Physical extreme sea level metrics may misrepresent future flood risk

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Abstract Estimating changes in the frequency or height of extreme sea levels (ESLs; e.g., the 100-yr event) is a popular approach for illustrating future coastal flood risk to societies under various climate change scenarios. However, these metrics only account for physical water levels (i.e., the hazard). They do not consider societal outcomes (e.g., loss of life, property damage). As a result, physical ESL metrics and associated thresholds may give misleading estimates of future coastal flood risk. This has implications for climate adaptation decision-making and risk communication efforts that seek to quantify changes in coastal flood risk under different climate scenarios. Here, we illustrate how some risk measures can lead to sizable differences in estimates of future coastal flood risk, relative to when only considering physical impacts by considering 1) projected ESLs under +2 °C and +5 °C temperature stabilization scenarios and 2) the current population exposure of 414 cities around the world. For some locations with a modest projected increase in the height of an ESL event, the corresponding change in local population exposure is substantial. This suggests that physical ESL metrics may be poor surrogates for capturing some societal impacts. Overall, we find that impacts are highly localized and depend on the gradient of the population versus elevation profile over the range of elevations between the current and future ESL height. While population exposure is just one measure, considering a variety of human system, natural resource, and ecosystem-based outcomes may provide a more complete snapshot of coastal flood risk under different climate scenarios. Such an approach would improve upon existing methods used by the Intergovernmental Panel on Climate Change (IPCC).

1 Introduction

Extreme sea levels (ESLs) are the occurrence or the level of a short-lived (hours to days), exceptionally high local sea-surface height, usually as a result of coastal storms, waves, or astronomical tides (Gregory et al, 2019). Observational studies have shown that ESLs are occurring at tide gauges with increasing frequency, largely as a result of rising mean sea level (MSL) due to global warming and other non-climatic, local factors (e.g., ground subsidence; Sweet and Park, 2014; Menéndez and Woodworth, 2010). The Intergovernmental Panel on Climate Change (IPCC) has conveyed projected changes in ESL events under different climate scenarios using ESL frequency amplification factors (AFs) and ESL hazard allowances (Church et al, 2013; Wong et al, 2014; Oppenheimer et al, in press). ESL frequency AFs (also called 'factors of increase' or

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'multiplication factors'; Vitousek et al, 2017; Taherkhani et al, 2020; Church et al, 2013) indicate the change in the expected frequency of a given ESL event (e.g., the 1-in-100-yr ESL event; Hunter, 2012; Buchanan et al, 2017; Rasmussen et al, 2018; Frederikse et al, 2020). For example, a 0.5 m increase in MSL for San Juan, Puerto Rico is expected to increase the frequency of the historical 100-yr ESL event from 0.01 events yr^{-1} to $\sim$30 events yr^{-1}, on average (i.e., an AF of 3000; Rasmussen et al, 2018). While frequency AFs describe how often ESLs are expected to occur under different climate scenarios, ESL hazard "allowances" correspondingly denote the vertical distance an asset needs to be raised in order to ensure that the expected number of ESL events is kept constant under uncertain sea level change (Hunter, 2012; Hunter et al, 2013; Buchanan et al, 2016; Slangen et al, 2017). Closely related to ESL allowances are return level AFs, which denote the relative change in the height of the water level associated with a given return period (Garner et al, 2017). ESL AFs (frequency and return level) and allowances have all been used as proxies for coastal flood risk, broadly speaking (Vitousek et al, 2017; Taherkhani et al, 2020; Buchanan et al, 2017; Vousdoukas et al, 2018; Kriebel et al, 2015; Frederikse et al, 2020). However, solely focusing on physically-based ESL metrics and thresholds may give misleading projections of future floods impacts on human systems, natural resources, and ecosystems.

A critical limitation of both ESL AFs and hazard allowances is that they only consider the physical heights of water, such as the height of the 100-yr ESL event. They do not consider the corresponding consequences of the event itself (e.g., population exposure or damage to property and natural resources). This is problematic for two reasons. First, some locations may be protected to a level above the height of the ESL event in question (i.e., no flood occurs), and second, there may exist little to no societal exposure at or below the ESL height (i.e., a flood occurs, but there is no societal impact). In such instances, physical ESL metrics may be a poor surrogate for both the estimation and management of coastal flood risk. If risk is defined by not only the probability of a damaging event occurring (e.g., the 100-yr ESL, or 1%/yr) but also by what the consequences are if it occurs (Kaplan and Garrick, 1981), then some measure of a societal impact should be accounted for. Otherwise, physical metrics alone may give misleading projections of coastal flood risk. For example, investigators that have focused on the frequency of exceedances of physical thresholds (e.g., the height of the 50-yr ESL event) have claimed that 0.5 m of MSL rise could lead to a doubling of "flood" events within decades for certain regions (Vitousek et al, 2017) or exponential increases in the frequency of "floods" (quotes imply authors mean ESLs; Taherkhani et al, 2020). While these claims may be true of the hazard (i.e., ESLs), they may not apply to the corresponding societal outcome (e.g., "a doubling of population exposure" or an "exponential increase in the rate of population exposure"). In the San Juan example, while the historical 100-yr ESL event is projected to occur $\sim$3000 times as often under a 0.5 m increase in MSL, there are currently $<$ 1,000 people living below the elevation of the 100-ESL event ($<$ 0.1% of the total city population; Fig. 1). Furthermore, risk metrics that include societal exposure may also have implications for adaptation decision-making. For instance, Rasmussen et al (2020) showed that when allowances do not account for the consequences of ESL events (e.g., property damage or population exposure), they can lead to sub-optimal design of flood defenses.

In this study, we highlight the limitations of ESL metrics that only consider the physical heights of water levels, such as ESL AFs (frequency and return level) and ESL allowances. Specifically, we consider how the current exposure of populations living in coastal cities may change relative to changes in ESL return levels. To do this, we connect ESLs measured at a global network of tide gauges to present-day population exposure for 414 coastal cities around the world. Exposure is estimated using the CoastalDEM elevation model (Kulp and Strauss, 2019). We project future changes in both the frequency and return levels of historical ESLs and the exposure of populations under two climate change scenarios (Sec. 3.1). We note that because we do not make future projections of population change, these are not estimates of future population exposure; rather they are intended to highlight the limitations of physical ESL metrics when quantifying coastal flood risk. We then also show how ESL allowances may under-predict the necessary design heights of adaptation measures needed to maintain constant societal exposure under uncertain MSL change (Sec. 3.2). While population exposure is used as the risk measure in this study, it is just one component of coastal flood risk, broadly speaking. A diversity of possible metrics exist. We illustrate how using other risk measures could capture other relevant components of the same "coastal risk story" (Sec. 3.3). This includes impacts to vulnerable demographics, property damage, critical infrastructure, loss of natural resources, and harm to ecosystem services (e.g., wetland loss). Future studies could use our framework to further explore these metrics using other datasets. We note that several studies have already estimated coastal flood risk globally (Hallegatte et al, 2013; Hinkel et al, 2014; Diaz, 2016; Hanson et al, 2011), but most do not make explicit comparisons to physical ESL metrics. However, Hauer et al (2020) recently noted differences between projections of physical ESL metrics and those that are based on population exposure in the U.S.

2 Framework

An overview of the sources of information used to generate population inundation estimates are given in Fig. S-1. Additional details and limitations to our approach are given in the supporting information (Secs. S-1.1 to 2.4). First, we estimate the present-day probability of ESLs of various heights at a global network of tide gauges using extreme value theory and a long-term record of hourly sea level observations (Sec. S-1.1). Second, we project changes in both the frequency and height of ESLs using local probabilistic projections of relative sea level change (RSLC)[1] that incorporate ice sheet mass loss estimates from structured expert judgment (Sec. 2.1). Third, we produce 1-dimensional, city-specific functions of population versus ground elevation to estimate the current population exposure to ESLs (Sec. 2.2). Fourth, by combining the population exposure damage functions with the future estimates of ESLs, we compute the change in the number of people exposed to various ESLs for each city using population exposure AFs (Sec. 2.3). Finally, we use damage allowances to calculate the height of flood defenses needed to maintain the current expected annual population exposure (Sec. 2.4).

2.1 Relative sea level change projections

Probabilistic, time-varying, local RSLC projections for each tide gauge are taken from the component-based study of Kopp et al (2014), except that ice sheet contributions are from the structured expert judgement (SEJ) study of Bamber et al (2019). Projections of RSLC after mid-century are highly dependent on ice sheet melt because of their potential for substantial contributions to global mean sea-level rise (Oppenheimer et al, in press; Kopp et al, 2019). However, incomplete understanding of the physical processes that govern ice sheet melt inhibits realistic representations in process-based models. In such cases of incomplete scientific understanding, SEJ using calibrated expert responses is one approach for estimating such uncertain quantities (as employed here). Each RSLC probability distribution is conditional on a scenario in which global mean surface air temperature (GSAT) stabilizes in 2100 at either +2 °C (consistent with the Paris Agreement; UNFCCC, 2015) or +5 °C (consistent with unchecked emissions growth; GSAT relative to 1850–1900; Hausfather and Peters, 2020). Samples from each RSLC probability distribution are used to shift the ESL return curves in the direction of the RSLC. Figs. 2A and 2D show the future (2070) ESL return curves for tide gauges located at San Juan (Puerto Rico) and Sewell's Point (Norfolk, USA). The "kinks" in the return curves appear as a result of the highest samples in the RSLC probability distribution causing the expected ESL frequency calculation to saturate and then subsequently increase the expected number of ESL events. Both the positioning and the presence of the kinks are sensitive to the choice of where the upper-tail of the RSLC distribution is truncated (Rasmussen et al, 2020). More details are provided in the supporting information (Sec. S-1.2).

2.2 Exposure analysis

We map flood extents for each city using the "bathtub" inundation modeling approach. This approach considers the vertical elevation of two surfaces, 1) the land and 2) a given ESL (e.g., 100-yr event). Here, we use land elevation from CoastalDEM, a modified version of NASA's Shuttle Radar Topography Mission (SRTM) digital elevation model (DEM) that uses a neural network trained using lidar-derived elevation data in the U.S.[2] to reduce SRTM errors (Kulp and Strauss, 2019; Farr et al, 2007). The SRTM is a near-global DEM commonly used for flood exposure modeling but is known to have large vertical bias (an estimated 3.7 m in coastal areas in the U.S.; Kulp and Strauss, 2018). This is important because coastal flood risk analysis is largely performed within this elevation range and these biases are on par with projections of future local

[1] Relative sea level change is defined as the change in local mean sea level relative to the sea floor or the underwater surface of the solid Earth (Gregory et al, 2019).

[2] NOAA Digital Coast Coastal Lidar, http://coast.noaa.gov/digitalcoast/data/coastallidar

RSLC over this century (generally < 2 m relative to 2000; Oppenheimer et al, in press). More details and limitations are provided in both the supporting information (Sec. S-1.3) and in Kulp and Strauss (2018, 2019). Connected components analysis excludes low-elevation inland areas that are not connected to the ocean. Return levels are taken from the nearest tide gauge within a 100-km radius of each city.

The vertical population profile of a city and existing flood defenses largely determines population exposure to a given ESL event. We produce 1-dimensional (vertical) population profiles using CoastalDEM and population density data from the WorldPop 2010 high resolution (3 arc second) gridded global population data set (Tatem, 2017). We note that this differs from Kulp and Strauss (2019), which uses LandScan population density. In order to simplify our analysis and also isolate the impact of RSLC on population exposure, we assume that population remains fixed in time. Thus, our results are not literal projections of future population exposure—which will depend upon population growth, the dynamic response of the population to RSLC, and new coastal adaptations—but are instead intended to highlight the impact of ESL events relative to changes in their frequency. Plots of population exposure profiles for San Juan (Puerto Rico) and Norfolk (USA) are given in Figs. 2B,E. Exposure profiles for all cities are included in the supporting data.

Most populations living in low-lying areas around the world (e.g., deltaic regions) are very likely protected by flood defenses such as levees, seawalls, and deliberately raised structures (e.g., buildings on stilts; Hallegatte et al, 2013). However, to our knowledge, location-specific levels of protection are not available at the global scale[3]. To account for flood defenses that provide a margin of safety, we make make multiple arbitrary assumptions regarding the current level of protection for all cities. Specifically, we produce results assuming spatially uniform "no protection" and protection up to the height of the 1- and 10-yr ESL event. These assumptions may greatly differ from reality and could lead to gross over-estimates for cities with existing flood protection that afford a high margin of safety from rare storms, such as London, New Orleans, Tokyo, Shanghai, and most major cities in the Netherlands (Nicholls et al, 2008; Hallegatte et al, 2013; Xian et al, 2018). Despite this, we still include protection assumptions for all cities to 1) limit the inclusion of the lowest elevations which are most prone to vertical errors in the DEM (Sec. S-1.3) and 2) to highlight the importance of the flood protection assumption and the need for accurate estimates thereof.

2.3 Estimating physical and population exposure amplification factors

Following Buchanan et al (2017), the ESL frequency AF for an event of height z^* under uncertain RSLC is $\mathbb{E}[N(z^* - \delta)/N(z^*)]$, where $N(z^* - \delta)$ is the expected number of exceedances of height z^* after considering RSLC δ (Sec. S-1.1). The ESL return level AF is given by $1 + \mathbb{E}[\delta]/z^*$. Here, we extend the ESL return level AF to changes in population exposure. We define the population exposure AF for an event of height z^* under uncertain RSLC as $\mathbb{E}[D(z^* + \delta)/D(z^*)]$, where $D(\cdot)$ is a 1-dimensional vertical population profile of a city (Sec. 2.2). Note that since $D(\cdot)$ is solely a function of z, the frequency amplification of population exposure events is equivalent to the ESL frequency AFs for the same city. Probability distributions of ESL AFs (frequency and return level) and population exposure AFs are produced for each tide gauge using the RSLC samples for each climate scenario (Sec. 2.1). Results are then taken from these distributions (Sec. 3).

2.4 Estimating population exposure allowances

While ESL and population exposure AFs are well suited to identify and communicate local coastal flood risks, damage allowances are perhaps more useful for informing the design of coastal flood defense efforts (e.g., determining optimal levee heights or how high to raise a residence to maintain a given margin of safety; Rasmussen et al, 2020). The damage allowance is the design height of a flood mitigation strategy (e.g., elevation of structures, levee height, necessary coastal retreat) needed to maintain a given integrated exposure metric under uncertain RSLC (e.g., current expected annual property damage). Here, we consider the expected annual population exposure (EAE). An overview of both sea level allowances and the EAE is given in the SI (Sec. S-1.4).

[3] However, Hallegatte et al (2013) give upper and lower estimates of flood protection for 136 major cities around the world based on surveyed responses from local experts. But these responses have not been verified, and local protection can vary within a city.

To offset additional population exposure due to RSLC, we create a “protected” population exposure function using an idealized representation of how a flood reduction strategy could impact the relationship between ESLs and population exposure. Specifically, we assume that the city population elevates by an amount A. This corresponds to a horizontal shift of the unprotected populated exposure function $D(z)$ (Sec. 2.2). This strategy is likely to be impractical in reality. However, it illustrates differences between allowance frameworks that both do and do not consider societal exposure. More realistic approaches for modeling protection strategies have been given (Rasmussen et al, 2020).

In order to maintain the historical EAE under uncertain RSLC, the current EAE must equal the projected EAE that includes both an arbitrary sea level change (δ) and the adjustment A to offset the change in EAE resulting from RSLC. This can be mathematically represented by:

$$\int_{A_{min}}^{\infty} \int_{\delta} D(z-A) f(z-\delta) P(\delta)\, \mathrm{d}\delta\, \mathrm{d}z = \int_{A_{min}}^{\infty} D(z) f(z)\, \mathrm{d}z, \tag{1}$$

where $D(z-A)$ is a protected populated exposure function that elevates all populations within the damage function by the height A such that the current EAE is maintained under RSLC and A_{min} is the height of the assumed current protection level (either no protection, the height of the 1-ESL event or the 10-yr ESL event; Sec. 2.2).

3 Results

3.1 Extreme sea level metrics may poorly predict population exposure

San Juan (Puerto Rico) illustrates how physical ESL metrics can overestimate local flood risks. By 2070, the expected frequency of the historical 100-yr ESL event increases from 0.01/yr to a noteworthy 30/yr (+2 °C) and 102/yr (+5 °C), on average (Tables 1,2; Fig. 2A). However, < 1,000 people (< 0.1% of the total population) are currently exposed to the historical 100-yr ESL event (Figs. 1C and 2B,C). While sea-level rise is expected to increase the height of the 100-yr ESL event from 0.7 m above MHHW to 1.2 m (+2 °C) and 1.4 m (+5 °C), the corresponding population exposure is still < 0.1% of the total population (Tables 1,2; Figs. 2B,C). This is due to a low gradient in the population profile over the range of increase in the return level, partially as a result of a steep shoreline around much of San Juan (Figs. 1A and 2B). On the other hand, Norfolk (USA) has both a much steeper population profile than San Juan over the range of increase in the expected 100-yr return level (Fig. 2E) and a greater fraction of its total current population is exposed to the 100-yr ESL event (2.3%; Tables 1,2). By 2070, the expected 100-yr ESL return level increases from 1.5 m above MHHW to 2.1 m (+2 °C) and 2.4 m (+5 °C). This increases the expected population exposure to the 100-yr ESL from ∼16,000 to 64,000 (+2 °C) and 104,000 (+5 °C; Tables 1,2; Figs. 2E,F). Results for an additional 17 other cities and their uncertainties are given in Tables 1,2.

Relationships between physical and societal metrics vary by city in part due to differences in RSLC and the shape of both the ESL return curves and population profiles (Fig. S-2). Globally, population exposure AFs vary from < 1 to > 10 (Fig. 3A). Cities are sorted by geographic region to look for more localized patterns (Fig. 3B; the region/city mapping is given in the supporting data files). Across most regions examined, ESL return level AFs generally underestimate risks related to population exposure. Notable exceptions are the western coasts of North America and South America. Within these regions, there is a greater fraction of cities with a stronger correlation between ESL return level AFs and population exposure AFs. This suggests that population profiles are more linear over the range of increases in the height of the 100-yr ESL, perhaps due to a smaller variance in ESLs as a result of 1) a narrower continental shelf that leads to a smaller tidal range (Pugh and Woodworth, 2014) and 2) fewer tropical cyclones (Knapp et al, 2010). Plots for 2100 and for the +5 °C scenario are given in the supporting information and results for all cities are tabulated in the supporting data files.

The 100-yr ESL is just one of many possible hazards. Integrated metrics, like the EAE (Section 2.4), considers the probability and consequence of all ESLs. The San Juan and Norfolk EAE for the historical (1991–2009) and future scenarios is denoted as filled colored circles on the x-axis in Figs. 2C,F. For both cities, the historical EAE is small, < 1,000 (assumes protection from the 10-yr ESL), but differences emerge under RSLC. By 2070, the EAE for Norfolk increases to ∼16,000 (+2 °C) and 45,000 (+5 °C), while the EAE for San Juan remains $< 1{,}000$ for both scenarios. However, flood protection assumptions can greatly change the EAE and the EAE AF. For instance, assuming that Norfolk has no flood protection, the EAE AF for 2070 is 3.4, but if assuming protection from the 10-yr event, it increase to 13.7 (Table S-5). The current and future EAE at cities around the globe under different protection assumptions are tabulated in the supporting data files.

3.2 Extreme sea level allowances versus population exposure allowances

The map in Fig. 4 shows the expected population exposure allowance needed to maintain the historical EAE for each city under projected 2070 RSLC (+2 °C). The population exposure allowance assumes all cities are currently protected against the 10-yr ESL (i.e., $\mathrm{A}_{min} = \mathrm{z}_{10}$, where z_{10} is the local return level of the 10-yr event) and that the historical EAE is maintained by elevating all populations within each city by the same amount A (Sec. 2.4). Globally, the exposure allowance ranges from < 0 m (i.e., where expected RSLC is negative) to > 2 m. For some regions, the 100-yr ESL allowance is quite similar to the population exposure allowance (Western North America, Europe, and Eastern South America), but for others, the relationship between the two is less strong (e.g., Eastern North America). The 100-yr ESL allowance sometimes both over- and under-predicts the allowance needed to maintain the current EAE. For most cities, the population exposure allowance for 2070 is larger than the expected RSLC (Tables 3 and 4; Fig. S-3).

3.3 The choice of the metric may impact estimates of flood risk

Many consequences can result from the same hazard, and most risk metrics only consider one consequence. For example, using a population exposure risk metric in New York City would not account for two major airports that are currently exposed to the 100-yr ESL event (LaGuardia and John F. Kennedy International; Fig. S-6B). Furthermore, risks estimated using population exposure may vary when considering specific population subgroups. For example, low household income residents of New York City ($<$\$50,000 yr^{-1}) are projected to have expected exposure increases ∼4-6% greater than when considering all household incomes (2100; Table S-1; Fig. S-5). While these differences are small, those that emerge when considering property damage are much larger. In New York City, the current expected damage from a 100-yr ESL event is roughly \$4 billion. By 2100, this number is expected to grow by roughly 3 and 4 fold under a +2 °C and +5 °C GSAT stabilization scenario, respectively (assumes constant 2017 US\$; Table S-2).

4 Discussion and Conclusion

Physical ESL metrics do not consider the harms of a particular ESL event to human systems, natural resources, and to ecosystem services. As such, they may misrepresent projected changes in coastal flood risk. Despite this, physical ESL metrics continue to be used in assessment reports and the scientific literature as proxies for estimating coastal flood risk under different climate change scenarios. This could lead to inaccuracies in risk communication and poor planning. Our analysis specifically considers ESL AFs (frequency and return level), ESL hazard allowances, and the impact of choosing different risk metrics. First, ESL return level AFs may both over- and under-estimate flood risks as shown by the city-level examples of San Juan and Norfolk, as well as within and across regions (Sec. 3.1). Both the current population exposure and the gradient of the population profile play a crucial role in determining the amplification of population exposure. Second, we show that sub-optimal flood protection design could occur if ESL allowances do not consider a specific consequence (e.g., population exposure; Sec. 3.2). However, within some regions, the population exposure allowance does not appreciably differ from the ESL allowance (Fig. 4). Third, we illustrate how coastal flood risk assessments can be strongly dependent on the chosen risk metric by considering household income, the siting of critical infrastructure, and property damage (Sec. 3.3).

All risk metrics have limitations in what they are able to communicate. Choosing what consequences to include in a risk assessment is subjective. There is no "best" metric. Many measures of risk are possible and all tell a part of the same "risk story". However, risk metric choice is critical for determining what kinds of information can come from a risk assessment, including that which can inform decision-making (Kunreuther and Slovic, 1996; Slovic et al, 1982; Slovic, 1987). Such limitations point to the importance of choosing a broad and balanced set of risk metrics. While hazard metrics are essentially value-free, different stakeholders may have different opinions about what risk metric is most relevant. These factors may include practicality (i.e., ease of calculation) and suitability (i.e., informing specific risk management decisions) (NRC, 1996). In this paper we use current population exposure as an example of a viable metric for estimating coastal flood risk, but have noted that others are possible.

We acknowledge a number of caveats. First—and perhaps most importantly—we emphasize that we do not make literal estimates of future population exposure to ESLs. Results presented in this paper are primarily intended to highlight the importance of including societal impacts when quantifying coastal flood risk. Second, almost all coastal cities have developed over time with some margin of safety against ESLs, but including these defenses and any spatial variation within cities is challenging without obtaining detailed and accurate data. In the absence of this information, we make multiple assumptions regarding uniform protection for each city. The protection assumptions do not impact AFs above the height of the protection level, but can significantly impact integrated metrics that consider all ESLs and impacts, such as the EAE (Table S-5). We encourage future efforts to compile accurate information on urban flood protection levels around the world. Third, exposure analyses are most sensitive to spatially-autocorrelated vertical errors in the DEM at local scales and when assessing population vulnerability at low elevations (e.g., < 0.5 m; Kulp and Strauss, 2019). The higher the elevation that population exposure is being assessed at (e.g., longer return periods, such as the 100-yr event), the less of an impact these errors will have on exposure (Kulp and Strauss, 2019). To assess the impact of elevation errors on population exposure AFs, we use the example of the 100-year ESL event in New York City (Fig. S-6A). Considering lidar topography as ground truth, we find that the EAE AFs are generally insensitive to errors in CoastalDEM; small differences only appear by 2100 for the +5 °C scenario (2.3 vs 2.6; Table S-4). This is despite CoastalDEM underestimating population exposure relative to lidar (connected components analysis not performed for this test; Tables S-3,S-4). Fourth, there exists no single, expertly agreed upon PDF of late-century ice sheet melt (Oppenheimer et al, in press). ESL metrics and allowances are sensitive to the characterization of this parameter and its uncertainty (Rasmussen et al, 2020). Choosing multiple plausible ice melt scenarios may better illustrate risks in cases where there exists no single, mutually agreed upon PDF (e.g., after mid-century; Oppenheimer et al, in press).

In conclusion, we suggest that future studies should avoid using physical ESL metrics as proxies for coastal flood risk. This includes avoiding language that conflates physical metrics with societal impacts (e.g., calling ESLs "floods"). Not doing so may miss important societal aspects that are overlooked when only viewing through a physical science lens. Additionally, to better illustrate coastal flood risk, broadly speaking, multiple risk metrics should be presented when possible.

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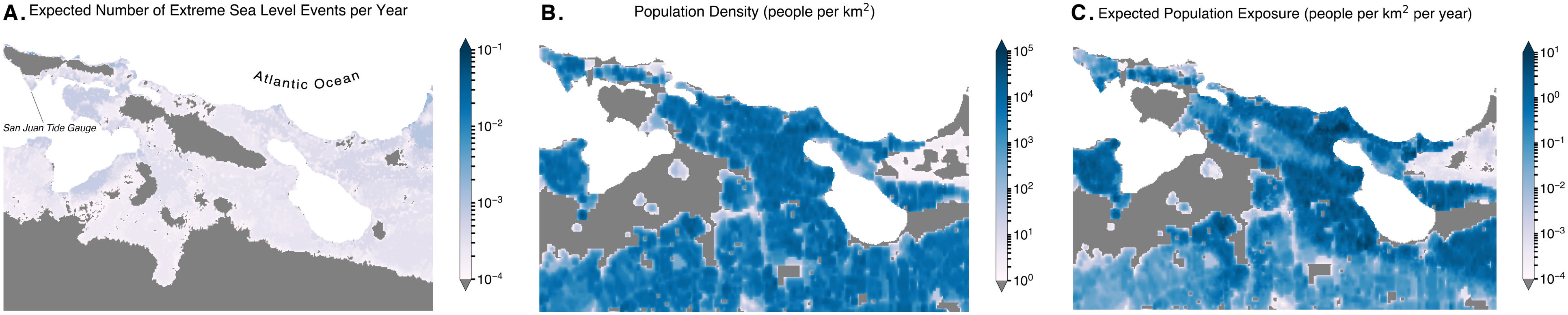

Fig. 1: **A.** A map of San Juan (Puerto Rico) showing the expected number of extreme sea level (ESL) events per year as estimated using 1) ESL return levels from the San Juan tide gauge (indicated), 2) ground elevation from CoastalDEM, and 3) the "bathtub" flood inundation method (Sec. S-1.3). **B.** Map showing population density (people per km^2) from the 2010 WorldPop global gridded population database (Tatem, 2017). **C.** Map showing the annual expected population exposure (people per km^2 per year)

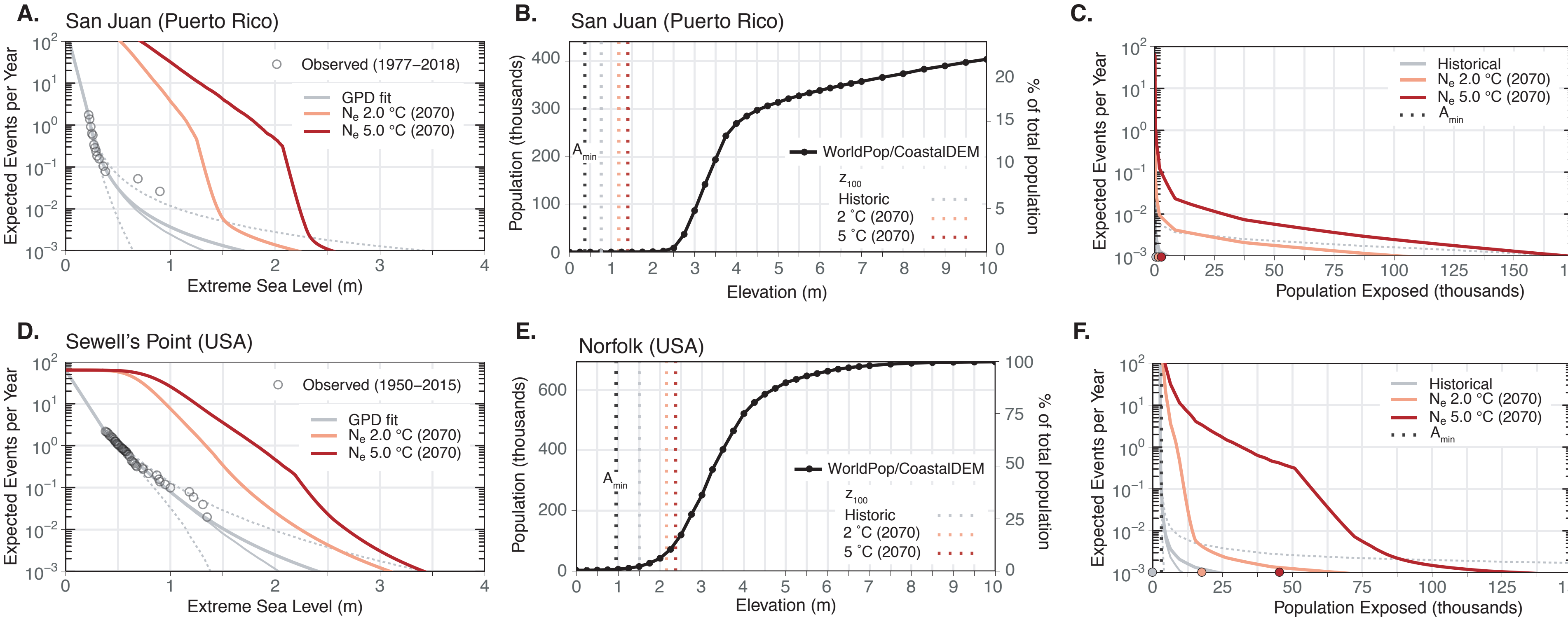

Fig. 2: **A.** Expected number of extreme sea level (ESL) events per year as a function of ESL height (meters above local mean higher high water; MHHW) calculated by fitting a generalized Pareto distribution (GPD) to tide gauge observations (open grey circles) at San Juan (Puerto Rico) for 1991–2009 mean sea level (MSL; thick grey line), projected relative sea-level rise (RSLR) in 2070 under a scenario in which global mean surface air temperature (GSAT) is stabilized in 2100 at +2 °C (orange line) and +5 °C (red line; GSAT relative to 1850–1900). Thin grey lines are the historical ESL return curves for the 5/50/95 percentiles of the GPD parameter uncertainty range (dotted/solid/dotted lines, respectively). **B.** A population exposure function that estimates the total population (left y-axis) and percent of total population (right y-axis) currently as risk of inundation as a function of ESL height (meters above MHHW) for San Juan (total population: 1.82 million). Filled black circles are population data from the 2010 WorldPop global gridded population database (Tatem, 2017) applied to the elevation surfaces of CoastalDEM (Kulp and Strauss, 2018). Linear interpolation is used to produce a continuous curve between the WorldPop data (black line). City boundaries are those as defined by Kelso and Patterson (2012) and may differ from actual political boundaries. Populations are assumed to remain constant in time. Denoted is the current level of protection (A_{min}), assumed to be the 10-yr ESL event, the height of the historical 100-yr ESL event (grey), and the expected heights of the 100-yr ESL event under a +2 °C (orange) and +5 °C (red) climate scenario. **C.** As for top left, but for the population exposed per event under 1991–2009 MSL (grey lines) and RSLR in 2070 under +2 °C (orange line) and +5 °C 2100 GSAT stabilization scenarios (red line). The projected future inundated population estimates assume that San Juan's population remains constant in time. Denoted are the assumptions of arbitrarily assuming that populations are protected below the height of the 10-yr ESL event. The expected annual population exposure (assuming protection from a 10-yr ESL event) is denoted with a filled colored circle on the x-axis for the historical period (grey) and for the +2 °C (orange) and +5 °C (red) scenarios. **Second Row:** As for Top Row, but for Norfolk (USA; total population: 695,000) using the expected number of ESL events from a tide gauge located at Sewell's Point (USA).

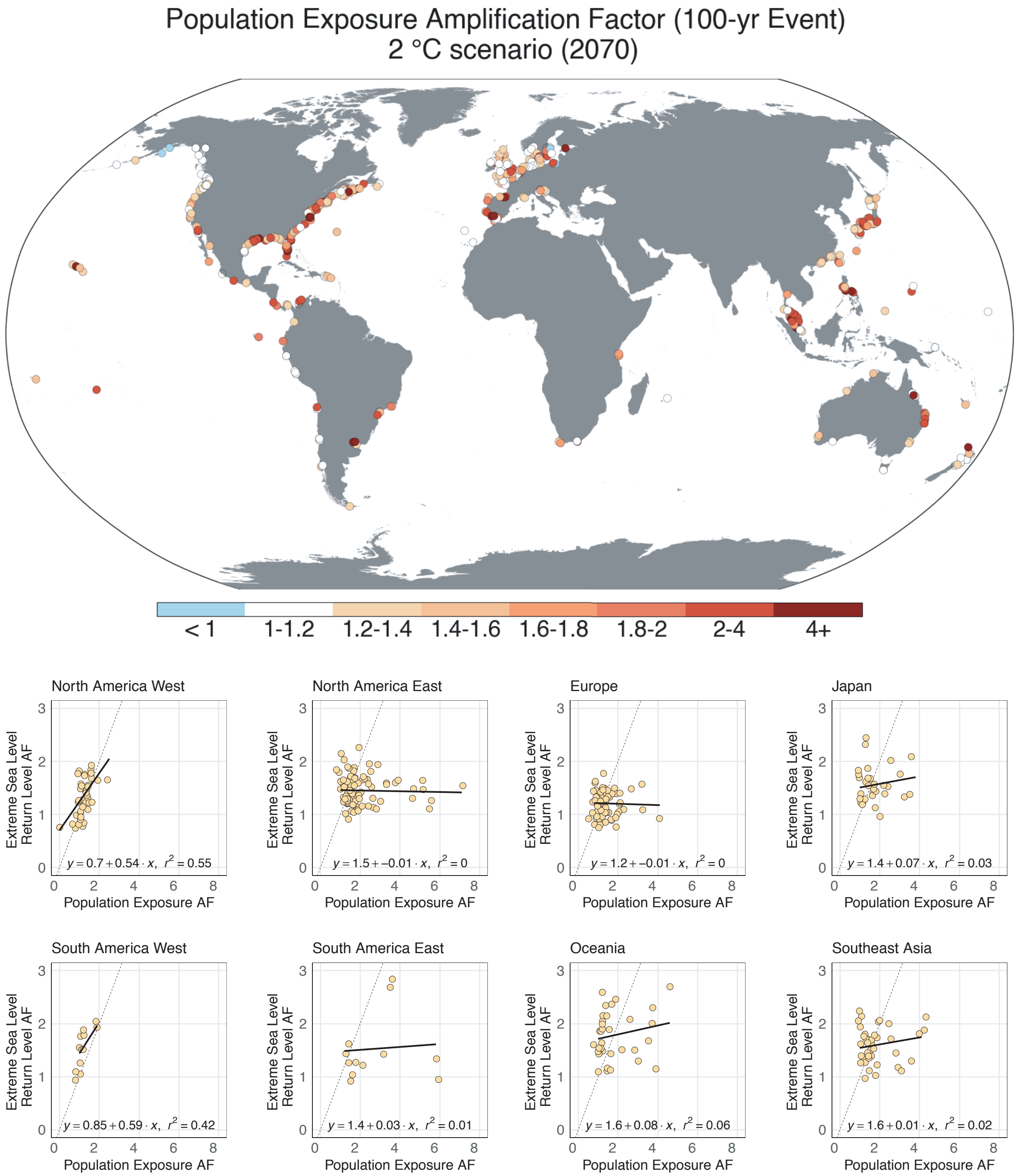

Fig. 3: **Map:** Population exposure AFs for cities for 2070 under a climate scenario where the global mean surface air temperature is stabilized in 2100 at +2 °C (relative to 1850–1900). Populations are assumed to remain constant in time. **Regional scatter plots:** Extreme sea level (ESL) return level AFs plotted against population exposure AFs for the 100-yr ESL event for 2070 for the same climate scenario as the map. A list of the cities in each defined region is given in the supporting data files. Note that some cities may not appear in the scatter plots if 1) current and future population inundation is zero, 2) the current inundation is zero but future inundation is non-zero (i.e., a population exposure AF of infinity), or 3) the population exposure AF is more than two times the standard deviation of all other cities within each region. Cities are not shown in the scatter plots if the population exposure AF is greater than two standard deviations from the mean of each region.

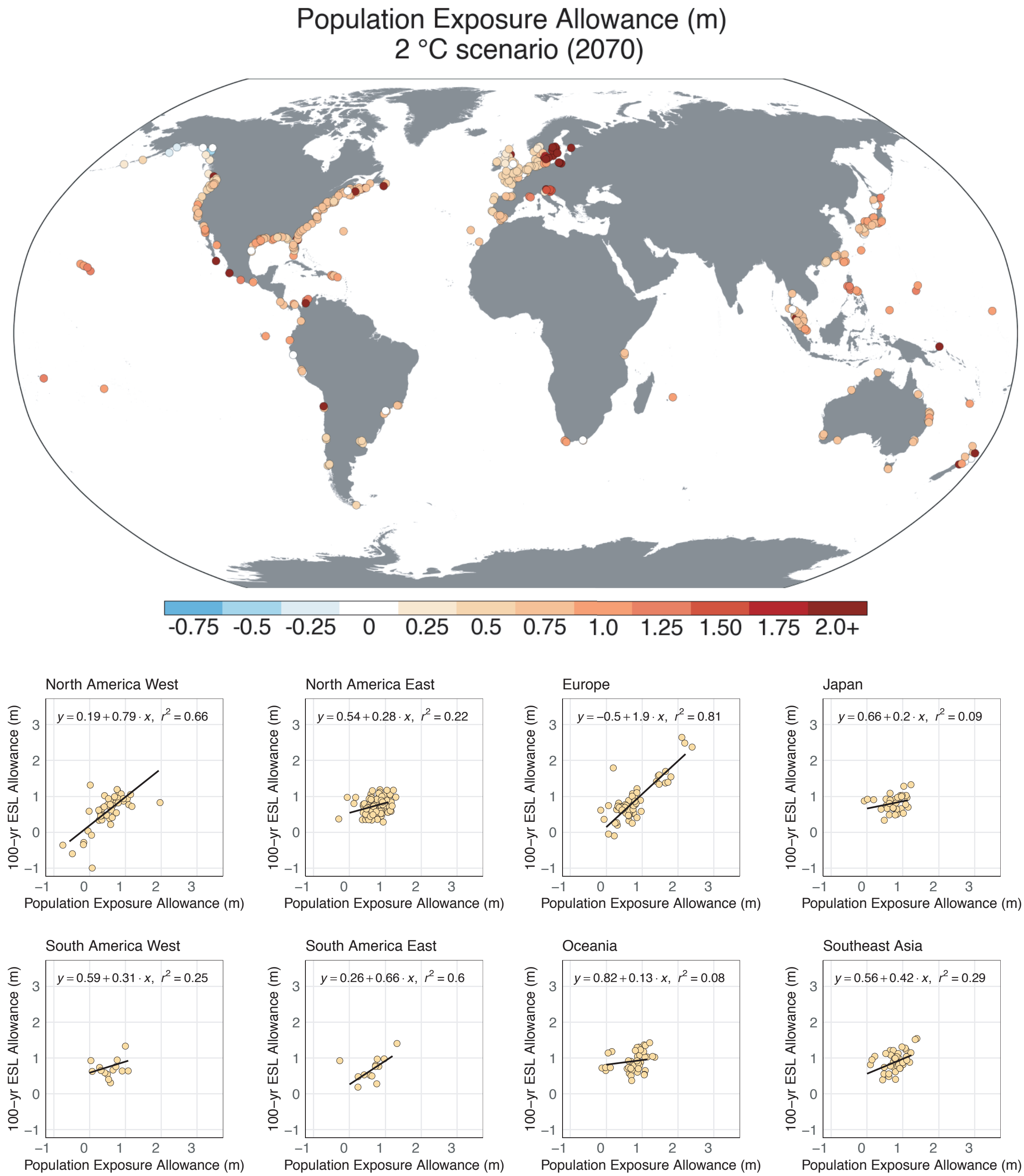

Fig. 4: **Map:** Population exposure allowances (also the design height of a flood protection strategy) for cities for 2070 under a climate scenario where the global mean surface air temperature is stabilized in 2100 at +2 °C (relative to 1850–1900). The population exposure allowance (also the design height of a flood protection strategy) maintains the historical annual expected population inundation exposure from extreme sea levels (ESLs) and assumes population distributions remain constant in time and that cities are protected from the current 10-yr extreme sea-level (ESL) event (1991–2009). Careful consideration should be given for cities in the Baltic and North Sea region. Difference of sign in modeled changes in ocean dynamics can lead to anomalously large allowances in comparison to relative sea level change (Fig. S-3). **Regional scatter plots:** ESL allowances for the 100-yr ESL event plotted against population exposure allowances for 2070 for the same climate scenario as the map. A list of the cities in each defined region is given in the supporting data files. Cities are not shown in the scatter plots if the population exposure allowance is greater than two standard deviations from the mean of each region.

100-yr ESL event			2070 (2.0 °C)					
	Historical		Physical metrics			Societal metrics		
City (Total population in thousands)	100-yr ESL (m)	% Pop exposed	RSLC (m)	ESL frequency AF	ESL level AF	Pop exposure AF	Pop exposed (thousands)	% increase
Buenos Aires, Argentina (11,980)	2.6 (2.1-3.3)	7.5%	0.4 (0.2-0.7)	3 (2-7)	1.2 (1.1-1.3)	1.5 (1.2-1.7)	1,321 (1,111-1,520)	3.5% (1.8-5.2%)
Copenhagen, Denmark (1,337)	1.1 (1.0-1.1)	1.5%	0.2 (-0.8-1.1)	991 (0-9677)	1.2 (0.3-2.1)	1.3 (0.0-3.2)	26 (0-63)	0.4% (-1.5-3.2%)
Dar es Salaam, Tanzania (2,322)	0.7 (0.6-0.7)	1.0%	0.5 (0.2-0.8)	2441 (254-6678)	1.7 (1.3-2.2)	1.7 (1.1-2.6)	39 (25-59)	0.7% (0.1-1.6%)
Hamburg, Germany (1,854)	4.0 (3.6-4.4)	14.9%	0.4 (0.1-0.7)	4 (2-9)	1.1 (1.0-1.2)	1.1 (1.0-1.2)	301 (285-320)	1.3% (0.4-2.3%)
Hong Kong, China (22,232)	1.8 (1.2-2.5)	32.9%	0.4 (0.1-0.8)	5 (1-12)	1.2 (1.1-1.4)	1.2 (1.1-1.4)	8,988 (7,788-10,111)	7.5% (2.1-12.6%)
Honolulu, HI, USA (466)	0.4 (0.3-0.4)	0.5%	0.5 (0.2-0.9)	12385 (942-14455)	2.4 (1.6-3.4)	4.6 (2.1-8.5)	11 (5-20)	1.8% (0.6-3.7%)
London, England (9,878)	0.9 (0.7-1.1)	1.8%	0.4 (0.2-0.7)	61 (4-188)	1.4 (1.2-1.7)	2.1 (1.4-2.9)	368 (252-515)	1.9% (0.8-3.4%)
Manila, Philippines (5,782)	0.8 (0.7-0.9)	36.5%	0.9 (0.6-1.2)	15443 (3322-*)	2.1 (1.8-2.5)	1.1 (1.1-1.2)	2,336 (2,249-2,440)	3.9% (2.4-5.7%)
New Orleans, LA, USA (711)	2.3 (1.2-4.1)	77.7%	1.0 (0.7-1.3)	4 (2-7)	1.4 (1.3-1.6)	1.2 (1.1-1.2)	643 (623-663)	12.7% (9.9-15.5%)
New York, NY, USA (12,520)	1.9 (1.5-2.3)	3.7%	0.6 (0.3-0.9)	11 (2-29)	1.3 (1.1-1.5)	1.4 (1.2-1.7)	654 (543-799)	1.5% (0.6-2.7%)
Norfolk, VA, USA (695)	1.5 (1.1-2.0)	2.3%	0.6 (0.4-1.0)	32 (4-81)	1.4 (1.3-1.6)	4.1 (2.2-7.3)	64 (35-114)	6.9% (2.8-14.2%)
Phuket, Thailand (159)	0.9 (0.8-1.0)	9.0%	0.5 (0.2-0.8)	1723 (37-7875)	1.5 (1.2-1.9)	1.2 (1.1-1.4)	17 (16-20)	1.9% (0.9-3.5%)
Rio de Janeiro, Brazil (9,110)	0.9 (0.8-1.1)	0.3%	0.5 (0.2-0.8)	992 (8-5242)	1.5 (1.2-1.9)	1.8 (1.3-2.5)	59 (43-80)	0.3% (0.1-0.5%)
San Diego, CA, USA (2,323)	0.7 (0.7-0.7)	0.2%	0.5 (0.2-0.8)	4726 (298-15431)	1.7 (1.4-2.2)	3.0 (1.6-5.7)	13 (7-25)	0.4% (0.1-0.9%)
San Juan, Puerto Rico (1,821)	0.7 (0.5-1.1)	0.0%	0.5 (0.2-0.8)	2918 (4-*)	1.7 (1.3-2.1)	1.4 (1.1-1.9)	0 (0-0)	0.0% (0.0-0.0%)
Shenzhen, China (12,518)	1.8 (1.2-2.6)	17.5%	0.4 (0.1-0.8)	5 (1-12)	1.2 (1.1-1.4)	1.2 (1.1-1.3)	2,651 (2,327-2,938)	3.6% (1.1-5.9%)
Sydney, Australia (3,483)	0.7 (0.7-0.7)	0.2%	0.4 (0.2-0.8)	3213 (60-16480)	1.6 (1.3-2.1)	1.2 (1.1-1.3)	9 (9-11)	0.0% (0.0-0.1%)
Tokyo, Japan (25,339)	1.5 (1.0-2.1)	5.5%	0.4 (0.1-0.7)	8 (1-18)	1.2 (1.1-1.5)	1.9 (1.1-3.0)	2,656 (1,610-4,278)	4.9% (0.8-11.3%)
Vancouver, Canada (1,810)	1.3 (1.1-1.6)	11.8%	0.2 (0.0-0.5)	28 (1-94)	1.2 (1.0-1.4)	1.0 (1.0-1.0)	218 (214-223)	0.2% (0.0-0.5%)

Table 1: Table listing both physical and societal extreme sea level (ESL) metrics for select major coastal cities. Given are the heights of the historical 100-yr ESL return period (meters relative to mean higher high water; expected/5th/95th percentile), the percent of the total population exposed to the expected 100-yr ESL event, 2070 probabilistic relative sea-level change (RSLC) (meters, relative to 1991–2009) from a climate scenario in which global mean surface air temperature (GSAT) is stabilized in 2100 at +2 °C (relative to 1850–1900; Bamber et al, 2019), ESL return period amplification factors (AFs) for the 100-yr ESL event, ESL return level AFs for the 100-yr ESL event, the population exposure AF, the estimated total population exposed to the future 100-yr ESL event (thousands), and the percent increase in the latter, relative the historical population exposure. The expected value and the 5/95 percentile of the estimate are given for each. The 5/95 percentile for the current ESL return period considers the uncertainty in the generalized Pareto distribution (GPD) parameters, while the 5/95 percentile for RSLC and AFs reflect the uncertainty from both contributions to local RSLC and from the GPD. The * denotes instances of when the height of the current 100-yr ESL event occurs more often than the present-day frequency of exceeding MHHW (given for each tide gauge in the supporting information). The mapping of tide gauges to cities is given in the supporting information.

100-yr ESL event			2070 (5.0 °C)					
	Historical		Physical metrics			Societal metrics		
City (Total population in thousands)	100-yr ESL (m)	% Pop exposed	RSLC (m)	ESL frequency AF	ESL level AF	Pop exposure AF	Pop exposed (thousands)	% increase
Buenos Aires, Argentina (11,980)	2.6 (2.1-3.3)	7.5%	0.6 (0.3-1.1)	8 (2-20)	1.2 (1.1-1.4)	1.6 (1.4-1.9)	1,449 (1,241-1,682)	4.6% (2.9-6.6%)
Copenhagen, Denmark (1,337)	1.1 (1.0-1.1)	1.5%	0.5 (0.1-1.0)	841 (10-5575)	1.5 (1.1-1.9)	1.6 (1.1-2.5)	31 (21-51)	0.9% (0.1-2.3%)
Dar es Salaam, Tanzania (2,322)	0.7 (0.6-0.7)	1.0%	0.7 (0.3-1.2)	4720 (620-6678)	2.1 (1.5-2.9)	2.3 (1.1-3.1)	52 (26-70)	1.3% (0.1-2.0%)
Hamburg, Germany (1,854)	4.0 (3.6-4.3)	14.9%	0.6 (0.3-1.1)	9 (2-22)	1.2 (1.1-1.3)	1.1 (1.1-1.2)	314 (293-338)	2.0% (0.9-3.3%)
Hong Kong, China (22,232)	1.8 (1.2-2.6)	32.9%	0.6 (0.2-1.2)	120 (2-155)	1.4 (1.1-1.7)	1.3 (1.2-1.5)	9,636 (8,437-10,847)	10.4% (5.0-15.9%)
Honolulu, HI, USA (466)	0.4 (0.3-0.4)	0.5%	0.8 (0.4-1.3)	14017 (14455-14455)	3.1 (2.0-4.7)	8.1 (3.2-18.4)	19 (7-43)	3.5% (1.1-8.6%)
London, England (9,878)	0.9 (0.7-1.1)	1.8%	0.6 (0.3-1.0)	223 (12-1242)	1.6 (1.3-2.1)	2.6 (1.8-4.1)	468 (310-728)	2.9% (1.3-5.6%)
Manila, Philippines (5,782)	0.8 (0.7-0.9)	36.5%	1.1 (0.7-1.6)	17547 (8662-*)	2.4 (1.9-3.0)	1.1 (1.1-1.2)	2,402 (2,276-2,597)	5.0% (2.8-8.4%)
New Orleans, LA, USA (711)	2.3 (1.2-4.2)	77.7%	1.2 (0.8-1.7)	94 (3-27)	1.5 (1.4-1.7)	1.2 (1.1-1.2)	655 (634-677)	14.4% (11.5-17.6%)
New York, NY, USA (12,520)	1.9 (1.5-2.3)	3.7%	0.8 (0.4-1.3)	228 (3-296)	1.4 (1.2-1.7)	1.6 (1.2-2.1)	738 (578-957)	2.2% (0.9-3.9%)
Norfolk, VA, USA (695)	1.5 (1.1-1.9)	2.3%	0.9 (0.5-1.4)	343 (7-1660)	1.6 (1.3-1.9)	6.6 (2.7-13.9)	104 (42-219)	12.6% (3.9-29.2%)
Phuket, Thailand (159)	0.9 (0.8-1.0)	9.0%	0.7 (0.3-1.2)	6012 (208-*)	1.7 (1.3-2.3)	1.4 (1.1-1.8)	19 (16-26)	3.2% (1.3-7.1%)
Rio de Janeiro, Brazil (9,110)	0.9 (0.8-1.1)	0.3%	0.7 (0.3-1.2)	3951 (30-14619)	1.7 (1.4-2.3)	2.2 (1.5-3.5)	71 (49-110)	0.4% (0.2-0.9%)
San Diego, CA, USA (2,323)	0.7 (0.7-0.7)	0.2%	0.7 (0.3-1.2)	9611 (798-15431)	2.0 (1.5-2.8)	4.5 (2.0-8.6)	20 (9-38)	0.7% (0.2-1.4%)
San Juan, Puerto Rico (1,821)	0.7 (0.5-1.1)	0.0%	0.7 (0.3-1.2)	10225 (10-*)	2.0 (1.5-2.7)	3.3 (1.2-5.4)	0 (0-1)	0.0% (0.0-0.0%)
Shenzhen, China (12,518)	1.8 (1.2-2.7)	17.4%	0.6 (0.2-1.2)	120 (2-155)	1.4 (1.1-1.7)	1.3 (1.1-1.4)	2,813 (2,496-3,131)	5.0% (2.5-7.6%)
Sydney, Australia (3,483)	0.7 (0.7-0.7)	0.2%	0.7 (0.3-1.1)	8942 (374-16480)	2.0 (1.5-2.7)	1.4 (1.1-2.6)	11 (9-21)	0.1% (0.0-0.4%)
Tokyo, Japan (25,339)	1.5 (1.0-2.2)	5.5%	0.6 (0.2-1.2)	455 (2-914)	1.4 (1.1-1.8)	2.6 (1.4-4.3)	3,635 (1,880-5,935)	8.9% (1.9-17.9%)
Vancouver, Canada (1,810)	1.3 (1.1-1.6)	11.8%	0.4 (0.1-0.9)	436 (2-1065)	1.3 (1.0-1.6)	1.0 (1.0-1.1)	221 (215-229)	0.4% (0.1-0.8%)

Table 2: As for Table 1, but for a climate scenario in which global mean surface air temperature (GSAT) is stabilized in 2100 at +5 °C (relative to 1850–1900; Bamber et al, 2019).

Allowances				2070 (2.0 °C)				
	Historical			Physical metrics		Societal metrics		
City (Total population in thousands)	100-yr ESL (m)	% Pop exposed	EAE (thousands)	RSLC (m)	100-yr ESL allowance	EAE (thousands)	% increase	Pop exposure allowance
Buenos Aires, Argentina (11,980)	2.6 (2.1-3.3)	7.5%	23	0.4 (0.2-0.7)	0.5	85	269.4%	0.5
Copenhagen, Denmark (1,337)	1.1 (1.0-1.1)	1.5%	2	0.2 (-0.8-1.1)	2.4	89	5481.4%	2.2
Dar es Salaam, Tanzania (2,322)	0.7 (0.6-0.7)	1.0%	1	0.5 (0.2-0.8)	1.0	46	3058.5%	0.8
Hamburg, Germany (1,854)	4.0 (3.6-4.4)	14.9%	24	0.4 (0.1-0.7)	0.5	73	207.1%	0.5
Hong Kong, China (22,232)	1.8 (1.2-2.5)	32.9%	524	0.4 (0.1-0.8)	0.5	5,611	970.8%	0.6
Honolulu, HI, USA (466)	0.4 (0.3-0.4)	0.5%	0	0.5 (0.2-0.9)	1.2	22	14353.0%	1.1
London, England (9,878)	0.9 (0.7-1.1)	1.8%	11	0.4 (0.2-0.7)	0.6	174	1504.1%	0.5
Manila, Philippines (5,782)	0.8 (0.7-0.9)	36.5%	156	0.9 (0.6-1.2)	1.3	2,350	1408.9%	1.2
New Orleans, LA, USA (711)	2.3 (1.2-4.1)	77.7%	36	1.0 (0.7-1.3)	1.0	475	1231.2%	1.1
New York, NY, USA (12,520)	1.9 (1.5-2.3)	3.7%	34	0.6 (0.3-0.9)	0.6	391	1056.1%	0.7
Norfolk, VA, USA (695)	1.5 (1.1-2.0)	2.3%	1	0.6 (0.4-1.0)	0.7	16	1271.2%	0.7
Phuket, Thailand (159)	0.9 (0.8-1.0)	9.0%	1	0.5 (0.2-0.8)	0.9	17	1541.3%	0.8
Rio de Janeiro, Brazil (9,110)	0.9 (0.8-1.1)	0.3%	3	0.5 (0.2-0.8)	0.8	50	1803.1%	0.8
San Diego, CA, USA (2,323)	0.7 (0.7-0.7)	0.2%	0	0.5 (0.2-0.8)	1.0	18	5635.2%	0.9
San Juan, Puerto Rico (1,821)	0.7 (0.5-1.1)	0.0%	0	0.5 (0.2-0.8)	0.7	0	232.5%	0.8
Shenzhen, China (12,518)	1.8 (1.2-2.6)	17.5%	160	0.4 (0.1-0.8)	0.5	1,730	980.7%	0.6
Sydney, Australia (3,483)	0.7 (0.7-0.7)	0.2%	1	0.4 (0.2-0.8)	0.9	9	1395.9%	0.8
Tokyo, Japan (25,339)	1.5 (1.0-2.1)	5.5%	98	0.4 (0.1-0.7)	0.5	1,104	1025.8%	0.6
Vancouver, Canada (1,810)	1.3 (1.1-1.6)	11.8%	18	0.2 (0.0-0.5)	0.4	177	866.2%	0.4

Table 3: Table listing both physical and societal extreme sea level (ESL) metrics for select major coastal cities. Given are the heights of the current 100-yr ESL return period [meters relative to mean higher high water (MHHW); expected/5th/95th percentile], the percent of the total population exposed to the expected 100-yr ESL events, the expected annual population exposure (EAE; thousands of people), 2070 probabilistic relative sea-level change (RSLC) (meters, relative to 1991–2009) from a climate scenario in which global mean surface air temperature (GSAT) is stabilized in 2100 at +2 °C (relative to 1850–1900; Bamber et al, 2019), the ESL allowance that maintains the frequency of the historical 100-yr event (meters above MHHW), the projected EAE (thousands), the percent increase in the EAE, and the population exposure allowance (meters above MHHW).

Allowances				2070 (5.0 °C)				
	Historical			Physical metrics		Societal metrics		
City (Total population in thousands)	100-yr ESL (m)	% Pop exposed	EAE (thousands)	RSLC (m)	100-yr ESL allowance	EAE (thousands)	% increase	Pop exposure allowance
Buenos Aires, Argentina (11,980)	2.6 (2.1-3.3)	7.5%	23	0.6 (0.3-1.1)	0.7	213	830.6%	0.8
Copenhagen, Denmark (1,337)	1.1 (1.0-1.1)	1.5%	2	0.5 (0.1-1.0)	1.1	32	1896.1%	0.9
Dar es Salaam, Tanzania (2,322)	0.7 (0.6-0.7)	1.0%	1	0.7 (0.3-1.2)	1.7	68	4493.5%	1.5
Hamburg, Germany (1,854)	4.0 (3.6-4.3)	14.9%	24	0.6 (0.3-1.1)	0.7	119	397.9%	0.7
Hong Kong, China (22,232)	1.8 (1.2-2.6)	32.9%	525	0.6 (0.2-1.2)	0.9	7,855	1396.5%	1.1
Honolulu, HI, USA (466)	0.4 (0.3-0.4)	0.5%	0	0.8 (0.4-1.3)	2.0	71	46941.1%	2.0
London, England (9,878)	0.9 (0.7-1.1)	1.8%	11	0.6 (0.3-1.0)	1.0	324	2888.1%	1.0
Manila, Philippines (5,782)	0.8 (0.7-0.9)	36.5%	156	1.1 (0.7-1.6)	2.0	2,563	1545.9%	1.9
New Orleans, LA, USA (711)	2.3 (1.2-4.2)	77.7%	36	1.2 (0.8-1.7)	1.3	559	1470.4%	1.7
New York, NY, USA (12,520)	1.9 (1.5-2.3)	3.7%	34	0.8 (0.4-1.3)	1.0	547	1517.9%	1.2
Norfolk, VA, USA (695)	1.5 (1.1-1.9)	2.3%	1	0.9 (0.5-1.4)	1.2	45	3745.6%	1.3
Phuket, Thailand (159)	0.9 (0.8-1.0)	9.0%	1	0.7 (0.3-1.2)	1.6	24	2152.5%	1.5
Rio de Janeiro, Brazil (9,110)	0.9 (0.8-1.1)	0.3%	3	0.7 (0.3-1.2)	1.4	83	3053.1%	1.4
San Diego, CA, USA (2,323)	0.7 (0.7-0.7)	0.2%	0	0.7 (0.3-1.2)	1.8	38	12326.7%	1.6
San Juan, Puerto Rico (1,821)	0.7 (0.5-1.1)	0.0%	0	0.7 (0.3-1.2)	1.5	1	995.1%	1.5
Shenzhen, China (12,518)	1.8 (1.2-2.7)	17.4%	160	0.6 (0.2-1.2)	0.9	2,336	1363.1%	1.1
Sydney, Australia (3,483)	0.7 (0.7-0.7)	0.2%	1	0.7 (0.3-1.1)	1.5	20	2995.9%	1.4
Tokyo, Japan (25,339)	1.5 (1.0-2.2)	5.5%	98	0.6 (0.2-1.2)	1.0	2,846	2809.1%	1.2
Vancouver, Canada (1,810)	1.3 (1.1-1.6)	11.8%	18	0.4 (0.1-0.9)	1.0	221	1107.6%	0.9

Table 4: As for Table 3, but for a climate scenario in which global mean surface air temperature (GSAT) is stabilized in 2100 at +5 °C (relative to 1850–1900; Bamber et al, 2019).

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Supplementary Information

S-1 Supplemental Methods

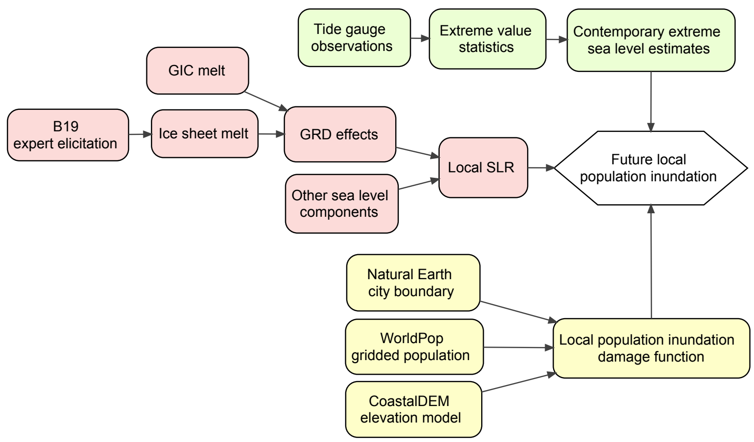


Fig. S-1: Flow of information used in this study to produce projected local population inundation estimates (white hexagon). Green rectangles are for extreme sea level estimation. Red rectangles are for sea-level rise projections. Yellow rectangles are for local population inundation estimates. B19 is Bamber et al (2019); SLR is sea-level rise; GIC are glaciers and ice caps; GRD are gravitational, rotational, and deformational effects; "Other sea level components" includes land water storage, oceanographic processes, and non-climatic background changes, such as glacial-isostatic adjustment.

S-1.1 Estimating extreme sea levels

We use long-term records of hourly or sub-hourly sea level observations from quality controlled tide gauges from the University of Hawaii Sea Level Center[4] and also supplement with other tide gauges from the GESLA2 data set (Woodworth et al, 2016). We limit our use of tide gauge records to only those that have record lengths $>$ 30 consecutive years in which each year has $>$ 80 percent of observations available. In total, we use 360 unique tide gauges, with median and average record lengths of 48 and $\sim$54 years, respectively (a list of the tide gauges used is given in the supporting information). For each day in the tide gauge record with $>$12 hours of data, we estimate the daily maximum sea level. We note that this temporal resolution only facilitates the estimation of still-water heights and is likely not sufficient to capture wave setup and swash contributions, which can be significant (Melet et al, 2018; Arns et al, 2017). To isolate the variation in ESL, we remove the effect of MSL change by subtracting the annual MSL from each daily maximum value (i.e., values are de-trended). The de-trended daily maximum tide values are then referenced to local mean higher high water (MHHW; relative to the de-trended mean sea level), defined as the average highest high tide at the tide gauge over a given period (here, either 1993–2012 or the last available 19-year period in the record). Daily maximum sea levels that are 1) above the 99th percentile and 2) within 3 days of each other are de-clustered to meet the statistical independence assumption of the extreme value approach (below).

[4] retrieved from: https://uhslc.soest.hawaii.edu, January 2020; (Caldwell et al, 2015)

We estimate the present-day probability of ESLs by applying extreme value theory to long-term hourly tide gauge records. Extreme value theory is a statistical extrapolation method that fits an extreme value distribution to empirical data in order to estimate the likelihood of events too rare to appear in an observational record (e.g., determining the height of 100-yr ESL event from a 30-yr record of tide gauge data). Following previous studies (Tebaldi et al, 2012; Buchanan et al, 2017; Rasmussen et al, 2018; Frederikse et al, 2020; Wahl et al, 2017), we estimate the annual expected number of ESL events of various heights at each tide gauge using a generalized Pareto distribution (GPD; Coles, 2001b,a). The GPD is a peaks over threshold modeling approach that describes the probability of a given ESL height conditional on the exceedance of a threshold (assumed to be Poisson distributed with mean λ). Various extreme value distributions and approaches to implement them have been proposed (Coles, 2001a), but in the case of ESL estimation there currently is not an agreed upon "best approach". Depending on the specific project goals, a particular extreme value modeling strategy may be preferred over another. For example, if the tide gauge record is short, a peaks over threshold approach that uses sub-annual extremes may be preferred over an approach that only uses annual maximums (Lang et al, 1999; Cunnane, 1973). The GPD has the advantage over other generalized extreme value models in that 1) unlike the annual maximum flood value modeling approach, it can accommodate sub-annual observations (i.e., retain more information), 2) unlike the more restrictive Gumbel distribution (Buchanan et al, 2017), it includes a parameter that allows for the flexibility for the distribution to take on different shapes (shape parameter, ξ, and its value depends on the characteristics of the underlying data), and 3) it can be combined with a Poisson rate parameter (λ) to translate ESL exceedance probabilities into expected numbers of annual ESL exceedances. The latter may be more intuitive and thus better for communicating the frequency of ESL events. Increases or decreases in storminess could change λ, but is not considered in this study. For a given tide gauge, the annual expected number of exceedances of height z is given by $N(z)$:

$$N(z) = \begin{cases} \lambda \left(1 + \frac{\xi(z-\mu)}{\sigma}\right)^{-\frac{1}{\xi}} & \text{for } \xi \neq 0 \\ \lambda \, \exp(-\frac{z-\mu}{\sigma}) & \text{for } \xi = 0 \end{cases} \tag{S-1}$$

where the shape parameter (ξ) governs the curvature and upward statistical limit of $N(z)$, the scale parameter (σ) characterizes the variability in the exceedances, and the location parameter (μ) is the threshold water-level above which return levels are estimated with the GPD—here the 99th percentile of daily maximum sea levels. Observed GPD threshold exceedances and the fitted GPD $N(z)$ for tide gauges located at San Juan (Puerto Rico) and Sewell's Point (Norfolk, USA) are given in Figs. 2A,D. The GPD parameters for all tide gauges are given in the supporting data files.

Selecting the threshold μ is critical element of the peaks over threshold approach. If the threshold is too low, it could bias in the estimates because the included values may not be extreme enough. On the other hand, if the threshold is too high, the variance might be too large because too few points are being included in the analysis (Lang et al, 1999). Here, the 99th percentile is used because it generally is above the highest seasonal tide, balances the bias-variance trade-off in the GPD parameter estimation (Tebaldi et al, 2012) and has been found to perform well at global scales (Wahl et al, 2017). The location parameter μ shifts as MSL changes. The storm climates and hydrodynamic characteristics of each site result in differences in the shape parameter (ξ) across sites. ESL frequency distributions with $\xi > 0$ are "heavy tailed", due to a larger variation in extremes (e.g., existence of tropical and extra-tropical cyclones). Distributions with $\xi < 0$ are "thin tailed" and have a statistical upper bound on ESLs. The GPD parameters are estimated using maximum likelihood, and their uncertainty is calculated from their estimated covariance matrix and is sampled using a Latin hypercube sampling of 1000 normally distributed GPD parameter pairs. Note that the fit of the GPD and the uncertainty bounds may not always well capture the observed exceedances (e.g., San Juan; Fig 2A). While we extrapolate estimates for ESL events up to the frequency of the 1000-yr event, we caution in using any estimate of ESL that exceeds four times the length of the observation record (Pugh and Woodworth, 2014). Events that occur with a frequency greater than λ (i.e., the expected number of exceedances of the GPD threshold per year) are outside of the support of the GPD and are modeled with a Gumbel distribution. Other probability mixture model approaches have been proposed that combine a GPD with another distribution (e.g., a Normal distribution; Ghanbari et al, 2019).

S-1.2 Relative sea level change projections

The other RSLC component contributions are from ocean thermal expansion, glaciers and ice caps, and land-water storage. General circulation model (GCM) output is used to generate the steric and glacial ice melt sea level components for each global mean surface air temperature (GSAT) stabilization scenario. The +2 °C scenario used the GCM outputs specified for the same GSAT scenario in Rasmussen et al (2018) and the +5 °C scenario used GCM outputs from the representative concentration pathway (RCP) 8.5 from Kopp et al (2014). Also accounted for are regional effects such as ocean dynamics (from GCM output), gravitational and rotational effects of ice mass redistribution, glacial isostatic adjustment, and other local vertical land motion factors (e.g., sediment compaction and ground water withdrawal). Probability distributions of local RSLC are produced using 10,000 Latin hypercube samples of each individual sea level component contribution. The probability distributions are truncated at the 99.9th percentile to remove samples that are deemed to be physically implausible (Oppenheimer et al, in press). As noted by Rasmussen et al (2020), both ESL frequencies and allowances are sensitive to truncation selection. More details and limitations to the RSLC projections are provided elsewhere (Kopp et al, 2014; Bamber et al, 2019; Rasmussen et al, 2020).

S-1.3 Exposure analysis

Both ESLs and CoastalDEM are referenced to local mean higher high water (MHHW), however, ESLs use tide gauge data for estimating MHHW, while CoastalDEM uses an estimation technique from National Oceanic and Atmospheric Administration's (NOAA) VDatum tool (version 3.7; Parker et al, 2003). This leads to differences in estimates of MHHW for some locations. To convert both data sets to a common vertical reference, an adjustment is made to the tide gauge ESLs to account for differences between the tide gauge estimates and the CoastalDEM ground elevations (adjustments are provided in the supporting data files).

When mapping tide gauges to cities there may be more than one tide gauge with in a 100-km radius (e.g., Willet's Point and the Battery in NYC, Fig. S-6A). In such instances, the tide gauge with the longest record is used (the tide gauges assigned to each city are listed in the supporting data files). While the height of a given ESL return period may vary within a city, in part due to complicated bathymetry and coastlines, Kulp and Strauss (2017) has shown that ESL population exposure results for the U.S. are generally insensitive to tide gauge assignment within a 100-km radius. In any case, more complex hydrodynamic inundation models that account for complex local geomorphology and include additional variables could be used to estimate local floods for cities across the globe. However, such an approach is out of the scope of this study. Moreover, more complex models may also not necessarily outperform simpler approaches, especially in active tropical cyclone regions (Hunter et al, 2017; Muis et al, 2016, 2017; Wahl et al, 2017), in part due to poor representation of tide-surge interactions (Arns et al, 2020) and short simulation periods that are less likely to produce rare, extreme events found in multi-decadal tide gauge records. For some locations, the height of the 100-yr ESL event can be under-predicted by up to 3 meters compared to tide gauge-derived estimates (supporting information of Muis et al, 2017).

The WorldPop population data are resampled to align with CoastalDEM raster (for more details, see Kulp and Strauss, 2019), integrated over select elevations (-2 to 13 m above MHHW, either 0.25 or 0.5 m increments), and then tabulated according to the satellite-derived urban footprint for each city from Natural Earth (which may differ from the actual administrative boundary; Kelso and Patterson, 2012). Coastal cities are only included in the analysis if there are populations with in the defined boundary at any elevation $<$ 13 m above local MHHW. Linear interpolation is used between each select elevation to produce a 1-dimensional continuous population exposure profile $D(z)$, where z is the ESL height. We note that z could be a vector to account for spatial differences in ESL height for the same return period within a city and also spatial variation in flood protection.

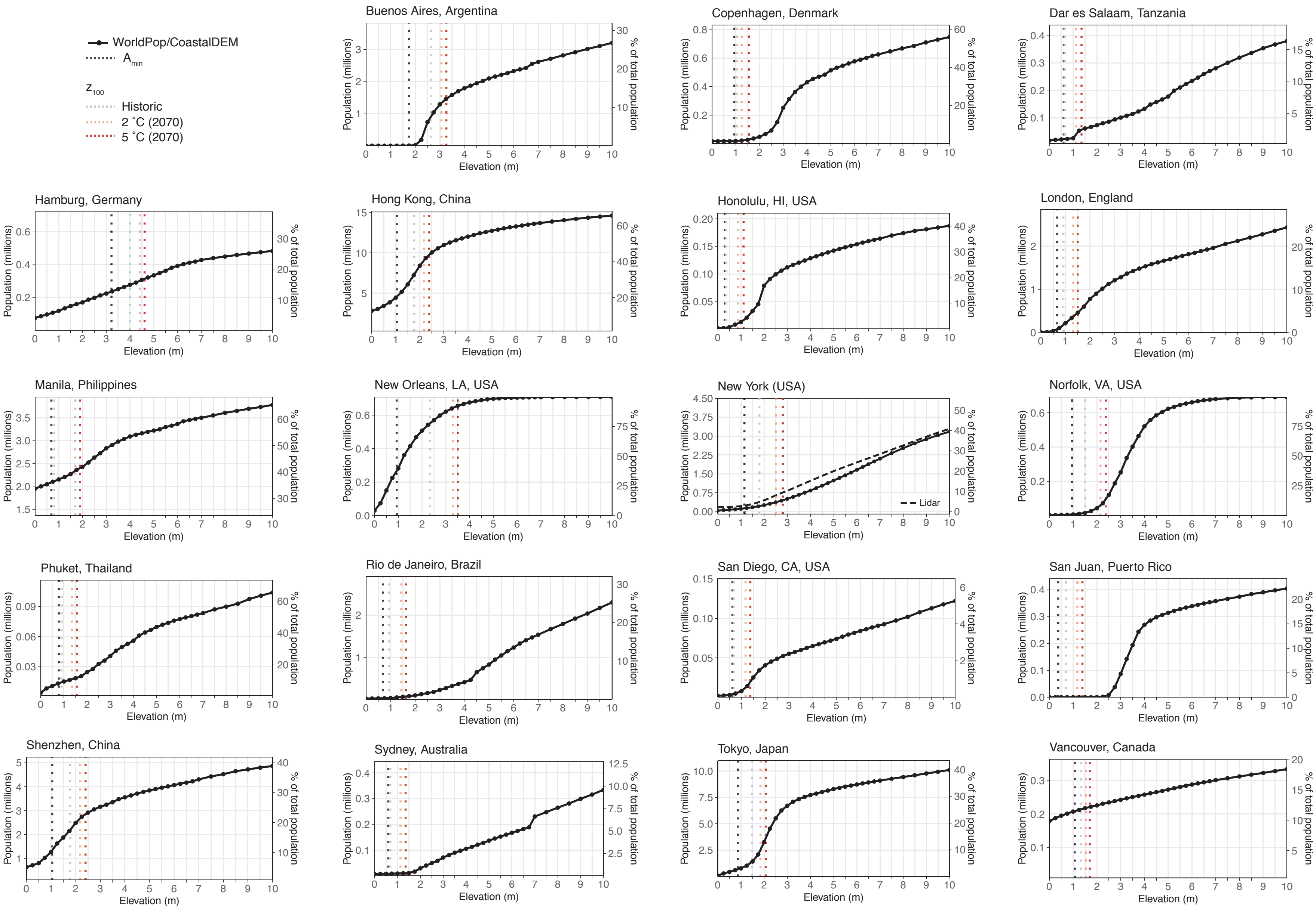


Fig. S-2: Population exposure functions that estimate the total population currently as risk of inundation as a function of ESL height (meters above MHHW) for cities given in Tables 1-4. Filled black circles are population data from the 2010 WorldPop global population database (Tatem, 2017) applied to the elevation surfaces of CoastalDEM (Kulp and Strauss, 2018, 2019). Linear interpolation is used to produce a continuous curve between the WorldPop data (black line). City boundaries are those as defined by Kelso and Patterson (2012) and may differ from actual political boundaries. Populations are assumed to remain constant in time. Denoted is the current level of protection (A_{min}), assumed to be the 10-yr ESL event, the height of the historical 100-yr ESL event (grey), and the expected heights of the 100-yr ESL event under a +2 °C (orange) and +5 °C (red) climate scenario. Also shown for New York City is a population profile generated using a 0.3-m horizontal resolution light detection and ranging (LiDAR)-derived digital elevation model for the City of New York (https://data.cityofnewyork.us/City-Government/1-foot-Digital-Elevation-Model-DEM-/dpc8-z3jc).

S-1.4 Estimating hazard allowances and annual population exposure

While ESL and population exposure AFs are well suited to identify and communicate local coastal flood risks, allowances are perhaps more useful for informing the design of coastal flood defense efforts (e.g., determining optimal levee heights or how high to raise a residence to maintain a given margin of safety; Rasmussen et al, 2020). Following Buchanan et al (2016), we calculate the ESL hazard allowance A that maintains a given annual exceedance probability (AEP) under uncertain RSLC δ, whose uncertainty is given by the PDF, $P(\delta)$,

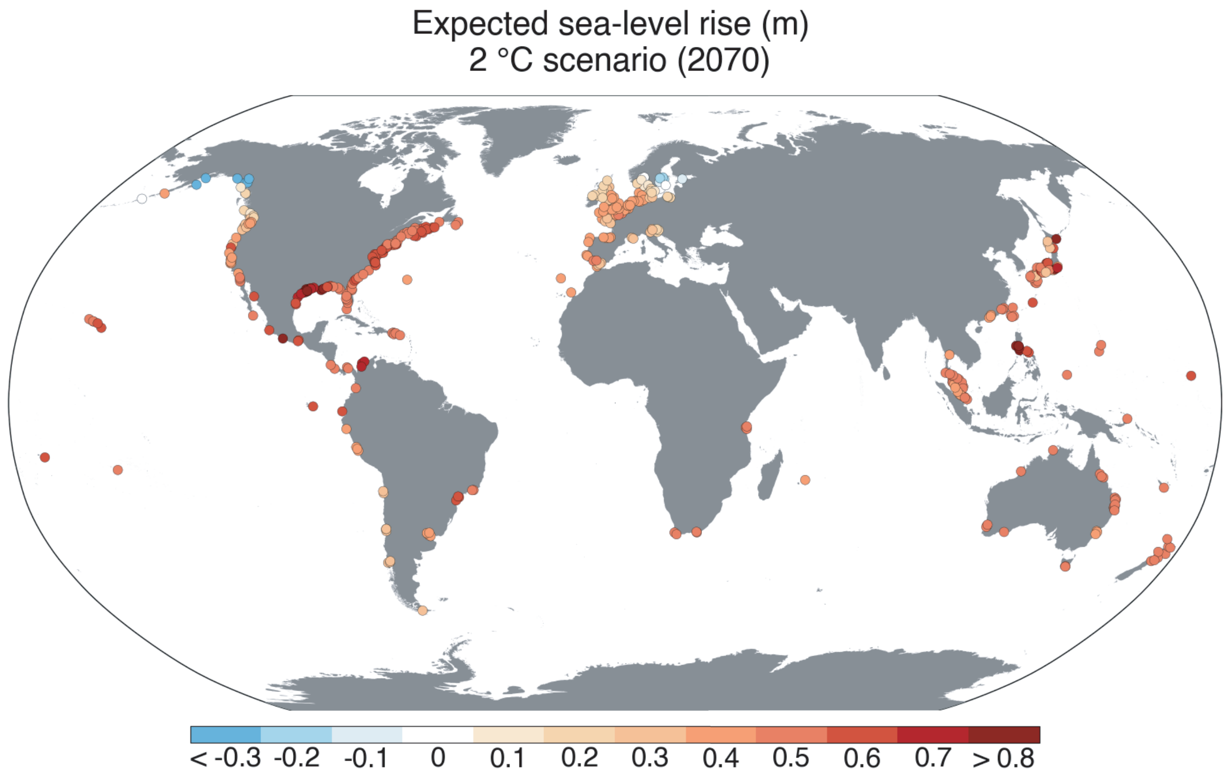
$$f(z^*) = \int_\delta f(z^* - \delta + A(z^*))P(\delta)\,\mathrm{d}\delta, \tag{S-2}$$

where $f(z^*)$ is the current AEP of a given ESL event with height z^* (e.g., the 100-yr event). For a given AEP, the hazard allowance can be interpreted as the horizontal distance between the expected historical and future ESL return curve (Fig. 2A). If δ is known, then $A = \delta$, but if δ is unknown, $A > \delta$ for mathematical reasons given previously (Hunter, 2012; Buchanan et al, 2016; Buchanan et al, 2017). Rasmussen et al (2020) extend the ESL hazard allowance concept to account for the societal impacts of ESL events by employing a simple, time-invariant damage function $D(z)$ that describes the relationship between ESLs and a societal impact (e.g., property damage or population exposure). The damage allowance is the design height of a flood mitigation strategy (e.g., elevation of structures, levee height, necessary coastal retreat) needed to maintain a given integrated exposure metric under RSLC (e.g., current expected annual property damage).

Here we consider the damage (population exposure) allowance needed to maintain the current expected annual population exposure (EAE). The projected EAE under RSLC is given by:

$$EAE = \int_{A_{min}}^{\infty} \int_\delta D(z) f(z - \delta) P(\delta)\,\mathrm{d}\delta\,\mathrm{d}z \tag{S-3}$$

where $f(z - \delta)$ is the PDF of ESLs after considering RSLC δ, $P(\delta)$ is the PDF of RSLC δ, $D(z)$ is the populated exposure function (Sec. 2.2), and A_{min} is the height of the assumed current protection level (either no protection, the height of the local 1-yr or 10-yr ESL event; Sec. 2.2).



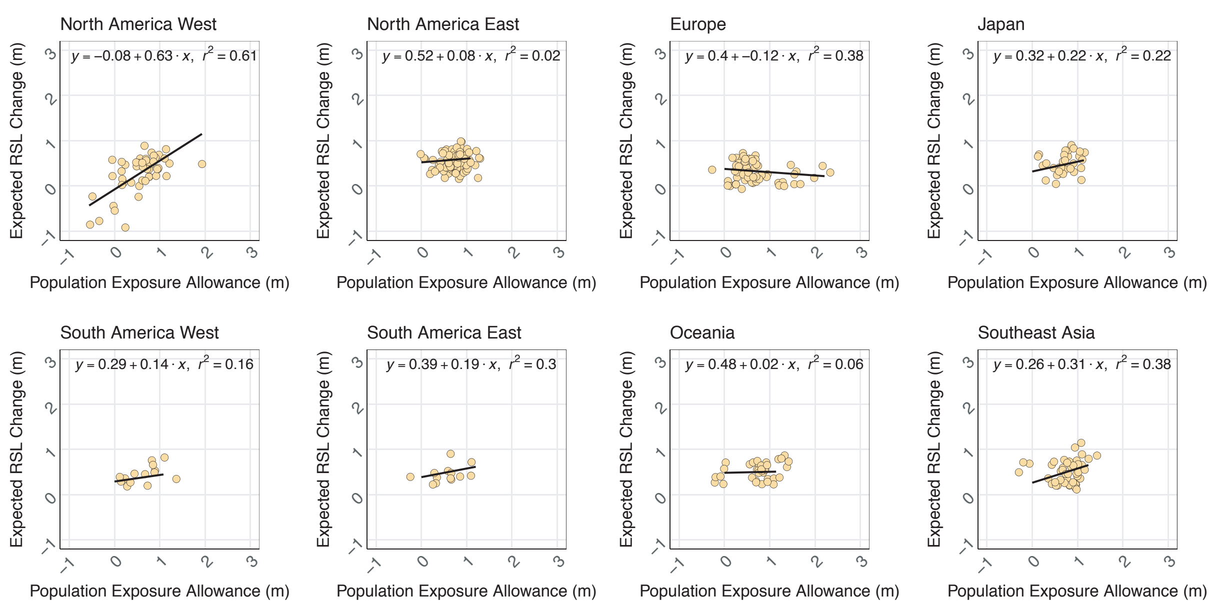


Fig. S-3: **Map:** Expected relative sea level (RSL) change (meters, relative to 1991–2009) for 2070 under a climate scenario where the global mean surface air temperature is stabilized in 2100 at +2 °C (relative to 1850–1900). **Regional scatter plots:** Expected RSL change plotted against population exposure allowances for 2070 that integrate over the entire RSL change probability distribution for the same climate scenario as the map. A list of the cities in each defined region is given in the supporting data files.

New York City	Population		Population Exposure AF 2070		2100	
Household income	Total (millions)	% Exposed (Current 100-yr ESL)	2.0 °C	5.0 °C	2.0 °C	5.0 °C
All incomes	8.05	2.8%	1.5 (1.2-1.9)	1.8 (1.3-2.4)	1.8 (1.3-2.6)	2.6 (1.6-4.4)
<$50,000 yr^{-1}	3.54	2.6%	1.5 (1.2-1.9)	1.8 (1.3-2.4)	1.9 (1.3-2.7)	2.7 (1.6-4.7)
$50,000-$100,000 yr^{-1}	2.06	2.9%	1.5 (1.2-1.9)	1.8 (1.3-2.4)	1.8 (1.3-2.6)	2.6 (1.6-4.4)
>$100,000 yr^{-1}	2.32	3.0%	1.5 (1.2-1.9)	1.8 (1.3-2.4)	1.8 (1.3-2.6)	2.5 (1.6-4.2)

Table S-1: Population exposure amplification factors for New York City by household income for 2070 and 2100 under climate scenarios in which global mean surface air temperature is stabilized in 2100 at +2 °C and +5 °C (relative to 1850–1900; Bamber et al, 2019). The expected value and the 5/95 percentile (in parentheses) of the estimate are given for each and reflects the uncertainty in both relative sea level change and the generalized Pareto distribution parameters. Also given are the total populations for each income group and the percent of the group population currently exposed to the 100-yr ESL event. Median household income is given by New York City census tract from the American Community Survey (2014-2018).

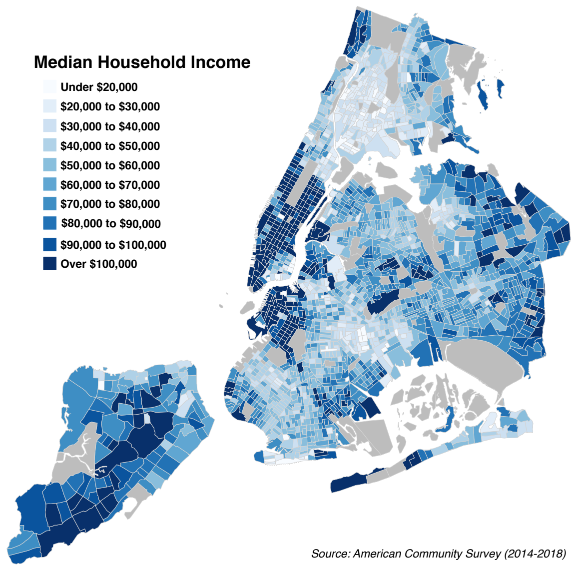


Fig. S-4: Median Household income by New York City census tract from the American Community Survey (2014-2018).

New York City		Property Damage AF			
		2070		2100	
	Current 100-yr ESL	2.0 °C	5.0 °C	2.0 °C	5.0 °C
Property Damage	\$4 billion (\$2-\$7 billion)	2.0 (1.4-2.9)	2.6 (1.6-3.9)	2.7 (1.5-4.3)	4.2 (2.0-7.8)

Table S-2: Property damage amplification factors for New York City for 2070 and 2100 under climate scenarios in which global mean surface air temperature is stabilized in 2100 at +2 °C and +5 °C (relative to 1850–1900; Bamber et al, 2019). The expected value and the 5/95 percentile (in parentheses) of the estimate are given for each and reflects the uncertainty in both relative sea level change and the generalized Pareto distribution (GPD) parameters. Also given is the current expected damage from the 100-yr ESL event with the 5/95 percentile estimates in parentheses (samples uncertainty in the GPD parameters only). Monetary amounts assume constant 2017 US\$. The methods for calculating the damage function are given in Rasmussen et al (2020).

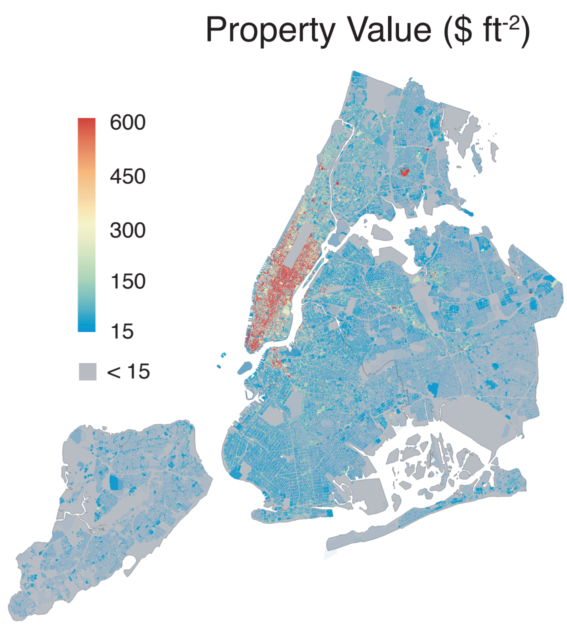


Fig. S-5: The estimated density of property for New York City (excludes land value) given as the tax assessed building value per square foot of building lot area (2017 US\$ ft^{-2}). Data are from the NYC Department of City Planning (NYC Planning, 2018).

2.0 °C	2010	2070		2100	
	Population (thousands)	Population (thousands)	Pop Exposure AF	Population (thousands)	Pop Exposure AF
Lidar	399 (293-564)	607 (488-745)	1.5 (1.2-1.9)	708 (518-938)	1.8 (1.3-2.4)
CoastalDEM	229 (168-324)	351 (280-440)	1.5 (1.2-1.9)	421 (297-596)	1.8 (1.3-2.6)

Table S-3: Estimated total population exposure and amplification factors for the 100-yr extreme sea level (ESL) event for New York City using 1) a 0.3-m horizontal resolution light detection and ranging (LiDAR)-derived digital elevation model for the City of New York (https://data.cityofnewyork.us/City-Government/1-foot-Digital-Elevation-Model-DEM-/dpc8-z3jc) and 2) CoastalDEM. Future projections assume a climate scenarios in which global mean surface air temperature is stabilized in 2100 at +2 °C (relative to 1850–1900; Bamber et al, 2019).

5.0 °C	2010	2070		2100	
	Population (thousands)	Population (thousands)	Pop Exposure AF	Population (thousands)	Pop Exposure AF
Lidar	399 (293-564)	687 (529-880)	1.7 (1.3-2.2)	917 (617-1,398)	2.3 (1.5-3.5)
CoastalDEM	229 (168-324)	405 (303-548)	1.8 (1.3-2.4)	589 (355-1,010)	2.6 (1.6-4.4)

Table S-4: As for Table S-3, but for a climate scenarios in which global mean surface air temperature is stabilized in 2100 at +5 °C (relative to 1850–1900; Bamber et al, 2019).

					2.0 °C								
		2010 EAE (millions)			2050 EAE AF			2070 EAE AF			2100 EAE AF		
City	Population (millions)	None	1-yr	10-yr	None	1-yr	10-yr	None	1-yr	10-yr	None	1-yr	10-yr
Shenzhen, China	12.52	1.07	0.70	0.70	1.3	2.0	2.0	1.6	2.5	2.5	2.3	3.5	3.5
Vancouver, Canada	1.81	0.20	0.13	0.13	1.0	1.6	1.6	1.0	1.7	1.7	1.1	1.8	1.8
New York, USA	12.52	0.22	0.15	0.15	1.4	2.1	2.1	1.8	2.6	2.6	2.8	4.1	4.1
London, UK	9.88	0.04	0.03	0.03	3.0	3.6	3.6	5.0	5.9	5.9	9.9	11.7	11.6
Buenos Aires, Argentina	11.98	0.03	0.03	0.03	2.0	2.1	2.1	3.4	3.5	3.5	11.7	12.1	12.2
San Diego, USA	2.32	<0.01	<0.01	<0.01	2.4	4.3	4.3	5.2	9.1	9.1	12.5	21.8	21.8
Rio de Janeiro, Brazil	9.11	0.03	0.02	0.02	1.3	2.2	2.2	2.0	3.3	3.3	4.1	6.7	6.7
Hong Kong, China	22.23	3.99	2.53	2.53	1.2	1.9	1.9	1.4	2.2	2.2	2.1	3.3	3.3
Manila, Philippines	5.78	2.06	1.24	1.24	1.1	1.8	1.8	1.1	1.9	1.9	1.3	2.2	2.2
Copenhagen, Denmark	1.34	0.02	0.01	0.01	2.3	3.8	3.8	4.9	7.8	7.8	15.1	24.4	24.4
Dar es Salaam, Tanzania	2.32	0.02	0.01	0.01	1.2	2.3	2.3	2.2	3.9	3.9	3.3	5.9	5.9
Sydney, Australia	3.48	0.01	<0.01	<0.01	1.1	1.8	1.8	1.2	2.0	2.0	3.2	5.2	5.2
Phuket, Thailand	0.16	0.01	0.01	0.01	2.0	2.3	2.3	2.3	3.4	2.3	3.4	3.4	3.4
Tokyo, Japan	25.34	0.55	0.38	0.38	1.4	2.1	2.1	2.0	2.9	2.9	5.9	8.7	8.7
New Orleans, USA	0.71	0.17	0.13	0.13	2.2	3.0	3.0	2.8	3.7	3.7	3.6	4.7	4.7
Norfolk, USA	0.69	<0.01	<0.01	<0.01	2.0	2.7	6.9	3.4	4.7	13.7	13.9	19.0	55.5
San Juan, Puerto Rico	1.82	<0.01	<0.01	<0.01	2.5	2.6	2.7	3.0	3.1	3.3	16.6	17.3	18.3

Table S-5: Expected annual population exposure (EAE; millions) under different assumptions of existing coastal flood protection (no protection and protection against the 1-yr and 10-yr events) and amplification factors (AFs) for the EAE for 2050, 2070, and 2100 under the same coastal flood protection assumptions and under a climate scenario in which global mean surface air temperature is stabilized in 2100 at +2 °C (relative to 1850–1900; Bamber et al, 2019).

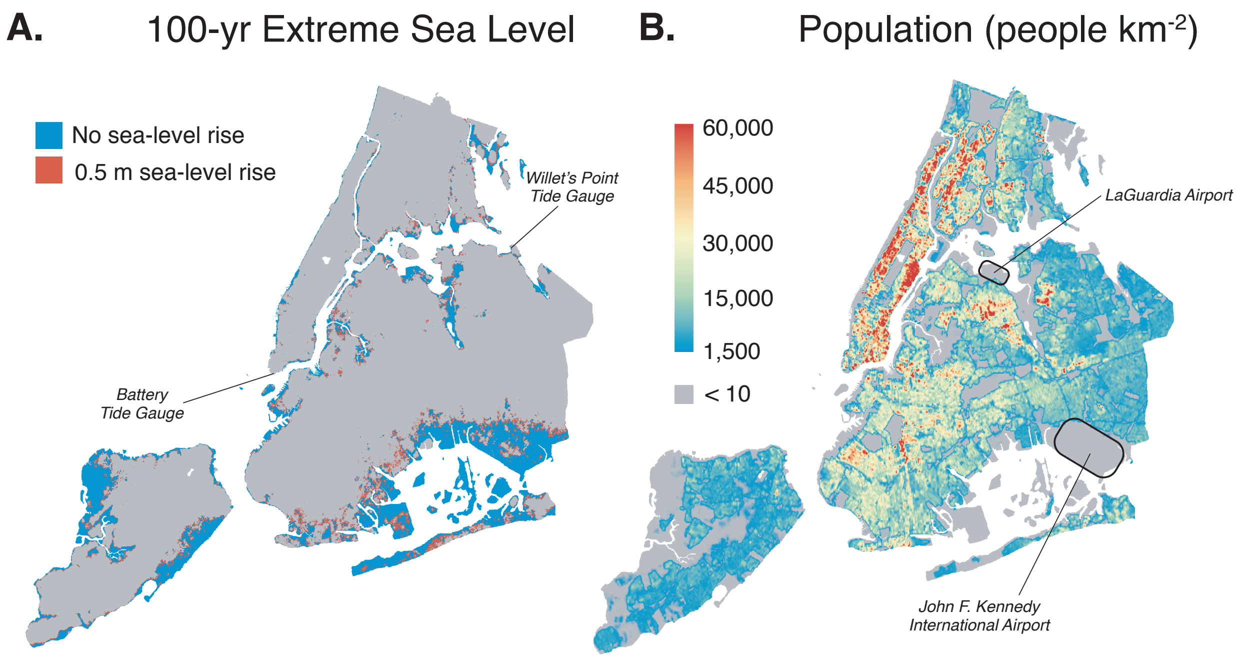


Fig. S-6: **A.** The estimated spatial flood extent for New York City as a result of the 100-yr extreme sea level (ESL) event under 1991–2009 mean sea level (blue) and with 0.5 m of sea-level rise (red; extent above 1991–2009 levels). The "bathtub" approach (Sec. 2.2) is used to model flood inundation using the height of the current and projected future 100-yr ESL event at a tide gauge located at the Battery. Topography data are CoastalDEM (Kulp and Strauss, 2018). **B.** The estimated population density (people km^{-2}) for New York City from the 2010 WorldPop global population database (Tatem, 2017). Highlighted are the locations of John F. Kennedy International and LaGuardia Airports, critical infrastructure at risk that is not represented using population data.