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# Housing market impairment from future sea-level rise inundation

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**Abstract**
The rate of future global sea-level rise will likely increase due to elevated ocean temperatures and land-ice loss. Coastal properties are expected to become more prone to coastal flooding in coming decades due to relative sea-level rise caused by both global and local factors. Translating sea-level rise projections into lost physical and economic value is critical for companies, governments, and regulators. We use probability distributions of local sea-level rise projections, National Oceanic and Atmospheric Administration (NOAA) coastal digital elevation models, and CoreLogic housing data to estimate the timing of future sea-level rise inundation and a range of housing market impairments in four U.S. coastal metros (Atlantic City, NJ; Miami, FL; Galveston, TX; and Newport-San Pedro, CA) for a series of climate scenarios. We implement a novel methodology, refining estimates for the timing for future inundation, considering both housing properties' elevation above the tidal datum (Mean Higher High Water-MHHW), and hydrologic connectivity to the ocean—a critical consideration where natural or human-built features alter the relationship between sea levels and inundation. The unique risk factors in our four metros (housing market, topography, and local sea level) illustrate how our methods are applicable across geographies and scales of observation. Our results provide an important perspective on the timing of future losses, the associated uncertainty, and highlight positive (high-skewed) asymmetry of risk from sea-level rise inundation. This information can aid planners, policy makers, and investors in cost-benefit decision making related to mitigation, adaptation, and remediation at the local and national levels.

**Keywords** Climate risk · Climate economics · GIS · Sea-level rise · Natural hazards · Housing

**JEL Classification** Q54 · R3 · D89

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## 1 Introduction

Climate change is a persistent and substantial threat to society and the functioning of economic systems (USGCRP 2018). Climate impacts are manifesting through more frequent and extreme weather events (NOAAa 2019), higher temperatures (IPCC 2021 AR6), and rising seas (Sweet et al. 2017). Sea-level rise (SLR) is one of the more pernicious consequences of climate change and will likely negatively impact large portions of the United States' (U.S.) population and economy in the coming decades. Roughly 40% of the U.S. population lives in coastal communities (NOAAb 2019), with approximately 7 million people and 1.9 million homes at elevations within 1.8 m (6 ft) above current sea level (Hauer et al. 2016; Rao 2017). As sea levels slowly rise, these locations will likely face increased nuisance flooding (Moftakhari et al. 2015; Sweet et al. 2017), enhanced storm surge inundation (Amante 2019), and permanent coastline changes. In extreme cases, some coastal areas may experience out-migration, and city planners may need to implement policies to facilitate population departure (Wrathall et al. 2019). Consequently, rising sea levels over the next century will potentially disrupt housing markets and cause large economic losses.

### 1.1 Climate change, sea-level rise, and economics

There is growing awareness from economists that climate change and climate risk are important for local and regional economic outcomes, especially regarding risk to coastal real estate markets. Recent empirical research suggests that properties exposed to coastal flooding from hurricanes have lower values than similar properties in unaffected areas (Ortega and Taspinar 2018). Multiple markets prone to SLR inundation are also starting to witness slower price appreciation growth (Mcalpine and Porter 2018). Furthermore, properties most prone to SLR inundation may face lower valuations compared with similar properties in less prone areas (Bernstein et al. 2019).

The banking and finance sector is beginning to consider the economic effects that climate change may pose for businesses, investors, and financial institutions in the coming decades. Attention is being focused on increased physical impacts from climate change, such as fires, floods, and hurricanes (FSB-TCFD 2017; Department of the Treasury 2021). In recent years, central banks around the world have started to examine potential climate-related financial stability issues, their potential role in mitigating economic risks from climate change, and the unique risks banks face from climate change, such as investments in areas more prone to extreme weather events (Federal Reserve Board of Governors 2020; Brunetti et al. 2021; Campiglio et al. 2018). Furthermore, private financial institutions are not only starting to better analyze physical climate risks but are also shifting their businesses and investment strategies, signaling the reallocation of financial capital away from carbon intensive industries, such as coal and other fossil fuels, towards more sustainable, renewable energy sources (Goldman 2019; Black 2019; CoBank 2019).

However, as the awareness of climate change grows, risk practitioners face challenges in assessing the economic costs of climate change. Notably, uncertainty in climate projections needs to be accounted for when estimating the economic implications of climate change, especially when assessing the potential impacts of future SLR on the U.S. housing market. For example, depending on carbon emissions, land-use changes, and other global, regional, and local factors that affect sea levels, SLR could displace between 4 and 13 million people in the U.S. over the next century (Hauer et al. 2016). Coastal communities are facing a wide range of risks from SLR, with differing social, economic, and financial costs. Properly accounting for the range of economic and financial risks that results from climate change and SLR uncertainty is crucial for balancing the financial costs and benefits of potential policy choices.

Our research offers the following contributions that can help practitioners to better account for local SLR risk: (1) We outline and employ a methodology for estimating property (parcel) level inundation elevation using free, publicly available National Oceanic and Atmospheric Administration (NOAA) inundation shapefiles and digital elevation models (DEMs); (2) identify when properties may be inundated using local SLR projections across a series of climate scenarios; (3) account for and discuss the importance of climate uncertainty for SLR risk analysis; and 4) present our results for diverse coastal metros, demonstrating how our approach can be applied to a variety of locations in the U.S. and at different scales of observation.

### 1.2 Climate change uncertainty and sea-level rise

#### 1.2.1 Climate models, scenarios, and uncertainty

Accounting for climate change uncertainty is critical for estimating the range of economic impacts associated with future SLR. Climate change uncertainty can be separated into three broad categories: climate scenario uncertainty, internal climate variability (i.e., natural climate variability separable from human influences), and model uncertainty (Hawkins and Sutton 2009). In concert, these sources of climate uncertainty can influence economic decision making and the costs attributed to climate change impacts such as SLR inundation (Heal and Millner 2014).

Future atmospheric greenhouse gas (GHG) concentrations are one major source of climate uncertainty. The scientific literature and climate policy publications outline a series of commonly used, independent scenarios known as Representative Concentration Pathways (RCP), e.g., RCP 2.6, 4.5, 6.0, and 8.5 (Rogelj et al. 2012; Moss et al. 2010; IPCC 2021 AR6). Each RCP scenario is associated with a time path of future atmospheric greenhouse gas (GHG) concentrations that results from differing socioeconomic, technology, and biophysical assumptions in specific integrated assessment models (IAMs). Using these independent sets of assumptions, the RCP scenarios depict progressively higher levels of GHG concentrations, elevated global temperatures, and, by extension, accelerated increases in global sea levels. For example, under RCP2.6, global GHG concentrations are projected to rise modestly to 490 parts per million (ppm) by 2100, global mean temperatures are projected to rise by 1.5 $^{o}$C, and global mean sea level is projected to rise by 49 cm. Under RCP8.5, GHG concentrations are projected to rise to 1370 ppm by 2100, mean temperatures are projected to rise by

4.9 $^{o}$C, and global mean sea level is projected to rise 79 cm (Moss et al. 2010; Kopp et al. 2017).[1] As these outcomes demonstrate, climate scenario uncertainty contributes to a wide range of potential outcomes and is especially important on longer-term horizons (>60 years; (Hawkins and Sutton 2009)). By extension, the economic consequences of climate change can be very different solely based on the climate scenario.

The second and third major sources of climate uncertainty are internal climate variability (natural variability) and modeling uncertainty. In the near term (<20 years), a majority of climate uncertainty is driven by internal variability (i.e., natural climate variation separable from human influences). This is especially true for regional scenarios (Hawkins and Sutton 2009). The global climate system is chaotic, which makes it sensitive to initial model parameters. In the medium term (20–50 years), model uncertainty, or the spread of estimates across various climate models, is the main contributor to climate uncertainty (Hawkins and Sutton 2009). As previously mentioned, global climate scenarios (i.e., GHG concentration scenarios) contribute most to total uncertainty when time horizons exceed 60 years into the future (Hawkins and Sutton 2009; Heal and Millner 2014). It is important to account for all three sources of climate change uncertainty to estimate the range of economic costs associated with future SLR over the next 80 years.

#### 1.2.2 Sea-level rise uncertainty

Large climate change uncertainty contributes directly to a wide range of future SLR projections through the end of the century and can make it challenging to assess potential economic costs from SLR. Under the low GHG concentration scenario (RCP2.6), projections for global mean SLR range from 0.3 to 0.8 m (5th to 95th percentiles) by the end of the century (Kopp et al. 2017). Under the high GHG concentration scenario (RCP8.5), mean SLR is expected to range from 0.5 to 1.2 m (5th to 95th percentiles) (Kopp et al. 2017). Uncertainty in local SLR projections can be even larger than in global projections. Kopp et al. (2014, 2017) provide local sea-level projections that are informed by a combination of expert community assessment, expert elicitation, and process modeling, and incorporate the various sources of climate uncertainty within GHG concentration scenarios (e.g., RCPs 2.6, 4.5, and 8.5). For example, future SLR estimates for Miami, Florida range from 0.2 to 1.0 m under RCP2.6 and between 0.4 to 1.4 meters under RCP8.5, by the end of the century (Kopp et al. 2017). SLR estimates for Atlantic City are even more uncertain, ranging from 0.3 to 1.3 m for RCP2.6 and from 0.5 to 1.7 m for RCP8.5, through 2100 (Kopp et al. 2017). Other additional factors, such as accelerated Antarctic ice sheet loss can further exacerbate uncertainty in global mean sea level and local SLR projections through this time span, amplifying the range of economic impacts from SLR (Deconto and Pollard 2016).

Our analysis incorporates uncertainty in future SLR projections caused by global climate change and regional and local processes to estimate a range of future city-level housing market value impairments. Specifically, we use probability distributions of local SLR projections (Kopp et al. 2014, 2017; Deconto and Pollard 2016), NOAA coastal digital elevation models (DEMs), and CoreLogic housing data to estimate housing market value impairment from future SLR inundation in U.S. coastal metros.

## 2 Methods and data

### 2.1 Housing market data and economic value analysis

We use CoreLogic housing information from their Deeds, Tax, and Tax History datasets to generate our housing market sample. Our housing market for this study spans roughly 590,000 unique residences across our four highlighted U.S. coastal metros. Supplemental material section 2 provides a comparative analysis for a total of 17 metros with nearly 5.7 million unique residences analyzed. We use precise geolocation information (latitude and longitude) available in the housing dataset to determine the current elevation above sea level for each property and to estimate the timing at which the property may be affected by local SLR. For each metro, we use the U.S. Postal Service city and ZIP code data to filter the CoreLogic housing data to include only ZIP codes within the four metropolitan areas (USPS 2020). Our housing market sample is restricted to single-family houses, townhomes, and 2–4 unit residential buildings.

For current housing price estimates, we index the most recent property transaction value available in our dataset to the current time period (2020) using CoreLogic ZIP code and county-level combined single-family housing price indexes. Adjusting financial values to the current year provides a time-consistent estimate of the value of each property and thereby allows us estimate the total value of the housing stock within each metro.

Our primary analysis is structured in terms of the counts of impaired residential units rather than the relatively less stable market (financial) values. We include economic dollar values in our results, as an adjunct to the primary physical (property counts) analysis in order to provide additional

[1] Under current carbon emission policies and energy transitions, empirical evidence would suggest that RCP8.5 is less likely, and we are currently closer to a medium GHG concentration scenario (RCP4.5) (Hausfather and Peters 2020).

context around estimated losses. As a baseline, when financial losses are mentioned, these losses can be interpreted as the current estimate of a property's value. Using the current property value for losses over time implies a discount rate of 0% per year, indicating that, absent of SLR, the relative value of the included properties is considered to remain constant over the rest of this century. This implied discount rate is within the range of rates used by other researchers (albeit at the lower end) and is consistent with persistently low real interest rates (Drupp et al. 2018; Bauer and Rudebusch 2020). Although we focus our results on property inundation counts (as counts are less subject to issues arising from long-term discount rate and values over time), we do evaluate losses under positive time discount rates of 2.6% and 4.0% per year, which lower financial values over time relative to nearer-term valuations (Arrow et al. 2013). Each of these discount rates can be considered meaningful in terms of recent empirical research (Giglio et al. 2021; Bernstein et al. 2019; Nordhaus 2013). Full methodological detail and explanation on these additional economic analyses are provided in the supplemental material, sections 1.1 and 1.2.

### 2.2 Local topography

Local topography has a large effect on the modeling of future coastal inundation from SLR and the impairment of individual housing markets. Much of the Atlantic and Gulf Coasts of the U.S. consist of low-lying areas with small terrain slope, which results in wide swaths of potentially flooded areas and impaired housing markets. Conversely, the Pacific Coast of the U.S. has many elevated areas with large terrain slope adjacent to the coastline, resulting in narrower swaths of land prone to SLR inundation and future impaired housing markets. DEMs depict the local topographies and are essential to modeling coastal flood risk and the future impairment of housing markets.

Accurate, high-resolution DEMs are needed to both delineate areas with low elevations below a projected sea-level and to determine hydrologic connectivity. Natural terrain features (e.g., gullies, hills) and human-made terrain features (e.g., culverts, levees) can enhance or impede the flow of water and affect flooding at inland elevations (Li et al. 2009; Poulter and Halpin 2008; Gesch 2009; Zhang et al. 2013; Amante 2019). The spatial resolution of the DEM is an important factor in coastal flood modeling, as it determines the ability to resolve these terrain features that can affect hydrologic connectivity. This ability is especially important for modeling the future housing impairment for coastal regions with low-lying areas protected by terrain features at present-day sea levels. For example, the DEMs for Atlantic City and Miami have spatial resolutions of 3 m and 5 m, respectively. We assume that these spatial resolutions are able to resolve the most important terrain features that could enhance or impede water flow, but the effect of the DEM spatial resolution is not rigorously quantified in our analysis. Furthermore, potential differences between DEM values and the "true" elevation represent the DEM vertical uncertainty, and such uncertainty can cause differences in the modeled coastal flood risk (Amante 2018; Amante 2019) and in housing impairment estimates.

We use geospatial data from NOAA's Sea-Level Rise Viewer (NOAAc 2019) to estimate the timing of inundation and associated housing market impairment. We use NOAA's Sea-Level Rise Viewer DEMs to determine each property's respective elevation above sea level at the tidal datum of Mean Higher High Water (MHHW) (i.e., the higher high water height of each tidal day observed over the National Tidal Datum Epoch). We also use NOAA's Sea-Level Rise Viewer inundation shapefiles, which were generated from NOAA's Sea-Level Rise Viewer DEMs. These shapefiles delineate areas that will be inundated at one-foot increments of SLR above MHHW (0–10 ft) (NOAAc 2019). Depending on local topography and the built-environment, some low-lying areas along the coast may be protected by natural levies or structures and might not be inundated (i.e., are not hydrologically connected) until sea-level rises well above their actual measured elevation (Poppenga and Worstell 2015). For this reason, it is important to account for hydrologic connectivity when estimating the inundation height and associated timing of impairment for a property.

### 2.3 Combined use of sea-level rise viewer DEMs and shapefiles

We use both the property elevations from the DEMs and the one-foot increment shapefiles to refine our estimates of the timing of inundation for each property.[2] The NOAA Sea-Level Rise Viewer shapefiles consider both the elevation and hydrologic connectivity when delineating areas prone to SLR inundation at 1 ft intervals. However, it will likely be many years to reach a single foot of SLR under most scenarios and additional temporal granularity is needed to refine estimates of the year of inundation for each property. Thus, we use both the property elevation from the DEM and the location of the property within the NOAA Sea-Level Rise Viewer shapefiles to estimate a more precise elevation and timing of inundation, while still accounting for hydrologic connectivity.

[2] We convert all DEMs from the original vertical datum of the North American Vertical Datum of 1988 (NAVD88) and vertical units of meters to the same vertical datum (MHHW) and vertical units (feet) as the Sea-Level Rise Viewer inundation shapefiles using NOAA's VDatum conversion tool (NOAAd 2019).

First, we identify the most restrictive coastal inundation shapefile (i.e., lowest sea-level rise increment inundation area that the property is located within). For example, a property with an elevation from the DEM of 1.7 ft may be located within the 2 ft, 3 ft, 4 ft,..., 10 ft Sea-Level Rise Viewer shapefile. If we identify the most restrictive shapefile for this property to be the 2 ft shapefile (i.e., the property is not located within the 1 ft shapefile but is within the 2 ft shapefile), we assume that there are no large terrain or human-made barriers to inundation and the inundation elevation is the DEM elevation. For that property, we estimate the year of inundation to be associated with the year at which the sea-level rise projection reaches the elevation of the property from the DEM (i.e., 1.7 ft; Fig. 1 Profile A).

In other cases, a property with an elevation of 1.7 ft may be located in the 4 ft, 5 ft, 6 ft,..., 10 ft Sea-Level Rise Viewer shapefile. This could occur if the property is located in an inland depression and surrounded by higher elevations from natural terrain barriers or human-made barriers, such as levees, which would protect the property until sea-level rises above those protective elevations. In such cases, we estimate the year of inundation to be associated with the year at which the sea-level rise projection reaches the most restrictive Sea-Level Rise Viewer shapefile increment (i.e., 4 ft; Fig. 1 Profile B), which gives a conservative estimate for the timing of inundation. See Fig. 1 for an illustrative example of the combined use of Sea-Level Rise Viewer DEMs and shapefiles to estimate the timing of inundation for a property.

Considering both the DEM value and Sea-Level Rise Viewer shapefiles increases the granularity of our estimate for the inundation year associated with each sea-level rise projection where terrain or human-made barriers that would prevent inundation are unlikely. Figures 2 and 3 illustrate the improved precision of using both the DEM and shapefiles to determine the timing of inundation compared to only using the shapefiles. By comparing across cities, such as Miami and Galveston, we observe differences in how our dual matching methodology performs in different locations. For a city like Miami, with a low-lying and moderately sloping topography (and few natural barriers), our inundation profile is smooth, with few noticeable jumps in the profile. A city like Galveston, with a more varied terrain (and some natural barriers), produces an inundation profile that is mostly smooth but with more noticeable jumps. This is due to our matching methodology applying the shapefile inundation elevation, where necessary, to account for protective features. The differences would be even more pronounced at a neighborhood or property level, underscoring the importance of our more granular inundation elevation estimates.

One potential limitation of this dual-approach is that this improved temporal granularity can lead to questionable results due to the uncertainty of the DEM. There are many sources of DEM uncertainty, including the spatial resolution, interpolation method, and elevation measurement uncertainty (Amante and Eakins 2016; Amante 2018). The vertical uncertainty of topographic elevation measurements using modern light detection and ranging (lidar) technology is generally on the order of 10–20 cm at one standard deviation (Amante 2018; Amante 2019). Modeling a single SLR projection at yearly time steps generally results in the annual SLR increment to be smaller than the DEM uncertainty. For example, the SLR increment within a year is typically on the order of millimeters, but the vertical uncertainty of the DEM is typically on the order of centimeters. As such, the annual sea-level rise increment is within the uncertainty of the DEM and can lead to questionable results for an individual SLR projection (Gesch 2018). This study does not incorporate DEM uncertainty into the analysis; however, previous research indicates the DEM uncertainty (on the order of centimeters) is a much smaller contribution to the uncertainty of coastal inundation modeling compared to the uncertainty of SLR projections (on the order of meters), especially in distant decades (Amante 2019). In our analysis, uncertainty in topographic DEMs derived from lidar measurements is much smaller than the uncertainty in SLR projections due to different RCP scenarios, and the full SLR probability distributions within a given RCP scenario provided by Kopp et al. (2014, 2017), and especially Deconto and Pollard (2016) that considers uncertainty in ice sheet loss and the contributions to sea-level rise. Therefore, using this dual-approach to estimate the year of inundation is deemed acceptable when determining a range of future coastal housing market impairment that incorporates SLR uncertainty into the distant future (i.e., through 2100).

### 2.4 Local sea-level projections

Coastal flooding occurs at the land–water interface, and, therefore, local information on the relative vertical movement between the land and water surface is required to model future flood risk and associated housing market impairment. Local sea-level projections account for both potential vertical movement in the land topography and changes in water levels. Local land topography can uplift or subside due to both long-term and short-term local or regional processes that include loss of glacial ice (glacial isostatic adjustment), human extraction of ground water, and tectonic processes (Horton et al. 2015; Church 2013). Changes in local water levels can also deviate from the global mean due to differences in ocean temperature, salinity, and currents (Nerem and Mitchum 2001; Cazenave and Nerem 2004; Lombard et al. 2005; Milne et al. 2009). Additional regular fluctuations of the climate system known

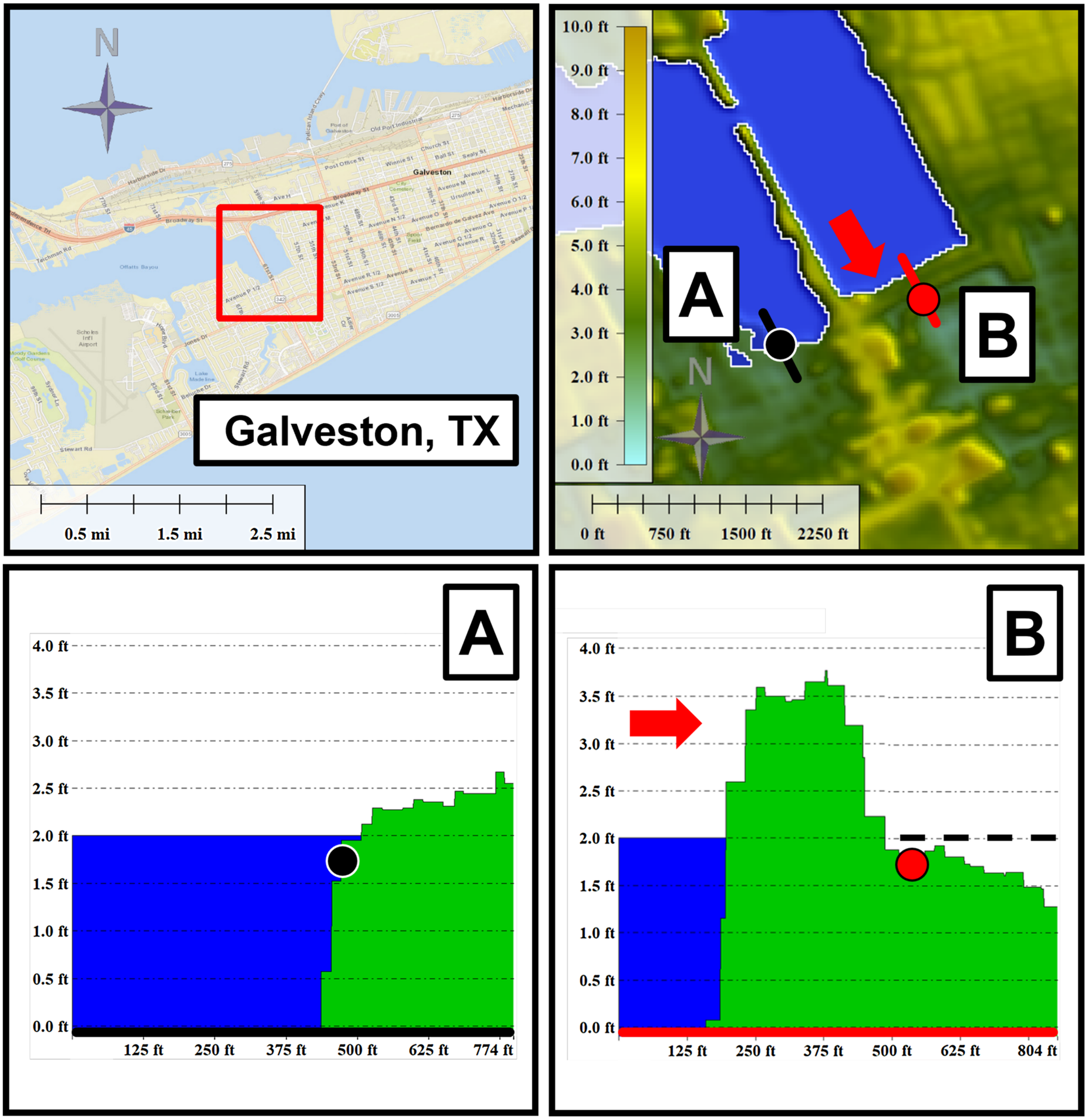



**Fig. 1** Illustrative example of the combined use of Sea-Level Rise Viewer DEMs and shapefiles to determine when a property at 1.7 ft elevation is inundated in Galveston, Texas. The blue area represents the 2 ft Sea-Level Rise Viewer shapefile that considers hydrologic connectivity overlaid on the DEM. Profile A shows an area that is hydrologically connected to the ocean where the estimated year of inundation for a property (black circle) is determined by the year at which the sea-level rise projection reaches the elevation from the DEM (i.e., 1.7 ft). Profile B shows an inland depression that is not hydrologically connected to the ocean due to terrain barriers (red arrow). In such cases, the estimated year of inundation of the property (red circle) is determined by the year at which the sea-level rise projection reaches the most restrictive Sea-Level Rise Viewer shapefile (i.e., 4 ft) that exceeds the elevation of the terrain barrier (i.e., 3.75 ft)

as oscillations or "modes," can also affect local sea levels. For example, the local sea level along the U.S. East Coast is affected by climate modes such as the North Atlantic Oscillation (Barnston and Livezey 1987; Hurrell 1995; Han et al. 2017) and the Atlantic Multidecadal Oscillation (Trenberth and Shea 2006; Wang and Zhang 2013; Han et al. 2017). These regional and local factors affecting the relative vertical movement between the land and water surfaces

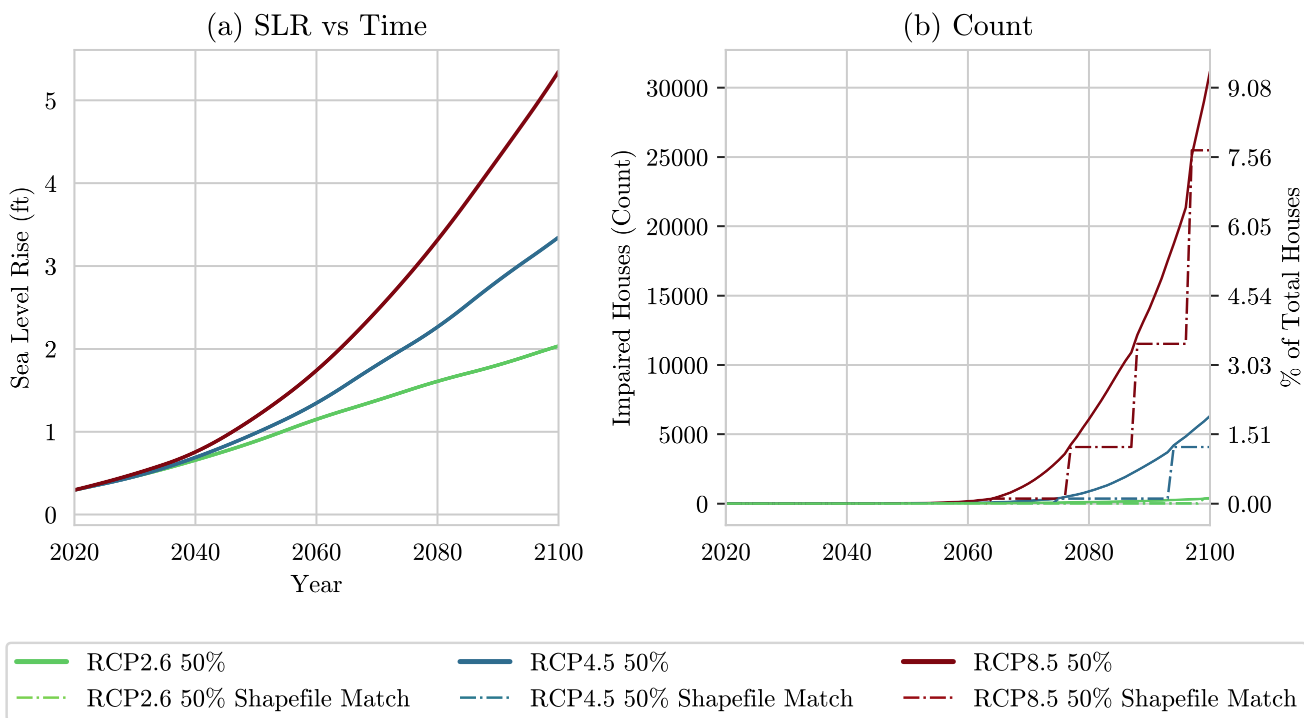



**Fig. 2** Combined use of sea-level rise viewer DEMs and shapefiles refines impairment estimates. Left side: Sea-level rise projection for Miami. (Deconto and Pollard 2016) Right side: Combined DEM and shapefile match (solid lines) vs. shapefile-only match (dashed lines)

necessitate using local SLR projections to accurately model future coastal flooding from SLR and associated individual housing market impairments.

We use local sea-level projections for Permanent Service for Mean Sea-Level (PSMSL) tidal stations from Kopp et al. (2014, 2017) to estimate a range of future housing value impairments. Our analysis uses SLR projections from 2020 to 2100 for three different climate scenarios (i.e., RCP 2.6, 4.5, and 8.5) and includes the SLR uncertainty within each of the RCP scenarios (10th, 25th, 50th, 75th, and 90th percentiles). These SLR projections account for the wide range of climate and sea-level uncertainty, allowing for an analysis of SLR housing impairment at the local level, while remaining climate scenario agnostic. We determine the local SLR projections for each property based on the nearest PSMSL tidal station matched to the centroid of the property's United States Postal Service (USPS) ZIP Code Tabulation Area shapefile. These local SLR projections, along with a property's inundation elevation (based on the dual match between NOAA Sea-Level Rise Viewer shapefiles and DEMs), determine the potential year of inundation for an individual property.[3]

The local SLR projections in Kopp et al. (2014, 2017) (K14) are commonly used by NOAA and other scientific agencies in their own local SLR projections (Sweet et al. 2017). The K14 results are a useful baseline for estimating local SLR and the economic consequences. However, K14 SLR projections do not account for factors that may cause accelerated ice sheet loss such as ice shelf hydrofracturing and ice cliff collapse. Deconto and Pollard (2016) (DP16) produce local sea-level projections that account for both the mechanisms of ice sheet hydrofracturing and ice cliff collapse, which are reinforcing factors that accelerate global mean sea-level (GMSL) rise and exacerbate risk to local coastal communities. To provide context, the median projected twenty-first century GMSL rise is expected to reach 0.59 m for the medium GHG concentration scenarios (RCP4.5) in K14 but under DP16, GMSL is expected to rise by 0.91 m. Local, relative SLR differences can be even

[3] With the climate risk field advancing quickly, other groups have started to produce proprietary national level flood risk models (First Street Foundation 2020). However, the granular private label flood data from these providers are only available at cost and use models not available in the public domain. Our SLR risk-matching methods

Footnote 3 (continued)

use publicly available spatial and climate risk datasets, which are freely available to risk practitioners. Thus, each component of our risk methodology is transparent and easy to replicate: (1) Refined measure of property inundation elevation; (2) Estimated timing of SLR inundation; (3) SLR risk accounting for climate uncertainty.

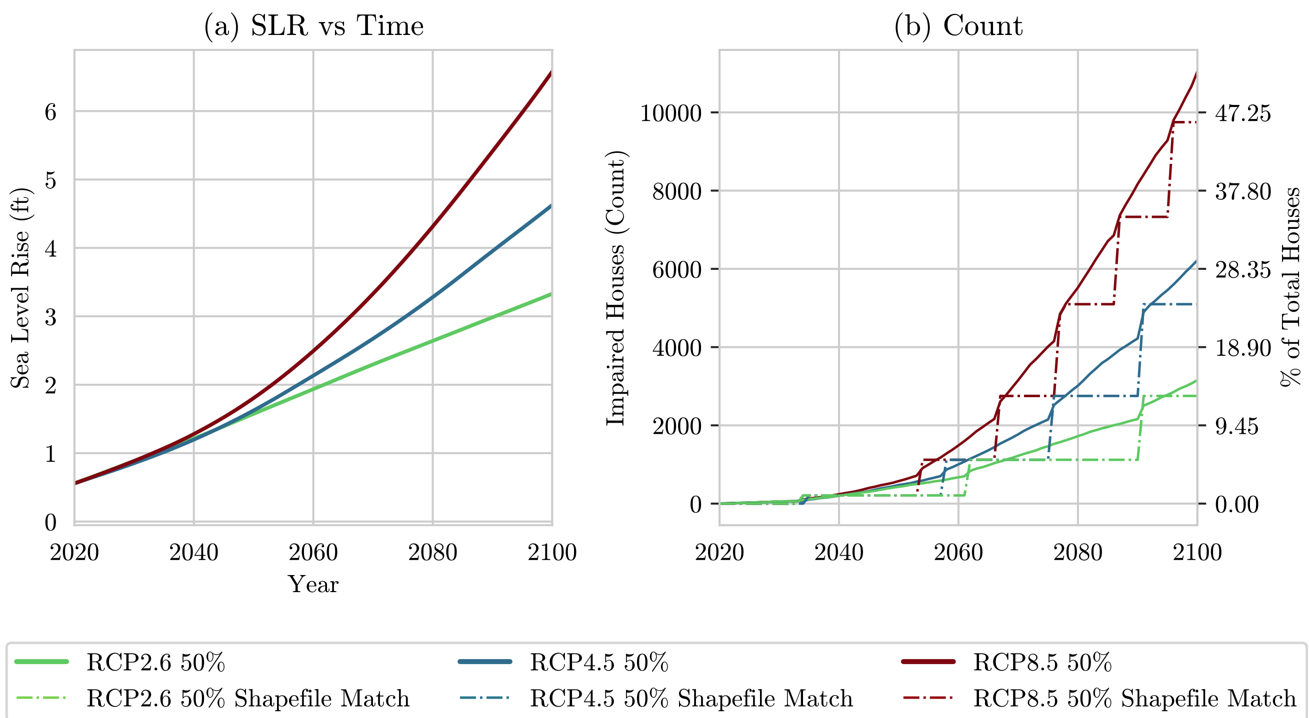



**Fig. 3** As Fig. 2, but for Galveston

more pronounced. We provide housing impairment estimates through 2100 for both K14 and DP16 in our analysis.

## 3 Results

Our results provide a range of housing market impairment estimates for each of the four U.S. coastal metros and the associated timing of those impairments. We chose to highlight these four metros, as they represent geographically diverse areas of the U.S. with unique risk factors (housing market exposure, topography, and local SLR risk), and their heterogeneity illustrates how our methods can be applied at various locations and geographic scales. Figure 4 shows area maps for each of the four metros we analyzed (i.e., Atlantic City, Miami, Galveston, and California: Newport-San Pedro). We focus our impairment estimates on property counts and provide value impairment estimates to better contextualize the economics losses for each metro. Specific impairment analyses (counts and values) for all 17 U.S. coastal metros are provided in the supplemental material section 2.

### 3.1 Atlantic City

Atlantic City, New Jersey is a small metro located on the east coast of the U.S and is expected to experience local SLR that exceeds the global average due to global, regional, and local processes (Amante 2019; Kopp et al. 2017; Deconto and Pollard 2016). Figure 5 (panel a) shows the sea-level rise trajectory for K14 and panel b shows the sea-level rise trajectory for DP16 through 2100. The respective uncertainty bands between 10th and 90th percentiles are shown by the dotted lines. Local sea level is expected to increase by 0.82 m under the medium (RCP4.5) GHG concentration scenarios (50th percentile) for K14 and is expected to increase by 1.2 m under the medium (RCP4.5) GHG concentration scenarios (50th percentile) for DP16. Our housing sample for Atlantic City (and nearby islands) has roughly 35,000 unique single-family houses compared with an estimated population of approximately 62,000 people (Census 2020). Atlantic City is situated on a barrier island, has a relatively high concentration of single-family houses in the metro, a fairly flat topographic gradient, and a large number of houses in areas at risk of SLR (directly on the coast with low elevation). Consequently, we estimate noticeable risk to Atlantic City's single-family housing market through 2100 both in K14 and DP16 (see discussion section for a more detailed description of local factors contributing to these impairments).

We estimate that 3146 properties (range 252 to 14,272) by count and $1.1 Bn. (range $0.1 to $4.7 Bn.) by value will be inundated by 2100 at the 50th percentile of RCP 4.5 under the base case K14 scenario. This equates to 9.0%

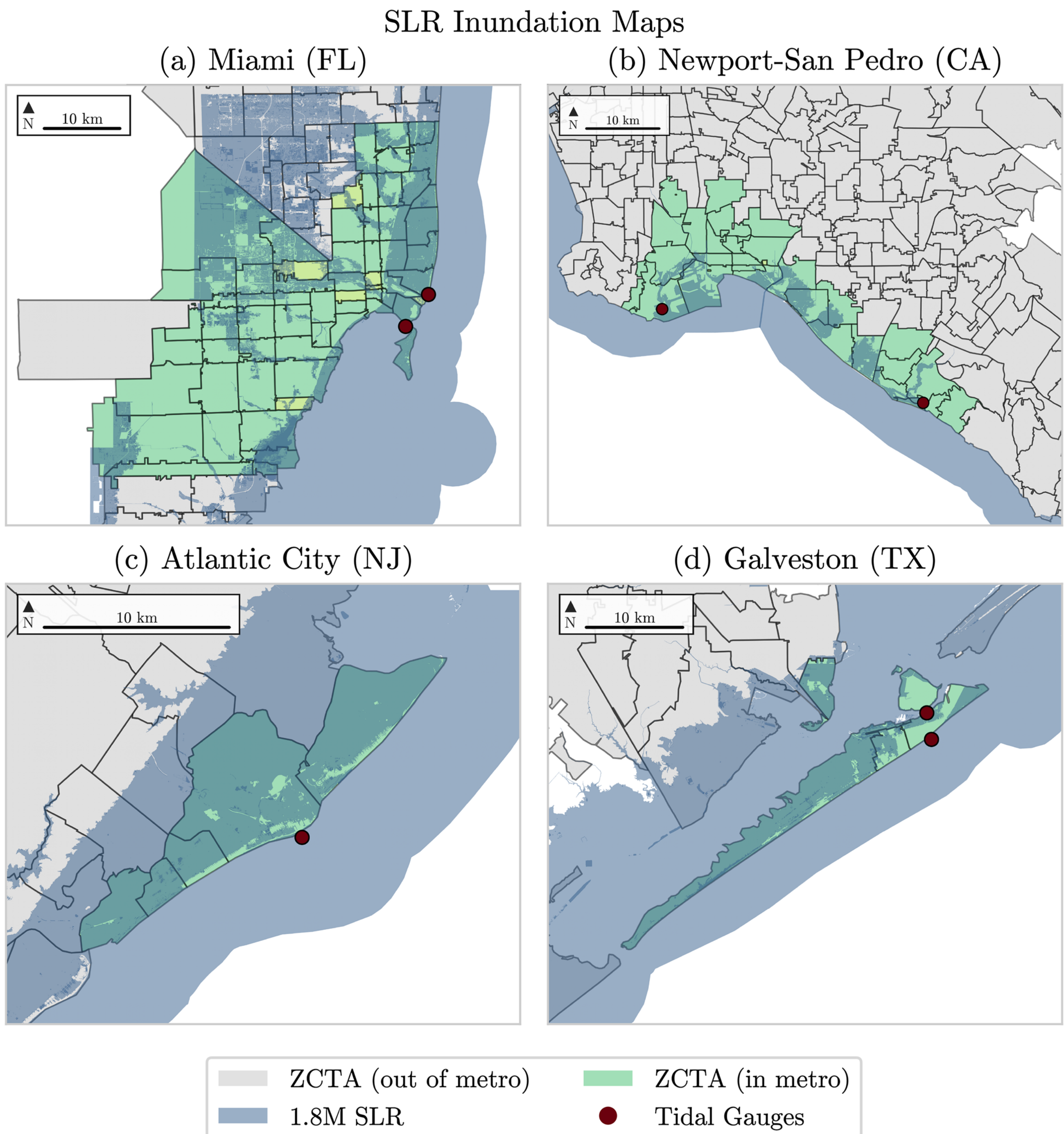



**Fig. 4** Four metro area maps; Metro areas are comprised of USPS Zip Code Tabulation Areas (ZCTA)

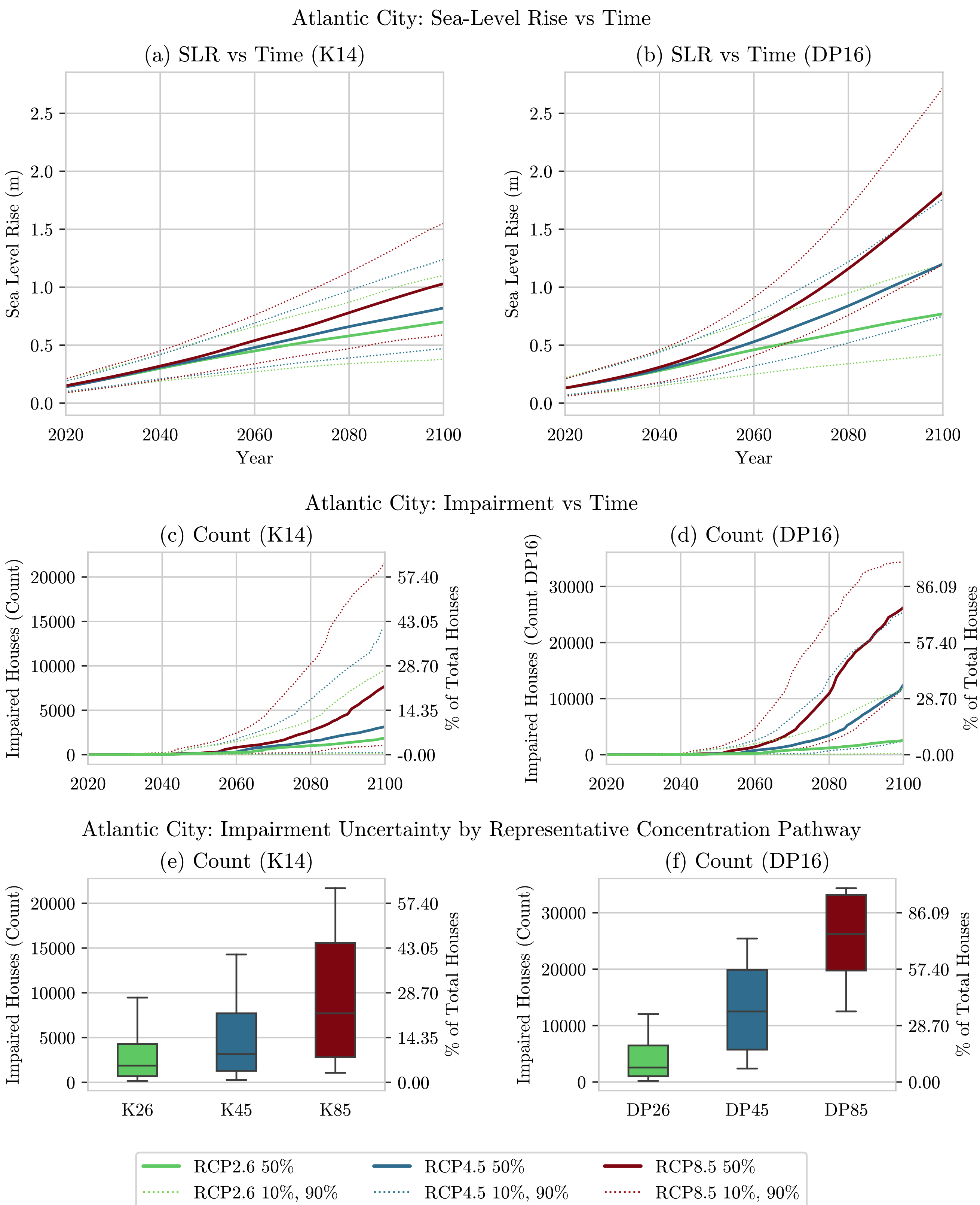
(range 0.7–41.0%) of our 35,000 property sample and 8.2% (range 0.8–35.4%) of those property values under that scenario (tiles c,e).[4]

Comparatively in the more extreme DP16 scenario (accounting for accelerated ice sheet melt), we estimate

[4] We focus our discussion of results on the medium GHG scenario (RCP 4.5) for both K14 and DP16 as recent scientific evidence would suggest that we are closest to the medium scenario (Hausfather and

Footnote 4 (continued)

Peters 2020). For detailed results across all metros and climate scenarios, see supplemental material section 2.


Atlantic City: Sea-Level Rise vs Time
(a) SLR vs Time (K14)
(b) SLR vs Time (DP16)
Sea Level Rise (m)
0.0
0.5
1.0
1.5
2.0
2.5
2020
2040
2060
2080
2100
Year
Atlantic City: Impairment vs Time
(c) Count (K14)
(d) Count (DP16)
Impaired Houses (Count)
Impaired Houses (Count DP16)
% of Total Houses
0
5000
10000
15000
20000
30000
-0.00
14.35
28.70
43.05
57.40
86.09
Atlantic City: Impairment Uncertainty by Representative Concentration Pathway
(e) Count (K14)
(f) Count (DP16)
0.00
K26
K45
K85
DP26
DP45
DP85
RCP2.6 50%
RCP2.6 10%, 90%
RCP4.5 50%
RCP4.5 10%, 90%
RCP8.5 50%
RCP8.5 10%, 90%

◂**Fig. 5** Atlantic City. **a** SLR path and uncertainty bands (10–90th percentile) through 2100 for RCPs 2.6, 4.5, and 8.5 (Kopp et al. 2014)—K14; **b** SLR path and uncertainty bands (10–90th percentile) through 2100 for RCPs 2.6, 4.5, and 8.5 (Deconto and Pollard 2016)—DP16; **c** Inundation path and uncertainty bands (10–90th percentile) for impaired property counts (left vertical axis) and percent of housing market (right vertical axis) for RCPs 2.6, 4.5, and 8.5 (Kopp et al. 2014)—K14; **d** inundation path and uncertainty bands (10–90th percentile) impaired property counts left vertical axis) and percent of housing counts (right vertical axis) for RCPs 2.6, 4.5, and 8.5 (Deconto and Pollard 2016)— DP16; **e** Box and whisker plot for impaired property counts through 2100 (left vertical axis) and share of housing market (right vertical axis) for RCP 2.6, 4.5, and 8.5—lower whisker 10th percentile, lower box 25th percentile, center line median, upper box 75th percentile, and upper whisker 90th percentile for K14; **f** Box and whisker plot for impaired property counts through 2100 (left vertical axis) and share of housing market (right vertical axis) for RCP 2.6, 4.5, and 8.5— lower whisker 10th percentile, lower box 25th percentile, center line median, upper box 75th percentile, and upper whisker 90th percentile for DP16. K26, K45, and K85 refer to results associated with RCP2.6, RCP4.5, and RCP8.5 from Kopp et al. (2014, 2017). DP26, DP45, and DP85 refer to results associated with RCP2.6, RCP4.5, and RCP8.5 from Deconto and Pollard (2016)

noticeably higher housing impairments though 2100. We estimate that 12,494 properties (range 2365 to 25,438) by count and $4.1 Bn. (range $0.8 to $9.3 Bn.) by value will be inundated by 2100 at the 50th percentile of RCP 4.5 under the DP16 scenario. This equates to 35.9% (range 6.8–73.0%) of our 35,000 property sample and 30.7% (range 6.2–70.1%) of those property values under RCP 4.5 (tiles d,f).

### 3.2 Miami

Miami and Miami Beach (combined as "Miami") is a relatively large metro in the southeast U.S. and is also expected to experience local SLR that exceeds the global average due to global, regional, and local processes (Kopp et al. 2017; Deconto and Pollard 2016). Figure 6a shows the sea-level rise trajectory for K14 and panel b shows the sea-level rise trajectory for DP16 through 2100. The respective uncertainty bands between 10th and 90th percentiles are shown by the dotted lines. Local sea-level is expected to increase by 0.65m under the medium (RCP4.5) GHG concentration scenario (50th percentile) for K14 and is expected to increase by 1.02m under the medium (RCP4.5) GHG concentration scenario (50th percentile) for DP16. Our housing sample for Miami has roughly 330,000 unique single-family houses and an estimated population of approximately 525,000 (Census 2020). Miami has a relatively high concentration of single-family houses, flat topography with numerous low-lying areas, and a concentration of homes in areas prone to SLR inundation (on the coast at lower elevations). We estimate moderate risk to Miami's single-family housing market through 2100 under K14 and noticeably higher risk under DP16 (see discussion section for a more detailed description of local factors contributing to these impairments).

We estimate that 588 properties (range 20 to 5857) by count and $0.7 Bn. (range $0.04 to $5.9 Bn.) by value will be inundated by 2100 at the 50th percentile of RCP 4.5 under the base case K14 scenario. This equates to 0.2% (range 0.01–1.8%) of our 330,000 property sample and 0.5% (range 0.03–4.5%) of those property values under that scenario (tiles c,e).

Comparatively in the more extreme DP16 scenario, we estimate higher housing impairments through 2100. We estimate that 6321 properties (range 347 to 27,522) by count and $6.4 Bn. (range $0.5 to $23.2 Bn.) by value will be inundated by 2100 at the 50th percentile of RCP 4.5 under the DP16 scenario. This equates to 1.9% (range 0.1–8.3%) of our 330,000 property sample and 4.9% (range 0.3–17.6%) of those property values under RCP 4.5 (tiles d,f).

### 3.3 Galveston

Galveston is a small metro on the Gulf Coast of U.S. that is also expected to experience local SLR that exceeds the global average due to global, regional, and local processes (Kopp et al. 2017; Deconto and Pollard 2016). Figure 7a shows the sea-level rise trajectory for K14 and panel b shows the sea-level rise trajectory for DP16 through 2100. The respective uncertainty bands between 10th and 90th percentiles are shown by the dotted lines. Local sea level is expected to increase by 1.04 m under the medium (RCP4.5) GHG concentration scenario (50th percentile) for K14 and is expected to increase by 1.41 m under the medium (RCP4.5) GHG concentration scenario (50th percentile) for DP16. Our housing sample for Galveston has roughly 21,000 unique single-family houses compared with an estimated population of approximately 54,000 (Census 2020). Galveston is on a barrier island and has a high concentration of single-family homes. Galveston's flat topography with numerous low-lying areas and concentration of homes in areas prone to SLR inundation (on the coast at lower elevations), put the city's single-family housing market at high risk from SLR inundation through 2100 both under K14 and DP16 (see Discussion section for a more detailed description of local factors contributing to these impairments).

We estimate that 3275 properties (range 1502 to 6027) by count and $1.1 Bn. (range $0.5 to $1.9 Bn.) by value will be inundated by 2100 at the 50th percentile of RCP 4.5 under the base case K14 scenario. This equates to 15.5% (range 7.1–28.5%) of our 21,000 property sample and 20.3% (range 9.8–34.3%) of those property values under that scenario (tiles c, e).

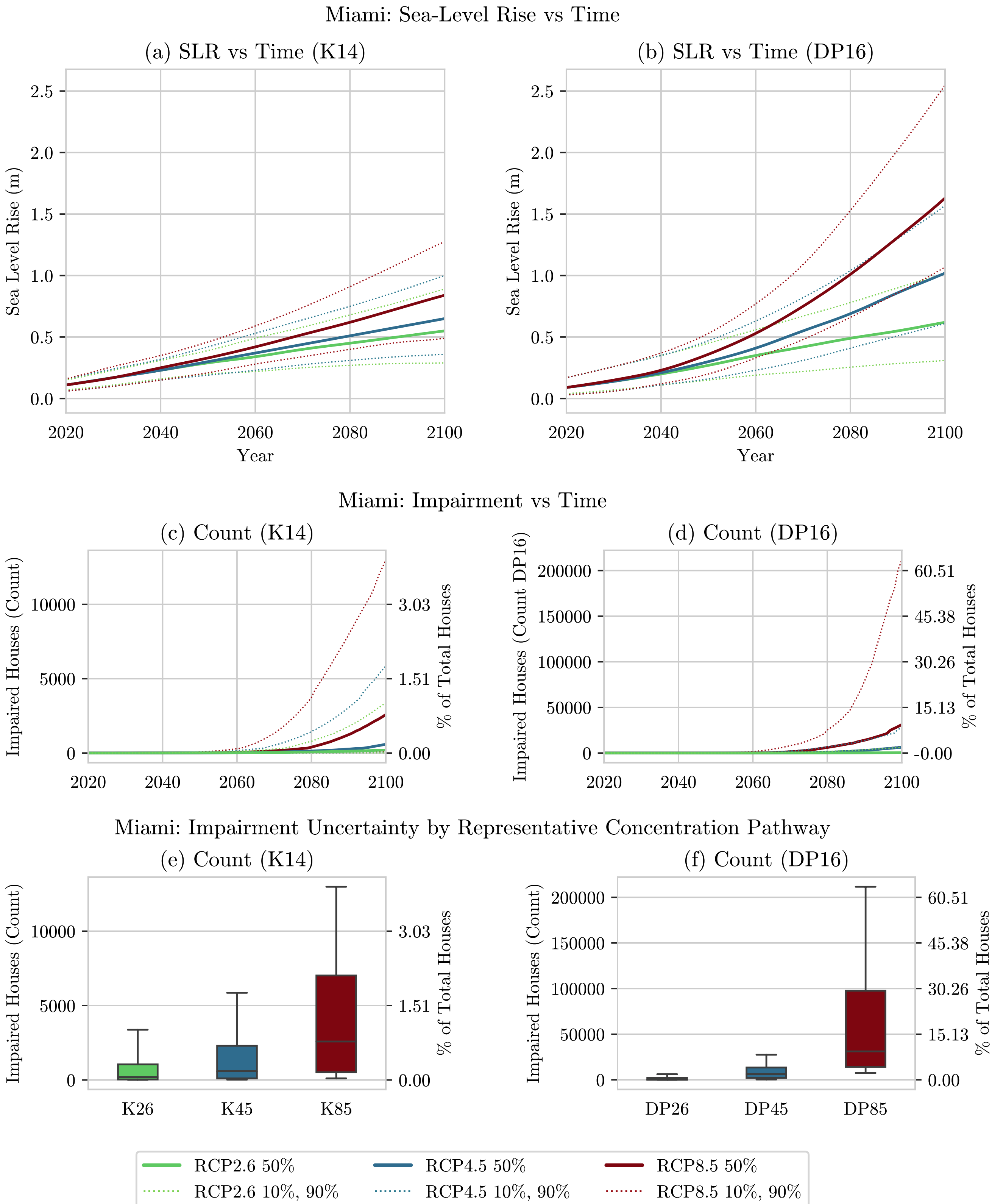



**Fig. 6** As Fig. 5, but for Miami

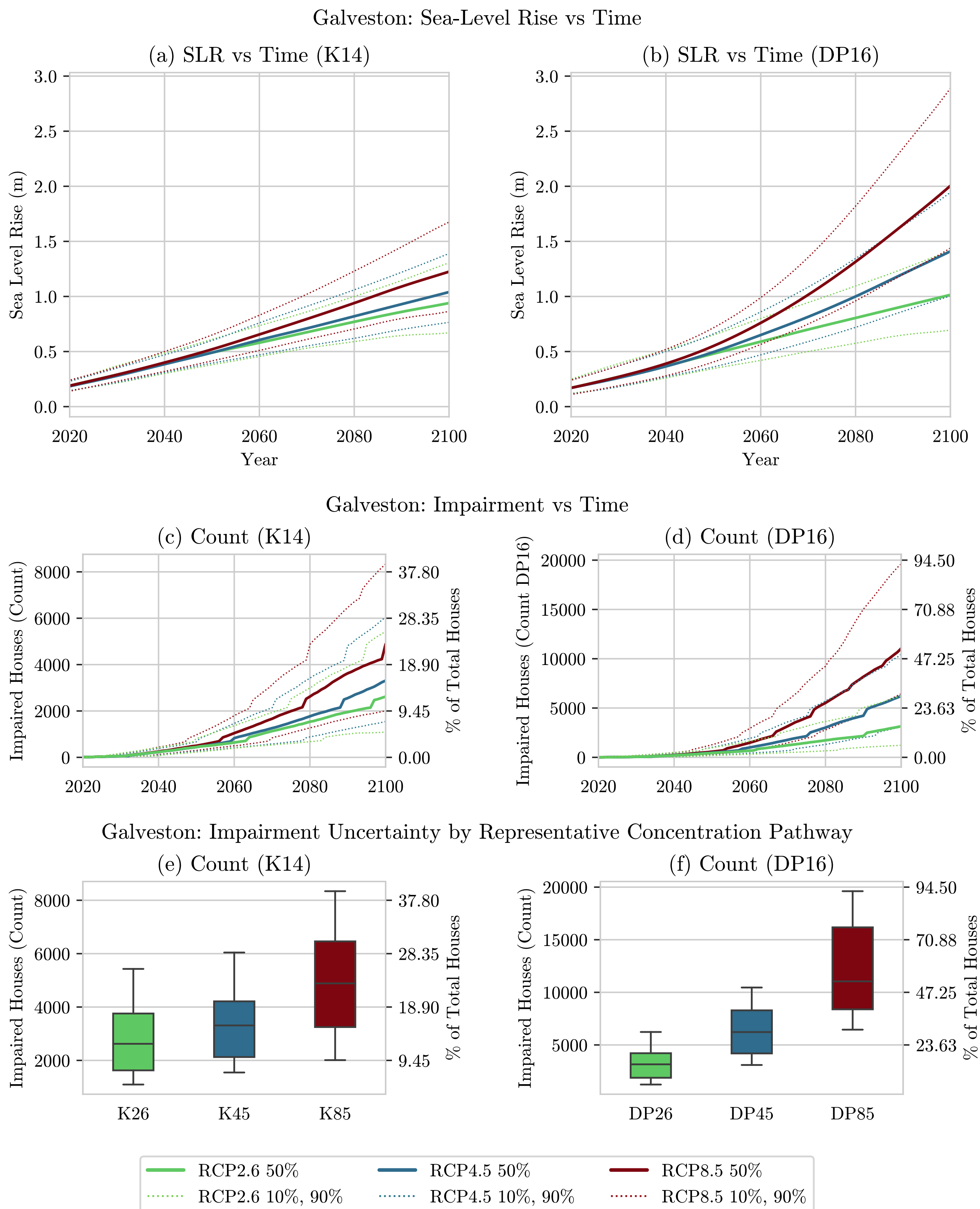



**Fig. 7** As Fig. 5, but for Galveston

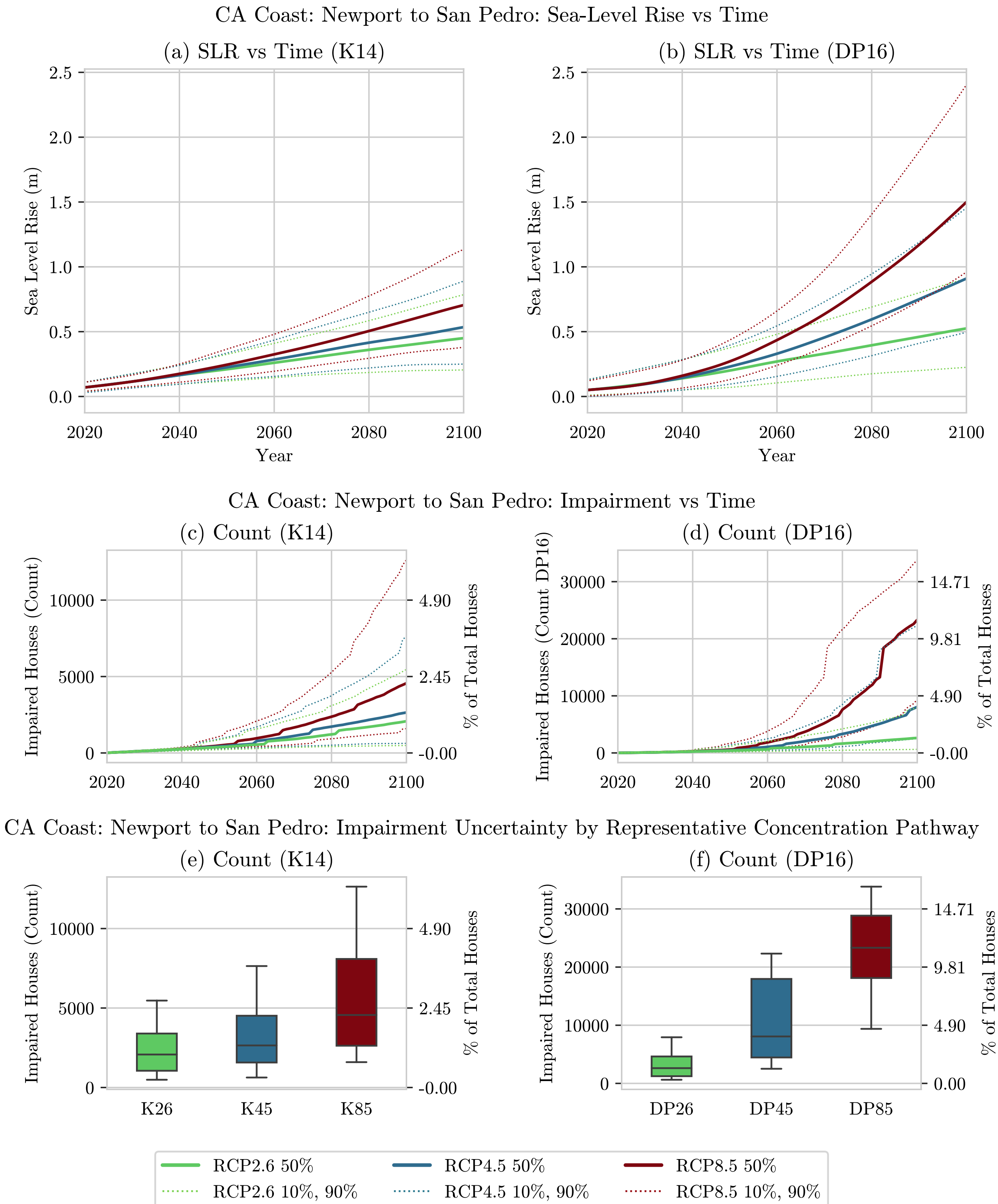



**Fig. 8** As Fig. 5, but for California: Newport–San Pedro

Comparatively in the more extreme DP16 scenario, we estimate much higher housing impairments through 2100. We estimate that 6181 properties (range 3040 to 10,447) by count and $1.9 Bn. (range $1.1 to $3.3 Bn.) by value will be inundated by 2100 at the 50th percentile of RCP 4.5 under the DP16 scenario. This equates to 29.2% (range 14.4–49.4%) of our 21,000 property sample and 35.0% (range 19.2–59.1%) of those property values under RCP 4.5 (tiles d,f).

### 3.4 California: Newport–San Pedro

California: Newport–San Pedro, is expected to experience local SLR that is near the global average (Kopp et al. 2017; Deconto and Pollard 2016). Figure 8 (panel a) shows the sea-level rise trajectory for K14 and panel b shows the sea-level rise trajectory for DP16 through 2100. The respective uncertainty bands between 10th and 90th percentiles are shown by the dotted lines. Local sea level is expected to increase by 0.54 m under the medium (RCP4.5) GHG concentration scenario (50th percentile) for K14 and is expected to increase by 0.91 m under the medium (RCP4.5) GHG concentration scenario (50th percentile) for DP16. Our housing sample for the California: Newport–San Pedro metro has roughly 204,000 unique single-family houses compared with a population nearing one million people (Census 2020). This area of the California coast has some low-lying beaches and a steep topographic gradient moving inland. With a relatively low concentration of single-family homes concentrated in areas prone to SLR inundation (on the coast at lower elevations), the single-family housing market in this area of the California coast is at a relatively lower risk from SLR inundation through 2100 under K14 compared to other metro areas analyzed such as Galveston or Atlantic City. However, our analysis does indicate markedly higher risk in the DP16 scenario (see discussion section for a more detailed description of local factors contributing to these impairments).

We estimate that 2493 properties (range 395 to 7583) by count and $2.7 Bn. (range $0.4 to $8.1 Bn.) by value will be inundated by 2100 at the 50th percentile of RCP 4.5 under the base case K14 scenario. This equates to 1.2% (range 0.2–3.7%) of our 204,000 property sample and 1.7% (range 0.3–4.9%) of those property values under that scenario (tiles c,e).

Comparatively in the more extreme DP16 scenario, we estimate much higher housing impairments through 2100. We estimate that 7874 properties (range 2202 to 22,303) by count and $8.4 Bn. (range $2.4 to $21.7 Bn.) by value will be inundated by 2100 at the 50th percentile of RCP 4.5 under the DP16 scenario. This equates to 3.9% (range 1.1–10.9%) of our 204,000 property sample and 5.1% (range 1.5–13.2%) of those property values under RCP 4.5 (tiles d,f).

## 4 Discussion

Overall, our analysis provides an estimate of SLR risk to single-family home markets, across a series of geographically diverse metros. Although all four metros highlighted show at least some risk from SLR, there are noticeable differences, with metros like Galveston and Atlantic City facing much greater risks than areas like southern California. Our analysis provides conservative lower-bound estimate of SLR impairments for a number of reasons. First, we restrict our housing sample to single family, townhouses, and buildings with four or less units. Roughly 17% of residences in the U.S. are 5 units or greater (i.e., condominiums or multifamily), which can have higher values than housing properties of four units or fewer. In some states, such as Florida or California, the proportion of residences that are condominiums or multifamily exceed the national average, ranging from 20 to 30% (Census 2017), and proportions for cities like Miami are larger yet. Additionally, our analysis focuses solely on the direct economic cost from terminal impairment from local SLR, which is just one component of total costs from rising seas. Increases in nuisance flooding and storm surge inundation enhanced from SLR, as well as changing risk perceptions to SLR as it is occurring, would substantially increase the count of units considered subject to impairment and add additional costs associated with rising seas (Amante 2019; Bernstein et al. 2019; Kirezci et al. 2020).

Even with these conservative estimates, we identify noticeable SLR risk for some metros (i.e., Galveston and Atlantic City) in the base case K14 scenario. Accounting for accelerated ice sheet contributions to SLR (DP16), all four metros highlighted show much larger SLR risk through 2100. Ultimately, our analysis provides useful insights on SLR impairment risk and differences across U.S. coastal metros. Furthermore, we generate an understanding of risk asymmetry across climate change scenarios. Lastly, and most importantly, our SLR risk-matching methodology using free, publicly available data provides estimates for the timing of SLR impairment, which can be useful for city planners, governments, and other climate risk practitioners.

### 4.1 Housing market exposure and local factors

Our analysis indicates that proximity of low-lying areas to the coast, the structure of coastal housing markets and the locations of single-family houses all contribute to housing market impairment within a city. Proximity to the coast has generally been considered a positive amenity that typically drives up home prices (Benson et al. 1998). However, as expected, the proximity of single-family houses to the coast, especially in low-lying areas along the Atlantic and Gulf Coasts, makes houses more prone to SLR inundation. For example, in our Atlantic City housing sample, 27,500 houses (79% of our Atlantic City housing sample) reside at an elevation within 6ft of the current sea level. Comparatively, Miami has roughly 49,600 houses (15% of our Miami housing sample) that reside at an elevation within 6 ft of the current sea level. Compared to Miami, Atlantic City's concentration of properties in close proximity to low-lying areas clearly suggests the likelihood of greater relative risk from SLR inundation, which is precisely what we observe in our results.

Although more properties at or near the coast are linked to greater relative risk from SLR, using cursory measures of "at risk," such as matching to 6 ft inundation shapefiles, are limited in assessing which properties will actually be affected by local SLR in the coming decades. For our four metros, the share of our housing sample within the 6 ft inundation shapefiles are Atlantic City (79%), Miami (15%), Galveston (47%), and California: Newport–San Pedro (14%). However, these cursory estimates do not incorporate local factors that influence the risk of properties to sea-level rise. Under RCP4.5 (K14; 50th percentile), the share of properties we estimate as inundated through 2100 are Atlantic City (9%), Miami (0.2%), Galveston (15.5%), and California: Newport–San Pedro (1.2%). Simply by comparing these summary statistics, we see that the cursory risk measures (SLR shapefiles alone) are limited when assessing actual risk. For example, Atlantic City (79%) has a much larger share of properties within the 6ft inundation shapefile compared to Galveston (47%), but the share of properties at risk under RCP4.5 (K14; 50th percentile) is higher in Galveston (16%) than Atlantic City (9%). These differences are attributable to local SLR projections as Atlantic City has a projected 2.7 ft SLR through 2100 under RCP4.5 (K14) compared to 3.4 ft in Galveston, and to the locations and elevations of individual properties in each metro. Ultimately, our results demonstrate that practitioners should account for local factors (e.g., housing locations, local topography, and local SLR) to comprehensively assess SLR risk in their local area.

### 4.2 Uncertainty and risk asymmetry

Two consistent features within our results are large uncertainties in housing market impairment and asymmetry of impairment risk. First, our results generally indicate a larger impairment uncertainty within each GHG concentration scenario than the uncertainty we find between each of the GHG scenarios (Figs. 5, 6, 7, and 8; tile). Using Atlantic City's high GHG scenario (RCP8.5) for K14 as an example, the range of impairment risk (90th–10th percentiles) is 20,600 units impaired (59% of total market by count), whereas the range of impairment risk is 5800 units impaired (17% of total market by count) between GHG concentration scenarios (RCP2.6 to RCP8.5 at the 50th percentile). This relationship of greater uncertainty *within* each GHG scenario compared to across GHG scenarios is generally consistent whether we analyze SLR risk in the base case (K14) or the accelerated ice sheet melt scenario (DP16). This speaks to the critical importance of accounting for SLR uncertainty distributions when estimating housing impairments *within* a given RCP scenario. A housing impairment analysis that focuses on median values of local SLR projections associated with each RCP scenario overlooks a highly important source of uncertainty.

Second, our results generally indicate asymmetric risk to the upside (positive skewness) across the three GHG concentration scenarios (RCPs 2.6, 4.5, and 8.5), except in some of the most at-risk metros under the most extreme scenarios. In general, when we review the box and whisker impairments, the upper portion of the box (50th to 75th percentile) is much larger than the lower portion of the box (25th to 50th percentile). In addition, the upper tails (to the 90th percentile) are typically longer than the lower tails (to the 10th percentile) (Figs. 6, 7, and 8; tiles e,f), indicating strong positive risk asymmetry, which suggests more potential impairment under a given GHG scenario than the median percentiles would indicate by themselves. For example, we witness this positive skewness (i.e., larger upper boxes and longer upper tails) for Miami (Fig. 6) under all GHG scenarios (both for K14 and DP16).

However, there are exceptions to the generally observed positive asymmetry. For example, we witness positive skewness across all GHG scenarios in K14 for Atlantic City (Fig. 5). However, in the most extreme SLR scenarios (i.e., RCP8.5 in DP16), our results indicate negative skewness or a left tail risk. Under the most extreme case SLR case, Atlantic City begins to run out of homes to impair (i.e., most of the city is under water at the 90th percentile for RCP 8.5 under DP16), due to Atlantic City's low-lying topography and the city's housing market being so close to the coast. Outside of these types of edge cases (e.g., most at-risk metros in the most extreme scenarios), our results generally indicate positive asymmetry of SLR risk.

Observed positive risk asymmetry is important as it provides motivation for cuts in GHG emissions sooner rather than later, which may temper climate risk and nudge the global climate towards lower risk GHG concentration scenarios (Hausfather and Peters 2020; IPCC 2021 AR6). Future energy and carbon policies aside, taking into consideration the risk asymmetry is also an important factor when assessing the overall risks coastal communities face from SLR through the end of the century.

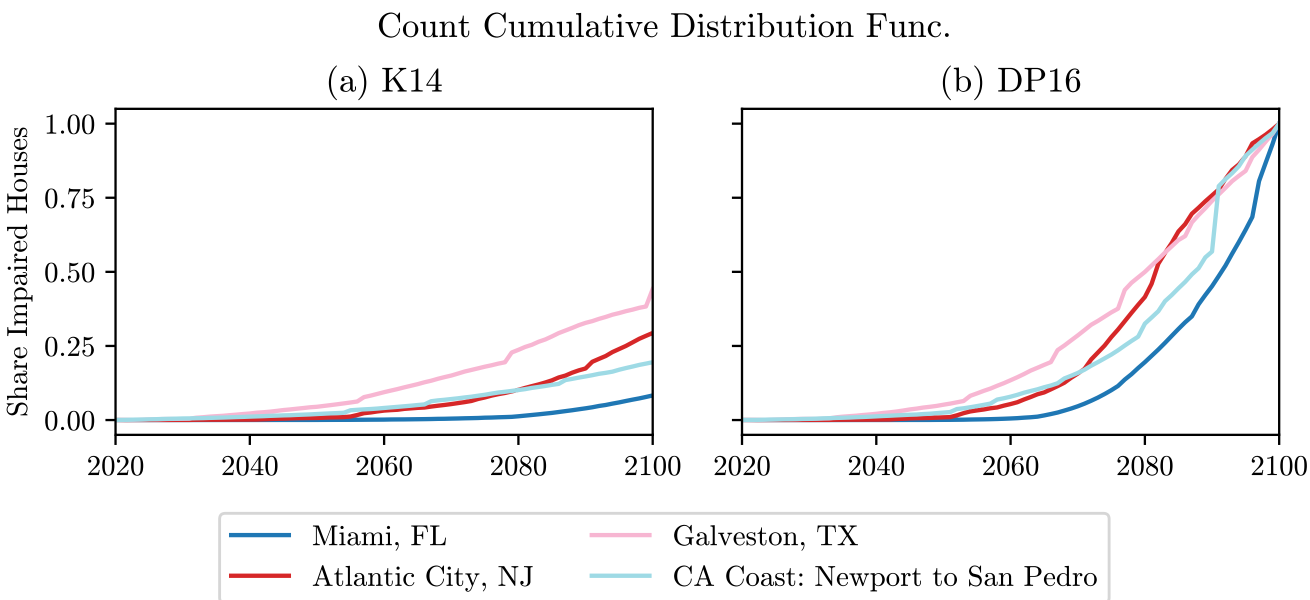



**Fig. 9** Cumulative distribution function (CDF) of Housing Impairment under RCP4.5 (Kopp et al. 2014, 2017; Deconto and Pollard 2016); Left side: CDF for property impairment counts (K14); Right side: CDF for property impairment counts (DP16).; *Note* (**a**) values are scaled to the cumulative values in panel (**b**), and therefore do not sum to 1

### 4.3 Policy implications, inundation timing, and economic risk

Importantly, our analysis estimates the timing of housing impairment exposures from SLR at the property and metro level. These inundation timing estimates can be of value for city planners and local governments charged with implementing longer-term, risk-mitigating physical infrastructure investments (e.g., levees, seawalls, etc.) or other climate policy actions (e.g., urban planning decisions or carbon policies). Both of these actions require a robust understanding and accounting of risks over time, to the best extent possible, which is one of the key goals of our research. By analyzing a diverse set of metros across the U.S., our research identifies the unique timing of risks an area may be facing from local sea-level rise. As an illustrative example, Fig. 9 shows the cumulative median housing impairment (counts and values) under the medium GHG concentration scenario (RCP4.5) through 2100 for Atlantic City, Miami, Galveston, and California: Newport–San Pedro under K14 (tile a) and DP16 (tile b). Tile a (K14) is scaled to the total impairment witnessed under tile b (DP16, the accelerated ice sheet scenario). For all four metros, property impairments are roughly doubled in DP16 compared to K14. Regardless of the magnitude of impairment, these cumulative distribution functions provide an insight into when SLR risk may occur in a given metro relative to other metros. For example, in Galveston, roughly 12% of properties are inundated by 2050 under K14 compared to 11%, 5%, 2% of properties being inundated by 2050 for California: Newport – San Pedro, Atlantic City and Miami, respectively. Comparing Galveston and Miami, for example, it is evident that SLR impairment takes place much sooner in Galveston, while Galveston and Atlantic City face a more similar impairment trajectory (not surprisingly as they are both barrier islands, subject to similar risks).

We also note that the differences between the K14 and DP16 impairment scenarios occur largely after 2060. Thus, it is important for planners and decision makers to recognize that relatively low levels of SLR from now until 2060 would not necessarily indicate that the beginning of accelerated ice sheet loss is not, in fact, occurring. Lack of recognition of these longer-term non-linear acceleration dynamics could distort important SLR-related decisions and needs to be carefully avoided to enable well-founded adaptive risk management. This highlights the possibility of timing mismatches between the perception of risk—and associated mitigation or adaptation strategies—and realized risk, which has been called the “tragedy of the horizon” (Carney 2015).

The relative timing of SLR risk is important for city planners, as this information can help improve decision making regarding where and when infrastructure could be built to reduce risks from SLR. By producing impairment estimates over time, we provide a measure of property exposure and cost from SLR inundation that urban planners can compare to the benefits of mitigation (balancing costs and benefits), helping them determine optimal mitigation policies and timing trajectories for their specific metro areas (Guthrie 2020).

Perhaps a less obvious implication for our research is the risk to city finances or national disaster programs from future SLR inundation. Our time series of local impairment estimates provide a rough proxy for erosion of the tax base over time, due to SLR in each city evaluated. As neighborhoods within a city face SLR inundation, out-migration may increase in the most at-risk areas. This out-migration, may in turn, erode the tax base for a city at a time when it needs to increase spending on risk mitigating infrastructure. On a national scale, these same dynamics pose potential problems for the viability of disaster relief programs. As sea-level rises and large areas of coastal cities are at greater risk from nuisance flooding and storm surge inundation, the cost to national flood insurance programs, as well as disaster relief programs, may also rise. Similar to local municipalities, higher costs may put significant strain on these national programs.

Finally, our results on housing market value at risk have links to the financial sector, bond markets, insurance companies, and financial regulatory agencies. Coincident with the housing value at risk from SLR is the potential strain that may emerge in home mortgage markets. Roughly 70% of homeowners have a mortgage on their property (Zillow 2013), and a negative effect on housing values may cause disruptions to home mortgage markets. Our results indicate that a majority of risk from SLR takes place toward the end of the century, which is outside the window of a standard 30-year mortgage. However, if these risks were unexpectedly embodied in housing values, this may reduce the creditworthiness of some outstanding mortgages as the loan to value ratios might decline (Keys and Mulder 2020; Keenan and Bradt 2020).[5] Even if a house is not currently prone to coastal inundation, future SLR and changes in risk perceptions may pose challenges for selling homes, refinancing a mortgage, or obtaining insurance due to concerns about the viability of that property. These secondary and more investment focused risks may be of concern to homeowners, lenders, and financial regulators.

## 5 Summary

We estimate a range of housing market value impairments at the property and metro level for select U.S. coastal metros through 2100, accounting for local topography and local SLR estimates that incorporate several sources of climate uncertainty. We utilize a novel spatial matching methodology, which allows us to estimate the timing of SLR inundation at the property level with refined temporal granularity. These property impairment estimates are then summed to create metro level SLR impairment estimates over time.

With nearly 40% of the U.S. population living along the coast, SLR is a substantial threat to coastal communities. Our analysis provides insight into housing market SLR risk for major coastal metros. These results provide a useful model for the timing of losses and asymmetry of risk from SLR inundation. Our risk-matching methods could be used by other researchers and practitioners to refine previous loss estimates for at-risk properties, assess SLR risk in other coastal markets (e.g., mortgages, commercial real estate, etc.), or be used to assess SLR risk for various housing strata and populations (e.g., owner occupied vs. renters, income level, etc.). All of these future research topics may benefit from the methodological approach outlined in this paper.

In the near term, our methods could also be utilized by policy makers, city officials, investors, and bankers in cost-benefit decision making related to mitigation, adaptation, and remediation policies at the local and national levels. Ultimately, our research provides a way (using publicly available data) to measure the direct economic costs from SLR inundation within coastal housing markets. Quantifying the range of future housing market impairment is a first step in mitigating economic risks from SLR inundation. Our conservative impairment estimates, which represent only a portion of the total housing market at risk from SLR inundation, contribute to the proper accounting of all climate-related risks.

**Electronic supplementary material** The online version of this article (https://doi.org/10.1007/s10669-022-09842-6) contains supplementary material, which is available to authorized users.

## Declarations

**Conflict of interest** The authors declare that they have no conflict of interest.

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