

Earth's Future

RESEARCH ARTICLE

10.1029/2020EF001963

Key Points:

- We analyze the monetary and social risk associated with coastal flooding for communities in the San Francisco Bay Area over the coming decades, 2020–2060
- In some San Mateo County communities, existing financial strain and costs associated with future coastal flooding put more than half of households at risk of displacement or bankruptcy
- Greater certainty in sea level rise is not necessary to identify communities with high financial instability and design adaptation interventions

Supporting Information:

Supporting Information may be found in the online version of this article.

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Citation:

Bick, I. A., Santiago Tate, A. F., Serafin, K. A., Miltenberger, A., Anyansi, I., Evans, M., et al. (2021). Rising seas, rising inequity? Communities at risk in the San Francisco Bay Area and implications for adaptation policy. *Earth's Future*, 9, e2020EF001963. <https://doi.org/10.1029/2020EF001963>

Received 12 JAN 2021

Accepted 8 JUN 2021

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Rising Seas, Rising Inequity? Communities at Risk in the San Francisco Bay Area and Implications for Adaptation Policy

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Abstract Increasing coastal flooding threatens urban centers worldwide. Projections of physical damages to structures and their contents can characterize the monetary scale of risk, but they lack relevant socioeconomic context. The impact of coastal flooding on communities hinges not only on the cost, but on the ability of households to pay for the damages. Here, we repurpose probabilistic risk assessment to analyze the monetary and social risk associated with coastal flooding in the San Francisco Bay Area for 2020–2060. We show that future coastal flooding could financially ruin a substantial number of households by burdening them with flood damage costs that exceed discretionary household income. We quantify these impacts at the census block group scale by computing the percentage of households without discretionary income, before and after coastal flooding costs. We find that for several coastal communities in San Mateo County more than 50% of households will be facing financial instability, highlighting the need for immediate policy interventions that target existing, socially produced risk rather than waiting for potentially elusive certainty in sea level rise projections. We emphasize that the percentage of financially unstable households is particularly high in racially diverse and historically disadvantaged communities, highlighting the connection between financial instability and inequity. While our estimates are specific to the San Francisco Bay Area, our granular, household-level perspective is transferable to other urban centers and can help identify the specific challenges that different communities face and inform appropriate adaptation interventions.

Plain Language Summary Increasing coastal flooding threatens urban centers worldwide. Projections of physical damages to structures and their contents can characterize the monetary loss, but they lack relevant socioeconomic context. The impact of coastal flooding on communities hinges not only on the cost, but on the ability of households to pay for the damages. Here, we show that future coastal flooding could financially destabilize a substantial number of households by burdening them with flood damage costs that exceed discretionary funds that households have left over after covering costs of living. We compute the percentage of households without discretionary income, before and after projected coastal flooding costs. We demonstrate that this percentage is larger than 50% for several communities in San Mateo County, highlighting the need for immediate policy intervention that targets existing, socially produced risk rather than waiting for potentially elusive certainty in sea level rise projections. Across all flood-affected census block groups in the County, we project increases in financial instability by an average of 17% from 2020 to 2060. This methodology is transferable to other urban centers and can help identify the specific challenges that different communities face and inform appropriate adaptation interventions.

1. Introduction

Natural hazards have always shaped our planet, but global climate change alters the nature of the risk they pose. Climate change is expected to both intensify existing hazards and create new, previously unknown types of hazards (Oppenheimer et al., 2014). Even when the nature of the new threat is known, such as in the case of rising sea level, there is deep uncertainty associated with the overall magnitude of the hazard

Funding acquisition: Leonard Ortolano, Derek Ouyang, Jenny Suckale
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Methodology: I. Avery Bick, Adrian F. Santiago Tate, Katherine A. Serafin, Alex Miltenberger, Ifeoma Anyansi, Max Evans, Leonard Ortolano, Derek Ouyang, Jenny Suckale
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and the rate at which it will increase over time (Bamber et al., 2019; Kopp et al., 2014, 2017). Low-lying, coastal metropolitan cities like the San Francisco Bay Area may be particularly affected as they face not only potentially compounding climate hazards (Revi et al., 2014; Zscheischler et al., 2018) from coastal flooding to wildfires but are also confronted with the challenges of urban growth and socioeconomic inequality.

Climate change and the sea level rise it may entail are not the only risks that communities are facing (Moser et al., 2012). Other systemic risks are socially produced by modern society (Giddens, 1990; Mileti, 1999; Tierney, 2014; U. Beck, 1992; U. Beck et al., 1994;). These social risks range from an increase in single-parent households and a decline in employment opportunities for minorities (Rossi, 1994) to general policy shifts in welfare and health (Blau, 1992; Jencks, 1995; M. M. Burt, 1992; Wright et al., 1998). One particularly important policy dimensions in the context of the San Francisco Bay Area are the lack of affordable housing, which appears to explain the majority of the variation in homelessness among U.S. metropolitan cities (Lee & Farrell, 2003; Quigley & Raphael, 2001; Wright et al., 2008).

Despite the potentially significant challenges that societal and climate change could pose to urban areas (Mitchell, 2015; Revi et al., 2014), adaptation has been slower and less decisive than called for by the Intergovernmental Panel on Climate Change (Oppenheimer et al., 2014; Noble et al., 2014). One reason for the slow response is that the degree of uncertainty and risk inherent to climate-change adaptation planning in coastal urban systems can be perceived as paralyzing by decision-makers and the public (e.g., Hulme, 2009; Patt & Weber, 2014). Political paralysis hence becomes a social risk in itself (Sunstein, 2002) since, in the context of sea level rise in urban areas, inaction might entail the biggest risks (Nicholls, 1995; Oppenheimer et al., 2014).

The goal of this paper is to advance a collaborative and equitable approach to sea level rise adaptation by quantifying the social and monetary risk associated with coastal flooding for communities in the San Francisco Bay Area over the next four decades, 2020–2060. We approach the problem through the model of scientific co-production (Bremer & Meisch, 2017; Lemos et al., 2018)—a process in which researchers and stakeholders produce knowledge together to promote the inclusion of diverse perspectives and enhance the use of knowledge in decision-making. Our analysis is the result of an ongoing community-engaged-learning course (Stanton et al., 1999) at Stanford University conducted in collaboration with several local stakeholders, including the Association of Bay Area Governments, the San Mateo County Office of Sustainability, multiple municipal governments, and nonprofit organizations like Youth United for Community Action.

The San Francisco Bay Area, California, is famous for its entrepreneurial spirit and culture of innovation. It is home to over 7.6 million people distributed across nine individual counties, which are connected by a vibrant economy and complex governance structure (McNeill, 2016). The associated urban development has caused housing shortages (Benner & Karner, 2016), a decline of mid-wage jobs, and a significant rise in socioeconomic inequality (Schafran, 2013). The primary concern voiced by our stakeholders is that sea level rise may exacerbate existing socioeconomic inequalities in the area and erode local communities, particularly historically disadvantaged communities. The concern is supported by scientific evidence documenting the contribution of natural hazards to wealth inequality in the past (Howell & Elliott, 2019).

To quantify the “monetary risk” posed by coastal flooding in the San Francisco Bay Area, we link probabilistic flood maps, building footprints, tax assessor data, and depth-damage curves. Using these inputs, we estimate the average annual loss (AAL) associated with flooding at the household level using the traditional framework of probabilistic flood risk assessment (see Figure 1). We perform this analysis at the household rather than the census block group level, because flood damage depends sensitively on the type of house. Throughout this manuscript, we use AAL as a proxy for the monetary risk posed by coastal flooding.

In contrast, we use the term “social risk” to describe socially produced risk such as homelessness (M. R. Burt et al., 2001), bankruptcy (Warren & Tyagi, 2004), and displacement (McAdam, 2010). In previous studies, these social factors have mostly been captured through descriptive indices such as the social vulnerability index (Cutter et al., 2012; Flanagan et al., 2011). While valuable for mapping out vulnerability at a regional scale, a community-scale metric centered on social risk that is less comprehensive but more specific could be valuable to prioritize risk-mitigation interventions. Within the context of our partner communities, homelessness stands out as on specific social risk that coastal flooding may exacerbate. Homelessness in the San Francisco Bay Area has increased significantly over the last couple of decades, as demonstrated

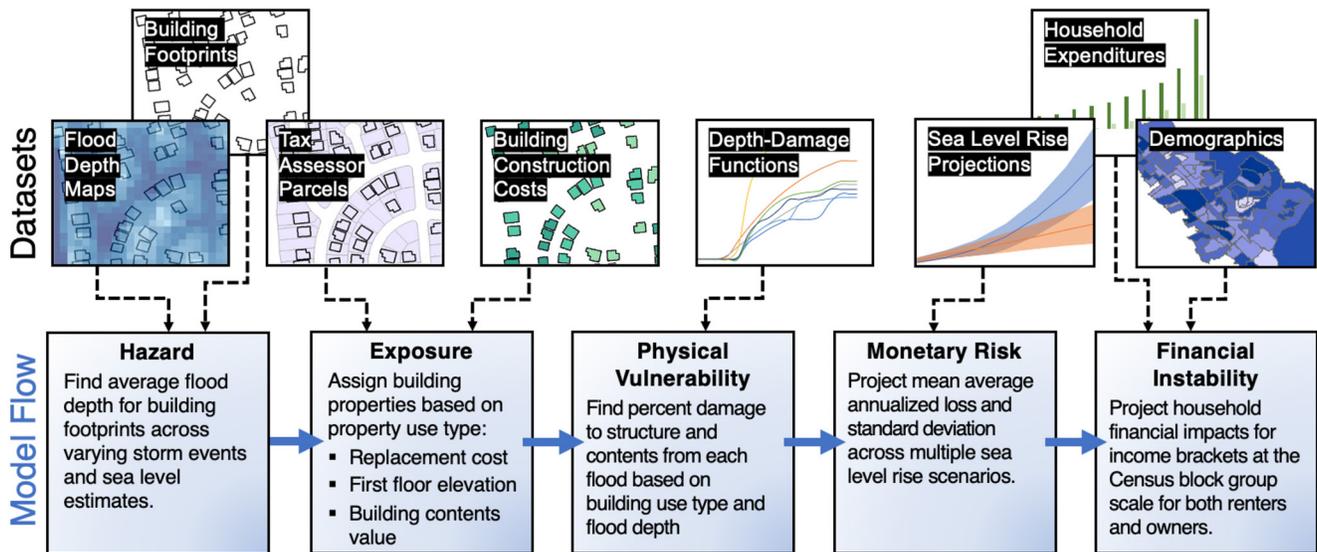


Figure 1. Data flow for the Stanford Urban Risk Framework (SURF). The Hazard Model overlays coastal flood maps (Ballard, 2016) on building footprint polygons (Microsoft, 2017) to calculate flood depths. The Exposure Model uses Corelogic tax assessor parcel data to determine building usage type and assigns a first floor elevation and building content value (U.S. Army Corps of Engineers, 2011) and a structure replacement cost (RSMMeans, 2017). The Physical Vulnerability Model then uses depth-damage curves (U.S. Army Corps of Engineers, 2003; U.S. Army Corps of Engineers, 1992, 1997) to relate flood depths to structure and content losses. The AAL Model projects annual damages from 2020 to 2060 using Representative Concentration Pathway sea level rise occurrence rates (Kopp et al., 2017). The Financial Instability Model estimates household discretionary income (U.S. Bureau of Labor Statistics, 2019; U.S. Bureau of Economic Analysis, 2019) and then distributes projected losses among households based on census block group-scale demographics (U.S. Census Bureau, 2017).

by reports at both the federal (The Council of Economic Advisers, 2019) and state level (California State Auditor, 2020).

Finding a meaningful metric for social risk is more challenging than for monetary risk. Here, we suggest that the availability of discretionary income, household income after accounting for necessities, may be an important socioeconomic tipping point at the household scale. Households without discretionary income are unlikely to accumulate sufficient personal savings to absorb temporary cost increases. In the absence of monetary reserves, a situational crisis such as a dislocation or an increase in housing costs could trigger homelessness (M. R. Burt et al., 2001; O’Flaherty, 2004; Snow & Anderson, 1993). Prior literature (Lee et al., 2010) has mostly related homelessness to what O’Flaherty describes as “a conjunction of unfortunate circumstances” (O’Flaherty, 2004). To capture this tipping-point dynamics, we classify households with zero or negative discretionary income currently as “financially unstable.” We then use the percentage of financially unstable households as a metric for the magnitude of the social risk in a community.

Our analysis demonstrates that coastal flooding in the Bay Area over the next four decades will repeatedly burden households that are already financially unstable. Different communities are impacted in different ways, with monetary risk being dominant for some and social risk being dominant for others. We emphasize that several of the communities with high social risk are also demographically different to communities with high monetary risk. Several of these demographic factors also affect social risk, including but not limited to the abundance of single-parent households (Rossi, 1994) and race (Paganini, 2019). It would be desirable to include more demographic factors into an improved and more comprehensive metric of social risk, but our current understanding is too limited to quantify their impact on social risk. Here, we only take the first step by whether and why an explicit distinction between monetary and social risk could be valuable for guiding an equitable approach to climate-change adaptation.

2. Model

Probabilistic risk assessment is a classical methodology for estimating risk posed by either natural or technological processes (Rowe, 1975). By overlaying hazard, exposure, and physical vulnerability (Gerl et al., 2016; Hammond et al., 2015; Merz et al., 2010), it estimates AAL. AAL represents the expected annual structure and contents damage from coastal flooding, aggregated over and averaged across our study period of 2020–2060. In the past, probabilistic risk assessment was often applied without considering essential social context (Freudenburg, 1988; Hoos, 1980; Mazur, 1985; Margolis, 1997). Many of its shortcomings hinge not on the analysis tool itself, but on how it is used in policy making (Freudenburg, 1988; Hoos, 1980; Mazur, 1985; Margolis, 1997). Here, we repurpose the methodology to prioritize local adaptation planning by adding the dimension of social risk to our analysis.

Our geospatial Python model, named the Stanford Urban Risk Framework (SURF), is comprised of five different models: Hazard, Exposure, Physical Vulnerability, AAL, and Financial Instability (see Figure 1). The Hazard model calculates the average flood depth of each building footprint for each flood's extreme water level. For each building, the Exposure Model then assigns mean and standard deviation values for structure replacement cost, contents value, and first floor elevation based on the building type. The Physical Vulnerability Model translates flood depths into structure and contents damage percentages based on empirical depth-damage curves (U.S. Army Corps of Engineers, 2011; U.S. Army Corps of Engineers, 1992, 1997, 2003). The AAL Model applies RCP sea level rise occurrence rates (Kopp et al., 2014, 2017) to project damages for the time period 2020–2060. Finally, the Financial Instability Model relates AAL to household income.

SURF uses high-resolution building-scale data to project AAL, but demographic information is only available in aggregated form. The Financial Instability Model hence uses Monte Carlo methods to translate census block group-scale household demographics to the building scale, distributing AAL based on assumptions about insurance coverage and renter and owner status. It then calculates the mean and standard deviation of household AAL across income brackets at the block group scale. We make the assumption that current household income and ownership status remain approximately constant across our study period. While this assumption is almost certainly untrue, any potential changes are exceedingly difficult to anticipate. Each of these models is detailed below. The Python code for executing SURF (with sample data and detailed instructions) is publicly available at <http://zapad.stanford.edu/sigma/ef-2021-inequityrisk-bayarea>.

2.1. Hazard Model

To quantify current and future coastal flooding hazard, SURF uses the flood maps by Our Coast Our Future (Ballard, 2016). These raster files show the spatial distribution of extreme water levels for varying return periods across different sea level rise scenarios: 1-, 20-, and 100-year floods for 0, 25, 50, and 75 cm of sea level rise. The maps were generated with the Coastal Storm Modeling System (CoSMoS) (Barnard et al., 2014) using Delft3D and a Digital Elevation Model (DEM) with 2 m horizontal resolution measured with LiDAR. The DEM does not account for changes over time such as subsidence. The climate forcing used in CoSMoS, e.g., wind direction, storm surge, and river discharge, is based on a downscaled global climate model (County of San Mateo Sea Level Rise Vulnerability Assessment, 2018). For each combination of sea level rise and flood return period, the Hazard Model overlays the corresponding water level raster on building polygons and calculates the mean water level by averaging all raster cells whose centers fall within their outline (Arcpy Zonal Statistics as Table Version 10.3, 2020).

2.2. Exposure Model

To define a given building's flood exposure, we need to determine structure value, content-structure value ratio (CSVR), and first floor elevation (FFE). While none of these data are available in existing data sources at the building scale, tax assessor parcel-scale data (Corelogic, 2017; San Mateo County, 2018) provide a property use code (PUC) attribute, such as single-family home or condo, which we relate to these three variables. We use a spatial join function to transfer PUC data from the parcel polygons to the building polygons, based on which parcel a building overlaps with most, linking individual buildings to a range of possible replacement cost, FFE, and CSVR values.

A 2011 U.S. Army Corps of Engineers survey provides mean FFE values across five San Mateo County locations for residential, commercial, industrial, and public structures, from which we generate an overall mean residential FFE of 1.06 ft and standard deviation of 0.83 ft for our study area (U.S. Army Corps of Engineers, 2011). It also provides standard values for the mean and standard deviation of the CSVF based on building use type. The report by the U.S. Army Corps of Engineers demonstrates that there is no systematic variation in FFE inside as compared to outside the regulatory floodplain for our study area. We also find that this absence of systematic variations between buildings inside and outside of the flood zone is borne out by a comparison of recent home sale prices (see Supporting Information).

We estimate the value of a given building in terms of its replacement cost since damage is a function of how much it costs to rebuild after a flood. We use proprietary \$/ft² construction cost data collected by RSMeans, including their estimated regional price factor of 1.33 to account for higher construction costs in the San Francisco Bay Area relative to the national average (RSMeans, 2017). We assign the replacement cost of each building based on PUC. For each use code, RSMeans provides construction cost estimates for multiple outer wall construction types. We assume an equal probability of each construction type and calculate a mean and standard deviation replacement cost, assuming a normal distribution. We apply these construction cost estimates instead of parcel-scale tax assessor estimates (Corelogic, 2017; San Mateo County, 2018) because California's Proposition 13 prevents re-assessments unless improvements are made or ownership changes, meaning that many of these parcel-scale data points have high variation and do not represent market values.

To calculate the total floor area for each building, we use the building polygons provided by Microsoft and OpenStreetMaps (Microsoft, 2017), which give a footprint area in addition to a maximum structure height. We utilize a Random Forest Classifier with 100 decision trees to predict an integer floor count based on a building's PUC, footprint area, and maximum height. Corelogic data provide floor counts for a subset of approximately 8,500 buildings in San Mateo County for various PUCs. We trained the classifier on 6,000 buildings and tested on the remaining 2,500, with a mean error of 0.21 floors. After predicting a floor count, we find total floor area by multiplying by building polygon footprint area. We then compute the total structure replacement cost for a given building by multiplying the total floor area by the replacement cost per square foot. To find the total content replacement cost, we multiply the structure cost by the CSVF.

The Exposure Model treats replacement cost per square foot, CSVF, and FFE as random variables with normal distributions and applies Monte Carlo methods to create 1,000 realizations of each building by drawing from these distributions, with the goal of capturing the uncertainty in building valuation and flood exposure. The normal distributions predicting these variables are dependent on a building's PUC. A table showing the assumptions made for all PUCs is available on the SURF code repository. Figure 2 shows how SURF pulls values for building replacement cost, CSVF, and FFE from normal distributions, which then inform the calculation of structure value, content value, and flood depth, respectively.

2.3. Physical Vulnerability Model

To estimate the physical vulnerability of structures and their contents, we use empirical relationships between depth of inundation and building damage by the USACE (U.S. Army Corps of Engineers, 1992, 1997, 2003, 2011), which are available on the SURF code repository. These depth-damage curves estimate the damage from flooding as a percentage of the building's value. We subtract the building's first floor elevation, as assigned in the Exposure Model, from the mean water level. We use the same approach to determine damage to a building's contents.

SURF assumes that no damage occurs at 0 feet of flooding despite many depth-damage curves reporting damage in this range. The reason is that 0 feet of flooding refers to flooding at the first floor elevation, and there can still be structural damage below that, especially if there is a basement. However, basements are rare in our study area. Wind and rain effects can also cause structural damages independent of flood depth, but these are not considered here.

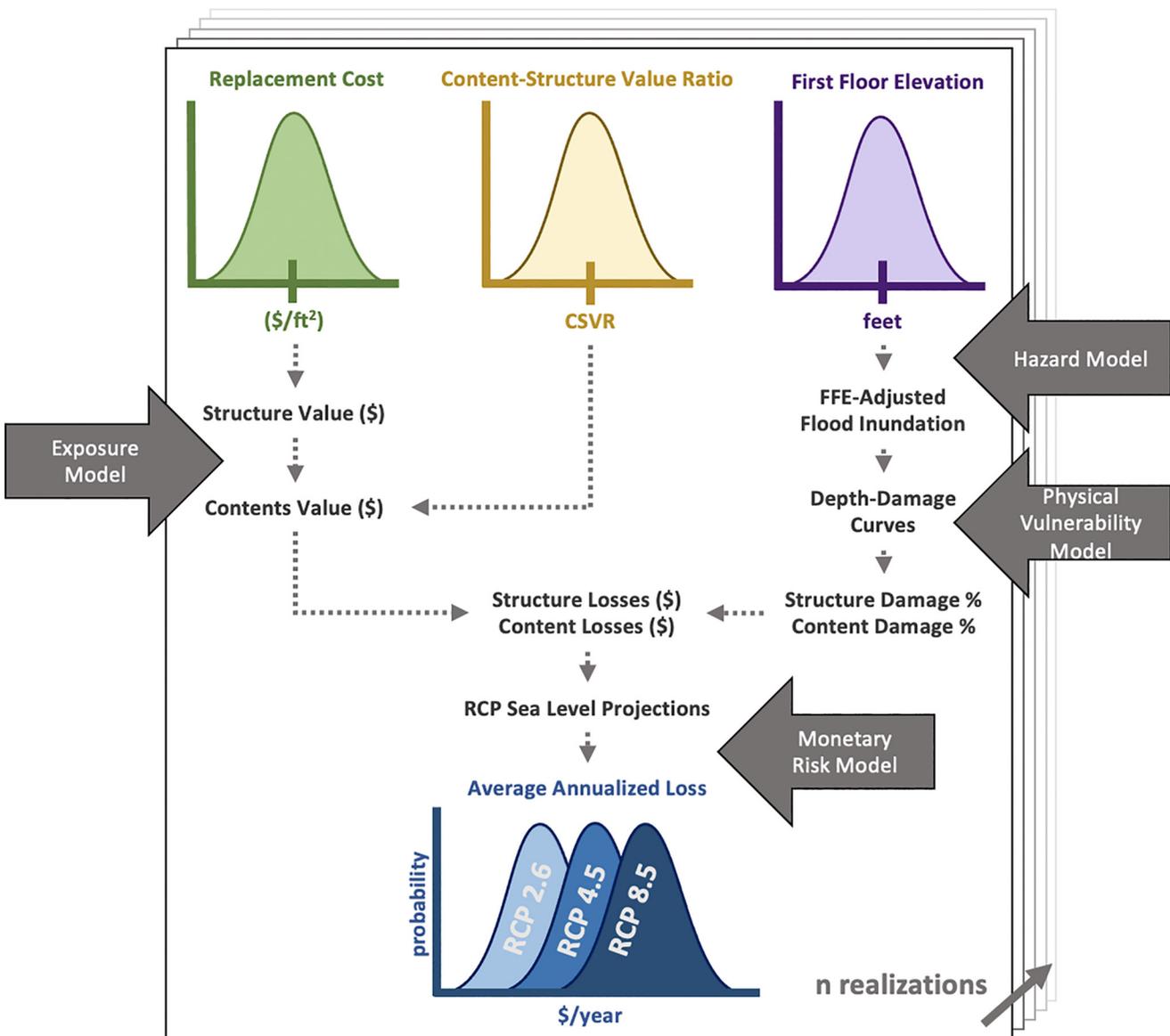


Figure 2. Flowchart of a single iteration of AAL calculation in SURF for a single building.

2.4. AAL Model

After each iteration of the Exposure Model, the AAL model calculates AAL for three Representative Concentration Pathway (RCP) projections by the Intergovernmental Panel on Climate Change: RCP 2.6, RCP 4.5, and RCP 8.5 (Kopp et al., 2014, 2017; Meinshausen et al., 2011; Pachauri & Meyer, 2014). Across all iterations, we obtain normal distributions from which we calculate the final AAL mean and standard deviation for each building under each of these scenarios. The three RCP projections represent carbon emissions beginning to decline around 2020, around 2050, or increase throughout the 21st century, respectively (Kopp et al., 2014, 2017; Meinshausen et al., 2011; Pachauri & Meyer, 2014). The projections incorporate a small ensemble of Antarctic ice-sheet simulations to include the possibility of a more rapid rise in sea level (DeConto & Pollard, 2016; Kopp et al., 2017). As detailed in the Supporting Information, we used the Matlab script from Kopp et al. 2017 to generate sea level rise exceedance rate tables for each of three RCP emissions scenarios for the San Francisco NOAA tide gauge (station ID: 9414290).

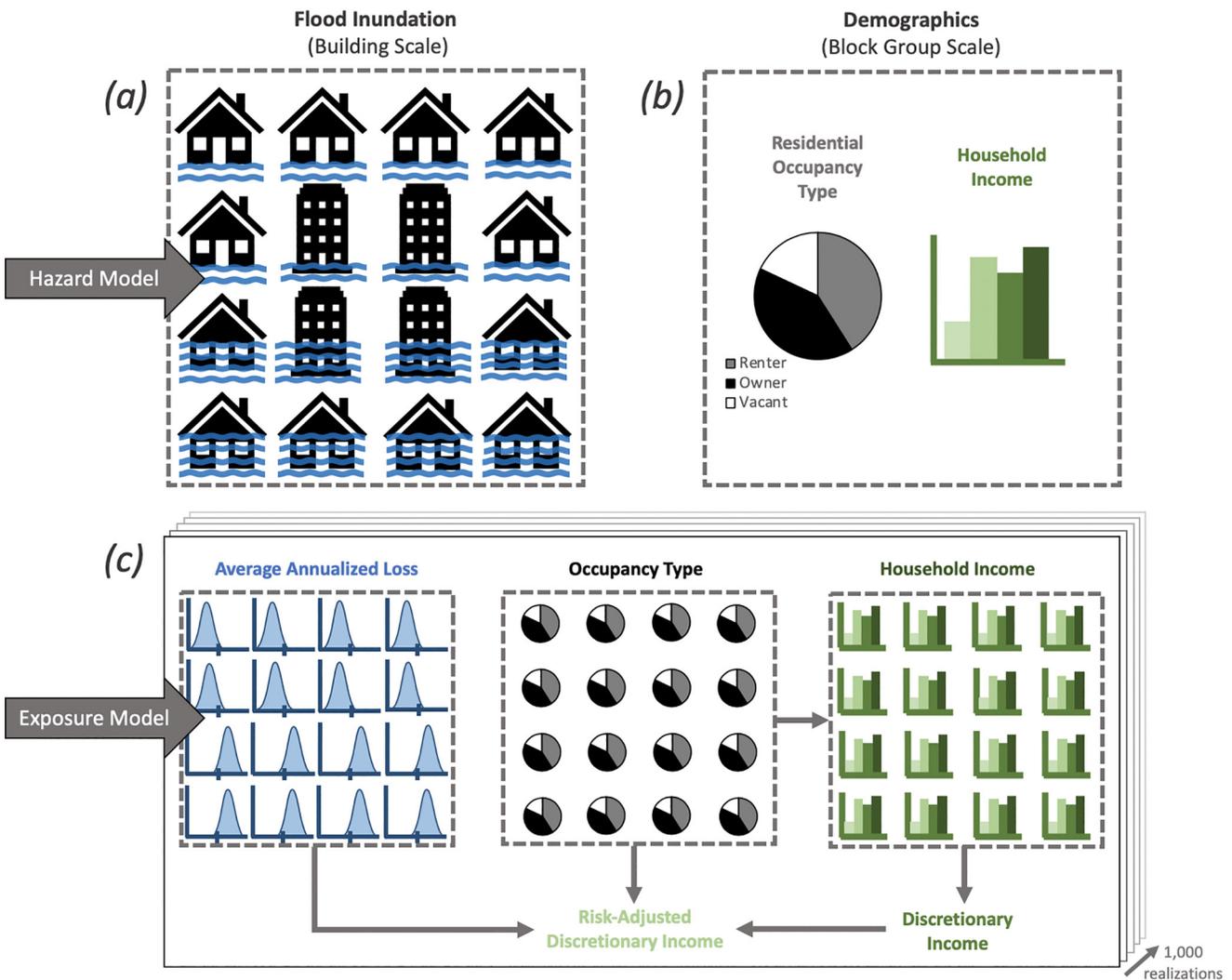


Figure 3. (a) Illustration of the SURF model's building-scale resolution for flood inundation, with the box representing a single census block group and (b) block group scale demographic data; and (c) flowchart of a single Monte Carlo realization in the Financial Instability Model, where we illustrate how the building-scale normal distributions of AAL calculated in the Exposure Model are combined with occupancy type and household income pulled from weighted integer distributions in order to estimate risk-adjusted discretionary income. In each iteration, a value is pulled from these distributions, which then inform the risk-adjusted discretionary income calculation for that household.

2.5. Financial Instability Model

The Financial Instability Model distributes AAL in a probabilistic manner across households in a census block group. To protect privacy, the U.S. Census Department does not share demographics or incomes at the household level. Instead, the information is aggregated and made available at the level of census block groups. We utilize the 2013–2017 American Community Survey (U.S. Census Bureau, 2017) to provide counts of households within various income brackets, as well as the number of renter-occupied households, owner-occupied households, and vacant household units, at block group resolution. Figure 3 illustrates that how household demographics at the block group scale are distributed among the individual residential housing units in that block group. The probabilities of a given household's occupancy status and income bracket allow for a weighted random sampling (SciPy, 2020) to determine—in each Monte Carlo realization—the demographics of the household occupying a given residential unit.

In a given model realization, we distribute AAL for a residential structure and its contents among households based on their floor of occupancy and their occupancy status (renter vs. owner). Ultimately, the Financial Instability Model calculates both the current discretionary income and the risk-adjusted discretionary

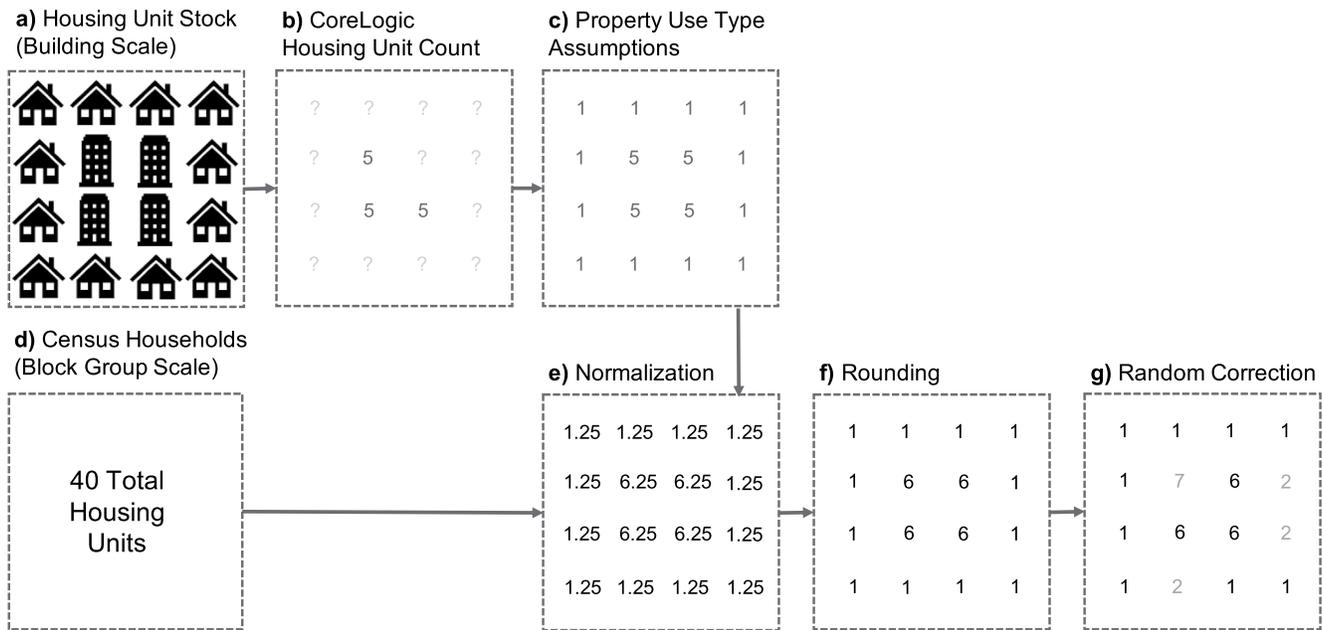


Figure 4. Randomized distribution of housing units among buildings.

income defined as the household's discretionary income minus its AAL and displacement costs. In each Monte Carlo realization, the model quantifies reductions in discretionary income and counts the number of households with negative discretionary income. We then assess the demographics at the census block level to identify the inequity dimension of financial instability and the social risk it entails. We note that our classification of financially unstable households is closely related to the term “at-risk” households, which is commonly used in the sociological literature (Lee et al., 2010).

2.5.1. Housing Stock and Demographics

A challenge in our Financial Instability Model is to identify how many housing units are contained in each residential building based on the residential building stock as identified through parcel-scale (Corelogic, 2017) and American Community Survey block group-scale counts of housing units (U.S. Census Bureau, 2017). Approximately 10% of the residential buildings in our study area lie on parcels with a known number of housing units in the Corelogic data set. To link these data sets and define the specific location of these units within a block group, we use a procedure (described below) that necessarily rests on making assumptions.

We first fill in information for the buildings on parcels with known unit counts from Corelogic (Figures 4a and 4b), which are primarily condos and multi-unit residential buildings. For the other parcels, we assign a unit count based on the PUCs (Figure 4c)—a single family home is assigned a single unit, for example. If there is more than one structure on a parcel, the number of housing units is assigned proportionally based on total building floor area.

We assume that the total number of housing units in a block group is equal to that estimated by the American Community Survey (Figure 4d). Note that Figure 4c shows 32 housing units for this example block group, while the census tells us there are 40 units. We use this census estimate to normalize the values in Figure 4c. For a single family home in our example with one unit, we multiply its fraction of the total housing units (1/32) by the number of missing units (8 units) to find the number of additional units to add (0.25 units) (Figure 4e). We then round the number of units to the nearest integer (Figure 4f). We correct rounding errors in the normalization procedure by random addition or subtraction of housing units from buildings—shown by the green numbers in Figure 4g. We then assign a floor number to each housing unit, starting on the ground floor and looping through all floors of the buildings until all housing units for that

building are defined. The floor number determines whether households are subject to any content damages (see Equation 4).

In each Monte Carlo realization of the Financial Instability Model, we place households in these housing units and assign demographics based on American Community Survey data. We create weighted integer distributions based on the probability of any given housing unit being of a certain income bracket or occupancy type (owner-occupied, renter-occupied, or vacant). As shown in Figure 3 and detailed in the next section, these properties then inform the calculation of discretionary income and risk-adjusted discretionary income.

2.5.2. Discretionary Income

We calculate discretionary incomes for households based on 2017 U.S. Bureau of Labor Statistics (BLS) estimates of national household expenses across 10 deciles of income (U.S. Bureau of Labor Statistics, 2019). We multiply the total non-discretionary expenses by a regional price parity of 1.30 to account for higher consumer prices in the Bay Area relative to the U.S. at-large (U.S. Bureau of Economic Analysis, 2019). For example, an average American household with \$100,000 of income would have a discretionary income of approximately \$28,000, but only approximately \$7,500 in the Bay Area as a consequence of the increased cost of goods and services.

In our study area, income brackets below \$75,000-\$100,000 show a negative discretionary income, even before accounting for projected flooding costs (see Figures 9d-9f). We note that the national-scale expenditure data may have surveyed a different proportion of household types than are present in our study area. Also, we do not account for factors such as heterogeneity in the cost of living within the study area, undisclosed income sources, savings, many people living in one residence to save money, or students taking out loans to support themselves through their education. Despite these limitations, a negative household discretionary income over several years is indicative of financial instability, because necessary savings to buffer even temporary expenses can not be accrued.

After we randomly assign an income bracket to a household, we pull an income value from a uniform distribution of the bracket range (i.e., \$75,000-\$100,000). We then linearly interpolate this value over the corresponding BLS income decile range (i.e., \$75,995-\$96,696) and national discretionary income estimates (i.e., \$17,808-\$27,845) and apply the regional price parity. The American Community Survey data do not show resolution above the \$200,000 or greater income bracket. For this bracket, we assume that households make between \$200,000 and \$1,000,000 annually.

2.5.3. Temporary Displacement Cost

During flood events, some households may be forced to temporarily relocate. We estimate the costs associated with temporary displacement of households due to flooding events according to the methodology outlined in a 2011 USACE Report (U.S. Army Corps of Engineers, 2011) detailing flooding impacts within our study area. For each flooding event, we use the USACE methodology to find a household displacement time as a function of the structural damage percentage (Equation 1). We then estimate the resulting cost imposed on a household through Equations 2 and 3. The displacement costs associated with discrete flood events are then annualized through the same methodology applied to calculate AAL and are subtracted from household annual discretionary income in the calculation of risk-adjusted discretionary income (see Equation 4).

Displacement time (t) in days if building structural damage (s) is greater than 10%:

$$t(\text{days}) = 30 + (s - 10) * 8 \quad (1)$$

Displacement Cost (D) if displacement time (t) is less than 365 days:

$$D(\$) = 500 + \frac{t}{30} * 2000 \quad (2)$$

Displacement Cost (D) if displacement time (t) is greater than 365 days:

$$D(\$) = 24,900 \quad (3)$$

2.5.4. Risk-Adjusted Discretionary Income

To calculate risk-adjusted discretionary income, we consider insurance policies under the National Flood Insurance Program (NFIP). Data from a stratified, random sample of 100 NFIP communities suggests that about half of single-family homes in the 100-years floodplains in the U.S. have flood insurance (Dixon et al., 2006). While the number of NFIP policies may be increasing, relatively low uptake rates are commonplace (Kousky & Michel-Kerjan, 2017) with insurance rates varying between 5% and 60% for different locations. Since large fractions of our study area fall within the 100-year flood plain, which will likely expand over time, we assume a 50% penetration rate across our study area based on the Dixon et al. (2006) estimates. This corresponds to an estimated uncompensated loss fraction of 0.372 (Sarmiento & Miller, 2006) for all households in our study area, meaning households pay for 37.2% of total flood AAL.

We find uncompensated loss by multiplying structure (AAL_{str}) and content AAL (AAL_{con}) by the uncompensated loss fraction (f) of 0.372. We make the assumption that renter households pay for uncompensated content losses but are not liable for structure damages ($AAL_{str} = 0$), which are split by owner households in that building (N_{own}). SURF distributes structure losses to occupying owners only, and does not directly account for homeowners not living in the study area. For example, if a building has only renter households in a given Monte Carlo iteration, then no structure damages from this building are assigned to any household.

For all households above a first-floor unit, we assume that content damages are zero ($AAL_{con} = \$0$) and that content losses are split by all first-floor units in that structure (N_{ffu}). In addition, all households face a displacement cost for every flood event causing more than 10% structural damage (see Equations 1–3). We then calculate the risk-adjusted discretionary income (ADI) by subtracting annualized structure damages, content damages, and displacement costs (D) from a household's annual discretionary income (DI):

$$ADI(\$ / year) = DI - D - \frac{f * AAL_{str}}{N_{own}} - \frac{f * AAL_{con}}{N_{ffu}}. \quad (4)$$

For each Monte Carlo realization for a given housing unit, we randomly assign household income and occupancy status, which inform the calculation of current discretionary income and risk-adjusted discretionary income (Equation 4). Within each realization, we also count the total number of financially unstable households within each income bracket with negative current discretionary income or negative risk-adjusted discretionary income. We then compute the mean and standard deviation of current discretionary income, risk-adjusted discretionary income, and financially unstable households within each income bracket across all realizations. This approach allows us to quantify the effect of coastal flooding on household discretionary income and the corresponding increase in the number of financially unstable households.

2.5.5. Renter and Owner Analysis

SURF uses American Community Survey household income data set variable B19001 to count the number of households in each income bracket and variable B25009 to calculate the fraction of renter and owner households in a block group. Owner households are subject to structural damage costs which renter households are not (see Equation 4). SURF assumes that the likelihood of a given household being a renter or owner is not dependent on income. However, we also run an edited version of the Financial Stability Model with alternative American Community Survey data which provides higher resolution on renter and owner status across incomes, but has lower resolution on income (see supporting information and Figure S5).

3. Results

3.1. Comparison of San Mateo County to Other Counties in the Bay Area

Many coastal communities in the Bay Area have elevations close to current sea level. Figure 5 shows the total water level along the inner Bay with a historic return period of 100 years for the sea level in 2000. To perform a regional assessment of coastal flooding risk in the San Francisco Bay, we first quantify the number of residential buildings identified from building footprint (Microsoft, 2017) and parcel data (Corelogic, 2017) exposed to coastal flooding. Next, we cut polygons representing census block groups to match the shoreline and calculate the flooded fraction of each. For each county, we calculate a median per-capita household income through a weighted average of the per-capita household incomes of each block group. Finally, we

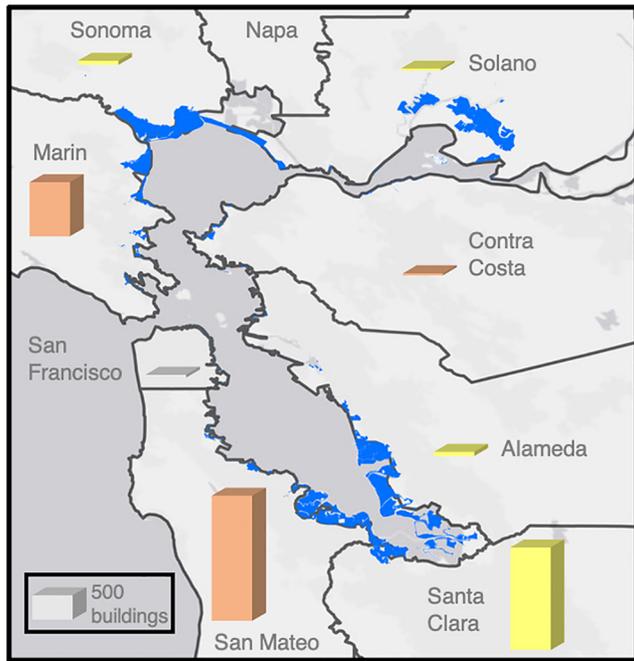


Figure 5. Illustration of a 100-year storm along the shoreline of the inner Bay for present-day sea level from 2000. The size of the bars indicates the number of residential buildings flooded under this event. Orange bars indicate that flooded block groups in the respective county have a lower median income than the county median, yellow bars indicate a higher median income, and gray bars indicate a difference of less than $\pm 2\%$. Napa County has no buildings in the coastal floodplain under this scenario. A summary of results is shown in Table 1.

estimate the average per-capita household incomes within the floodplain using a double-weighted average that incorporates both the number of households and the flood coverage fraction in each block group.

Out of the nine counties, three stand out in terms of the number of households flooded at approximately present-day sea level from 2000: Marin, San Mateo, and Santa Clara. The total number of flooded buildings is highest for San Mateo County. Also, the household median income in the floodplain is about \$30,000 lower than the 2017 County median of \$115,300 for a family of four (San Mateo County Department of Housing, 2017) (see Table 1), suggesting that lower-income census block groups in San Mateo County currently face disproportionate exposure to coastal flooding. In Figure 5, the color of the bars associated with each county indicate whether the median household income in the flooded zone is above (yellow) or below (orange) the county's median household income.

Santa Clara County has the second highest number of exposed buildings, but the median household income within the flooded zone is currently higher than the county mean. However, there is significant socioeconomic variability in the flooded area that is not captured at this level of aggregation that likely obscures the impact on low-income communities or low-income households in block groups with an average or high median income. Marin County also stands out in our analysis as an area where coastal flooding might disproportionately affect low-income households.

For the portion of the inner bay that falls within San Mateo County, we project that 87 census block groups with approximately 52,000 households will be affected by coastal flooding between 2020 and 2060. For the remainder of this manuscript, we refer to these 87 block groups as our study area. Assuming no changes to building inventory, that all damages are repaired, and no new coastal flooding interventions, our model projects that residential structures and contents in the County will incur

an AAL between 2020 and 2060 of approximately \$1.11 billion ($\pm \3.41 million) under the Representative Concentration Pathway (RCP) 8.5, \$936 million ($\pm \3.06 million) under RCP 4.5, and \$835 million ($\pm \2.86 million) under RCP 2.6.

Our simulations suggest that monetary risk increases sharply in San Mateo County toward the end of our study period and becomes increasingly dependent on climate scenarios and their assumptions regarding future anthropogenic emissions (see Figure 6). From 2040 to 2060, total RCP 8.5 AAL for residential buildings in the County increases from approximately \$711 million in 2040 ($\pm \2.65 million) to \$3.09 billion by 2060 ($\pm \7.89 million), in contrast to RCP 2.6 where AAL changes from \$701 million in 2040 ($\pm \2.62 million) to \$2.28 billion ($\pm \6.19 million) by 2060. These estimates suggest that continued greenhouse-gas emissions starting in 2020 will manifest as larger coastal flooding damages beginning primarily in the mid-21st century, leaving a valuable window of opportunity for mitigating risk.

3.2. Coastal Communities Where Social Risk Dominates

Every household within the projected flood plain will be burdened by flood damage costs, but the ramifications for the financial security of individual households and for the communities as a whole depend sensitively on the socioeconomic context. Figure 7 shows the percent of financially unstable households for both current (A) and future (B) conditions in our study area under the RCP 8.5 projection. As detailed in the model section, we classify households as financially unstable under current conditions if they have zero or negative discretionary income after accounting for the high Bay Area cost of living. We do not account for AAL when identifying existing financial instability. We classify households as being prone to future financial instability if their risk-adjusted discretionary income is zero or negative.

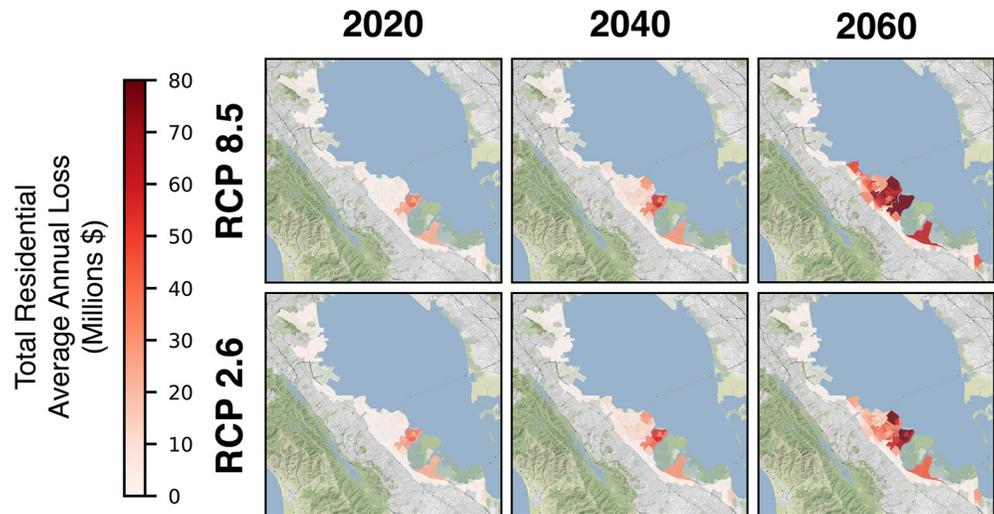


Figure 6. Spatial distribution of total average annual losses for residential structures and contents in 2020, 2040, and 2060 under the RCP 8.5 and RCP 2.6 sea level rise scenarios.

We project that approximately 9,871 (± 378) households could be pushed into the financially unstable category under RCP 8.5 from incurring average annual coastal flooding damages between 2020 and 2060, 8,181 households under RCP 4.5 (± 386), and roughly 7,285 (± 386) additional households under RCP 2.6. The uncertainty in these estimates is governed primarily by the randomized assignment of households based on demographic data (U.S. Census Bureau, 2017) to housing units at the census block group scale, as shown in Figure 3.

As noteworthy as these increases are, Figure 7a also demonstrates that some communities are already confronted with a high percentage of existing financial instability. For example, we estimate that about 1,860 households in East Palo Alto, around half (51%), are already in the unsustainable situation of having negative discretionary income without considering projected AAL (see Figure 7a). While an astonishing number at first sight, it is consistent with other evidence of financial struggles, such as an assessment that as many as 42% of students in this area (Medina, 2017), may already be homeless or “highly mobile.” The existing

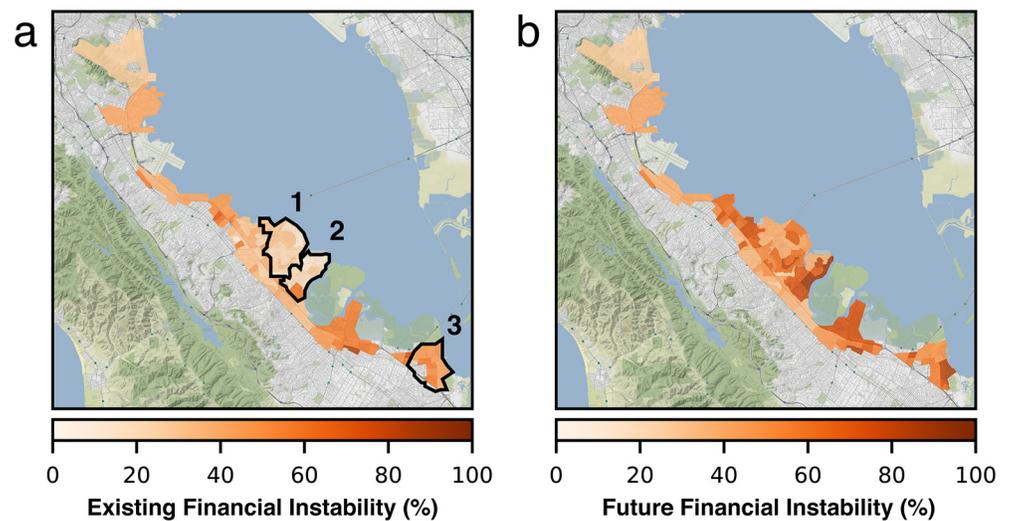


Figure 7. Percentage of financially unstable households—households with negative discretionary income based on average cost of living (U.S. Bureau of Labor Statistics, 2019)—for (a) existing demographics and (b) including average annual household damages under RCP 8.5 between 2020 and 2060. Labels 1, 2, and 3 denote Foster City, Redwood Shores, and East Palo Alto, respectively.

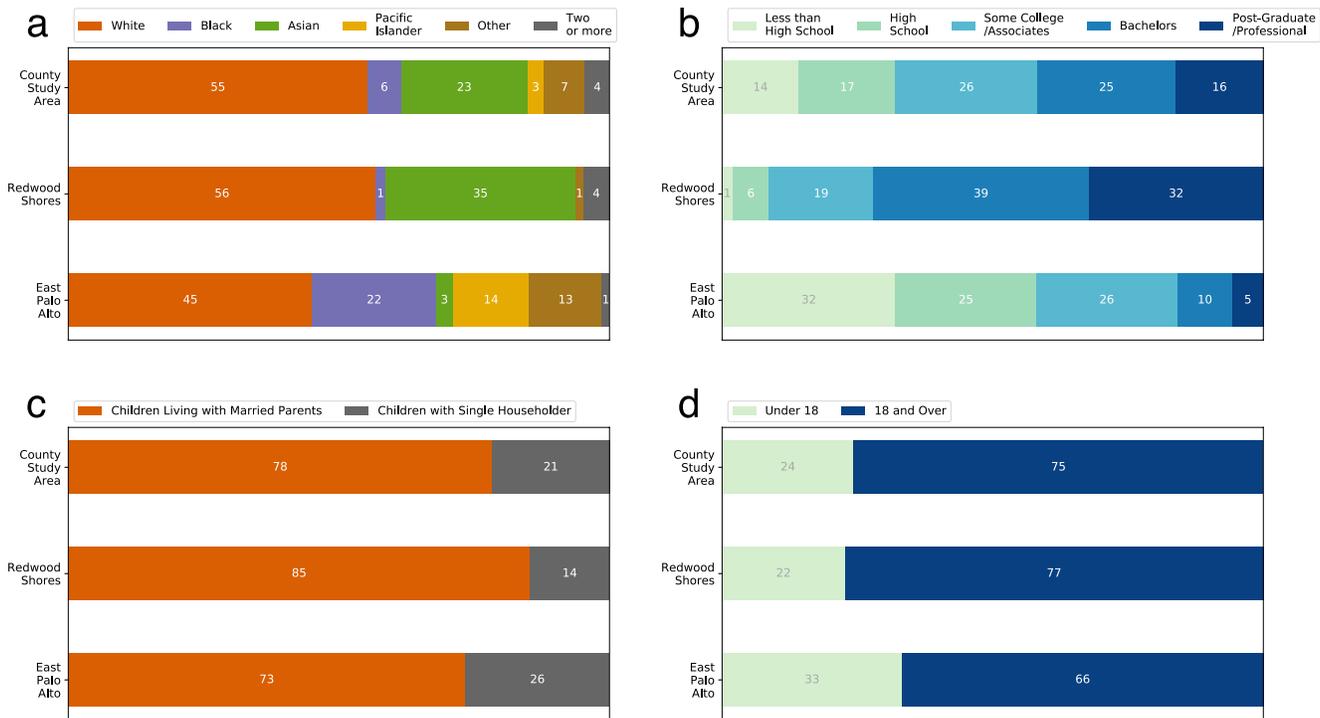


Figure 8. Demographic distributions for (a) racial identities, (b) educational attainment for residents over 25, (c) percent of children living with married parents vs. with a single householder, and (d) percent of residents over and under 18 years old for the San Mateo County study area, Redwood Shores, and East Palo Alto.

financial instability of 51% in Figure 7a contrasts with a future financial instability of 62% in Figure 7b. While increasing, future financial instability is clearly dominated by the status quo in East Palo Alto, which reflects existing socioeconomic inequality.

The existing socioeconomic inequality could be amplified by coastal flooding, which will burden financially unstable households with additional costs. Even if these costs are comparatively small, financially unstable households might not be able to absorb them given the likely absence of savings in households with zero or negative discretionary income. As a consequence, they may face displacement, bankruptcy or homelessness. Based on this evidence, we propose that the percentage of financially unstable households under current conditions could be used as a proxy for the prevalence of social risk in a given community. We emphasize that this choice of proxy limits our conceptualization of social risk to the present. While imperfect, given that social risk is undoubtedly evolving, changes in the demographics and incomes of urban communities are notoriously difficult to predict and we prefer not to speculate.

Another shortcoming of using financial instability as a proxy for social risk is its focus on household income when there is no doubt that many demographic factors contribute to social risk. This relationship is evident in East Palo Alto, which is more racially diverse and less educated with a higher percentage of children and an elevated percentage of children living with a single householder than the County as a whole (see Figure 8). While not including these demographic factors quantitatively, social risk as measured here is hence closely related to equity.

3.3. Coastal Communities Where Monetary Risk Dominates

Our model shows that our study area faces relatively high monetary risk throughout (see Figure 6). Among the largest increase in financial instability (i.e., ~124%) will occur in Redwood Shores, a jump from 23% to 71%, or 1,197 to 3,752 households under RCP 8.5 (see Figure 7). Redwood Shores is hence an example of community where monetary risk dominates and where current social risk is low.

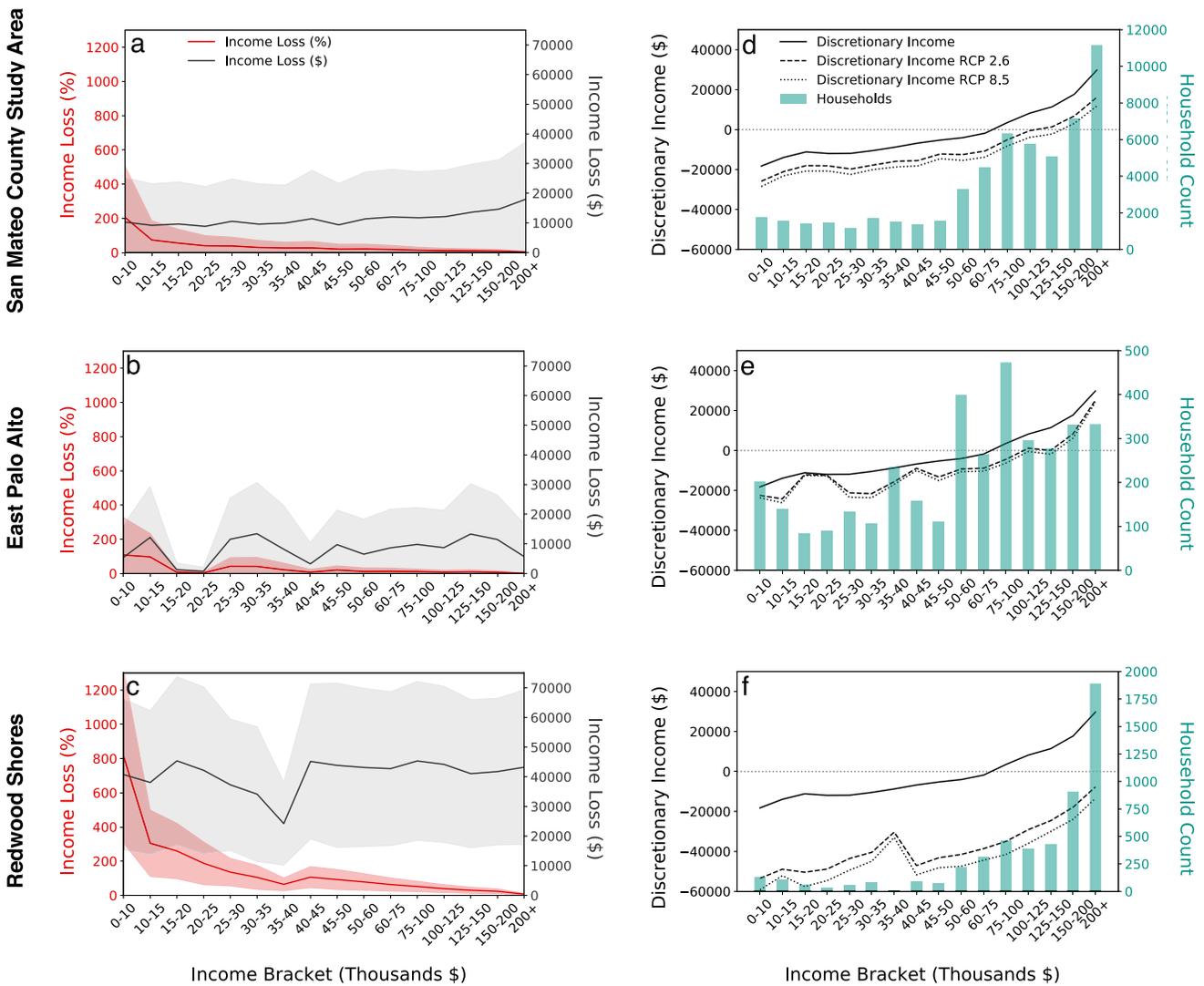


Figure 9. Illustration of income losses due to average annual coastal flood damage costs between 2020 and 2060. Plots a–c show both total income loss (black) and income loss as a percentage of total income (red) by bracket for the RCP 8.5 projection. Plots d–f show how household discretionary income is impacted by average annual losses under both RCP 8.5 and RCP 2.6. East Palo Alto results are for the subset of block groups which intersect flood plains in the analysis, as shown in Figure 10.

The distribution of monetary risk across different income groups in San Mateo County is deconstructed in Figure 9. Subplots a–c illustrate impacts on total household income across income brackets while subplots d–f show the effects on household discretionary income under RCP 2.6 and 8.5 (see Equation 4). Across the San Mateo County study area, average household losses increase gradually by income (Figure 9a), partly because of increased exposure in high-income areas like Redwood Shores and partly because losses are proportional to square footage, which correlates positively with household income. The number of households within each income bracket varies significantly by geography (Figures 9d–9f), but households earning more than \$200,000 are by far the largest income bracket in the County (Figure 9d).

We note that SURF may overestimate the number of new financially unstable households from the “\$200,000+” income bracket, as it assumes these households earn between \$200,000 and \$1,000,000 annually, though some likely earn far higher. Nevertheless, our model demonstrates that concerns of financial instability are not limited to low-income communities but may concern relatively affluent communities as well, particularly as sea-level continues to rise. While the “\$200,000+” income bracket may face the largest AAL, a much greater loss as a percentage of income is borne by the fewer households in the lower income

Table 1
Table Accompanying Figure 5

County	Median household income	Flooded buildings	Median flooded block groups income versus county median income (%)
Sonoma	\$75,097	91	28.52
Solano	\$72,526	42	14.82
Santa Clara	\$108,543	2,137	43.66
Contra Costa	\$93,449	38	-38.59
Marin	\$108,455	1,126	-31.29
Napa	\$77,201	0	0.00
San Francisco	\$92,699	61	0.37
Alameda	\$87,357	89	37.72
San Mateo	\$107,978	2,603	-29.96

Note. We list the number of flooded buildings for all counties in the San Francisco Bay Area as well as the median household income in census block groups affected by flooding, compared to the total median income in each county.

brackets (Figures 9a–9c), exacerbating pre-existing socioeconomic inequities associated with cost-of-living in the Bay Area.

San Mateo County is relatively wealthy, with a median household income of \$115,300 for a family of four (San Mateo County Department of Housing, 2017). However, both income and exposure patterns vary widely from region to region. In Redwood Shores (Figures 7a, 10a, label 2), for example, a large portion of the community has both high exposure to coastal flooding and relatively high income, with about 67% of households (~2,900) at or above the median income in San Mateo County. Compared to East Palo Alto (Figure 7a, label 3), few households in Redwood Shores are currently financially unstable, but we project that a substantial portion of households could face such a large AAL that they will become financially unstable in the future.

A comparison of the risk-adjusted discretionary income for climate scenarios RCP 2.6 and 8.5 shows that the trends in mean income losses we project here are not sensitively dependent on the assumed climate change scenario until mid-century, where the two scenarios will begin to diverge more over time (Griggs et al., 2017).

Household Demographics

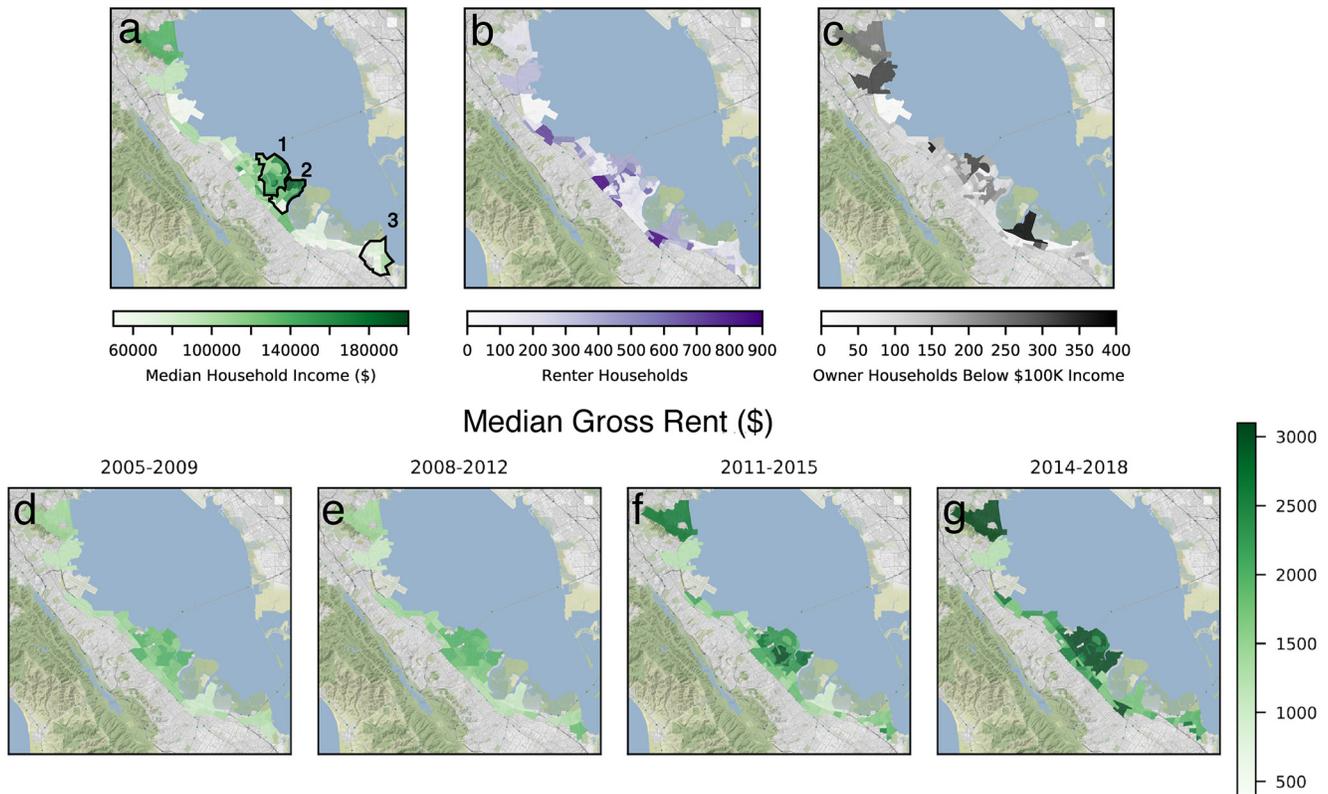


Figure 10. Spatial distribution at the census block group scale for (a) median household income, (b) number of renter households, and (c) number of owner households. Median gross rent (d)–(g) in dollars from US Census American Community Survey 5-years estimates at the census tract scale (2005–2009 and 2008–2012) and census block group scale (2011–2015 and 2014–2018) (American Community Survey 5-year estimates, 2020). Labels 1, 2, and 3 denote block groups in Foster City, Redwood Shores, and East Palo Alto, respectively.

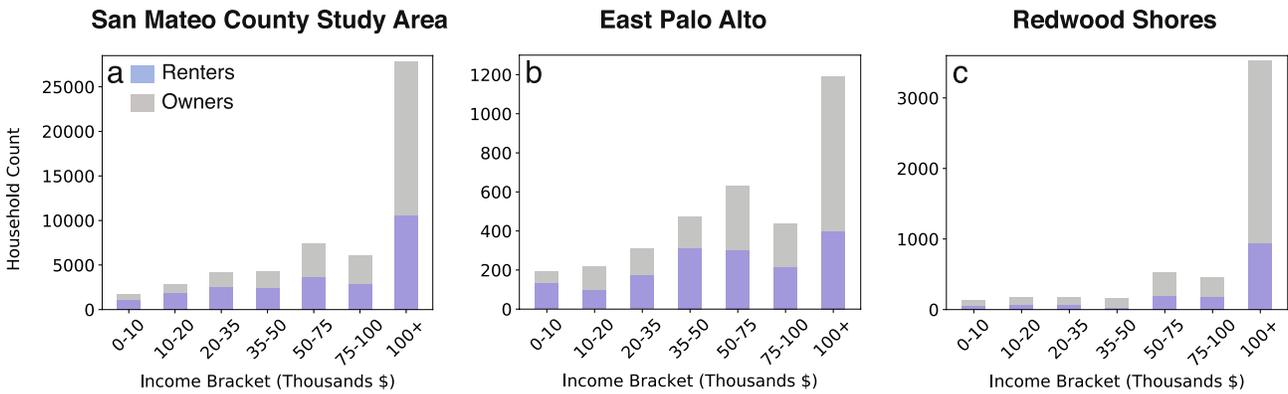


Figure 11. Renter and owner household counts by income bracket in the San Mateo County study area, East Palo Alto and Redwood Shores.

3.4. Differences in the Implications for Renter and Owner Households

Increasing sea level rise could drive depressions in coastal property values with different impacts for owners and renters. For example, both damaged and non-damaged houses experienced a negative price impact after Hurricane Sandy in New York, driven by increased flood insurance rates and perceived risk from buyers (Ortega & Tapinar, 2018). However, coastal properties in Savannah, Georgia, showed small price discounts of only a few percent from 2007 to 2016 despite being exposed to several feet of sea level rise (J. Beck & Lin, 2020). Similar price discounts were found for high-risk properties in Miami-Dade County, FL, but interestingly these were lower for highly priced properties purchased as non-primary residences, suggesting a greater risk tolerance by wealthy buyers (Fu & Nijman, 2020).

Taken together, it is not clear how future flood risk affects property values. Even if property values are affected by risk, it is not clear that reduced property values translate into reduced rents. While Bernstein et al. (2019) find a 7% reduction in sales prices for homes exposed to sea level rise, they find no reduction in rental rates. It is also possible that owners facing increased flood damage and insurance costs over time could pass on the additional cost to renters, exacerbating rent prices. In the specific case of the San Francisco Bay Area, it is difficult to discern the impact of risk in rent pricing from larger economic factors. Figures 10d–10g) shows that the median gross rent for the study area has been increasing irrespective of the actual monetary risk, suggesting that climate risks may be secondary to housing market dynamics in determining rent prices.

Figure 11 shows that the ratio of owner households is particularly high in the uppermost income bracket, of \$100,000 or more per year, both at the County scale (a) and within East Palo Alto (b) and Redwood Shores (c). Within the income brackets below \$100,000 per year, owners and renters are represented in roughly similar proportions at the county scale, with renters slightly over-represented in East Palo Alto and slightly under-represented in Redwood Shores. In addition to these differences in income, renters may face greater displacement risk. On the other hand, low-income owners (see Figure 10c) are burdened with both structure and content damages. While the majority of owner-occupied households make over \$100,000 annually in Redwood Shores (Figure 11c), there are hundreds of households below this income threshold for whom coastal flooding could be particularly precarious.

We estimate that in Redwood Shores, the average owner-occupied household could face \$42,400 in average annual losses between 2020 and 2060 (Figure S5), much higher than the projected \$15,800 average for owners across the study area. For renters, we project mean annual content damages of \$18,800 in Redwood Shores and \$5,100 across the study area (Figure S5c and S5d). Projected coastal flooding damages are concentrated in areas like Redwood Shores and Foster City, which have seen particularly large increases in rent since the mid-2000's (Figures 10d–10g). This could lead to higher-income renter households moving to lower-risk areas and leading to higher housing competition and displacement risk for existing residents.

4. Implications for Adaptation Planning

Current flooding along the Californian coasts is dominated by wave-driven processes and seasonal water-level anomalies such as El Niño events (Barnard et al., 2015; Serafin et al., 2017; Barnard et al., 2017), both of which act independently of sea level rise. The flooding costs we project here for the next few decades, 2020–2060, are hence not sensitively dependent on sea level rise (see Figure 6). However, the validity of our projections hinges on the validity of the RCP model suite and would be limited if dynamic ice-sheet instabilities lead to much more rapid sea level rise than currently expected (Bamber et al., 2019; Kopp et al., 2014, 2017) or if extremes in coastal water levels become more frequent (Arns et al., 2017; Barnard et al., 2014, 2017; Young et al., 2011).

Keeping these caveats in mind, our AAL estimate of approximately \$835 million–\$1.11 billion per year for San Mateo County may appear manageable as compared to the Bay Area's gross domestic product of \$748 billion in 2017 and global cost estimates (Hinkel et al., 2014). However, the goal of risk reduction policy as defined in the Sendai Framework is to “reduce losses in lives, livelihoods and health” and, as such, intentionally goes beyond monetary risk, measured here through AAL, alone. One step toward a more comprehensive approach to risk reduction is to put this monetary risk into context with other risks that a community is facing to assess loss to livelihoods. The aggregation of monetary risk at the County level obscures the variability of impact at the scale of individual communities within the County. A more granular, household-level view is necessary to identify the implications of coastal flooding on livelihood for different communities in the area.

In some communities, such as East Palo Alto (see Section 3.2), social risk clearly dominates, but monetary risk is still considerable. We estimate that about 50% of the households in East Palo Alto currently have zero or negative discretionary income, meaning that necessary living expenses such as food and housing absorb, or exceed, income even without considering AAL. While an astonishing number at first sight, it is consistent with other evidence of financial struggles, such as an assessment that as many as 42% of students in Ravenswood school district (Medina, 2017), which encompasses East Palo Alto, may be homeless or “highly mobile.” In other communities, such as Redwood Shores (see Section 3.3), the current social risk is low, but the monetary risk is high. If unaddressed, the risk-adjusted discretionary income of a large percentage of households could drop to zero or below in the future, with our projections showing an increase from 23% financially unstable households currently to 71% over the next four decades (see Figure 7).

In our model, only monetary risk increases over time. For example, we project that the monetary risk associated with flooding over the coming four decades would increase the percentage of financial unstable households in East Palo Alto by about 10%. We assume that social risk remains unchanged in that period as it primarily reflects our current, unequal community structure designed by past policy choices (Blaikie et al., 2005; Mileti, 1999; Tierney, 2014). There is no doubt that it can, and will, evolve in time, but we do not capture this effect here. We prefer not to speculate about the potential future urban development in our study area, partly because it is our choice how to shape it. Nonetheless, given all of these caveats and the fact that climate change is ultimately also socially produced, it is justified to raise the question why it might be valuable to distinguish between monetary and social risk in climate adaptation planning.

Identifying communities with a high social risk emphasizes that the risk in these communities is not driven primarily by flooding. While there is no doubt that the monetary risk in some of the communities with high social risk is substantial and needs addressing, tackling only the monetary risk in isolation may not be sufficient to ensure an equitable future for these communities. Insurance, for example, reduces the impact of an uncertain future cost by imposing a certain, present-day premium (Borch et al., 2014). Financially stable households can hence hedge their future monetary risk by purchasing flood insurance. Financially unstable households, in contrast, are primarily exposed to immediate social risk. They may have good reasons for not choosing to buy insurance to hedge against future monetary risks, particularly if their ability to remain in their current community of residence is uncertain itself.

Subsidies required as part of the National Flood Insurance Act of 1969 were intended to make the insurance affordable, but the implementation of this intention encountered many practical difficulties (Anderson, 1974). Equity concerns around flood insurance are also not limited to insurance coverage. An analysis of claims submitted between 1998 and 2008 (Holladay & Schwartz, 2010) showed that “the wealthiest

counties in the country filed 3.5 times more claims and received over a billion dollars more in claim payments than the poorest counties,” suggesting that flood insurance is most effective for households that can afford relatively high-priced property and the insurance necessary to protect it. Similar issues surrounding equity have recently been documented in the context of disaster aid dispersed to households after the declaration of major disasters (Domingue & Emrich, 2019) and in the federal buyout of flood-prone homes (Elliott et al., 2020).

There might be ways to improve the National Flood Insurance Program, such as through a voucher program (Kousky & Kunreuther, 2014; Nance, 2015; Shively, 2017; Zhao et al., 2016). Nonetheless, policy interventions that tackle monetary risk through either engineered structures, such as flood walls, or policy instruments, such as flood insurance, may not meet the needs of communities with high social risk. An equitable approach to climate-risk mitigation may need to go beyond these classical interventions and could include increased community-level innovation and investment in social capital and preparedness. Community action can act more swiftly and often in a more targeted way than region-wide policy intervention (O'Brien & O'Keefe, 2015; Tierney, 2014). It would be aided by county, state, or federal support but could occur at the scale of individual communities by developing support plans for financially unstable households and co-designing interventions that are authentic to the community. Bay Area communities have previously demonstrated its potential for emergent collective action in response to disaster scenarios such as the 1906 San Francisco Earthquake (Solnit, 2010) and could rise to the challenge again.

Currently, however, classical monetary risk reduction measures still represent the default approach as exemplified by “Foster City Measure P,” which entails voluntary self-taxation of \$90 million to raise existing sea walls in Foster City (see Figure 7) by up to eight feet. Once built, the sea wall will reduce flooding in Foster City, but it will also alter local and regional flooding patterns in adjacent communities (Wang et al., 2018). It could represent a monetary risk transfer from a community with low social but high monetary risk to neighboring communities with high social risk and greater demographic diversity (see Figure 10). Despite this risk transfer being small in monetary value, it is concerningly reminiscent of inequitable risk transfer in the context of environmental hazards in the United States (Bullard, 1990) and globally (Roberts & Parks, 2006).

This study builds on a long line of research into the disproportionate impact of disasters on specific communities groups (Cutter et al., 2012; Flanagan et al., 2011) and our changing relationship to risk (Curran, 2016; Tierney, 2014; U. Beck, 1992). Our priority here is to make this increasing understanding actionable to advance equitable climate-change adaptation. Of particular concern in the context of the Bay Area is homelessness, which increases exposure to all weather extremes and is a driver of injury and potential loss of life during flood events (Schmitt & Rossmann, 2019). Homelessness also creates future social risk by increasing health problems, developmental delays and educational issues, particularly among children (Buckner, 2008; Molnar et al., 1990; Rafferty & Shinn, 1991). A soaring of homelessness over recent years in California in general and urban areas in particular (California State Auditor, 2020; The Council of Economic Advisers, 2019) emphasizes the need for intervention.

5. Conclusion

In our understanding, a socially sustainable community is one that enables households across all income groups to remain part of the community. By projecting the average annual loss associated with coastal flooding over the next four decades and putting these costs into context with discretionary household income as constrained from the Census, we quantify both the monetary and social risks in our study area along the inner bay in San Mateo County. In communities where social risk dominates, a significant portion of households is already financially unstable, even without accounting for the monetary risk associated with coastal floods. In communities where monetary risk dominates, the portion of financially unstable households could increase significantly over the next four decades, raising concerns about the social sustainability of both types of communities. We note that the distinction between monetary and social risk is at least partially artificial, since the two risks are ultimately interrelated. Nonetheless, we argue that making a deliberate distinction could help identify how we can complement traditional risk-mitigation strategies, such as flood insurance or the construction of levees, with community-level innovation that advances equity in climate-change mitigation. Instead of adopting a “one-size-fits-all” approach that only targets monetary

risk, we suggest co-producing a wider spectrum of adaptation strategies that is conscious of social risks and prioritizes community needs.

Data Availability Statement

Data, methods, and Python code used to produce these results can be found at <http://zapad.stanford.edu/sigma/ef-2021-inequityrisk-bayarea>.

Acknowledgments

This study is a product of the Stanford Future Bay Initiative. We thank all students who participated in the 2017–2018 and 2018–2019 academic years, particularly, Kate Roberts, Indraneel Kasmalkar, Jinal Mehta, Nathan de Ropp, and Jeremy Smith. We also thank Mariano Balbi and the Stanford Urban Resilience Initiative for inspiring our building-damage model. Our work was generously supported by Stanford Impact Labs and the following units, which are part of (or affiliated with) Stanford University: the Bill Lane Center for the American West; the Haas Center for Public Service; the School of Earth, Energy and Environmental Sciences; the Department of Civil and Environmental Engineering; the Institute for Computational and Mathematical Engineering; the UPS Foundation Endowment Fund; the Center for Sustainable Development and Global Competitiveness; Stanford Professionals in Real Estate; the Dawe family; and the Woods Institute for the Environment. The study was also partially inspired and funded by the National Science Foundation through the Office of Polar Programs awards PLR-1744758 and PLR-1739027. The arguments presented here were shaped profoundly by the experience and feedback of representatives from the following local government and community organizations: County of San Mateo Office of Sustainability; City of East Palo Alto; City of Redwood City; City of San Mateo; City of Foster City; City of Burlingame; North Fair Oaks Community Council; Association of Bay Area Governments; Metropolitan Transportation Commission; Bay Conservation Development Commission; San Francisco Creek Joint Powers Authority; U.S. Army Corps of Engineers; El Concilio of San Mateo County; Acterra; Siena Youth Center; Youth United for Community Action; Rebuilding Together Peninsula. We also thank to anonymous reviewers for valuable suggestions that greatly improved the manuscript.

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