2. Methods

To assess the exposure of affordable housing (and of general housing for comparison), we use the core methodology of Kulp and Strauss (2017), who defined *expected annual exposure*—the quantity of some variable (such as housing stock) expected to be exposed to at least one coastal flood-risk event in a given year.

In this paper, we assess vulnerability of individual buildings and their contained housing units by computing their expected annual exposure. We introduce a new metric, *expected annual flood-risk events*, the *total* expected number of flood-risk events each building/unit could experience. Both of these quantities can be made unconditional to SLR sensitivity to emissions by integrating across the distribution of potential SLR, given an emissions scenario.

This analysis is performed by refining a digital elevation model (DEM) to reference local high tide and enforce hydrological connectivity given any water height threshold; integrating SLR projections and flood height exceedance probabilities to generate a function estimating the annual and daily probabilities of at least one coastal flood above a height threshold in a given year; and applying this function to each building and year of interest, from which expected annual exposure and flood-risk events can be computed and aggregated within any administrative area. The inputs, models, and outputs of the analysis are illustrated in figure 1 and described in detail below.

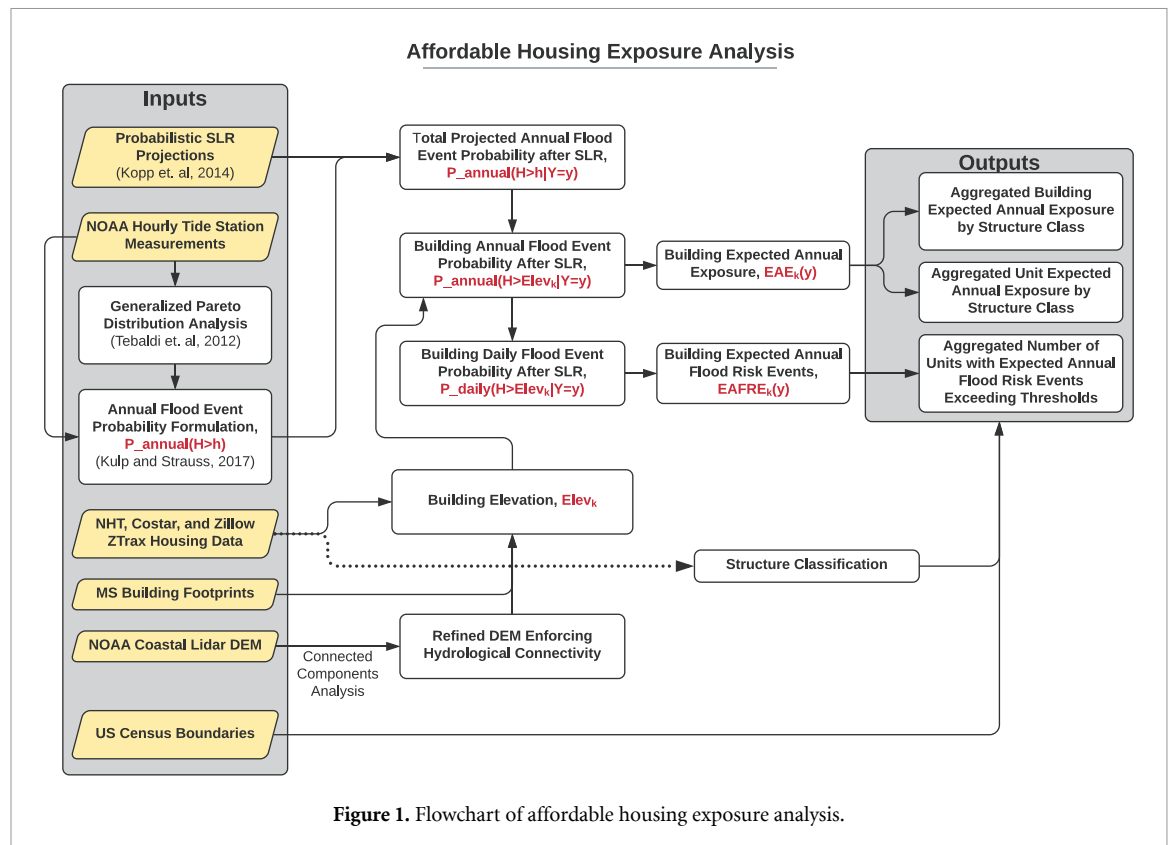
### 2.1. Digital Elevation Models

To assess topography, we employ lidar-derived DEMs compiled and distributed by NOAA (NOAA 2015), supplemented with the USGS Northern Gulf of Mexico Topobathymetric DEM (USGS 2014) in Louisiana, and the USGS National Elevation Dataset (Gesch *et al* 2002) in the small fraction of land not covered by the preceding DEMs. These data have a continuous vertical resolution, and a horizontal resolution of about 5 m, except in parts of LA (3 m) and Norfolk, VA (1 m). We then recompute elevations relative to local mean higher high water (MHHW) levels at nearest neighbors in NOAA’s VDatum grid (version 2.3.5; Parker *et al* 2003), measured in the National Tidal Datum Epoch (1983–2001).

Topography or levees isolate some low-lying areas from the ocean. To account for known protective features and to facilitate downstream computations, the DEM is further refined by raising individual grid cell heights in identified isolated regions. Designated pixel elevations are raised until they match the lowest water level connecting each cell to the ocean despite protective features. We use the following procedure.

We consider flood heights between 0–10 m above MHHW at quarter-meter intervals, denoting the  $i$ ’th such height in this sequence by  $h_i$ . For each  $i$ , we generate a binary inundation surface  $S_i(lat, lon)$ , equal to one where the DEM’s elevation is less than  $h_i$ , and zero otherwise. For each grid cell below 10 m, we note the minimum value of  $i$  for which  $S_i(lat, lon) = 1$ , denoting this index by  $I(lat, lon)$ .

We then incorporate levee data and use connected components analysis to remove isolated areas within each inundation surface, which produces new, connected binary surfaces denoted by  $\tilde{S}_i(lat, lon)$ . Data from the Mid-term Levee Inventory (FEMA/USACE,



acquired September 2013) is used to identify levees and other flood control structures. In Louisiana, we supplement this with data from Louisiana's Coastal Protection and Restoration Authority (Flood Protection GIS Database as of June 2015), and in Massachusetts, by Chris Watson at University of Massachusetts Boston, April 2014, based on MassGIS's Digital Orthophoto Topographic Breaklines, April 2003. We treat levees as impassible barriers, as these data lack information regarding levee strength or height. This could cause certain areas protected by weak levees to appear less vulnerable than they truly may be.

As before, for each grid cell below  $\sim 10$  m, we compute  $\tilde{I}(lat, lon)$ , the smallest value of  $i$  in which  $\tilde{S}_i(lat, lon) = 1$ . Where no such value of  $i$  exists (meaning the cell is isolated from the ocean up to a water height of more than 10 m), we reassign its elevation to 10 m—higher than any plausible combination of SLR and one year return level this century in the United States, thereby effectively removing it from further consideration. If  $I(lat, lon) = \tilde{I}(lat, lon)$ , we assume this grid cell is not hydrologically isolated and do not modify its elevation. Otherwise, where  $I(lat, lon) < \tilde{I}(lat, lon)$ , meaning a cell is hydrologically isolated up to a water height of at most  $\sim h_{\tilde{I}(lat, lon)}$ , we reassign its elevation to  $h_{\tilde{I}(lat, lon)}$ .

## 2.2. Sea level rise

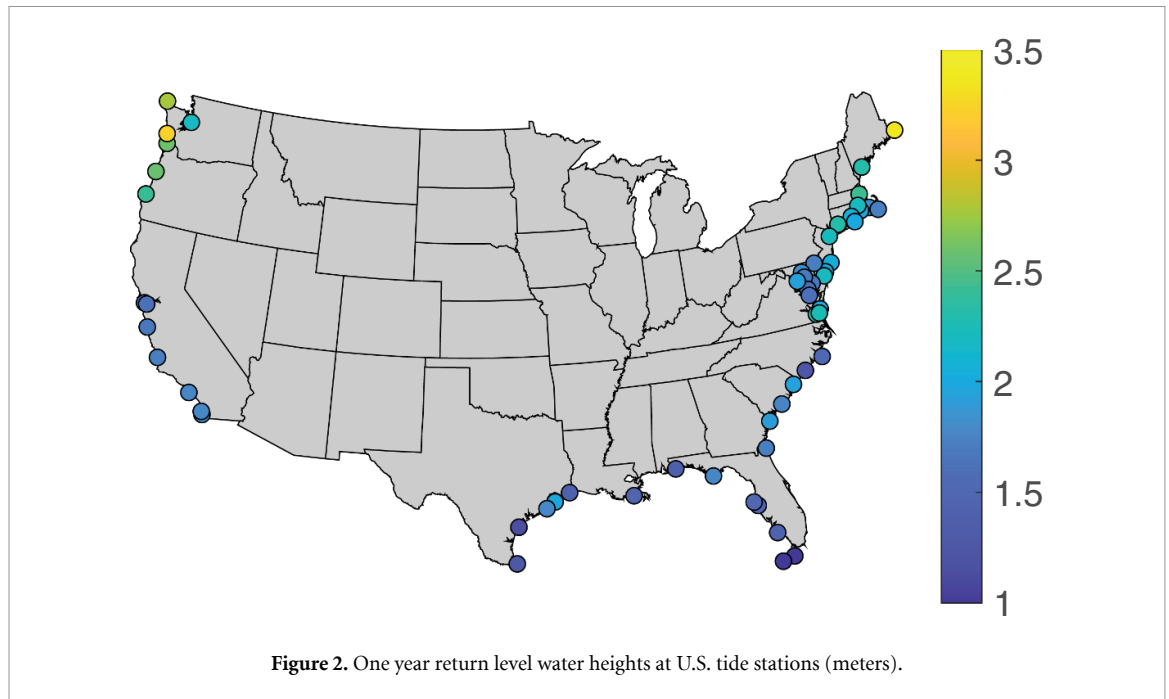
SLR is not geographically uniform. Because SLR is driven by global, regional, and local factors, the rise of local relative sea levels differs from the global mean. These factors include changes to temperature

and salinity (i.e. steric processes), land-ice melt, changes in the Earth's rotation and gravitational field associated with water-mass redistribution (e.g. from land-ice melt; Mitrovica *et al* 2011), dynamic ocean processes (Levermann *et al* 2005), as well as glacial isostatic adjustment (GIA; Farrell and Clark 1976) and other drivers of vertical land motion. To localize SLR, we use probabilistic SLR projections from Kopp *et al* (2014)—hereafter denoted by K14—which account for these time- and geographically-varying components. The K14 projections are conditional on global carbon emissions scenarios, including Representative Concentration Pathways (RCPs) 2.6, 4.5, and 8.5 (Van Vuuren *et al* 2011).

## 2.3. Annual Flood Event Probabilities

We use the formulation derived in Kulp and Strauss (2017) to construct  $P_{\text{annual}}(H \geq h)$ , the probability of the highest water height of the year exceeding  $h$ . This function is defined at each of 71 U.S. tide gauge stations with at least 30 years of hourly records, based on Tebaldi *et al* (2012), Supplementary Information (SI) table 1 ([stacks.iop.org/ERL/15/124020/mmedia](https://stacks.iop.org/ERL/15/124020/mmedia)). The one year return levels for these stations are shown in figure 2. The station-distance sensitivity analysis presented in Kulp and Strauss (2017) suggests that the spatial density of these locations is sufficient for expected annual exposure analysis across the U.S. coastline.

Given the (adjusted) elevation of a building's geolocation (see section 2.6),  $Elev(lat, lon)$ ,  $P_{\text{annual}}(H \geq Elev(lat, lon))$  reflects the annual probability of at least one flood risk event, in the



absence of SLR. Making the assumption that the return level curves stay constant relative to sea level, and treating the year 2000 as the baseline case where  $SLR(2000) = 0$ , we incorporate a specific SLR projection to predict the flood event probability for any given year,  $y$ ,  $P_{annual}(H \geq Elev(lat, lon) | SLR(y) = x) = P_{annual}(H \geq Elev(lat, lon) - x)$ .

Since for each emissions scenario considered, K14 provides a set of probabilistic distributions with 10,000 Monte Carlo samples of relative sea-level change for each tide gauge, we denote each sample as the function  $SLR_{(j)}(y)$  for  $j \in [1, \dots, 10000]$ . We can estimate the probability, unconditional on model sensitivity, as:

$$P_{annual}(H \geq Elev(lat, lon) | Y = y) \approx \frac{1}{10000} \times \sum_{j=1}^{10000} P_{annual}(H \geq (Elev(lat, lon) - SLR_{(j)}(y))). \tag{1}$$

Making the simplifying assumption that the probability of a flood event on one day is independent of any other day, we can also estimate the *daily* probability of a flood event as:

$$P_{daily}(H \geq Elev(lat, lon) | Y = y) \approx 1 - (1 - P_{annual} \times (H \geq Elev(lat, lon) | Y = y))^{1/365}. \tag{2}$$

#### 2.4. Expected Annual Exposure and Flood-Risk Events

The probability of annual flooding,  $P_{annual}(H \geq Elev_k | Y = y)$ , where  $Elev_k$  is the land elevation of building  $k$ , reflects the annual probability of *at least*

*one flood* higher than the ground elevation of that individual building. Multiplying this probability with the number of housing units within the building ( $Units_k$ ) represents the expected annual number of units exposed. Summing the values of this metric across all buildings within some administrative area (i.e. a particular city, state, etc) results in that area's total expected annual exposure of units. Although some units in an exposed building may not be directly flooded, access points (e.g. entrances, stairs) and amenities (e.g. electricity, water supply and sewage systems) may be affected.

Similarly, the product of the structure's *daily* flood event probability with  $Units_k$  results in the expected *daily* exposure of units. With the assumption of daily independence, we can estimate the total number of expected annual flood-risk events by multiplying expected daily exposure by 365.

#### 2.5. Housing data

##### 2.5.1. Affordable housing stock: Subsidized

We utilize a comprehensive dataset of federally subsidized affordable housing buildings as of November 2018. This dataset was collected through the National Housing Preservation Database (<https://preservationdatabase.org/>), managed by the Public and Affordable Housing Research Corporation and the National Low Income Housing Coalition, and analyzed by the National Housing Trust (NHT). Information collected for this analysis included each building's address, latitude/longitude coordinates, number of units, number of subsidized units, government program, and funding source (i.e. government agency, shown in table 1). In this analysis, housing supported by any federal program is considered

subsidized. An affordable housing building can be subsidized by more than one program.

While some cities and states have additional programs to subsidize housing, many do not report comprehensive and publicly available data on the locations of housing supported by these programs. It is also common for state programs to provide gap financing to properties that are already subsidized through federal programs. We include housing subsidized directly by federal programs, which captures the vast majority of government-subsidized affordable housing. We include housing subsidized directly by known state-funded subsidies, which make up 2% of all subsidized housing in the database.

### 2.5.2. Affordable housing stock: Market-driven

Although there is no universally accepted definition of unsubsidized affordable housing, the term is generally applied to housing that is rented below market rates or ~ 30% of median income levels, without rental assistance (such as government subsidies or tax credits; NLIHC 2019, HUD 2019). Below-market-rate housing also tends to be low quality (e.g. Hood 2005, Nordby *et al* 2017). To identify and locate below-market-rate housing, we use the CoStar Building Rating System, a national rating for commercial and multifamily buildings on a universally recognized 5-Star quality scale, following the approach of the Urban Land Institute (Nordby *et al* 2017).

CoStar's rating distinguishes properties based on their age, physical condition, and amenities. We classify properties that are rated one- or two-stars as market-driven affordable housing because these buildings tend to rent at levels that are below market rate due to their age and need of significant repairs (Nordby *et al* 2017). For example, one-star buildings are characterized as being practically non-competitive with respect to typical multi-family investments and possibly functionally obsolete. Two-star units are characterized as having simply functional structures, below average finishes, inefficient use of space, and minimal or no shared amenities. Commercial real estate information (including each building's address, latitude/longitude coordinates, quality rating, and number of units) was collected in December 2018.

### 2.5.3. General housing stock

In the context of this study, a methodologically commensurate comparison of the exposure of affordable housing to that of the general housing stock requires a source of general housing information with address-level data. Although the 2010 U.S. Census (US Census 2011) includes data on all types of housing units, such as single-family homes, condos, and apartments, it is only available as totals at census block scale. As a result, we use housing data from Zillow's ZTRAX database, which includes latitude/longitude coordinates, to characterize the general housing stock. The ZTRAX

data serves as a broad indicator of general housing because it includes only housing units that are zoned for non-commercial use, meaning apartments are not included in the dataset. These data were collected in June 2018.

## 2.6. Building Footprints

We further refine the geographic representation of our affordable housing stock (subsidized and market-driven) and general housing stock datasets using Microsoft's U.S. Building Footprints database (<https://github.com/Microsoft/USBuildingFootprints>). Since points are poor representations of the areal extent of a building, building latitude and longitude locations are linked with the Building Footprints database and each point is assigned to the building footprint that contained it, or its nearest building footprint. If any part of a building is on land at a lower elevation than a given water height (according to the DEMs described in section 2.1), we considered the entire structure exposed, as well as all units within it, if applicable. This is a conservative measure, as not all buildings will necessarily suffer damage if water reaches the corner of a house, though those with basements or split levels still may.

## 3. Results and discussion

In the following results, we assess the threat of coastal flooding to individual affordable housing units nationwide, tabulating results to the national, state, and city levels. This analysis enables the identification of locations where affordable housing is the most at risk and where the potential exposure of affordable housing may be disproportionately high compared to housing overall.

As the size of affordable housing buildings varies from single-family homes to apartment complexes, we present results on the units within buildings to reflect the threat facing affordable housing residents. Focusing on units is also helpful because flood damage to a part of a building could impact all of the units in the building (e.g. by way of flooded access points, such as entrances or stairs, or service interruptions, including electricity, water supply, and sewage systems).

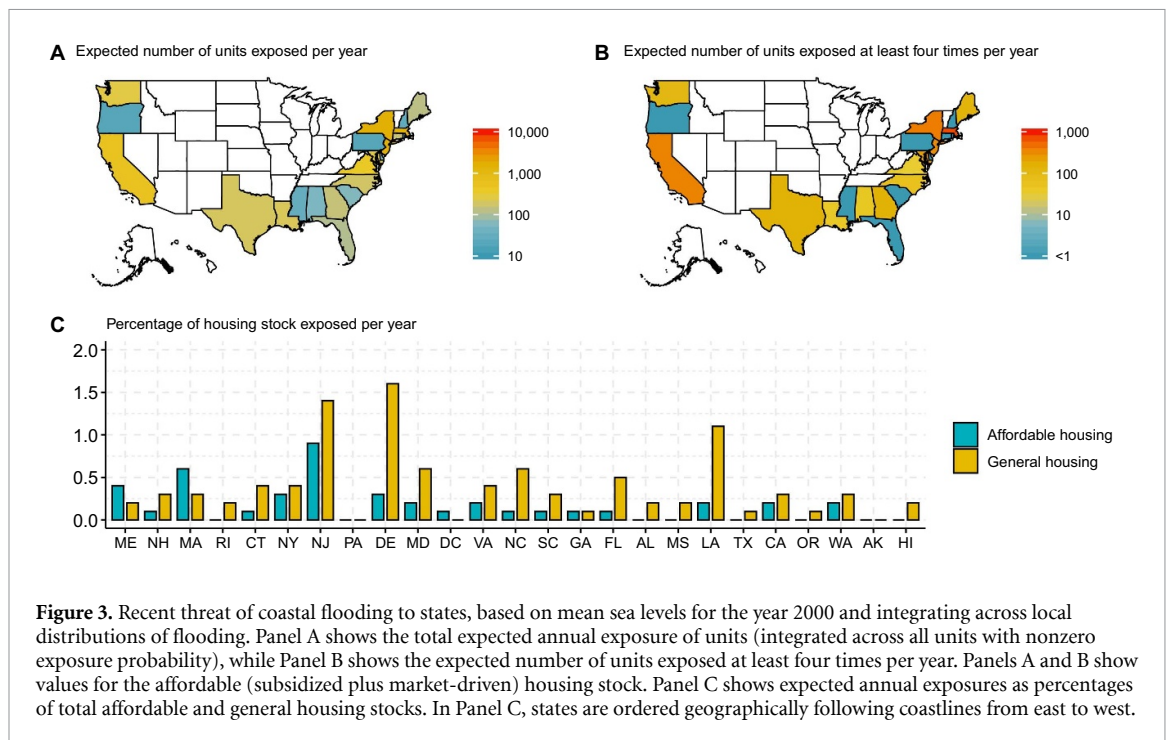
### 3.1. Recent threat

Using mean sea levels for the year 2000 as a baseline for comparison with future threat (section 3.2), we found that 7,668 affordable housing units were recently at risk of flooding per year in the United States. Figure 3 illustrates the recent vulnerability among states. New Jersey has the highest number and percentage of its affordable housing stock exposed (1,640, ~ 1%; figure 3.a,c; SI table 2). New York and Massachusetts are also within the top three states at risk in terms of the number of units exposed



**Table 1.** Federal programs and corresponding funding agencies subsidizing affordable housing.

Program	Funding source
Project-based (Section 8)	U.S. Department of Housing and Urban Development (HUD)
Supportive housing for the elderly (Section 202)	HUD
HOME Investment Partnerships Program	HUD
Public Housing	HUD
Subsidized mortgage properties (Section 236)	HUD and Federal Housing Administration (FHA)
FHA-Insured Mortgages	FHA
Low-Income Housing Tax Credit Program	Internal Revenue Service
Rural Rental Housing program (Section 515)	U.S. Department of Agriculture (USDA)
Multi-Family Housing Loan Guarantees (Section 538)	USDA
State funded rental subsidy	State level



**Figure 3.** Recent threat of coastal flooding to states, based on mean sea levels for the year 2000 and integrating across local distributions of flooding. Panel A shows the total expected annual exposure of units (integrated across all units with nonzero exposure probability), while Panel B shows the expected number of units exposed at least four times per year. Panels A and B show values for the affordable (subsidized plus market-driven) housing stock. Panel C shows expected annual exposures as percentages of total affordable and general housing stocks. In Panel C, states are ordered geographically following coastlines from east to west.

(1,574, and 1,530, respectively)—an order of magnitude more than the other coastal states (figure 3.a). Massachusetts, Maine, and the District of Columbia are noteworthy in that the percentage of the affordable housing stock exposed markedly exceeds that of the general housing stock.

Looking at the number of flood-risk events per unit exposed shows another threat dimension (figure 3.b). Although California, for example, has about a third as many exposed units as New Jersey, it has roughly the same number of units exposed to flooding at least four times per year (358) as New Jersey (313; SI table 2). We chose at least four times per year because this corresponds to an average of at least once per quarter, although actual flood-risk events may be seasonally clustered. Along with New Jersey, Massachusetts, New York, and California, affordable housing units in Maryland are the most at risk of repetitive flooding, with an over 200 units exposed to at least four flood-risk events per year in each of these states. By contrast, units in Rhode Island, New

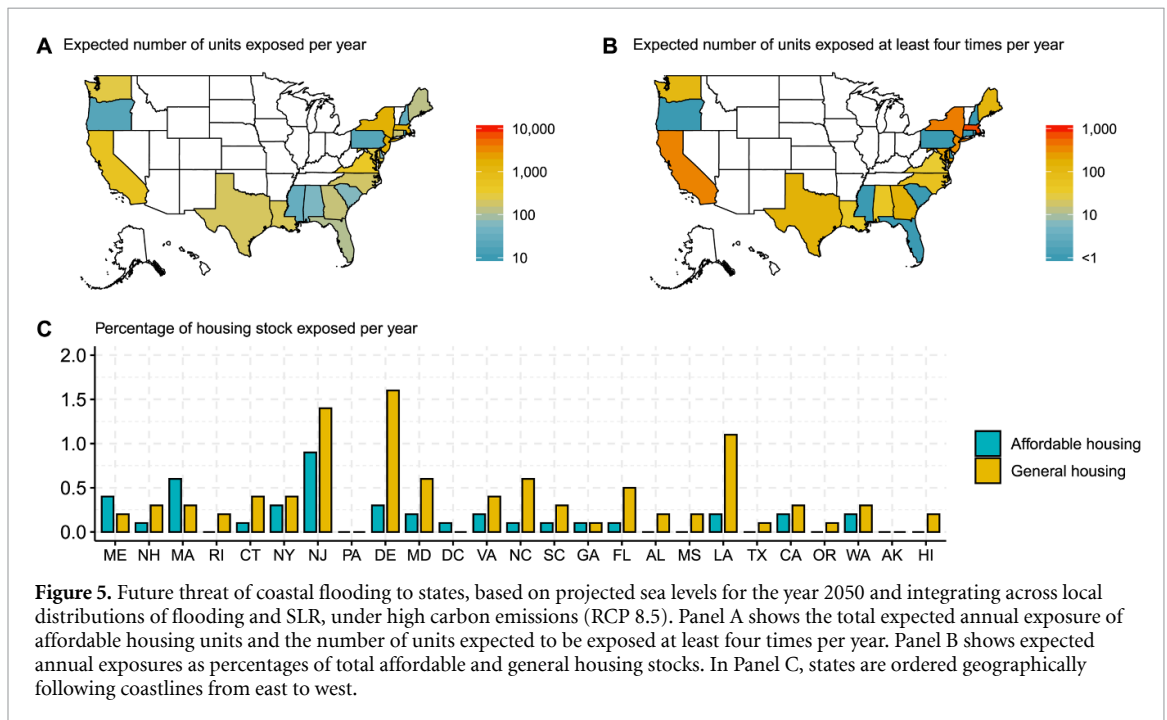
Hampshire, and Oregon are some of the states least at risk to more than one flood event per year.

Cities as well as states vary dramatically in the vulnerability of their affordable housing to flood risk. Figure 4 shows the top 20 cities recently at risk of coastal flooding, in terms of the absolute number of units exposed (see SI table 3 for all cities). Threats are primarily clustered in smaller cities in California and in the northeastern United States. New York City has the largest number of units exposed per year (1,373), even though these units make up less than 1% of the city’s supply of subsidized affordable housing (figure 4.a,c). The second most at-risk city in absolute terms is Atlantic City. Its significant number of units exposed per year (618) consists of more than 10% of the city’s affordable housing stock. With a similar number of units exposed (609), Boston ranks third; more than half of its at-risk units face at least four flood-risk events per year.

Five of the top-ranked cities have more than 200 units that face flood-risk at least four times per year,



**Figure 4.** Recent threat of coastal flooding to the top 20 cities exposed (in absolute terms), based on mean sea levels for the year 2000 and integrating across local distributions of flooding. Panel A shows the total expected annual exposure of affordable housing units and the number of units expected to be exposed at least four times per year. Panel B shows expected annual exposures as percentages of total affordable and general housing stocks. Cities are ordered geographically following coastlines from east to west.



**Figure 5.** Future threat of coastal flooding to states, based on projected sea levels for the year 2050 and integrating across local distributions of flooding and SLR, under high carbon emissions (RCP 8.5). Panel A shows the total expected annual exposure of affordable housing units and the number of units expected to be exposed at least four times per year. Panel B shows expected annual exposures as percentages of total affordable and general housing stocks. In Panel C, states are ordered geographically following coastlines from east to west.

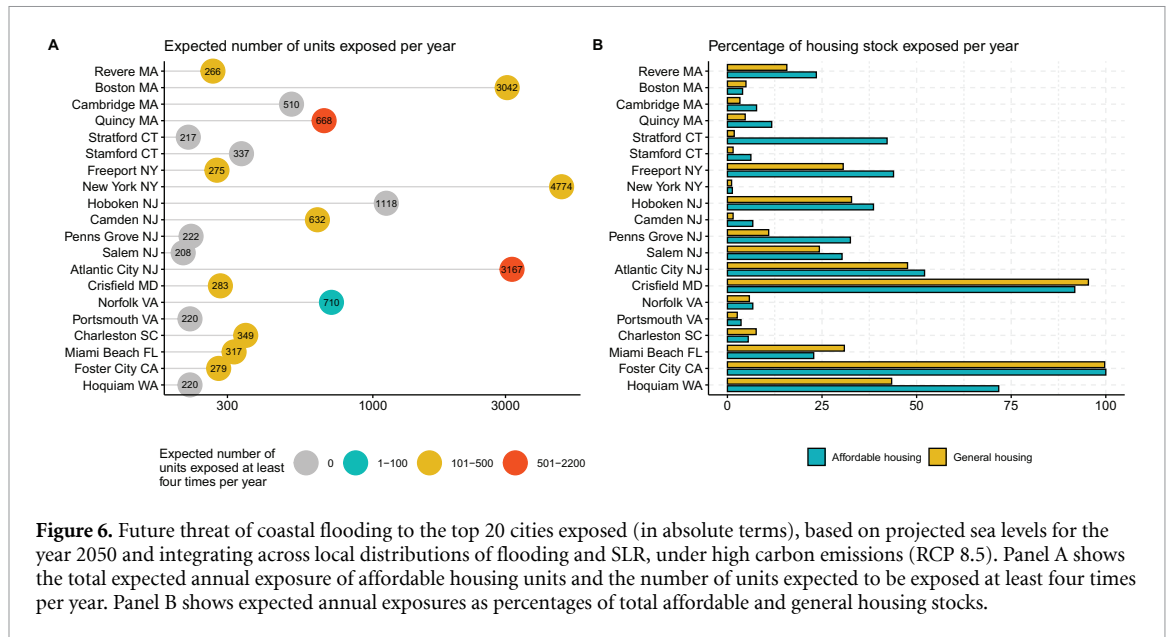
on average, including those in New York City; Boston; Foster City, CA; Revere, MA; and Crisfield, MD. Exposure may be overestimated in Foster City, CA, where new levees may not have been included in the Mid-term Levee Inventory. The percentage of the affordable housing stock exposed exceeded that of the general housing stock in nearly all of the top-ranked cities, with the greatest disparities in relative terms in Corte Madera and Suisun City, CA, and in Woodlawn, VA (figure 4.c).

**3.2. Future threat**

To estimate future threat of coastal flooding to affordable housing, we focused on risks posed by

2050. This 30 year outlook reflects threats that could affect current residents. The projected threats could also affect private developers and government entities, as this time period spans the typical duration of loans and other financial instruments. Results presented here assume continued high carbon emissions (represented by RCP8.5); however, there is little difference in projected SLR across carbon emission scenarios by the mid-21st century (Kopp *et al* 2014). Results for 2100 and for other RCPs are listed in SI tables 2–4.

The mid-term change in risk is significant, with the aggregate number of affordable units exposed in the United States more than tripling by 2050 to 24,519



**Figure 6.** Future threat of coastal flooding to the top 20 cities exposed (in absolute terms), based on projected sea levels for the year 2050 and integrating across local distributions of flooding and SLR, under high carbon emissions (RCP 8.5). Panel A shows the total expected annual exposure of affordable housing units and the number of units expected to be exposed at least four times per year. Panel B shows expected annual exposures as percentages of total affordable and general housing stocks.

units. Table 2 shows the ranking of states in terms of units exposed per year in 2050. New Jersey remains the most vulnerable state, as measured by both the absolute and relative number of units exposed. In New Jersey, the number of units exposed approaches seven thousand per year, a four-fold increase from the year 2000, and equal to the aggregate number of units recently exposed across the country.

New York and Massachusetts remain within the top three states at risk in terms of the absolute and relative number of units exposed (figure 5.a,c). Pennsylvania, Florida, and South Carolina face the greatest percentage increase in the expected annual exposure from 2000 to 2050 (792%, 774%, and 669%, respectively; table 2). Across coastal states, a large majority of exposed affordable housing units are subsidized (72%; see SI table 4 for exposure by program). In 2050, the affordable housing stock is estimated to be markedly more exposed relative to the general housing stock in Massachusetts, New York, New Hampshire, Pennsylvania and the District of Columbia (figure 5.c).

By 2050, most coastal states are estimated to have at least some affordable housing units exposed to flood risk events at least four times per year (table 2, figure 5.b). Nearly half of New Jersey's large stock of exposed affordable housing units could flood at least four times per year. Delaware, Washington, and South Carolina had zero affording housing units exposed to flooding at least four times per year in the year 2000, but approximately one hundred units exposed to such frequent flooding by 2050 (76, 103, and 119 units, respectively).

Table 3 shows the ranking of the top 20 cities in terms of annual number of units exposed by 2050. The top 20 cities account for 75% of the United State's aggregate expected annual exposure. These most vulnerable cities are highly concentrated along

the northeastern corridor and in California. In some of these cities, with relatively smaller affordable housing stocks, over 90% of the stock is exposed (Crisfield, MD and Revere, MA).

New York City remains the most vulnerable city in absolute terms, with the number of units exposed exceeding 4,000 per year by 2050. However, these units represent less than 2% of the city's affordable housing stock and rich cities like New York generally have more resources to bolster protection than poorer ones. For example, New York City not only plans to increase its supply of affordable housing by 50% in 10 years, but has also revised its building design guidelines to address the projected impacts of climate change (NYC 2014, NYC 2019).

The rankings of cities include many smaller and less wealthy cities, where risk management efforts may be lower. Aside from New York City and Boston, all of the top-ranked cities have populations of  $\sim 200\,000$  or less ( $m = 71\,106$ ,  $sd = 60\,922$ ; U.S. Census 2019). Four cities in New Jersey are of particular concern: Atlantic City, Camden, Penns Grove, and Salem. These top-ranked cities are some of the poorest in the country, with average median household income (\$28,618) half of the national median, and a correspondingly high demand for affordable housing (U.S. Census 2018a). In addition, their proportion of people of color (81.2%) is double the national average (U.S. Census 2018a). In most of these New Jersey cities, about a third of the affordable housing stock is projected to be exposed, a 321% to 957% percentage increase in exposure from the year 2000 (table 3). This extensive exposure in multiple cities could put a major strain on the state and is particularly concerning since many affordable housing units in New Jersey are still being rehabilitated even seven years after Hurricane Sandy (e.g. Ortiz *et al* 2019).

**Table 2.** Future threat of coastal flooding to states, based on projected sea levels for the year 2050, under high carbon emissions (RCP 8.5). States are ranked by the expected number of units exposed per year (expected annual exposure). The best estimate of the number of units exposed is shown, integrating across the full SLR probability distribution, as well as estimates under the 5th and 95th percentiles of the SLR distribution. The percentage of affordable housing exposed, percentage of the exposed affordable housing stock that is subsidized, percentage increase in exposure from the year 2000, and the number of units with at least two or four annual expected flood risk events are also shown.

Rank		Units exposed per year				Units with X or more flood-risk events per year		
		# (5th-95th)	% of affordable housing	% subsidized	% increase from 2000	two	three	four
1	New Jersey	6,825 (3 877–10 155)	3.7	80	316	3 855	867	3 066
2	New York	5,293 (2 676–9 019)	1.1	47	236	867	867	867
3	Massachusetts	4 818 (2,172–9 463)	2.0	82	215	1 858	1 858	1 272
4	Virginia	1 473 (841–2 340)	0.8	76	273	368	368	248
5	Florida	963 (408–1 599)	0.8	32	774	606	606	443
6	California	738 (655–831)	0.2	40	40	650	650	650
7	Connecticut	695 (321–1,098)	0.7	85	344	0	0	0
8	Louisiana	685 (494–937)	0.6	96	220	176	176	176
9	South Carolina	474 (262–702)	0.5	63	669	403	403	119
10	North Carolina	435 (388–583)	0.2	100	136	290	290	286
11	Washington	385 (316–453)	0.2	91	50	350	350	103
12	Maryland	365 (311–436)	0.2	100	43	288	288	288
13	Texas	332 (271–412)	0.1	96	66	146	146	146
14	New Hampshire	215 (94–288)	0.8	100	652	263	263	0
15	Pennsylvania	175 (80–223)	0.1	100	792	222	222	0
16	Georgia	151 (150–152)	0.1	100	1.0	150	150	150
17	Maine	150 (128–200)	0.4	39	19	125	125	125
18	District of Columbia	90 (79–106)	0.1	81	31	0	0	0
19	Delaware	78 (77–81)	0.4	99	29	76	76	76
20	Alabama	64 (61–67)	0.1	90	9	43	43	43
21	Mississippi	56 (48–66)	0.1	94	76	0	0	0
22	Oregon	52 (34–76)	0.1	100	163	0	0	0
23	Rhode Island	4 (2–7)	0	87	148	0	0	0
24	Hawaii	2 (0–7)	0	98	*	0	0	0
	Total	24,518 (13,745–39,300)	0.7	72	219	10,737	10,737	8,058

Notes: \* indicates division by zero.

**Table 3.** Future threat of coastal flooding to the top 20 cities exposed (in absolute terms), based on projected sea levels for the year 2050, under high carbon emissions (RCP 8.5). Cities are ranked by the expected number of units exposed per year (expected annual exposure). The best estimate of the number of units exposed is shown, integrating across the full SLR probability distribution, as well as estimates under the 5th and 95th percentiles of the SLR distribution. The percentage of affordable housing exposed, percentage of the exposed affordable housing stock that is subsidized, percentage increase in exposure from the year 2000, and the number of units with at least two or four annual expected flood risk events per unit exposed are also shown.

Rank		Units exposed per year			Units with X or more flood-risk events per year		
		# (5th-95th)	% of affordable housing	% subsidized	% increase from 2000	two	four
1	New York NY	4774 (2 290–8 371)	1.3	49	248	10,183	457
2	Atlantic City NJ	3167 (1 996–4 191)	52.1	87	412	2 842	2 183
3	Boston MA	3 042 (1 088–6 445)	4.0	89	400	994	407
4	Hoboken NJ	1 118 (476–1 889)	38.6	88	411	0	0
5	Norfolk VA	710 (360–1 165)	6.7	72	523	134	14
6	Quincy MA	668 (554–837)	11.7	64	31	511	511
7	Camden NJ	632 (345–1 008)	6.7	54	321	235	225
8	Cambridge MA	510 (117–1 241)	7.7	67	1278	0	0
9	Charleston SC	349 (198–528)	5.5	50	546	275	119
10	Stamford CT	337 (165–479)	6.2	69	327	0	0
11	Miami Beach FL	317 (139–481)	22.8	28	1074	322	169
12	Crisfield MD	283 (262–307)	91.8	100	20	258	258
13	Foster City CA*	279 (279–279)	100	78	0	279	279
14	Freeport NY	275 (230–288)	43.9	35	129	280	280
15	Revere MA	266 (266–266)	23.5	100	0	266	266
16	Penns Grove NJ	222 (77–413)	32.5	39	957	120	0
17	Portsmouth VA	220 (98–402)	3.6	51	610	0	0
18	Hoquiam WA	220 (181–244)	71.7	91	62	247	0
19	Stratford CT	217 (101–334)	42.2	100	352	0	0
20	Salem NJ	208 (64–388)	30.3	98	1056	0	0

Notes: \*Exposure may be overstated in Foster City, CA, where new levees may not have been included in the Mid-term Levee Inventory.

The majority of the top-ranked cities face exposure to flooding at least four times per year, which could pose maintenance and public safety challenges. This risk highlights the importance of flood resilience measures to help residents and city managers cope with increasingly frequent flooding, which may be particularly challenging in the less wealthy top-ranked cities, such as Camden, New Jersey.

### 3.3. Implications for the preservation of affordable housing

Flooding can wreak havoc on buildings and the residents who live in them. Even low levels of flooding can damage belongings, disrupt electrical equipment, contaminate water sources and septic systems, generate mold, and block roads (Moftakhari *et al* 2017, Sweet *et al* 2018). These impacts may increase maintenance costs, threaten public health, and cause profound disruptions to families already struggling to make ends meet. Because affordable housing units are frequently in poor repair to begin with, additional damage from flooding may be particularly challenging—and expensive—to remedy.

This study's findings demonstrate that if communities aim to preserve affordable housing stock in coastal areas, significant resiliency planning and investment is likely to be needed. Inaction could result in high risk for residents who may lack access to sufficient resources to prepare and recover from flooding impacts. As coastal flood risks to affordable housing units tend to be highly concentrated, flood protection measures in key cities and neighborhoods could help protect a large number of affordable housing residents. The number of expected annual flood-risk events for individual buildings (or aggregated within administrative areas) could be used to help identify hot spots of repetitive flooding, and where to invest in coastal protection or other adaptation measures for the greatest impact relative to cost. Over time, investment in these areas may pay off in terms of not only damage avoided, but also harm avoided to individuals and families in need.

As community resilience investments are made, complementary policies may be needed to protect against the displacement (and potential homelessness) of residents. Infrastructure improvements such as flood defenses can result in new amenities that can attract wealthier households and drive up property values and rents (e.g. Keenan *et al* 2018). The issue of improving the resilience of affordable housing, without compromising its affordability, is complex and increasingly being recognized in both public and private spheres. For example, it has become a focus of public-private partnership programs such as Energy Efficiency for All (EEFA 2019), which upgrades energy efficiency in multi-family affordable housing complexes, and the Urban Land Institute's Urban Resilience Program (Urban Land Institute 2018), which shares resilience information and strategies.

Such efforts are critically important to help avoid systemic effects which may deepen cycles of poverty. A reduction in affordable housing could have multiple downstream consequences for individuals and families (e.g. affecting equitable access to public transportation, healthcare, and other services) as well as for regional and local economies, which may lose part of their labor forces. The loss of affordable housing in coastal communities may also drive up housing costs in adjacent communities as competition for a dwindling supply of low-cost housing intensifies (e.g. Keenan *et al* 2018). Ultimately, increasing the overall supply of resilient affordable housing is critically needed to help ensure that communities can absorb the impacts of increased flooding among other climate-related hazards.

## 4. Conclusion

Climate-change-driven sea level rise will continue to amplify coastal flooding in the coming decades. To better understand the potential impact on vulnerable U.S. populations and to aid resiliency planning, we assess the growing exposure of affordable housing with unprecedented geographic resolution and national comprehensiveness. Knowledge of the estimated number of affordable housing units exposed to at least one flood-risk event per year as well as the total number of flood-risk events facing an area's affordable housing stock could help inform strategic resilience planning. Because coastal flood risks are highly concentrated, flood-threat reduction measures (physical, financial, or regulatory) in key cities and states could help protect a large number of affordable housing residents. Localities where frequent exposure to extreme coastal water levels is projected for affordable housing may require near-term measures to successfully reduce flood threats.

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