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Sea level rise impacts on residential real estate value in Hawaiʻi

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Abstract
This paper examines the impact of sea level rise (SLR) exposure on residential property values in Hawaiʻi by employing a repeat sales methodology on coastal properties transacted between 2000 and 2022. Our analysis reveals that properties exposed to a projected 3 ft of SLR appreciate by 0.8% less annually than unexposed properties. This depreciation effect is particularly pronounced on Oʻahu (-1.4% annually) and Hawaiʻi Island (-1.1% annually). The discount is in part explained by local buyers, with properties they purchase incurring a significantly higher annual penalty compared to those acquired by non-local buyers. Seawalls are associated with higher home appreciation rates; however, they do not offset the penalty associated with SLR exposure. Our work provides new evidence on the forward-looking capitalization of climate change exposure into housing markets, demonstrating that buyer origin—potentially representing differing beliefs or knowledge of risk—has a significant influence.

Keywords Sea level · Housing markets · Climate change · Repeat sales · Hawaiʻi

1 Introduction

Climate change is causing rapid sea level rise (SLR) across the globe (IPCC 2023). The IPCC (2021) predicts 2.1–3.2 ft of SLR, relative to pre-industrial levels, under business-as-usual emissions by 2100. Values substantially more than 3.2 ft are also possible given

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uncertainties in ice sheet dynamics (Church et al. 2013; IPCC 2021; Nicholls and Cazenave 2010). Under the high emissions Representative Concentration Pathway (RCP 8.5), 12–20% of global GDP, equating to \$8.8–14.2 trillion (\$2011), could be at risk by 2100 due to SLR and episodic coastal flooding (Kirezci et al. 2020). Impacts of SLR on coastal communities include, for example, increased occurrence, severity, and duration of coastal flooding, groundwater inundation, increased storm surges, exacerbated coastal erosion, and community displacement (Anderson et al. 2015; Oppenheimer et al. 2019; Nicholls et al. 2007; Rotzoll et al. 2013; Sweet et al. 2014).

Hawai‘i offers an interesting case study in assessing the economic implications of SLR due to its heightened exposure as an island state with substantial coastal development adjacent to sandy beaches. This study builds on a narrower case study from the island of O‘ahu that found a negative and statistically significant relationship between SLR exposure and real estate transactions between 2014 and 2019. This study expands the prior O‘ahu case study to the entire State of Hawai‘i, leveraging a more comprehensive real estate transactions dataset. This dataset also enables an improved econometric identification strategy by adopting a repeat-sales methodology that minimizes omitted variable bias due to the potential exclusion of time-invariant property characteristics. In addition, we control for differential time trends based on location and coastal proximity to ensure that identification stems from the differences in appreciation trends between at-risk and not-at-risk properties over time. We investigate how the market prices SLR risk at various exposure levels, from 1 to 6 ft, to capture long-term risk perceptions. Additionally, with this dataset, we can examine heterogeneity in risk-based pricing across counties, property types, and buyer characteristics (local and non-local).

Our analysis reveals that, on average, properties exposed to 3 ft of projected SLR experience a 0.8% lower annual appreciation rate than unexposed properties. This effect is primarily driven by O‘ahu and Hawai‘i islands, with yearly depreciation rates of 1.4% and 1.1%, respectively. There is no significant difference in exposure penalty between multifamily dwellings and single-family homes. We find weaker evidence for Maui and Kaua‘i, possibly due to their higher proportion of out-of-state buyers.[1] Notably, local buyers appear more attuned to SLR risks, with properties purchased by locals facing a 1.4% annual exposure penalty at 2 ft of SLR, compared to only 0.7% for non-local buyers. Lastly, seawalls are associated with higher property appreciation rates of 1–1.3% annually but do not significantly mitigate the SLR exposure penalty. Our results suggest that climate change impacts are being capitalized into residential real estate values in Hawai‘i, albeit likely more slowly than coastal managers might prefer for disincentivizing investment in sensitive and high-risk coastal areas (Bremer et al. 2022). These results can help to inform cost–benefit analyses of climate adaptation interventions.

[1] For this study, Maui refers to Maui County, the terms O‘ahu and Honolulu County are used interchangeably, and Hawai‘i island, also known as the Big Island, refers to Hawai‘i County. Hawai‘i refers to the State of Hawai‘i.

2 Literature review

2.1 SLR impacts in Hawai‘i

In Hawai‘i, SLR of 3.2 ft is projected to cause $19 billion ($2013) in statewide damages, including structural and land degradation, displacement of nearly 20,000 residents, flooding of approximately 38 miles of primary roadways, and inundation of around 6,500 buildings (Hawai‘i Climate Change Mitigation and Adaptation Commission 2017). Like many other coastal regions, the Hawaiian Islands experience natural erosion into the ocean, while the effects of SLR have intensified this risk (Tavares et al. 2020). Approximately 34% of the state’s coastline faces moderate to high exposure risk to coastal erosion, with Maui, O‘ahu, and Kaua‘i being the most vulnerable (Onat 2018). The legal definition of shoreline in Hawai‘i is the highest wash of waves, unlike the mean high tide line in most other coastal states. Beaches are considered a public trust resource in the State Constitution (Vance and Wallsgrove 2006). As SLR causes the shoreline to recede inland, private coastal properties lose land to the dynamic, public beach (Vance and Wallsgrove 2006). While more than 13 miles of beaches across the state have already eroded, studies of historical shoreline change show that 70% of beaches on Kaua‘i, O‘ahu, and Maui shorelines are receding landward (Fletcher et al. 2012; Hawai‘i Climate Change Mitigation and Adaptation Commission 2017). Despite coastal laws that prioritize the protection of beaches, properties have been granted the ability to build seawalls that serve to protect private property but at the expense of the public beach (Summers et al. 2018); however, Act 16 (2020) amended State law (HRS Ch. 205A) to end this practice. Without the ability to build legal seawalls, some homeowners have resorted to illegal protective measures such as building unpermitted seawalls or moving sand (Cocke 2021, 2022). Coastal hardening provides some level of protection to landward areas (though not from groundwater inundation), but also potentially causes increasing erosion through a process called “flanking” to neighboring properties (Romine and Fletcher 2012).

Figure 1 provides a visual depiction of the effects of coastal erosion and SLR in Hawai‘i, highlighting the vulnerability of coastal homes to encroaching waters and the urgent need for adaptation measures.

2.2 SLR and property values

There is growing research suggesting a negative relationship between SLR exposure and relative property values, with considerable regional variation. Prior research indicates even minimal exposure to high tide flooding impacts property values and rental rates in the continental US (Lee and Zheng 2023; Lee 2023). Bernstein et al. (2019) applied residential real estate transaction data in the continental United States between 2007 and 2019 and found an average 7% decline in coastal property values that will be exposed to 6 ft of SLR. Keys and Mulder (2020) identified a 5% discount for SLR-exposed Florida housing between 2018 and 2020. McAlpine and Porter (2018) reported a loss of over $465 million in market value from tidal flooding in Miami-Dade County between 2005 and 2016. Fu et al. (2016) projected real estate market losses by 2050 exceeding $300 million in Hillsborough County and $900 million in Pinellas County under 3 ft of SLR. Tyndall (2021) found that Long Island housing exposed to 6.6 ft of SLR experienced 1% lower appreciation rates between 2000 and 2017.

Fig. 1 Impacts of SLR and coastal erosion on beachfront properties. Photo credit: Conrad Newfield

However, some studies have found no significant relationship between SLR exposure and housing prices (Ann Conyers et al. 2019; Murfin and Spiegel 2020). This divergence in real estate markets' reaction to SLR underlines the complexity of the issue and underscores the need for more granular and region-specific studies to generate a more nuanced understanding of the SLR-property value relationship.

Relevant to the case of Hawai'i, Tarui et al. (2023) employed a hedonic analysis to investigate the impact of SLR exposure on residential property values for the island of O'ahu. Analyzing property transaction data from 2014–2019, the study found that properties exposed to 3.2 ft of SLR sell at a 9–14% discount compared to comparable unexposed properties. This study builds on this prior approach with an improved, state-wide dataset as well as an upgraded identification strategy using a repeat sales approach.

2.3 Climate risk beliefs and property values

Emerging research on climate risk beliefs sheds light on the varied housing market responses to SLR exposure. Bernstein et al. (2019) document that the SLR discounts are larger in markets with sophisticated investors (e.g., non-owner-occupied properties), while community beliefs about SLR risk primarily influence pricing for less sophisticated investors (e.g., owner-occupied properties). Extending this work, Bernstein et al. (2022) show that partisan differences in climate beliefs generate substantial residential sorting patterns. Republicans are significantly more likely than Democrats to own SLR-exposed homes, with a Republican-Democrat ownership gap of 4–5 percentage points for moderately exposed properties, rising to 10 percentage points for highly exposed ones. This gap more than doubled between 2012 and 2018 and persists after conditioning on property characteristics, local amenities, and individual demographics. The durability and magnitude of these patterns suggest that differences in climate beliefs meaningfully influence long-horizon financial decisions.

Gallagher (2014) found that flood insurance take-up spikes immediately after a flood event but steadily declines to baseline levels within several years as residents appear to "forget" past flood information. Crucially, this temporal discounting occurs even when statistical information about flood probabilities remains unchanged, indicating that psychological rather than informational factors drive risk perception dynamics. The evidence suggests that prolonged exposure to climate risks absent catastrophic realizations may generate systematic underweighting of low-probability, high-impact events. Bakkensen and Barrage (2022) develop a dynamic housing market model showing that belief heterogeneity can generate pricing differentials across coastal markets through sorting and equilibrium variation, helping explain the mixed evidence on flood risk capitalization. They conduct a door-to-door survey in Rhode Island revealing that coastal flood zone residents have significantly lower risk perceptions and higher amenity valuations than inland residents, with 40% reporting they are "not at all" worried about flooding over the next decade. Calibrating the model to these survey responses and flood risk projections under SLR, they estimate that coastal home prices exceed fundamentals by 13% in Rhode Island, with larger overvaluations in more climate-skeptical or high-risk regions.

Hawai'i residents consistently express higher climate concern than the national average, and buyers active in Hawai'i's housing market originate disproportionately from states with lower climate concern levels (Howe et al. 2015; Fig. A1). Since 1988, Hawai'i has voted consistently for the Democratic presidential candidate.[2] These patterns, in light of the existing literature, point to several mechanisms through which local (in-state) and non-local (out-of-state) buyers may differentially value SLR-exposed properties. Climate beliefs shaped by political or cultural factors may lead buyer groups to assign different weights to long-term SLR risks. Beyond belief heterogeneity, local buyers extended coastal exposure may generate divergent risk assessments. Local buyers could be heightening risk awareness through direct observation of gradual environmental changes, or normalizing risk through repeated non-occurrence of extreme events in spite of prolonged and increasing exposure. Lastly, information asymmetries may drive valuation differences because local buyers potentially possess superior knowledge regarding local adaptation efforts, infrastructure resilience, or institutional barriers to future climate investments.

2.4 Modeling SLR and property values

Hedonic modeling is a common technique for analyzing coastal housing markets, necessitating extensive controls (Bin et al. 2008; Krause 2014). Standard specifications for coastal real estate markets include variables for ocean view, waterfront, distance to the coastline, and beaches (Dumm et al. 2016; Jin et al. 2015; Walsh et al. 2019). As such, significant challenges arise in specifying the hedonic model to decompose the amenity value of coastal access from discounts for SLR exposure. The inherent ambiguities regarding appropriate functional form and housing attributes create inconsistencies in implicit price estimates (Wallace and Meese 1997). In addition, collinearity between coastline proximity and cli-

[2] https://ballotpedia.org/Presidential_voting_trends_in_Hawaii

mate risks poses specification issues, because waterfront properties exhibit substantial premiums unrelated to flood risk (Atreya and Czajkowski 2019; Bin et al. 2011). Where viable, alternative approaches have gained preference over pure hedonic models due to challenges associated with the availability, accuracy, and consistency of pertinent variables, as well as the complexity of formulating the model (Nagaraja et al. 2014). The repeat sales analysis introduced by Bailey et al. (1963) can provide a more robust estimate of the impact of a specific characteristic on property value. It effectively addresses the shortcomings of traditional hedonic models by tracking the same property across sales and reducing omitted variable bias due to unobserved time-invariant heterogeneity (Nagaraja et al. 2014; Palmquist 2005). The repeat-sales specification also allows us to evaluate the price effect of a characteristic that is not uniform across properties (Kousky 2010; Palmquist 2005).

Recent studies analyzing the impact of climate change on property values have utilized a repeated sales regression approach to estimate effects over time. Beltrán et al. (2019) examined the impact of flooding on residential prices in England between 1995 and 2014 using a repeat sales model, finding large price discounts of 24.9% for inland flooding and 21.1% for coastal flooding immediately after a flood event. However, these discounts diminish over time and become statistically insignificant after 4–5 years. Kousky (2010) employed a repeat sales model to show that while 100-year floodplain property prices in St. Louis County, Missouri were unaffected after severe 1993 flooding, 500-year floodplain prices declined 2–5% and riverfront property prices fell 6–10%, indicating updated flood risk assessments by homeowners.

In repeat sales analysis, property fixed effects account for inherent differences in average prices across properties due to structural characteristics whereas time-fixed effects control for overall market trends. Interacting the static SLR exposure variable with year enables the estimation of changing impacts over time as climate risk perceptions evolve. Differential time trends can be estimated based on coastal proximity to control for potentially shifting preferences for beach access, as in Tyndall (2021), which found properties near the coast but relatively safe from SLR experienced an appreciation premium. Our repeat sales approach builds on recent methodological advances in hedonic Difference-in-Differences (DiD) models. Banzhaf (2021) demonstrates that DiD hedonic models can identify direct price impacts on affected properties, which serve as lower bounds on total welfare effects even when broader market pricing structures shift in response to changing conditions. This theoretical foundation validates our empirical strategy for measuring the minimum economic impact of SLR risk exposure.

A limitation of the repeat sales approach is that it does not consider changes in housing characteristics, such as renovations, which could affect a property's value between sales. Prior research has demonstrated that the potential for omitted variable bias resulting from minor unobserved changes in housing characteristics in repeat sales analysis is minimal (Billings 2015). Another main concern with the use of the repeated sales methodology is sample selection bias (Gatzlaff and Haurin 1997). The sample of repeat sales properties may not be representative of the housing market (Case et al. 1991; Nagaraja et al. 2014; Wallace and Meese 1997). For example, certain types of properties, such as newly constructed properties, starter homes, properties suitable for rehabilitation, and homes with defects not immediately obvious to the buyers, are more likely to sell multiple times (Clapp and Giaccotto, 1999). The issue of sample selectivity may be mitigated if the price trends observed in the repeated subsample closely mirror those of all properties that were sold (Tyndall 2021).

3 Data

To conduct a repeat sales analysis, we utilize datasets on real estate transactions and SLR projections. Other important attributes such as the physical coastline and seawall data are also employed.

Transaction data obtained from Black Knight, a financial services company, are selected to only include properties that were sold at least twice between 2000 and 2022. This data provides critical transactional information, including the exact date of the transaction and characteristics of interest (i.e. type of dwelling and buyer's address). Buyers are classified as local if they have an in-state address and non-local if they have an out-of-state address. To ensure the analysis focuses on arm's length transactions and excludes outliers, the dataset is restricted to properties with sale prices between \$50,000 and \$50,000,000. The trends in mean and median property prices for the repeated sales coastal sample are compared to the full coastal sample, which includes all sales (Fig. 2), giving correlation coefficients of 0.994 and 0.998, respectively. This indicates that the repeated sales sample is a good representation of the overall housing market. Furthermore, a Kolmogorov–Smirnov test on the density of log sale prices for the comprehensive and repeated sales samples (Fig. 3) indicates that the two distributions are similar (p = 0.97, D = 0.04).

Using ArcGIS software, we overlay the SLR inundation projections onto our parcel data, creating a spatial map. As in Tarui et al. (2023), a parcel is considered inundated if more than 30% of its area is flooded under a particular SLR projection scenario. This process results in a dummy variable for each uniquely identifiable parcel, indicating its exposure to SLR. Our parcel-level exposure classification captures different risk types by property structure.

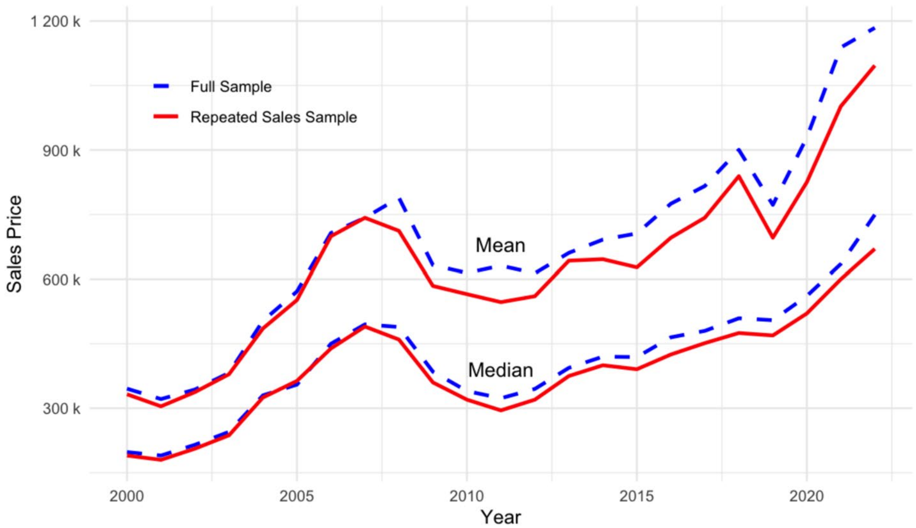

Fig. 2 Mean and median nominal prices for the repeated sales sample from 2000 to 2022 closely resemble those of all transactions during the same period

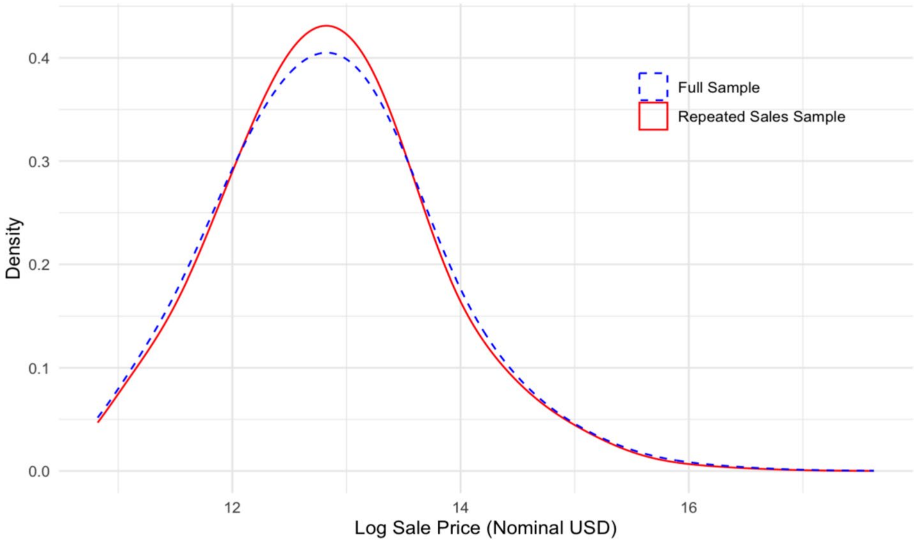

Fig. 3 Density plots of log nominal sale prices for the full and repeated sales samples

For single-family homes, parcel inundation corresponds to direct unit-level exposure. For multifamily properties, parcel inundation represents building-level exposure, as we cannot identify individual unit elevations within structures. Our analysis therefore measures direct inundation risk for single-family residences and building-level inundation risk for multifamily properties.[3] We repeat this overlaying process with other shapefiles to continue adding attributes for each tax parcel, i.e., distance to the coast and presence of seawalls. Where seawalls are placed seaward of a beachfront parcel, we manually identify these parcels using map viewer functionality in ArcGIS. We categorize "seawall neighbors" as properties without a seawall but adjacent to a property with one, and indirect seawall properties as those directly landward of a seawall property or a beachfront/waterfront road.

Following Bernstein et al. (2019), we limit our analysis to properties within 0.25 miles of the coastline, merging parcel data with transactions using Tax Map Key identifiers. The quarter-mile restriction balances the tradeoff between retaining a larger number of SLR-exposed properties in the sample and accounting for NOAA's exposure measure becoming less precise with distance from the shoreline.[4] The resulting dataset (visualized in Fig. 4) comprises parcels that had two or more sales between 2000 and 2022, along with their various proxies for exposure status to future SLR, sale price for each transaction, date of transaction, and physical attributes such as the presence of seawalls and the distance to the coastline.

[3] In practice, most coastal multifamily housing in Hawai'i is elevated with residential units above ground level. Building-level inundation disables shared infrastructure (elevators, electrical systems, parking), which may be interpreted as a mix of unit-level isolation risk and inundation risk.

[4] While this may understate broader market responses, it enables cleaner identification by focusing on directly affected properties. NOAA's SLR projections represent the best available estimates, with any measurement error likely biasing our estimates toward zero. Our main results remain statistically robust but attenuate slightly when using wider bandwidths of 0.5, 0.75, 1, and 2 miles (see Supplementary Information).

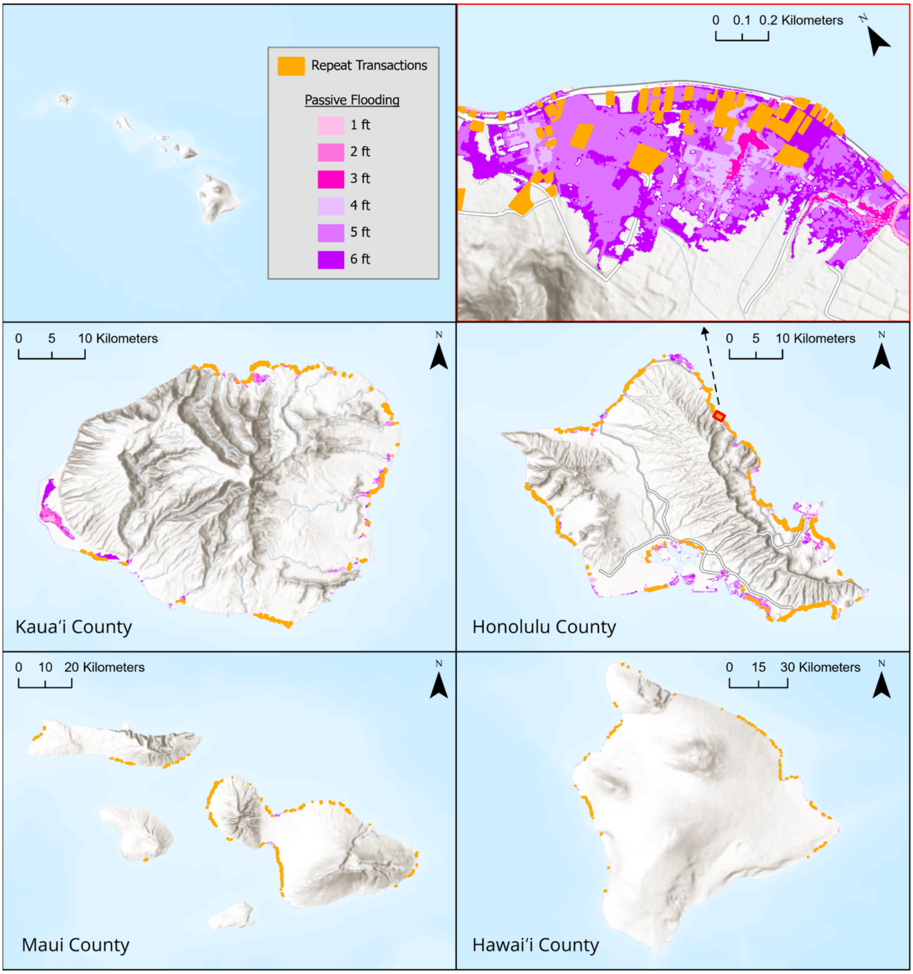

Fig. 4 Repeat transactions (red) within a 0.25-mile coastal buffer overlaid with NOAA passive flooding shapefiles (1–6 ft of SLR)

Table 1 presents the descriptive statistics of our repeat sales coastal property sample across four major Hawaiʻi counties from 2000 to 2022. The data reveal significant property characteristics, transaction patterns, and environmental risk exposure variations among Honolulu County, Maui County, Kauaʻi County, and Hawaiʻi County. Notably, the coastal real estate market is dominated by multi-family properties, comprising 73% to 89% of transactions across the islands. Mean sale prices range from $498,000 in Hawaiʻi Island to $770,000 in Kauaʻi, with substantial disparities between mean and median prices indicating skewed distributions likely due to high-end property sales. In our analysis, we utilize logged sales price as our dependent variable, which approximately follows a normal distribution (Fig. 3).

A striking feature of the coastal property market across Hawaiʻi is the prevalence of out-of-state buyers, particularly in Maui County (64%), Kauaʻi (74%), and Hawaiʻi Island

Table 1 Summary statistics of coastal properties with repeat sales in the state of Hawai‘i (2000–2022)

	State	O'ahu	Maui County	Kaua'i	Hawai'i Island
Sales Price (USD)					
Mean	638,500	682,668	602,710	769,958	498,474
Median	370,000	400,000	365,000	455,000	280,000
Minimum	50,000	50,000	50,000	50,000	50,000
Maximum	39,250,000	31,498,000	39,250,000	35,660,000	30,200,000
Beachfront Sale Price (USD)					
Median	469,000	515,000	457,000	375,000	N/A
Coastal Proximity (miles)					
Mean	0.12	0.13	0.12	0.11	0.11
Transaction Characteristics					
Count	68,657	30,450	23,314	5,801	9,092
Unique Properties	25,054	11,376	8,328	2,149	3,201
Avg. Times Sold	2.74	2.68	2.80	2.70	2.84
Single-family	21%	27%	11%	22%	27%
Multifamily	79%	73%	89%	78%	73%
In-state buyer	49%	66%	36%	26%	41%
Out-of-state buyer	51%	34%	64%	74%	59%
Beachfront	20%	15%	33%	32%	N/A
Seawall Characteristics					
Seawall	11%	6%	17%	20%	N/A
Seawall Neighbors	1.6%	0.5%	3.4%	2.5%	N/A
SLR Exposure					
Exposed 1 ft	13%	8%	11%	33%	24%
Exposed 2 ft	16%	13%	13%	33%	28%
Exposed 3 ft	30%	38%	19%	34%	30%
Exposed 4 ft	39%	52%	26%	37%	30%
Exposed 5 ft	44%	56%	34%	43%	32%
Exposed 6 ft	50%	63%	40%	50%	33%

All prices are in nominal terms. A combination of satellite imagery and coastal erosion transects (Fletcher et al. 2012) were used to identify beachfront housing; for Hawai'i Island no erosion transects exist and the few houses with sand seaward of them are along rocky shorelines

(59%) (in contrast to O‘ahu’s 34%). This trend underscores the appeal of Hawai‘i’s coastal properties as an investment or vacation home opportunity for non-residents—though we also cannot parse out from our data whether non-local buyers move into properties full-time after purchase. Overall, the data also highlight the vulnerability of these properties to climate change, with 19% to 38% of coastal transactions exposed to potential 3-foot SLR, depending on the island.

Figure 5 illustrates the proportion of out-of-state buyers for various categories of coastal real estate transactions in Hawai‘i from 2000 to 2022. This shows that beachfront properties consistently attract the highest proportion of non-local buyers, with percentages ranging from 65 to 80% throughout the period.[5] Expanding more broadly to coastal properties,

[5] The top 10% of non-coastal transactions by price exhibit a lower proportion of out-of-state buyers (30-40%) compared to the coastal and beachfront averages, indicating a relatively strong non-local presence in the coastal segment. This indicates that on average coastal proximity, rather than price, drives non-local buyer preference.

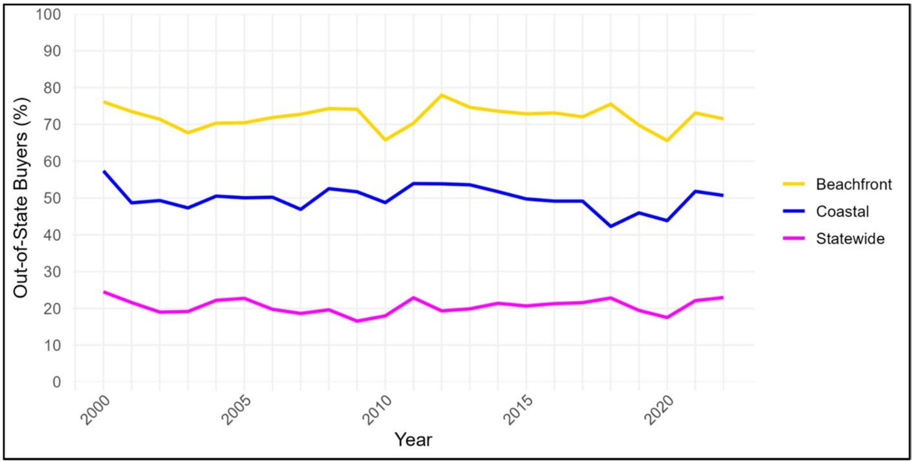

Fig. 5 The proportion of out-of-state buyers for transactions between 2000 and 2022. The statewide line omits coastal transactions, whereas the beachfront line represents a subset of the coastal transactions

including those within 0.25 miles of the shore, show a strong appeal to out-of-state buyers, with proportions generally between 45 and 55%. Comparing the prevalence of out-of-state buyers within beachfront and coastal properties to those statewide is also illuminating, as this proportion is much lower at 20–25% of buyers. The trends are reasonably consistent over the 22 years.

4 Methods

Our main regression specification is presented in Eq. 1, as in Tyndall (2021).

$$\log\left(\mathrm{P_i}\right) = \beta_0 + \beta_1\left(\mathrm{E_i} \times \mathrm{Y_i}\right) + \lambda\left(\mathrm{D_i^d} \times \mathrm{Y_i}\right) + \psi\left(\mathrm{Z_i} \times \mathrm{Y_i}\right) + \mathrm{H_i} + \mathrm{M_i} + \epsilon_\mathrm{i} \tag{1}$$

The dependent variable $log(P_i)$ is the logged sale price where i indexes the parcel; Y_i a continuous variable generated from the transaction date (i.e., a property sold in the sixth month of 2012 would take the value of 2012.5); and E_i serves as a placeholder for the SLR exposure definitions that inundate the property. The dummy variable D_i^d captures whether the center of the property falls within a particular coastal distance band d. In our main specification, d consists of dummy variables for 0–0.01 miles, 0.01–0.02 miles, 0.02–0.04 miles, 0.04–0.08 miles, 0.08–0.16 miles, and 0.16–0.25 miles from the coastline. Variable Z_i represents the ZIP code where the parcel is located, while H_i and M_i denote parcel and year-month fixed effects, respectively. All specifications hereon use two-way clustered standard errors. Spatially, we cluster our standard errors at the ZIP code level split between exposed and non-exposed observations, allowing the possibility of error correlation within local areas that share exposure status. Temporally, we cluster our standard errors at the year-month level.[6]

[6] Depending on the nature of the serial correlation, standard errors may be clustered at the quarterly or yearly level. Such changes in the specification of clustered standard errors do not change our main results.

Our regression specification captures the dynamic relationship between key variables over time. The repeat sales methodology controls for time-invariant property-specific characteristics but does not account for time-varying factors. For instance, properties may appreciate at different rates due to shifts in locational or coastal preferences. To address this potential source of bias and capture the temporal effect of variables on price trends, we incorporate an interaction term between a time-invariant variable and a continuous year variable in our regression specification. Specifically, $(Z_i \times Y_i)$ captures the time trend by ZIP code, while $(D_i^d \times Y_i)$ controls the time trend related to coastal proximity. Controlling for the time trend of coastal proximity allows us to compare homes at similar distances from the coast but with different SLR risks. Similarly, controlling for the time trend of ZIP code allows us to compare homes in similar areas with different SLR risks. Year-month fixed effects M_i account for all time variation and macroeconomic conditions at the time of sale. It is worth noting that coastal trend controls may suffer from multicollinearity issues as they are highly correlated. Our main results remain robust to their exclusion.

Expected SLR exposure E_i is a binary variable indicating whether a property is exposed. Since the definition of exposure remains constant over time, the impact of E_i on property prices is controlled in levels by the inclusion of property fixed effects H_i. However, its impact on property prices can vary over time. Our source of identification couples exposure with a continuous year variable $(E_i \times Y_i)$ and tracks how changing market preferences over time influence the effect of exposure on property price trends.[7] Our primary coefficient of interest, β_1, quantifies the average yearly difference in price appreciation between exposed and unexposed properties. Specifically, we isolate the average change in the logged price for a given property attributable to shifts in market preference for SLR exposure, observed between two sales of the same property.

Using a binary variable for exposure means that, while some control properties face higher SLR risk, potentially attenuating treatment effects, it enables identification from highly comparable properties. For instance, properties exposed to 1 ft of SLR have natural controls in nearby properties not exposed to 1 ft of SLR. In contrast, if we restricted our control group to only properties never exposed to any SLR risk, we would exclude potentially valuable controls that are geographically proximate to properties exposed at 1 ft but are themselves only exposed at higher thresholds. Properties completely unexposed to any SLR risk tend to be located further inland, making them less suitable controls. In the supplementary information, we present additional results using properties never exposed to SLR as controls, which reveal slightly larger appreciation penalties as expected (Table A7 and Fig. A6).

$$\log\left(\mathrm{P_i}\right) = \sum\nolimits_{j\in J}\beta_{1j}\left(\mathrm{E_i}\times \mathrm{Y_i}\times \mathrm{C_{ij}}\right) + \lambda\left(\mathrm{D_i^d}\times \mathrm{Y_i}\right) + \psi\left(\mathrm{Z_i}\times \mathrm{Y_i}\right) + \mathrm{H_i} + \mathrm{M_i} + \epsilon_i \quad (2)$$

While Eq. 1 looks at the aggregate statewide impact of SLR exposure, Eq. 2 allows this effect to vary across counties. Specifically, Eq. 2 includes the indicator variable term C_{ij} for $J=\{$Oʻahu, Maui, Hawaiʻi, Kauaʻi$\}$ with $j \in J$. Coastal communities may have heterogeneity in residents' risk perceptions and preferences. Note that we utilize level means coding, which models each county separately and tests the hypothesis if β_{1j} significantly differs

[7] We also estimate a flexible spline model to capture non-linear time trends in the exposure effect (Supplementary Information, Section D).

from zero. Each β_{1j} coefficient represents the average yearly difference in log price for exposed properties compared to unexposed properties within that specific county. The alternative reference level coding (relative to some base category) would have instead tested the hypothesis if the effect in one county differed from the effect in another. The advantage of using level means coding is that it allows us to identify spatial nuances in how SLR exposure impacts property values on each island rather than simply comparing the effects between different counties. Individual county-level time trends are not included as they would be collinear with ZIP code time trends.

We employ a variety of triple difference model specifications to investigate whether the price penalty differs based on specific observable property attributes(s) that take the following general form:

$$\log(P_i) = \beta_0 + \beta_1 (E_i \times Y_i) + \sum_{k=1}^{K} \beta_{2k} (X_{ik} \times E_i \times Y_i) + \sum_{k=1}^{K} \beta_{3k} (X_{ik} \times Y_i) + \lambda \left(D_i^d \times Y_i \right) + \psi (Z_i \times Y_i) + H_i + M_i + \epsilon_i \tag{3}$$

Equation 3 extends our base model to examine how property characteristics interact with SLR exposure effects over time. The coefficient β_{2k} on the interaction term $(X_{ik} \times E_i \times Y_i)$ captures how each property characteristic k modifies the SLR exposure effect over time. We include $(X_{ik} \times Y_i)$ to control the possibility that a home with a different property characteristic may appreciate differently over time regardless of exposure status. Our specification can accommodate up to K characteristics at any time.

In one specification, we consider single-family home status as the characteristic X_{i1} and examine how the SLR exposure effect differs between single-family and multi-family residences. A negative and significant β_{21} would imply a larger price penalty for single-family homes compared to multi-family units. At the same time, a positive coefficient would indicate that the exposure risk is more prominent in multi-family home valuations. The coefficient on β_{31} would capture how single-family homes have appreciated differently than multi-family homes. In another specification, we consider seawalls as the characteristic X_{i1} and examine how the SLR exposure effect varies for properties with this feature. A positive and significant β_{21} would suggest that seawalls provide a protective benefit, mitigating the price penalty associated with SLR exposure. Conversely, a negative coefficient would indicate that properties with seawalls face a larger price penalty, potentially due to a perceived increase in vulnerability. The coefficients on β_{31} capture how properties with seawalls have appreciated differently compared to those without, regardless of their exposure status.

Lastly, we investigate the impact of buyer location (in-state versus out-of-state) on property prices in relation to SLR exposure. This analysis is motivated by the query of Bernstein et al. (2019) in regard to differentiated climate beliefs by buyer type that influences real estate values. For our purpose, we discern whether local buyers, who may have more intimate knowledge of local risk factors, price SLR risk differently from out-of-state buyers, who bring a different level of sophistication or risk perception to their purchase decisions. We utilize the following specification:

$$\log(P_i) = \beta_0 + \beta_1 (E_i \times Y_i) + \beta_2 (\mathrm{NL}_i \times E_i \times Y_i) + \lambda \left(D_i^d \times Y_i \right) + \psi (Z_i \times Y_i) + H_i + M_i + \epsilon_i \tag{4}$$

Here, NL_i is a dummy variable, which is one if the latter transaction is purchased by a non-local. A positive and significant β_2 would indicate that the price penalty is less if the purchaser is based out of state. A negative coefficient would imply that the price penalty would be higher for out-of-state buyers.

5 Results

We first examine how different levels of SLR exposure affect housing price appreciation rates. By analyzing binary indicators across various SLR heights, we uncover non-linear relationships between exposure severity and price discounts. Figure 6 visualizes these results from model 1. Properties facing 1–3 ft of SLR until inundation exhibit statistically significant annual depreciation rates ranging from 0.9% to 0.8%, with the magnitude of the effect inversely related to the level of exposure. This pattern suggests an acute market response to imminent SLR impacts. However, for properties exposed beyond 3 ft, we note a diminishing impact of exposure on appreciation rates (for example −0.9% at 1 ft to −0.4% at 6 ft). Furthermore, the estimates for 4–6 ft of exposure have wide confidence intervals and lose statistical significance. This could reflect temporal discounting of long-term risks by market participants or uncertainty regarding policy or future mitigation efforts, making it challenging to value SLR risk. Given our results on distance decay patterns, we focus our subsequent analysis on properties exposed to 3 ft of SLR as our primary treatment variable.

Table 2 summarizes the main results associated with models 1, 2, and 3. The central finding from our study reveals a compelling pattern for SLR impacts in Hawai‘i: residential properties located in areas projected to be flooded by an SLR of 3 ft experienced an annual price appreciation rate that is 0.8% lower compared to similar properties not exposed to

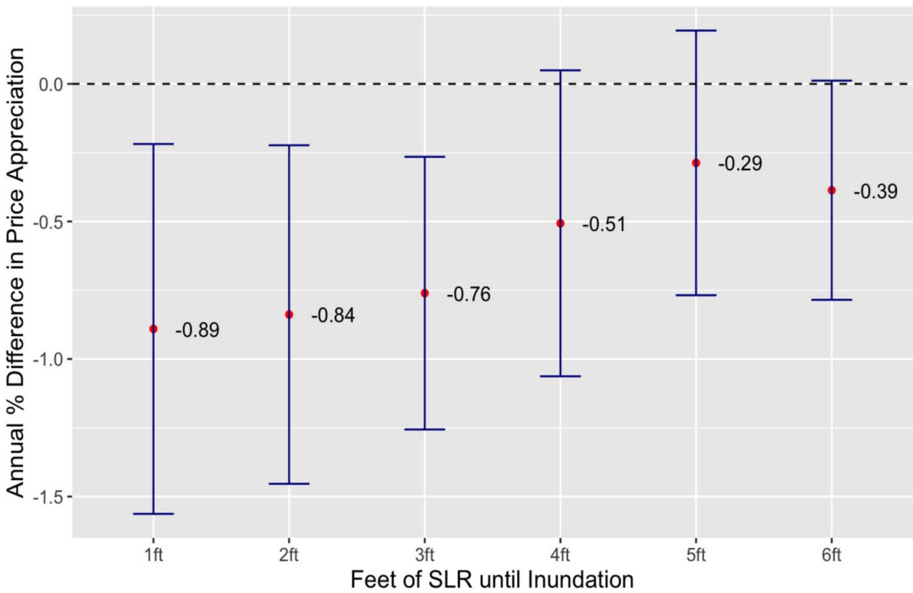

Fig. 6 Estimates from Eq. 1, partitioned by the level of SLR required to inundate the property, for repeat sales transactions from 2000 to 2022. Each point represents the effect of SLR exposure on the annual property appreciation rate, with 95% confidence intervals shown as bands, calculated using two-way clustered standard errors by ZIP code and year-month. Estimates where the zero line falls outside the confidence bands are statistically significant at the $p<0.05$ level

Table 2 Main regression results (2000–2022)

Equation	(1)	(2)	(3)
Exposure x Year	−0.008*** (0.003)	−0.008*** (0.002)	
Single-family × Year		0.000* (0.000)	
Single-family x Exposure × Year		−0.000 (0.000)	
O'ahu × Exposure × Year			−0.014*** (0.005)
Maui County x Exposure x Year			−0.002 (0.001)
Hawai'i x Exposure × Year			−0.011*** (0.001)
Kaua'i x Exposure × Year			0.001 (0.006)
R^2	0.898	0.898	0.898
Adjusted R^2	0.834	0.834	0.834
Coastal Distance Trends	✓	✓	✓
ZIP Trends	✓	✓	✓
Property FE	✓	✓	✓
Time FE	✓	✓	✓
Transactions	68,657	68,657	68,657
Properties Represented	25,054	25,054	25,054
Properties Exposed	7,694	7,694	7,694
Single-family Properties	5,451	5,451	5,451
Single-family Exposed	608	608	608

*$p<0.1$; **$p<0.05$; ***$p<0.01$. The table presents OLS estimates corresponding to Eqs. 1, 2, and 3. Exposure is a dummy variable equal to one if a property is inundated by 3 ft of SLR. The (Exposure x Year) coefficient represents the annual difference in price appreciation trends between exposed and non-exposed properties. (Single-family x Exposure x Year) evaluates whether exposed single-family homes face a steeper appreciation rate penalty from SLR over time than exposed multi- family units. (County x Exposure x Year) allows the SLR exposure effect to vary across counties. Standard errors, reported in parentheses, are two-way clustered at the ZIP code and year-month levels

this risk. To elucidate the underlying drivers of the observed appreciation discount we also examine the differential impacts SLR has on other counties. The elevated risk of future SLR is significant across counties at 3 ft of SLR, with an annual price penalty of 1.4% for O‘ahu, 1.1% for Hawai‘i Island, but no discernible impact for Maui and Kaua‘i.[8] Further analysis using Eq. 3 reveals that the exposure penalty is statistically equal for single and multifamily dwellings (0.8% annual depreciation). This suggests that markets price habitability loss similarly across direct inundation (single-family) and unit-level isolation risk from infrastructure disruption (multifamily).

Detailed county results in Fig. 7 highlight that O‘ahu exhibits the most pronounced effects, with statistically significant annual depreciation rates ranging from −1.9% for 1 foot of SLR exposure to −1.4% for 3 ft, indicating a non-linear relationship where market responses are more acute for relatively imminent risks. This robust pricing pattern is corroborated on Maui, where only 1–2 ft of exposure show marginally significant negative effects (approximately −0.4%), while higher exposure levels remain statistically insignificant. Hawai‘i Island demonstrates consistent negative impacts across all exposure levels (−1.2% to −1.0%), suggesting a more uniform risk assessment. In contrast, Kaua‘i presents no statistically significant effects across all exposure levels, indicating potential differences in risk perception. These findings highlight the complexity of climate risk pricing in real

[8] Since model 2 employs means-level coding, coefficient significance indicates differences from zero. A joint F-test of county-specific exposure coefficients ($F=8.64$, $p<0.001$) rejects the null hypothesis that SLR exposure has no effect on price appreciation in any county.

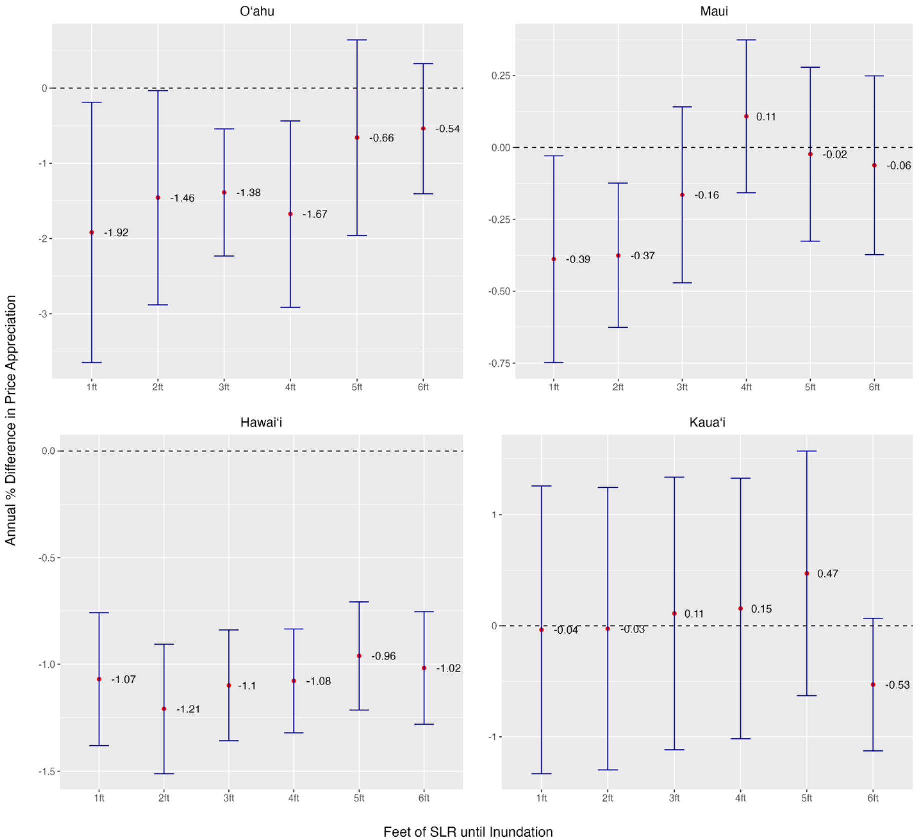

Fig. 7 County-level estimates from Eq. 2, partitioned by the level of SLR required to inundate the property. Each point represents the effect of SLR exposure on the annual property appreciation rate within each county, with 95% confidence intervals displayed as bands. The intervals are calculated using two-way clustered standard errors by ZIP code and year-month. Estimates where the zero line falls outside the confidence bands are statistically significant at the $p<0.05$ level

estate markets, suggesting that buyers may be discounting long-term risks or struggling to quantify uncertainties associated with higher levels of SLR exposure. The observed variations across islands underscore the importance of local contextual factors in shaping market responses to climate risks.

The analysis delineated in Table 3, derived from Eq. 3, focuses on the role of seawalls in mitigating property value declines due to risk exposure. The results reveal a significant positive relationship between seawalls and property value appreciation, with coefficients for the (Seawall × Year) interaction term ranging from 1% to 1.3% higher annual appreciation across exposure definitions from 1 to 4 ft.[9] We find no substantial evidence that seawalls either mitigate or exacerbate the exposure penalty for properties that are both exposed and protected.

[9] We focus on 1–4 ft of SLR, as beyond that, most (>98%) properties with seawalls are exposed.

Table 3 Effect of seawalls on real estate appreciation (2000–2022)

Exposure definition	1 ft	2 ft	3 ft	4 ft
Exposure x Year	−0.013** (0.005)	−0.012*** (0.004)	−0.010*** (0.003)	−0.007** (0.003)
Seawall x Exposure x Year	0.002 (0.006)	0.001 (0.005)	−0.002 (0.004)	−0.005 (0.004)
Seawall x Year	0.010*** (0.003)	0.011*** (0.003)	0.012*** (0.003)	0.013*** (0.004)
R^2	0.898	0.898	0.898	0.898
Adjusted R^2	0.834	0.834	0.834	0.834
Coastal Distance Trends	✓	✓	✓	✓
ZIP Trends	✓	✓	✓	✓
Property FE	✓	✓	✓	✓
Time FE	✓	✓	✓	✓
Transactions	59,565	59,565	59,565	59,565
Properties Represented	21,853	21,853	21,853	21,853
Properties Exposed	2,532	3,226	6,748	9,043
Seawall Properties	2,744	2,744	2,744	2,744
Seawall & Exposed	1,381	1,559	1,808	1,995

*$p<0.1$; **$p<0.05$; ***$p<0.01$. The table presents OLS estimates corresponding to Eq. 3. The (Exposure x Year) coefficient is the annual difference in price appreciation trend between exposed and non-exposed properties. The coefficient on (Seawall x Year) captures the difference in annual appreciation rates between properties with seawalls versus those without. The triple difference term (Seawall x Exposure x Year) captures a differential price penalty for at-risk homes with seawalls compared to at-risk homes without seawalls. Standard errors, reported in parentheses, are two-way clustered at the ZIP code and year-month levels

Table 4 reports differential SLR exposure effects for local versus non-local buyers by looking at properties that transacted exactly twice.[10] Local buyers exhibit stronger price responses to SLR exposure, particularly at lower levels. For properties purchased by locals, the exposure penalty is 1.8% annually for 1 ft exposure and 1.4% for 2 ft exposure. Conversely, non-local buyers' penalty is less at 0.7% for both 1 and 2 ft of exposure. This stark contrast suggests local buyers appear much more attuned to SLR risks. That out-of-state buyers represent a disproportionately large number of transactions for coastal properties, especially beachfront housing, likely inflates prices for the exposed homes in this market.

In Table 5, we examine the impact of SLR on property values for different buyer–seller interactions, using mean-level coding to estimate exposure penalties. For our sample of properties that sold exactly twice, we apply the specification from Eq. 2 letting the effect vary by buyer interaction i.e. C_{ij} for $j=$ {non-local to non-local, non-local to local, local to non-local, and local to local}. This allows us to observe the average yearly difference in property appreciation for exposed properties compared to unexposed properties within each type of transfer category. We find that transactions involving local buyers show consistently significant and negative coefficients, indicating exposure penalties that are convincingly different from zero. Local-to-local transactions exhibit substantial penalties, ranging from 1.4% to 0.6% annually across the 1–4 ft thresholds. In contrast, non-local to local transactions show even larger effects, from 2.2% for 1 ft exposure to 0.8% for 4 ft exposure. SLR risk is more consistently priced into property values when a local is present on the buyer's side. In contrast, non-local to non-local transactions display relatively consistent penalties

[10] Descriptive statistics for the sold-twice sample are provided in the Supplementary Information.

Table 4 Effect of buyer type on real estate appreciation (2000–2022)

Exposure definition	1 ft	2 ft	3 ft	4 ft	5 ft	6 ft
Exposure x Year	−0.018***	−0.014***	−0.012***	−0.008**	−0.004	−0.006**
	(0.006)	(0.005)	(0.003)	(0.004)	(0.003)	(0.003)
Non-local x Exposure x Year	0.011**	0.007*	0.003	0.003	0.001	0.001
	(0.005)	(0.004)	(0.003)	(0.003)	(0.002)	(0.002)
R^2	0.924	0.924	0.924	0.924	0.924	0.924
Adjusted R^2	0.830	0.830	0.830	0.830	0.830	0.830
Coastal Distance Trends	✓	✓	✓	✓	✓	✓
ZIP Trends	✓	✓	✓	✓	✓	✓
Property FE	✓	✓	✓	✓	✓	✓
Time FE	✓	✓	✓	✓	✓	✓
Transactions	26,866	26,866	26,866	26,866	26,866	26,866
Properties Represented	13,433	13,433	13,433	13,433	13,433	13,433
Properties Exposed	1,711	2,170	4,288	5,605	6,293	7,099

*$p<0.1$; **$p<0.05$; ***$p<0.01$. The table presents OLS estimates corresponding to Eq. 4. The (Exposure x Year) coefficient is our reference category and captures the annual price appreciation penalty of exposure for homes purchased by locals. The (Non-local x Exposure x Year) coefficient captures how different the price penalty is for properties purchased by non-locals. The sample is restricted to properties that sold exactly twice. Standard errors, reported in parentheses, are two-way clustered at the ZIP code and year-month levels

Table 5 Effect of buyer–seller interaction on real estate appreciation (2000–2022)

Exposure Definition	1 ft	2 ft	3 ft	4 ft	5 ft	6 ft
Non-local to Non-local × Exposure × Year	−0.008***	−0.008**	−0.010**	−0.006*	−0.005*	−0.007***
	(0.003)	(0.003)	(0.003)	(0.004)	(0.003)	(0.003)
Local to Local x Exposure × Year	−0.014**	−0.012**	−0.011**	−0.006*	−0.002	−0.004
	(0.007)	(0.006)	(0.003)	(0.003)	(0.003)	(0.003)
Non-local to Local x Exposure × Year	−0.022***	−0.016***	−0.012***	−0.008*	−0.006	−0.006*
	(0.007)	(0.006)	(0.004)	(0.004)	(0.004)	(0.003)
Local to Non-local x Exposure × Year	−0.004	0.000	−0.006**	−0.001	0.001	0.001
	(0.004)	(0.004)	(0.002)	(0.002)	(0.002)	(0.002)
R^2	0.924	0.924	0.924	0.924	0.924	0.924
Adjusted R^2	0.830	0.830	0.830	0.830	0.830	0.830
Coastal Distance Trends	✓	✓	✓	✓	✓	✓
ZIP Trends	✓	✓	✓	✓	✓	✓
Property FE	✓	✓	✓	✓	✓	✓
Time FE	✓	✓	✓	✓	✓	✓
Transactions	26,866	26,866	26,866	26,866	26,866	26,866
Properties Represented	13,433	13,433	13,433	13,433	13,433	13,433
Properties Exposed	1,711	2,170	4,288	5,605	6,293	7,099

*$p<0.1$; **$p<0.05$; ***$p<0.01$. The table presents OLS estimates corresponding to Eq. 2 for different types of buyer interactions (Non-local to Non-local, Local to Local, Non-local to Local, Local to Non-local). The (Interaction x Exposure x Year) coefficient captures whether the price penalty in that interaction is statistically different from zero. The sample is restricted to properties that sold exactly twice. Standard errors, reported in parentheses, are two-way clustered at the ZIP code and year-month levels

across exposure levels (0.7% to 1% annually), while local to non-local transactions show the least consistent effects, with only the 3 ft level being significant.

6 Market expected timing of SLR risk

We translate our estimates into the market's expected timing of SLR risk following Bernstein et al. (2019). For any property, its value *V* represents the discounted sum of future benefits *B*. For unexposed properties *u*, we assume these cash flows continue in perpetuity. Given discount rate *r,* the net present value is given by:

$$V_u = \sum_{t=1}^{\infty} \frac{B}{(1+r)^t} = \frac{B}{r} \tag{5}$$

For exposed properties e, we assume it becomes worthless at time of inundation T. It also faces an appreciation penalty p, meaning that its cashflows are discounted at a higher rate of (r+p). The net present value in this case can be represented as:

$$V_e = \sum_{t=1}^{\mathrm{T}} \frac{\mathrm{B}}{(1+r+p)^t} = \frac{\mathrm{B}}{r+p} - \frac{\mathrm{B}}{(r+p)(1+r+p)^T} \tag{6}$$

Let R be the ratio of value of exposed to unexposed:

$$R = \frac{V_e}{V_u} = \frac{\mathrm{r}}{\mathrm{r+p}}\left[1-(1+r+p)^{-T}\right] \tag{7}$$

Taking natural logs and isolating for T from Eq. 7 yields:

$$\mathrm{T} = -\frac{\ln\left(1-\frac{r+p}{r}R\right)}{\ln(1+r+p)} \tag{8}$$

We assume that properties are observably equivalent at the start of the sample. For a 1% appreciation in an unexposed property, an identical exposed property appreciates by (*1+p*). We can thus empirically estimate R from our 2000–2022 sample of repeat sales where g is the average annual appreciation for a property in our sample:

$$R = \left(\frac{1+\mathrm{g}+\mathrm{p}}{1+\mathrm{g}}\right)^{23} \tag{9}$$

Our estimates in Fig. 6 for 1–3 ft of SLR inform our values for the appreciation penalty *p*. Based on appreciation penalties for 1–3 ft of SLR from Fig. 6, *R={0.826, 0.835, 0.850}*.[11] We take the long-run discount rate *r=0.026*, following Giglio et al. (2015).

[11] Estimated coefficients from Tarui et al. (2023) and Bernstein et al. (2019) indicate the impact of specific SLR exposure levels on log property prices. The logged value of R corresponds to the exposure penalty in their models. Using our values of R based on the annual appreciation penalty, we estimate a value differential of 16–19%, closely aligning with their findings.

Solving for T yields the implied number of years until the market expects SLR to materialize, based on current price differentials and appreciation rates. Our value of T ranges from 46 years for properties exposed to 1 ft of SLR, 48 years for properties exposed to 2 ft, and 51 years for properties exposed to 3 ft of SLR. While determining whether the SLR exposure discount that investors apply is correct is beyond the scope of this paper, our results suggest that our estimates are consistent with the low emission SLR scenario for Hawai‘i (Sweet et al. 2022).

7 Discussion and conclusion

Our research contributes to the growing literature on the real estate impacts of climate change. Using a repeat sales methodology, we find that from 2000–2022, properties in Hawai‘i exposed to up to 1 ft of SLR showed a 0.9% lower annual appreciation rate compared to similar unexposed properties. Properties exposed to up to 3 ft of SLR showed a 0.76% price discount in their annual appreciation rate. Our estimated market timing expectations for SLR risk, ranging from 46 to 51 years, appear plausible and align with low emission SLR scenarios for Hawai'i (Sweet et al. 2022). As SLR projections and policy debates become more salient, expectations about the future viability and value of exposed properties appear to shift. Our findings are consistent across all four counties; however, statistically significant only for O‘ahu and Hawai‘i islands. For more immediate risk, though still long-term in many ways (1 ft of SLR exposure), O‘ahu shows a price appreciation discount more than double that of other islands. O‘ahu is Hawai‘i’s most densely populated island, with extensive coastal urbanization. The heightened sensitivity to flooding threats on O‘ahu likely reflects the level of SLR risk saliency, climate change beliefs, and perceptions about the viability of adaptation options.

Benetton et al. (2025) document that housing price responses to flood risk vary by floor level, consistent with a mechanism in which direct physical exposure drives risk capitalization. In contrast, we find no meaningful difference in price penalties between single-family and multifamily properties, despite multifamily units in Hawai'i typically being elevated above ground level. In multifamily buildings, flooding of electrical infrastructure, elevators, or access points can render all units functionally uninhabitable without major renovation, even absent direct water intrusion. Thus, while the relevant risk channel might differ—direct inundation for single-family homes versus functional unit level isolation (or direct inundation) for multifamily units—the market appears to price both forms of habitability loss similarly. Figure A9 in the Supplementary Information shows that only direct building inundation matters for pricing, and not the risk of isolation (Logan et al. 2023) from neighborhood-level loss of function.

Overall, properties exposed to SLR may be discounted because buyers perceive a decreasing ability to protect them from future SLR impacts, even if the land is not yet experiencing inundation, as in the case of 6 ft of SLR. The detection of statistically significant price reductions in properties at up to 6 ft exposure level suggests that the market is capitalizing risks over a protracted horizon. Our main findings are congruent with Bernstein et al. (2019), a comprehensive analysis across the United States, demonstrating that real estate markets adjust prices downward in proportion to the assessed long-horizon risks of SLR exposure. Unlike the study by Tyndall (2021) on Long Island real estate, which found risk internalization only starting at 6.6 ft SLR exposure, our analysis also detects significant pricing adjustments in Hawaiʻi even at 1 ft of SLR exposure. Notably, and in contrast to Bernstein et al. (2019), we find local buyers drive the SLR exposure discount for 1–2 ft of SLR. Non-local buyers show a strong preference for beachfront housing in Hawaiʻi, which is disproportionately exposed to SLR. While this may reflect lower levels of information or saliency, it may also stem from belief heterogeneity. Hawaiʻi is a consistently Democratic state, with residents expressing stronger climate concern than the national average (Howe et al. 2015; Supplementary Information, Section A). Figure A1 confirms this pattern: local buyers report higher perceived personal risk and stronger support for climate action than out-of-state buyers. As such, local factors appear to drive much of the statewide discount for exposed coastal housing. Our results remain robust to excluding short-horizon resales and investment-driven transactions, alleviating concerns that the observed discounts reflect speculative behavior rather than long-term risk pricing (Supplementary Information, Section B).

The issue of seawalls has and continues to be a contentious point in Hawaiʻi's approach to coastal management, particularly under SLR. We find that the presence of a seawall has a positive and statistically meaningful effect on residential real estate value; however, this amenity effect does not statistically differ between exposed and unexposed properties. This might point to concerns regarding the long-term efficacy of seawalls as a property protection measure for highly vulnerable locations.

Our finding that buyers are discounting exposed properties increased over time suggests long-term awareness of SLR risks. Recent real estate disclosure laws of SLR exposure and shoreline erosion control structures adopted in Hawaiʻi (Act 179, 2021, and Act 231, 2023, respectively), provide future opportunities to study the role of explicit knowledge of SLR risk and how it is capitalized into market values. Similar analysis could also be extended to commercial real estate.

While our analysis focuses specifically on impacts on property values, this is just one aspect of a broader, multidimensional landscape of SLR impacts and risks facing coastal communities. A holistic understanding of the ecological, social, and economic impacts of both SLR and SLR response strategies is critical for informed decision-making. This study's findings imply how real estate markets play a role in prompting changes in coastal development and therefore opportunities for management. Though our results show that climate change impacts are being capitalized into residential real estate values in Hawaiʻi, it is likely at a rate (e.g. up to 51 years) lower than what coastal managers might prefer for the purpose of disincentivizing investment in sensitive and high-risk coastal areas. These results can therefore help to inform cost–benefit analyses of additional climate adaptation interventions.

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Data availability The datasets generated during and/or analyzed during the current study are available on request except for variables related to housing transaction and assessment. More information on accessing the housing data can be found at http://www.BlackKnightInc.com/.

Declarations

Ethics approval and consent to participate This article does not contain any studies with human or animal participants performed by any of the authors.

Consent for publication All authors gave explicit consent to submit the manuscript.

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