Rainfall, Fire Risk and Housing Prices in Hawaii*

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February 9, 2025

Abstract

This paper identifies the market responses to rainfall and fire risks in Hawaiian real estate by exploiting spatial variations in precipitation patterns and fire risk exposure. Using transaction-level housing data from 2000-2019, we document three key findings. First, rainfall shocks depress property values, highlighting the disruptive impact of extreme precipitation. Second, wildfire risk also reduces property values, underscoring the market's sensitivity to fire-related hazards. Third, the negative impact of rainfall shocks is moderated in fire-prone areas, suggesting that markets value the fire-mitigating benefits of increased rainfall. Our findings contribute to the understanding of how compound climate risks are capitalized in real estate markets and highlight the importance of considering such risk interactions in climate adaptation policy.

Keywords: Climate Change, Rainfall, Wildfires, Housing Markets, Hawaii
JEL Classification: R10, R30, Q51, Q54

*This paper is funded in part by a grant from the National Oceanic and Atmospheric Administration, Project A/AS-1-HCE-4; which is sponsored by the University of Hawaii Sea Grant College Program, SOEST, under Institutional Grant No. NA22OAR4170108 from NOAA Office of Sea Grant, Department of Commerce. The views expressed herein are those of the author(s) and do not necessarily reflect the views of NOAA or any of its subagencies.

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1 Introduction

Climate change is fundamentally altering global weather patterns, with profound implications for various sectors of the economy. Recent assessments by the Intergovernmental Panel on Climate Change (IPCC) indicate that each of the last three decades has been progressively warmer than any preceding decade since 1850, contributing to more frequent and intense extreme weather events (Change, 2007). In the United States, the Environmental Protection Agency reports that regions experiencing extreme single-day precipitation events have increased by approximately half a percentage point per decade between 1910 and 2020 (U.S. Environmental Protection Agency, 2021). These climatic shifts are increasingly influencing real estate decisions, as potential homebuyers express growing hesitation about purchasing properties in areas prone to climate-related risks (Redfin, 2022)

This study investigates the impact of rainfall[1] shocks on Hawaii's real estate market, incorporating the effects of heterogeneous fire risk. Hawaii presents a unique setting for this analysis due to its diverse microclimates resulting from the islands' steep topography and the complex interplay between terrain, trade winds, and land effects (Sen Roy and Balling, 2004; Giambelluca et al., 2013). The islands' mountains obstruct the pr evailing northeast trade winds, leading to abundant precipitation on windward slopes and creating dry rain shadows in leeward areas (Figure 1).

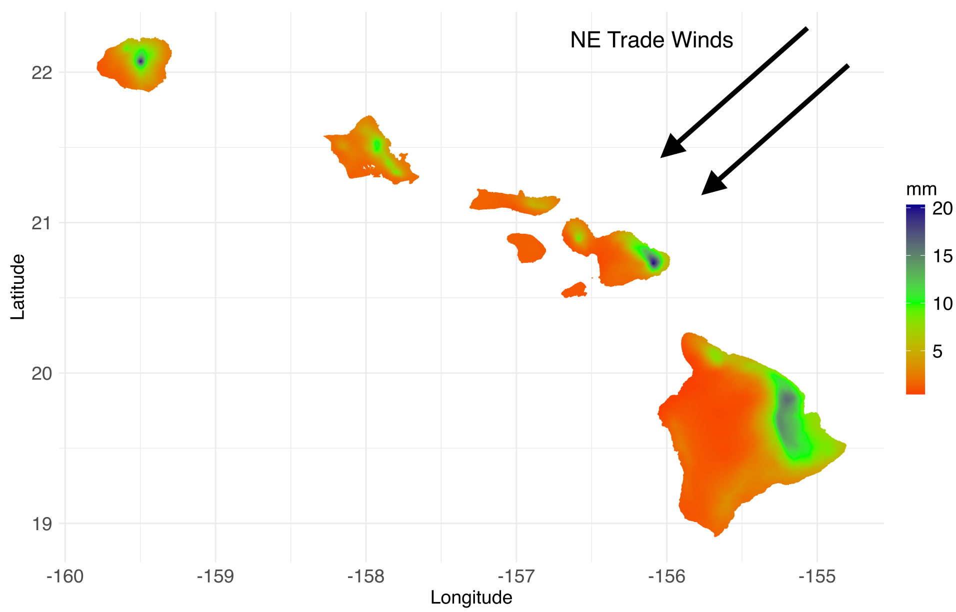

Figure 1: Average Daily Rainfall 1990-2019

[1]For this study *rainfall* and *precipitation* are analogous because inhabited areas in Hawaii only experience liquid precipitation.

Rainfall patterns in Hawaii have shifted in recent decades with historically dry regions becoming drier while wet regions have grown wetter (Chen and Chu, 2014; Elison Timm et al., 2013). The state has also experienced more extreme precipitation events at both ends of the distribution. For example, in 2018, Kauai's north shore received 1262 mm of rain in 24 hours (nearly half its annual rainfall) causing catastrophic flooding that isolated communities for months. Changes in precipitation patterns have led to increased water shortages in dry areas while amplifying risks of runoff, erosion, and flooding in wet regions (State of Hawaii Climate Change Portal, 2024).

These dynamics are further complicated by their interactions with fire risk. The August 2023 Lahaina wildfire underscores Hawaii's susceptibility to destructive fires, revealing how precipitation may create countervailing effects across fire-prone zones. As Figure 2 illustrates, some high-risk areas have grown wetter while others have become drier, potentially leading to mixed outcomes. Drought conditions increase the availability of combustible fuel, while excessive precipitation promotes vegetation growth that can later serve as fire fuel (Westerling et al., 2006; Lima et al., 2018; Puxley et al., 2024; Volkova et al., 2019; Hernández Ayala et al., 2021). Conversely, wet conditions can mitigate fire risk by reducing ignition probability by maintaining soil moisture,(Abatzoglou and Williams, 2016), and limiting the accumulation of dry fine fuels (Van Blerk et al., 2021). This effect has been documented in tropical ecosystems (Spracklen et al., 2012) as well as in urban and forested areas (Sakai et al., 2004). Our study offers the first empirical evidence of how these nuanced precipitation-fire risk interactions are reflected in property values. By examining the spatial heterogeneity of precipitation changes and their implications for fire risk, we highlight the complex ways in which climate dynamics shape economic outcomes in the housing market.

We employ two complementary estimation approaches to identify the response of consumers to rainfall variability and fire risk. First, we implement a hedonic pricing model that controls for a wide array of observable differences across properties and neighborhoods using detailed information on housing characteristics. Second, we estimate a repeat sales model that introduces property fixed effects, accounting for both observed and unobserved time-invariant differences across properties. Our findings indicate that increases in rainfall consistently reduce property values; however, this negative effect is substantially moderated in areas with high fire risk, suggesting that markets value rainfall's fire mitigation benefits. A one standard deviation increase in cumulative rainfall index reduces prices by 1.9 percent in low-fire-risk areas but only 0.8 percent in high-risk areas. This pattern holds across multiple rainfall measures: each additional day of extreme rainfall (above the 99th percentile) reduces values by 0.8 percent in low-risk areas but just 0.2 percent in high-risk areas. While wet conditions show heterogeneous effects across fire risk zones, extremely dry conditions (below the 1st percentile) uniformly reduce property values by 0.5 percent per day regardless of fire risk exposure but moderate dry spells have no impact. These findings persist in repeat sales specifications and when using a dynamic measure of actual wildfire exposure instead of static risk designations.

The remainder of the paper is organized as follows. Section 2 reviews the relevant literature, focusing on

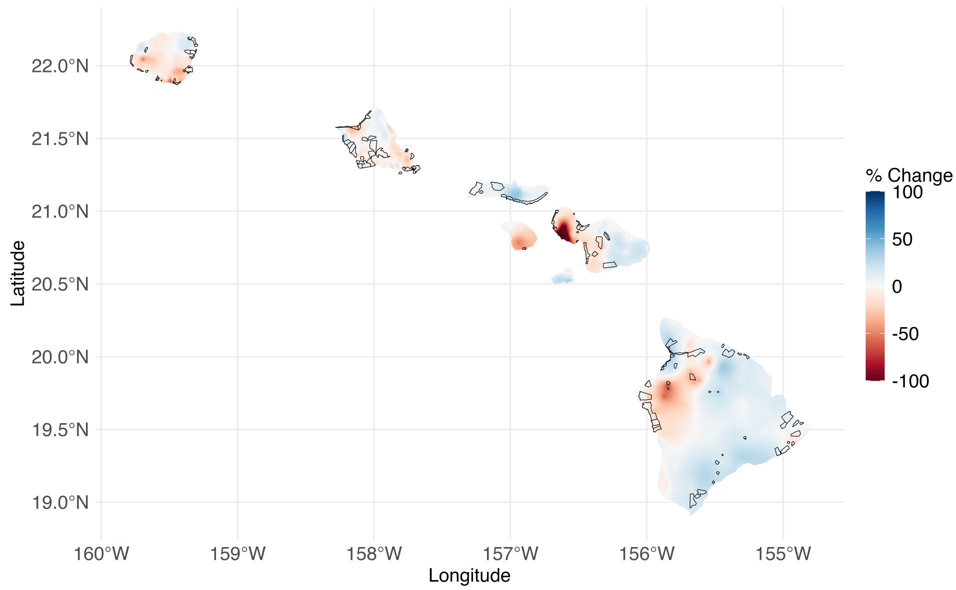

Figure 2: Percentage change in daily mean rainfall between 1990–1999 and 2010–2019. Black polygons indicate at fire-risk communities. (Source: Hawaii Climate Data Portal).

the impact of climate change on the real estate market and the application of hedonic pricing models. Section 3 describes the data and Section 4 outlines the empirical approach. Section 5 presents the main findings, while Section 7 discusses the implications of our results and suggests directions for future research.

2 Literature Review

Our study contributes to three distinct but interconnected strands of literature: the economic impacts of climate change on real estate markets, the relationship between environmental amenities and property values, and the methodological approaches to measuring climate-related price effects in housing markets.

A growing body of research documents how climate risks are increasingly capitalized into real estate values. Recent work has established that markets discount properties exposed to sea level rise (SLR) nationally, with the magnitude varying based on local adaptation capacity and risk awareness (Keys and Mulder, 2020; Bernstein et al., 2019; Fu et al., 2016; Tyndall, 2023; Tarui et al., 2023; Tedesco et al., 2019). Similar pricing patterns have been observed for other climate hazards. Wildfires have been linked to increased mortgage delinquency (Issler et al., 2020) and reduced residential property values (Dong, 2024), hurricanes and extreme heat to declines in commercial real estate returns (Addoum et al., 2024; Cvijanovic and Van de Minne, 2024). This extensive body of work highlights the responsiveness of real estate markets to climate risks, though the channels and magnitudes remain subjects of ongoing debate.

The relationship between precipitation and property values presents a particularly complex case due to rainfall's dual role as both an amenity and a disamenity. Early hedonic studies found a negative impact of rainfall on property values (Blomquist et al., 1988; Clark and Cosgrove, 1990). Torrential rainfall and flooding risk are associated with lower housing prices (Bin and Landry, 2013) and tighter lending standards (Blickle et al., 2024; Avril et al., 2023). Overall, households generally prefer less precipitation and more seasonal variation (Englin, 1996).

Recent work reveals important nuances in this precipitation property value relationship. Goodwin et al. (2021) show that increased rainfall in Mexico City reduces particulate matter pollution, indirectly boosting home prices through improved air quality. Mueller et al. (2018) document how post-wildfire flooding risks in Arizona create compound effects on property values, highlighting the interplay between different climate hazards. Lamas Rodríguez et al. (2023) find a negative correlation between ecological deterioration caused by excessive rainfall and house prices in Mar Menor, Spain. Choi and Lee (2016) look at the physical amount of rainfall as one cause of the flood and find that both the average annual rainfall and rain intensity (amount of rainfall per rainy day) negatively affect property prices. Overall, this strand of literature suggests that rainfall's impact on property values is negative but may vary based on its interaction with other environmental factors.

Our study advances this literature by examining how fire risk mediates the relationship between precipitation and property values. While previous research has studied these factors separately, we provide the first evidence of their interaction in real estate markets. This approach builds on work showing that environmental amenities can have heterogeneous effects based on local conditions (Albouy et al., 2016; Bakkensen and Barrage, 2017; Gibbons et al., 2014).

Methodologically, our work contributes to a debate about the appropriate empirical strategies for identifying climate-related price effects. The traditional hedonic approach (Rosen, 1974) has been widely used to estimate implicit prices of environmental amenities but faces challenges from omitted variables and the spatial correlation of climate features. To address this, first, we include a host of controls in our regression framework including basic property characteristics (square footage, rooms, property age, home type, slope etc.), coastal proximity controls as properties close to the coast command a premium (Tarui et al., 2023; Tyndall, 2023; Jin et al., 2015), and elevation controls as high elevation is viewed as an amenity due to superior views (Gordon et al., 2013) or as insurance against risks such as SLR (Tyndall, 2023). Second, we utilize a repeat sales method to address omitted variable concerns (Palmquist, 2005). Our implementation of both approaches demonstrates how they can provide complementary evidence on climate-property value relationships.

Hawaii provides an ideal setting for this analysis due to its diverse microclimates and varying exposure to fire risk. Following Englin's (1996) caution against national-level precipitation studies, we focus on a region where spatially granular rainfall measurement is available and fire risk varies substantially in small geographic areas. To measure precipitation, we construct z-score based indices, which have been widely used in climate impact studies due to their simplicity, reliability in assessing climate vulnerability (Nam and Kim, 2013; Pauline et al., 2021; Shahabfar et al., 2012; Nourani et al., 2021; Zaveri et al., 2023). We also consider a suite of alternative measures such as fractional deviation of monthly rainfall from its average historical level (Duflo and Pande, 2007; Sarsons, 2015), rainfall shocks (Jayachandran, 2006; Kaur, 2019; Sarsons, 2015; Shah and Steinberg, 2017), and counts of extreme rainy and dry days, identified by a percentile threshold (Suppiah and Hennessy, 1998; Endo et al., 2005; Méndez-Lázaro et al., 2014).

This paper contributes to our understanding of how climate risks affect real estate markets. We provide novel evidence on the interaction between precipitation patterns and fire risk in determining property values, showing how one environmental factor can moderate the impact of another. Our analysis also highlights the critical importance of local environmental context when examining how climate affects economic outcomes. Finally, our methodological approach, which employs both repeat sales and hedonic pricing methods as complementary tools, offers a template for future research on the intricate interactions between climate and property valuation.

3 Data

This study employs real estate transaction data and key property characteristics from Black Knight, a financial services firm. Our analysis is underpinned by property assessment and deed data. The deed data provides critical transactional information, including the exact date of the transaction and the classification of the property as either residential or commercial. The assessment data offers insights into property features such as the number of rooms, living area, age of the property, and type (e.g., single-family dwelling vs. multi-family dwelling). These two datasets are merged using the Assessor Parcel Number (APN), a unique identifier for each property. This study focuses exclusively on residential properties. We used transactions between 2000 and 2019 and excluded transactions priced below \$50,000 or above \$50,000,000 to retain arm's length transactions and remove outlier influence.

In the subsequent phase, we integrated environmental data, starting with publicly accessible daily rainfall rasters from the Hawaii Climate Data Portal. This product is gridded at a high resolution of 250 meters, allowing us to use it effectively with detailed micro-transaction data. Additionally, we procured GIS shapefiles from the Hawaii Statewide GIS Program's Geospatial Data Portal, which offered detailed spatial geometries of tax parcels and delineations of coastlines across the principal Hawaiian islands. These rainfall rasters were overlaid onto our parcel geometries to generate a spatial map. The projection chosen for this analytical exercise was the WGS-1984, deemed most suitable for our geographic study area. For each day from January 1, 1990, through December 31, 2019, we assigned to each parcel the daily precipitation value as its value at the parcel's geographical center. This procedure was then replicated with additional shapefiles, augmenting the dataset with other critical spatial attributes such as elevation and coastal distance. We mapped elevation rasters onto parcels to calculate the average gradient of the parcel (slope). Utilizing APN as the unifying property identifier, we merge this augmented dataset with Black Knight data.

Figure 3: Average Monthly Rainfall (mm) from 1990 to 2019

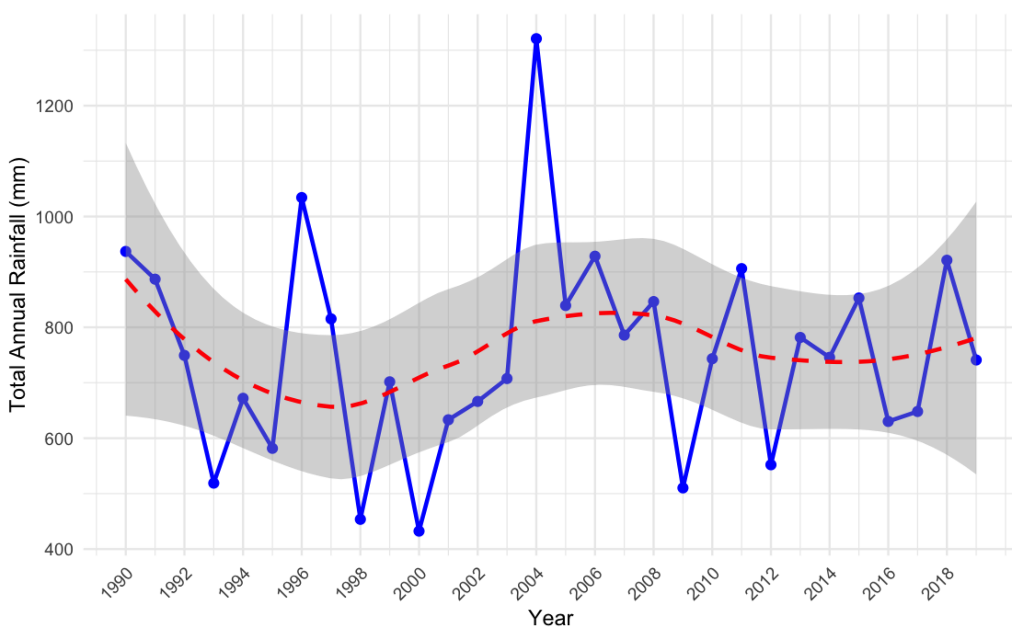

Figure 4: Total Annual Rainfall (mm)

Figure 3 illustrates average monthly rainfall patterns for the state and for properties in our sample from 1990–2019. While the sample properties exhibit higher average rainfall overall, the pattern closely aligns with statewide seasonal fluctuations. Rainfall in Hawaii is characterized by distinct wet (November–March) and dry (April–October) seasons. During wet season, trade winds bring precipitation primarily to windward areas, supplemented by winter storms that can produce rainfall across the islands. In dry season, precipitation declines significantly, especially in leeward regions, although windward areas continue to receive some rainfall driven by trade winds. The long-term trend in total annual rainfall remained relatively stable from 1990 to 2019 (Figure 4, dashed red line). However, properties in our sample experienced more days with rainfall exceeding 75mm [2] and longer stretches of consecutive extreme rainfall days in the post-2000 period than in the previous years (Figure 5). Five-year moving averages suggest this shift represents a structural change in precipitation patterns rather than isolated weather events, particularly evident in the mid-2000s when both metrics mostly exceeded their full-sample means.

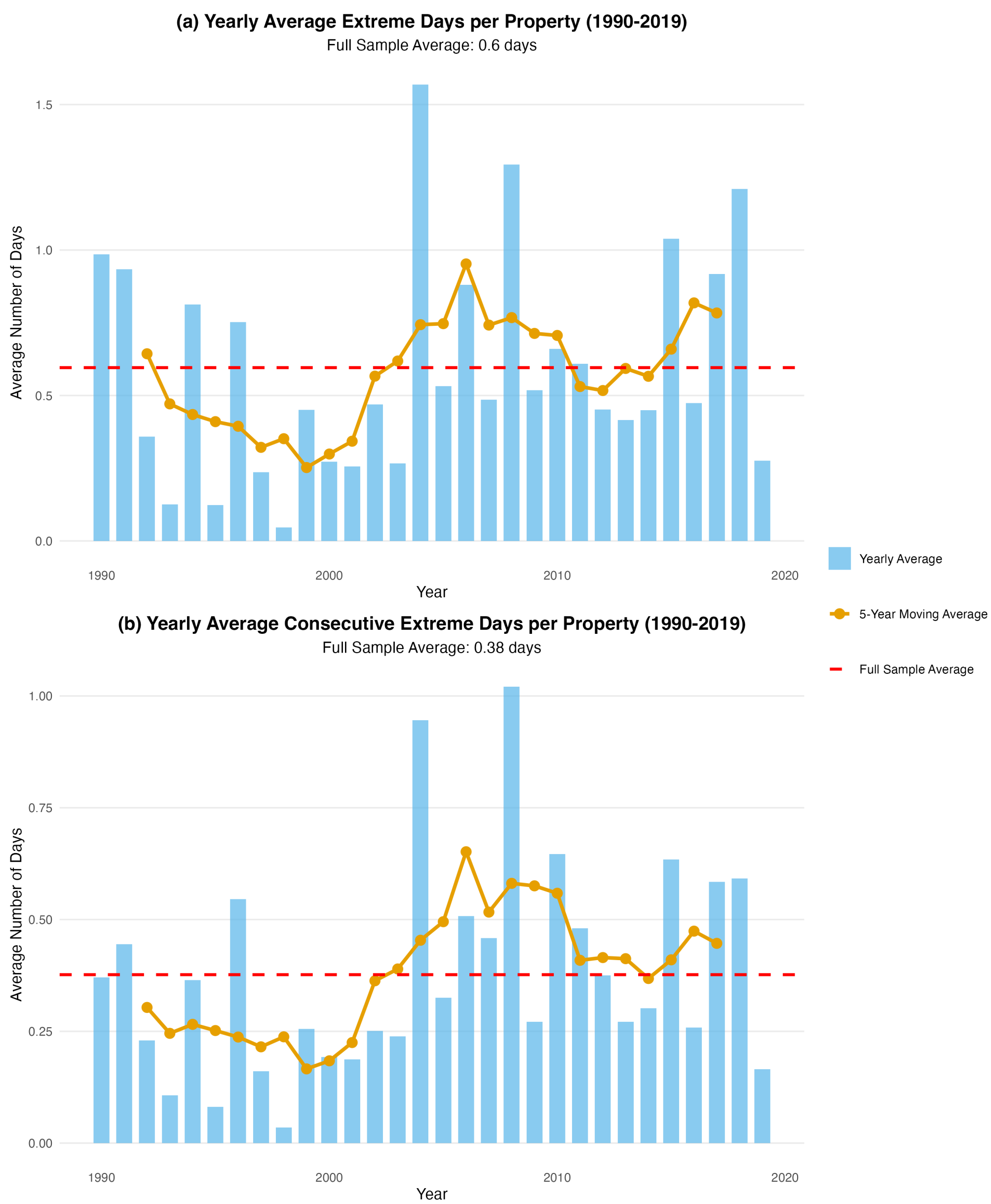

Figure 5: Average Extreme Precipitation Days by Property

[2] We follow the common practice in climate studies of using 75mm as a cutoff for extreme rainfall. This rule of thumb threshold has been adopted in regional studies (Beguería and Vicente-Serrano, 2006) and appears in Hawaiian climate assessments and academic work (Chu et al., 2009; Kunkel et al., 2022).

We obtain fire risk data from the Hawaii Statewide GIS Program's Communities at Risk (CAR) from the Wildland Fires layer. Initially compiled in 2006-2007 by the Department of Land and Natural Resources, this dataset provides risk ratings of High, Medium, or Low for major populated areas across the Hawaiian islands. The fire risk assessment follows guidelines developed by the National Association of State Foresters in June 2003, created in response to the National Fire Plan and the Healthy Forests Restoration Act (HFRA). These guidelines outline a process for identifying and prioritizing communities at risk from wildland fires, considering factors such as fire occurrence, hazard conditions, values protected, and protection capabilities. In our analysis, we designate a community at risk of fire if rated as either high or medium risk. Despite the data being collected in 2006-2007, the Hawaii Statewide GIS Program confirmed in October 2022 that these boundaries and risk ratings remain valid and unchanged over time.

A natural question arises: are property buyers in Hawaii aware of the fire risk? While there are no legal requirements for fire risk disclosures in the state, the issue is prominent. With approximately 0.5% of Hawaii's total land area burning annually, a rate comparable to or even exceeding that of any other U.S. state - fire risk is arguably a salient concern for buyers. Figure 6 shows the total area burned statewide across the years. Furthermore, evidence suggests homebuyers respond to publicly available wildfire risk information. Donovan et al. (2007) found that after Colorado Springs Fire Department's risk ratings became publicly accessible, properties in high-risk areas saw their previous amenity premiums offset by increased risk awareness among buyers.

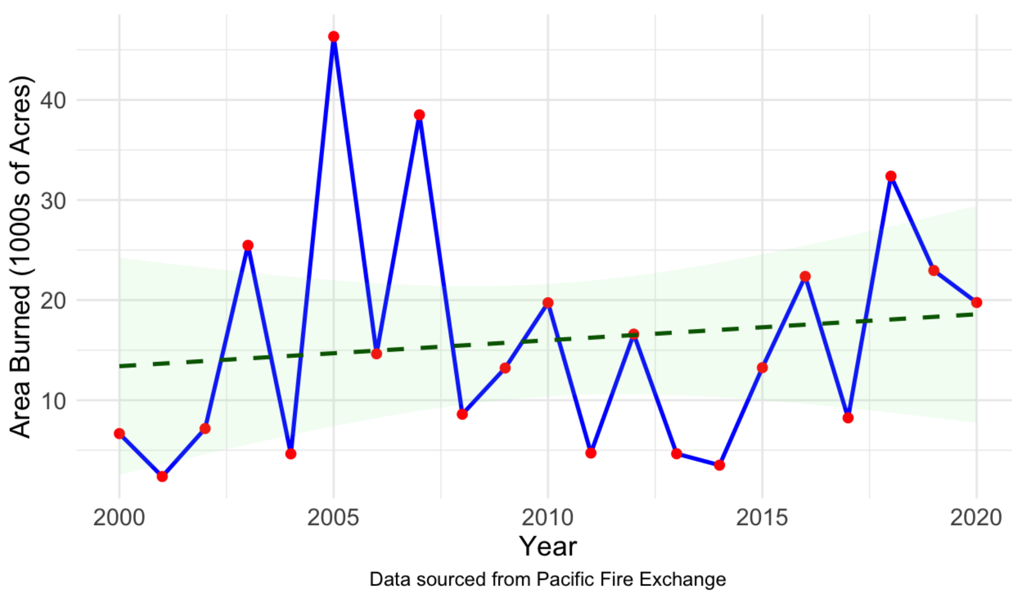

Figure 6: Annual Area Burned Statewide

In the appendix, we complement our analysis with a real-time measure of fire exposure based on actual wildfire occurrences rather than designated risk zones. We construct a dynamic index that captures the spatiotemporal variation in fire risk by incorporating the size, proximity, and frequency of fires. The results

Table 1: Summary Statistics (2000-2019)

	Mean	Median	Sd	Min.	Max.
Panel A: Full Sample					
Sales Price	495,513	356,773	698,757	50,000	46,117,500
Fire Risk	0.59	1	0.49	0	1
House Age	26	26	18	0	166
Square Footage (1000)	1.4	1.1	0.82	0.1	21
# Bedrooms	2.7	3	1.2	1	18
Slope	3.6	2.3	4	0	47
Elevation (m)	98	25	172	0	1584
Coastal Distance (m)	2,659	1,456	3,347	0.47	25,108
Single Family	0.41	0	0.49	0	1
Six Month Daily Avg (mm)	2.6	1.9	2.4	0.02	35
Panel B: Repeat Sales Sample					
Sales Price	474,870	345,000	644,470	50000	46,117,500
Fire Risk	0.62	1.00	0.49	0	1.00
House Age	25	25	17	0	166
Square Footage (1000s)	1.3	1.1	0.80	0.1	17
# Bedrooms	2.6	3	1.2	1	15
Slope	3.6	2.3	4	0	42
Elevation (m)	97	24	171	0	1469
Coastal Distance (m)	2,632	1,410	3,334	0.47	24,614
Single Family	0.4	0	0.49	0	1
Six Month Daily Avg (mm)	2.57	1.85	2.33	0.02	35.14

Note: Descriptive statistics for all transactions. Fire Risk is a binary indicator. Zero house age indicates the property was sold the same year it was built. All prices are nominal. N = 268,406 for the full sample and N = 180,044 for the repeat sales sample.

from this time-varying measure reinforce our main findings on the relationship between wildfire exposure and property values.

Our final dataset consists of 268,406 observations covering 158,405 unique properties in the four counties of Maui, Kauai, Honolulu, and Hawaii. Restricting this to properties that sold more than once, 33% of observations drop out. Table 1 provides descriptive statistics for the full sample and repeat sales subsample, highlighting key property characteristics and differences across the datasets. The nominal median sales price for the full sample was $356,773, while the repeat sales subsample had a slightly lower median of $345,000. Properties in the full sample were, on average, 26 years old, with a mean size of 1,400 square feet, and 59% were located in high fire risk areas. The average six-month daily rainfall was 2.6 mm across both samples. Table 2 further disaggregates the full sample by fire risk, illustrating notable differences. Properties in high-fire-risk areas were generally newer (mean age of 22 years) and larger (1,400 square feet on average) compared to low-fire-risk areas (mean age of 31 years, 1,300 square feet). Average six-month daily rainfall was higher in low fire-risk areas (3.2 mm) than in high fire-risk areas (2.2 mm). These differences underscore the geographic and environmental variation in the dataset, enabling an in-depth analysis of rainfall impacts on property values across fire risk profiles.

Table 2: Comprehensive Sample Summary Statistics split by Fire Risk (2000-2019)

	Low Fire Risk					High Fire Risk				
	Mean	**Median**	**Std. dev.**	**Min.**	**Max.**	**Mean**	**Median**	**Std. dev.**	**Min.**	**Max.**
Sales Price	505,352	365,000	724,534	50,000	46,117,500	488,610	350,000	680,005	50,000	41,775,000
House Age	31	31	18	0	162	22	21	16	0	166
Square Footage (1000)	1.3	1.1	0.87	0	21	1.4	1.2	0.79	0	14
# Bedrooms	2.5	2	1.3	1	18	2.7	3	1.1	1	16
Slope	3.4	1.9	4.2	0	42	3.8	2.6	3.9	0	47
Elevation (m)	101	18	201	0	1,584	95	30	148	0	1,401
Coastal Distance (m)	2,652	1,486	3,629	0.49	25,108	2,663	1,439	3,134	0.47	22,887
Single Family	0.38	0	0.49	0	1	0.42	0	0.49	0	1
Six Month Daily Avg (mm)	3.2	2.2	2.8	0.031	35	2.2	1.7	1.9	0.016	16

Note: Descriptive statistics for all transactions categorized by high fire risk (N = 110,676) and low fire risk (N = 157,730). All prices are nominal.

Figure 7 shows the distribution of sales prices which has a rightward skew. In our regression specifications, we use logarithm-transformed nominal sales price as our dependent variable, which approximately follows a normal distribution. Figure 8 shows that median home prices in Hawaii have continued to appreciate since 2000, reaching a high in 2007, right around the time of the global financial crisis. They then depreciated until 2011 but have since been appreciating steadily, reaching new highs near the end of our sample. Importantly, Figure 8 also plots the median sales price trend of the repeated sales sub-sample, which only includes properties that sold more than once. While repeat sales address the issue of unobserved differences in housing characteristics, the method may be less precise than hedonic models due to smaller sample sizes and potential selection bias issues (Gatzlaff and Haurin, 1997; Haan and Diewert, 2011; Case and Quigley, 1991). However, if the quality of homes is similar, arbitrage will force prices for the repeat sample to grow at the same rate as the prices for the full sample (Clapp et al., 1991), which is what we observe in Figure 8. The trends of the repeated sales and the full sample of sales are very closely related, with a correlation coefficient of 0.99. Conducting a Kolmogorov–Smirnov (KS) test on the density of log sales price of the repeat sale and full sample, we fail to reject the null hypothesis that there is no difference between the two distributions (D = 0.05, p = 0.69)[3]. Overall, the repeat sales sample is representative of the complete set of home sales.

[3]The K-S test compares the empirical distribution function of one sample to another sample. Comparing the two distribution functions generates a D value, which represents the maximum distance between two curves, as well as a corresponding p-value.

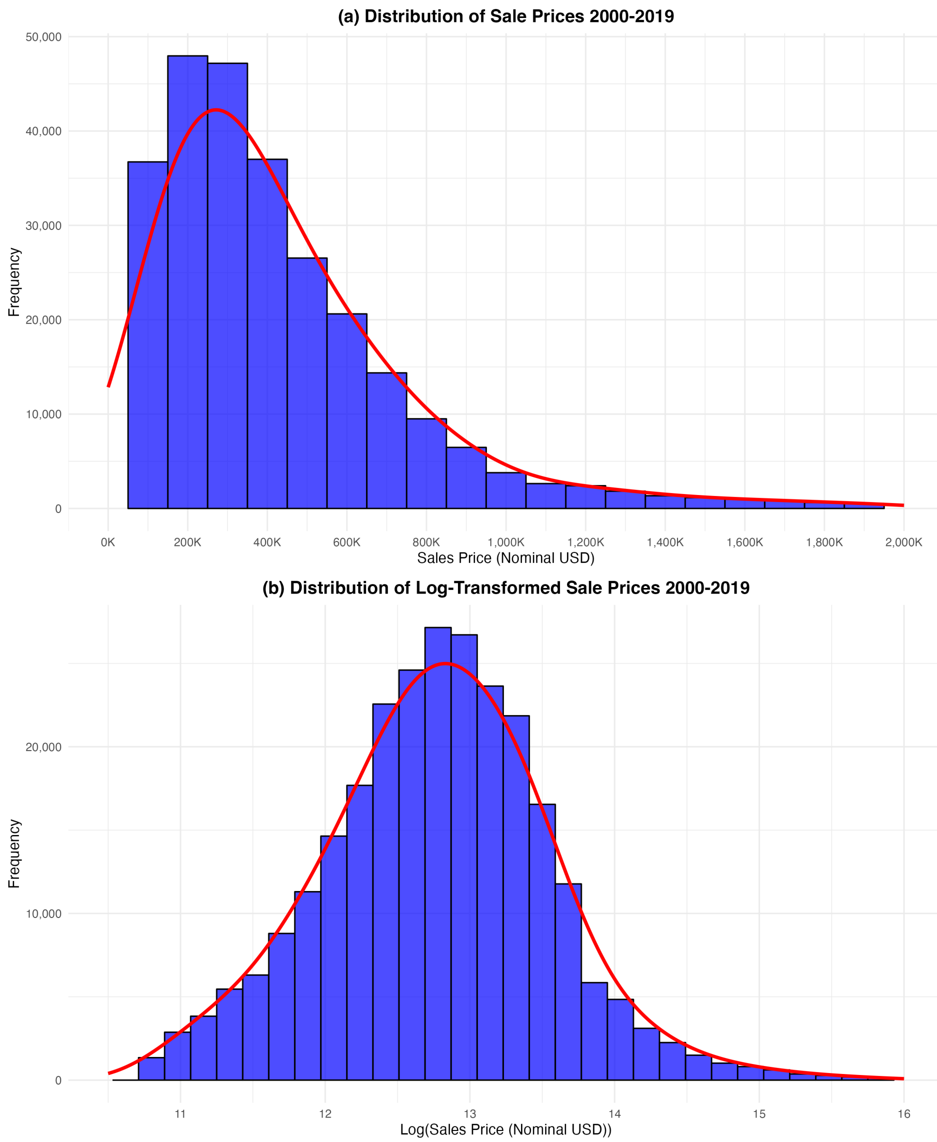

Figure 7: Nominal Sales Price Distributions 2000-2019

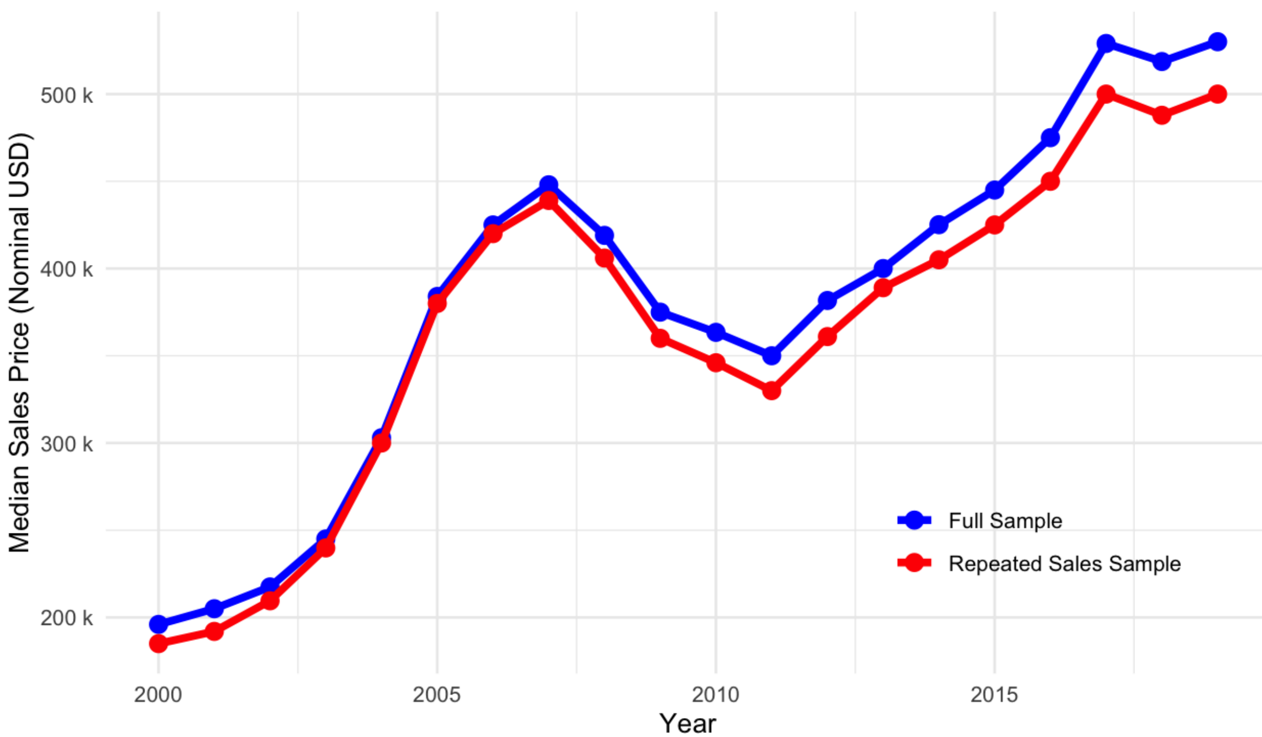

Figure 8: State Level Trend in Median Sales Price by Sample Type

4 Precipitation Measures

To quantify the relationship between precipitation patterns and property prices, we utilize various indices: Cumulative Rain Index (CRI), Fractional Deviation (FD), Shock Index (SI), Rain Event Count (REC), and Dry Event Count (DEC). Each index is computed for individual property transactions. For notational simplicity, we suppress the time subscript throughout our discussion of these indices, though each measure is calculated specific to a property's transaction date.

4.1 Cumulative Rain Index (CRI)

Z-score-based indices, or standardized precipitation anomalies, are widely used in the literature to quantify precipitation variability (Zaveri et al., 2023). Typically, these involve subtracting location-specific rainfall from its long-term mean and dividing by the standard deviation across the entire sample. As Zaveri et al. (2023) states, rainfall variability measured in this manner reflects random draws from the climate distribution. The resulting z-score represents the standard deviations from the long-run mean for a specific location and time. Our Cumulative Rain Index (CRI) extends this concept with some modifications. We define lookback periods (90, 180, or 365 days) before each property's transaction date. We compare this lookback period with a mean for the same calendar days during the prior 10 years, controlling for both location-specific and seasonal factors.

Calculating the long-term mean based on 10 years of daily observational data preceding our lookback period offers several advantages. First, it captures recent weather trends, as the baseline adjusts with each property's transaction date, allowing the index to adapt to evolving precipitation patterns potentially influenced by climate change. Second, according to Gourley (2021), recent weather conditions have a more statistically significant impact on house prices than long-term averages. Third, the approach flexibly adjusts for the volatility of weather, i.e. whether a property is in a region with a stable climate or one experiencing rapid changes, the index will reflect the relevant recent conditions relative to the norm. Our index is calculated as follows:

- For each property i, we consider N days (N = 90, 180, 365) of daily rainfall data immediately preceding the transaction date. This is our lookback period.
- For property i with transaction date t, we identify the same N calendar days in each year during the ten-year base period preceding the lookback period. For example, assuming $N = 180$ and the property sold on January 1, 2010, the lookback period would be July 5, 2009, to January 1, 2010 (180 days). The base period would cover July 5 to January 1 for each year from 1999 to 2008. This approach ensures consistency in seasonality between the lookback and base periods.
- The CRI for property i is the difference between the cumulative rainfall in the lookback period R_{lookback_i} and the mean of the cumulative rainfalls in each year of the base period μ_{base_i}, scaled by the standard deviation of the cumulative rainfall per year in the base period $\sigma^*_{\text{base}_i}$. Note that the base period means

and standard deviations are computed from ten cumulative rainfall observations (one for each year in the base period).

$$\text{CRI}_i = \frac{R_{\text{lookback}_i} - \mu_{\text{base}_i}}{\sigma_{\text{base}_i}} \tag{1}$$

For robustness, we also analyze the index constructed using a fixed 1990-1999 base period to examine the impact of long-term climate change rather than short-term weather variations.

4.2 Fractional Deviation (FD)

We use a commonly used measure of rainfall shocks constructed to account for seasonality, i.e., the fractional deviation of monthly rainfall from its average level (Sarsons, 2015; Duflo and Pande, 2007). The average is calculated for each month using data from 1990 to 1999. This fixed base period allows FD to account for long-term shifts in rainfall patterns, making it a potential proxy for climate change over the years. We define a shock for each of the 12 months preceding the transaction date and sum them to obtain the overall rainfall shock for each property. Specifically:

- For property i in month m, calculate the historical average across $BaseYears = \{1990, 1991, \ldots, 1999\}$. This gives us twelve average values for January through December.

$$\bar{R}_{i,m} = \frac{1}{10} \sum_{y \in \text{BaseYears}} R_{i,m,y} \tag{2}$$

- For each of the twelve months m preceding the transaction, calculate the fractional deviation from the historical average of that month.

$$\delta_{i,m} = \frac{R_{i,m} - \bar{R}_{i,m}}{\bar{R}_{i,m}} \tag{3}$$

- Sum the deviations for each of the 12 months preceding the transaction date and divide by twelve to compute the average fractional deviation for property i:

$$\text{FD}_i = \frac{1}{12} \sum_{m=1}^{12} \delta_{i,m} \tag{4}$$

4.3 Shock Index (SI)

We construct a seasonally adjusted measure of rainfall shocks based on the approach used in Sarsons (2015), Kaur (2019), and Jayachandran (2006).

- For each property i and each month m (January through December), we compute the 80th and 20th percentile total rainfall values, denoted as $P80_{i,m}$ and $P20_{i,m}$, respectively. These percentiles are computed using total rainfall data across the $BaseYears = \{1990, 1991, \ldots, 1999\}$, providing ten data points for each month.

- For each of the twelve months preceding the transaction month, we look at the total monthly rainfall $R_{i,m}$ and define a discrete shock $S_{i,m}$ to represent a positive, negative, or no shock.

$$S_{i,m} = \begin{cases} +1, & \text{if } R_{i,m} > P80_{i,m} \\ -1, & \text{if } R_{i,m} < P20_{i,m} \\ 0, & \text{if } P20_{i,m} \leq R_{i,m} \leq P80_{i,m} \end{cases} \tag{5}$$

- Calculate the average of the monthly shocks over the twelve months preceding the transaction date to obtain the rainfall shock measure for property i:

$$\text{Shock}_i = \frac{1}{12} \sum_{m=1}^{12} S_{i,m} \tag{6}$$

4.4 Rain Event Count (REC) and Dry Event Count (DEC)

To capture the frequency of unusual rainfall events and their potential impact on property prices, we employ metrics called Rain Event Count (REC) and Dry Event Count (DEC). These measures are designed to quantify how often precipitation deviates significantly from historical norms, providing a measure of extreme weather occurrences. REC focuses on unusually wet periods, calculated at the 90th, 95th, and 99th percentiles of historical rainfall. Conversely, DEC captures unusually dry periods, focusing on the 1st, 5th, and 10th percentiles. By examining both extremes, we aim to provide a comprehensive picture of precipitation anomalies that could influence property valuations. This approach allows us to capture not just the intensity but also the frequency of extreme weather events, which may have non-linear effects on property markets. The indices are calculated as follows:

- For each property transaction, we consider 365 days (12 months) of daily rainfall data immediately preceding the transaction date. This is our lookback period.
- For the same property, we use historical data over the past 10 years to calculate the respective percentile thresholds.
- For REC we count the number of days in the lookback period that exceed these thresholds.
- For DEC we count the number of days in the lookback period that are below these thresholds.

4.5 Precipitation Summary Statistics

Panel A of Table 3 presents summary statistics for our rainfall measures, revealing substantial variations in precipitation patterns across our comprehensive sample. These measures are designed to capture different aspects of rainfall shocks, from cumulative deviations to extreme events. The Cumulative Rain Index (CRI_{365}), which measures the standardized deviation of rainfall over a 365-day lookback period, shows a mean of 0.13 and a median of 0.07. This slight positive skew, coupled with a standard deviation of 1.30 and a range from -5.62 to 6.66, indicates that while on average, properties experienced slightly wetter conditions than historical norms, there was considerable variability, with some areas experiencing significantly drier or wetter conditions. The Fractional Deviation (FD) measure captures the average cumulative rainfall anomalies over the 12 months preceding each property transaction. With a mean of 0.1 and a median of 0.01, it suggests that, on average, properties experienced slightly higher cumulative rainfall in the year leading up to the transaction compared to their historical norms. Specifically, the mean indicates that over the year leading up to the transaction, the property experienced a consistent pattern of increased rainfall, averaging 10% more than what is typically expected based on historical data. The median of 0.01 implies that half of the observations had an average fractional deviation within 1% of their historical average over the 12 months. The standard deviation of 0.43 and the wide range from -0.85 to 3.24 highlight significant variability in rainfall patterns across different properties and periods. In extreme cases, some areas experienced only 25% of their normal cumulative rainfall (severe drought conditions), while others received more than three times their typical amount (extreme excess rainfall) in the year preceding a transaction.

The Shock Index (SI), which discretizes monthly rainfall into positive, negative, or no shocks based on historical 80th and 20th percentiles, provides additional insight into the frequency and direction of rainfall anomalies. With a mean of 0.05 and a median of 0.00, it suggests a slight tendency towards positive rainfall shocks in our sample period. The full range of -1.00 to 1.00 indicates that some properties experienced consistently dry or consistently wet conditions relative to their historical norms over the 12 months preceding the transaction.

We measure extreme rainfall frequency using Rain Event Counts (REC) above the 90th, 95th, and 99th percentiles over a 365-day period. On average, properties have 39.40 days (median 39) above the 90th percentile, 20.64 days (median 20) above the 95th, and 4.47 days (median 4) above the 99th, closely matching theoretical expectations of 37, 18, and 4 days, respectively. Maximum values of 119, 64, and 29 days reflect substantial spatial variation. Dry Event Counts (DEC) are lower: 33.5 days (median 36) below the 10th percentile and 0.40 days (median 0) below the 1st percentile. Notably, properties experience more than eleven times as many days above the 99th percentile than below the 1st, indicating a skew toward wet extremes.

Panel B demonstrates similar patterns, indicating consistency in rainfall measures across the repeat sales subsample. Overall, the variability in precipitation patterns, from sustained shifts in average rainfall to fluctuations in extreme wet and dry events, offers a robust foundation for analyzing the impact of changing rainfall regimes on property values across Hawaii's diverse micro-climates.

Table 3: Rainfall Measure Summary Statistics

	Mean	Median	Sd	Min	Max
Panel A: Full Sample					
CRI_{365}	0.13	0.07	1.30	-5.62	6.66
FD	0.09	0.01	0.43	-0.85	3.24
SI	0.05	0.01	0.49	-1.00	1.00
$REC_{>90\%}$	39.40	39.00	13.09	4.00	119.00
$REC_{>95\%}$	20.64	20.00	8.62	0.00	64.00
$REC_{>99\%}$	4.47	4.00	3.21	0.00	29.00
$DEC_{<10\%}$	33.48	36.00	20.32	0.00	124.00
$DEC_{<5\%}$	13.50	14.00	12.57	0.00	83.00
$DEC_{<1\%}$	0.40	0.00	1.69	0.00	23.00
Panel B: Repeat Sales Sample					
CRI_{365}	0.15	0.09	1.31	-5.41	6.66
FD	0.10	0.01	0.44	-0.85	3.24
SI	0.06	0.01	0.49	-1.00	1.00
$REC_{>90\%}$	39.59	39.00	13.18	4.00	119.00
$REC_{>95\%}$	20.76	20.00	8.69	0.00	64.00
$REC_{>99\%}$	4.49	4.00	3.26	0.00	29.00
$DEC_{<10\%}$	32.87	36.00	20.42	0.00	123.00
$DEC_{<5\%}$	13.21	13.00	12.50	0.00	69.00
$DEC_{<1\%}$	0.38	0.00	1.61	0.00	22.00

Note: Rainfall measure descriptive statistics based on all transactions (N = 268,406) and repeat sales transactions (N = 180,044). The Cumulative Rain Index (CRI) is calculated over a lookback period of 365 days before the transaction date, reflecting cumulative rainfall deviations. Fractional Deviation (FD) captures rainfall shocks using monthly deviations from a historical average for each of the 12 months preceding the transaction date. The Shock Index (SI) is based on discrete monthly rainfall shocks, where rainfall in each of the 12 months deviates beyond the 80th or below the 20th percentiles of historical values. Rain Event Count (REC) and Dry Event Count (DEC) quantify extreme daily events, counting the number of days exceeding or falling below-specified rainfall percentiles within the 365-day lookback period.

5 Methods

We use a hedonic regression to examine the heterogeneous impact of rainfall on property values between 2000-2019 across areas with different levels of fire risk. Our estimating equation 7 controls for housing characteristics to isolate the effect of precipitation changes:

$$\log(P_{it}) = \beta_1 W_{it} + \beta_2 F_i + \beta_3 (W_{it} \cdot F_i) + X_{it}\gamma_x + Y_t + C_i + \epsilon_{it} \tag{7}$$

The variable P_{it} represents the log-price of property i in transaction year t, W_{it} is a placeholder for our wetness measure, F_i is a binary variable that is one if fire risk is high, the vector X_{it} represents the property characteristics including property type (Single Family vs Multi Family), house age, living area square footage, total rooms, number of bedrooms, slope of the property, and 20 equal sized control bins for elevation and coastal proximity. Year-month fixed effects Y capture market-wide fluctuations in home prices over time, and census tract fixed effects C absorb time-invariant neighborhood characteristics. Consequently, our identification stems from within census tract variation in our wetness measure. The coefficient β_1 captures the average effect of changes in precipitation on log property prices in areas with low fire risk ($F_i = 0$), holding all other factors constant. For high fire risk areas ($F_i = 1$), the β_2 coefficient represents the price premium or discount associated with high fire risk regardless of precipitation levels, and the β_3 coefficient shows how the effect of precipitation on property prices differs in high fire risk areas compared to low fire risk areas. The total effect of precipitation on log property prices in high fire risk areas is given by $\beta_1 + \beta_3$.

To account for the possibility of unobserved differences in housing characteristics, we also estimate a repeat sales model given in equation 8. The repeat sales approach isolates the average difference in log price experienced by a specific property due to changes in precipitation levels between sales, while also accounting for how this effect varies with fire risk. Identification now stems from variations in precipitation through time across repeat sales.

$$\log(P_{it}) = \beta_1 W_{it} + \beta_2 (W_{it} \cdot F_i) + \beta_3 (F_i \cdot T_i) + \beta_4 (C_i \cdot T_i) + Y_t + H_i + \epsilon_{it} \quad (8)$$

Property fixed effects H_i control for all time-invariant characteristics of the property, including those that are observable (such as location, elevation, or basic structural features) and those that are unobservable, mitigating the concerns for omitted variable bias. The year-month fixed effects Y_t continue to control for market-wide temporal variation and the interpretation of β_1 and β_2 remains the same: heterogeneous impact of precipitation in high and and low fire risk areas. Note that we do not control directly for F_i, as being in high vs low risk is absorbed by the property fixed effects. We do control for the possibility that properties may appreciate differently in high fire risk areas by including $(F_i \cdot T_i)$, where T_i is a continuous year variable generated from the transaction date (i.e., a property sold at the end of the sixth month of 2012 would take the value of 2012.5). The coefficient β_3 captures the yearly difference in price appreciation between high and low fire risk properties. Similarly, the term $(C_i \cdot T_i)$ captures the time trend in property appreciation by census tract which accounts for how preferences for different census tracts may have changed over time.

For both hedonic and repeat sales specifications, we apply a two-way clustering adjustment to standard errors since ϵ_{it} may be correlated across space and time. The effect of precipitation on properties in the same neighborhood is likely similar, which justifies clustering at the census tract level. Temporally, we cluster at the year-month level to account for the correlation of precipitation patterns within months.

6 Results

Our hedonic model provides insights into how various property characteristics and rainfall patterns influence housing prices in Hawaii, with a particular focus on areas with different levels of fire risk (Table 4). The control coefficients in our hedonic model align with conventional expectations in the real estate literature. We find that living area is positively associated with property values, with each additional 1,000 square feet corresponding to a 25% higher price ($p<0.01$). This substantial effect underscores the premium placed on spacious homes in the Hawaiian market. Similarly, each additional bedroom is associated with a 3% price increase (p<0.01), reflecting the value of functional living space. Single-family homes command a significant premium of 20% (p<0.01) over multi-family dwellings. The positive coefficient for average slope (0.5% per unit increase, p<0.01) suggests that properties on steeper terrain are more valuable. Conversely, house age has a small negative effect (-0.4% per additional year, p<0.01), indicating a preference for newer properties. Irrespective of precipitation, properties in high-fire-risk areas sell at about an 8-15% discount.

Table 4: Hedonic Regression Results

	Dependent Variable: Log(Sales Price)						
	CRI_{365}	FD	SI	$REC_{>90}$	$REC_{>99}$	$DEC_{<10}$	$DEC_{<1}$
Index	-0.019***	-0.061***	-0.024**	-0.003***	-0.008***	0.000	-0.005***
	(0.003)	(0.013)	(0.011)	(0.000)	(0.001)	(0.000)	(0.001)
Index × Fire Risk	0.011***	0.067***	0.042***	0.002***	0.010***	-0.001***	0.000
	(0.002)	(0.011)	(0.009)	(0.000)	(0.001)	(0.000)	(0.002)
Fire Risk	-0.083**	-0.086**	-0.084**	-0.148***	-0.124***	-0.082**	-0.082**
	(0.038)	(0.038)	(0.038)	(0.039)	(0.038)	(0.038)	(0.038)
House Age	-0.004***	-0.004***	-0.004***	-0.004***	-0.004***	-0.003***	-0.004***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Living Area (1000 sq. ft.)	0.252***	0.252***	0.252***	0.252***	0.252***	0.252***	0.252***
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
Bedrooms	0.030***	0.030***	0.030***	0.030***	0.030***	0.030***	0.030***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
SFR	0.202***	0.201***	0.202***	0.202***	0.201***	0.202***	0.202***
	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)
Avg. Slope	0.005***	0.005***	0.005***	0.005***	0.005***	0.005***	0.005***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Num. Obs.	268,406	268,406	268,406	268,406	268,406	268,406	268,406
R^2	0.728	0.728	0.728	0.728	0.728	0.728	0.728
Adj. R^2	0.716	0.716	0.716	0.716	0.716	0.716	0.716
Census FE	Y	Y	Y	Y	Y	Y	Y
Year-month FE	Y	Y	Y	Y	Y	Y	Y

Note: Significance levels: *** p<0.01, ** p<0.05, * p<0.1. Two-way clustered standard errors in parentheses. This table presents hedonic regression results with various rainfall measures. CRI_{360} (Cumulative Rainfall Index, 360-day), FD (Fractional Deviation), SI (Shock Index), REC (Rain Event Count), and DEC (Dry Event Count) capture different aspects of precipitation patterns. Subscripts for REC and DEC indicate percentile thresholds, with both measures calculated based on a 365-day lookback period.

Turning to variables of primary interest, we find that higher precipitation levels, as proxied by various measures, negatively affect property values in low-fire-risk areas. The Cumulative Rain Index (CRI_{365}) coefficient indicates that a one unit higher index, representing one standard deviation higher rainfall at a particular location, is associated with a 1.9% decline in property values ($p < 0.01$) in low fire risk areas. However, the effect differs markedly in high-fire-risk areas, where the same increase corresponds to only a 0.8% decrease in property values. Additional measures, including the Fractional Deviation (FD), Shock Index (SI), and Rain Event Count (REC), provide further insights. A one-unit increase in FD is associated with a 6% decline in property values ($p < 0.01$) in low-fire-risk areas. This negative impact is fully reversed in high-fire-risk areas, where a mild positive effect of 0.6% is observed. Similarly, a one-unit increase in SI corresponds to a 2.4% decline in property values ($p < 0.05$) in low-fire-risk areas, while high-fire-risk areas exhibit a 1.8% increase in property values.

In low fire risk areas, an additional day of rainfall above the 90th percentile ($REC_{>90}$) is associated with a 0.3% decrease in property values (p<0.01), while an additional day above the 99th percentile ($REC_{>99}$) corresponds to a 0.8% decrease (p<0.01). In high fire risk areas, the coefficients are 0.1% and 0.2%, respectively.

The Dry Event Count (DEC) measures show that dry days must be very extreme to negatively impact property values. An additional day below the 10th percentile (DEC< 10) has no impact on property values, but an additional day below the 1st percentile (DEC< 1) of rainfall is associated with a 0.5% decrease in property values ($p < 0.01$) in both high and low fire risk areas. Notably, the effect of dry conditions does not show a significant interaction with fire risk, unlike the wet conditions captured by REC. This suggests that the relationship between precipitation patterns and fire risk may not be reciprocal: increased wetness reduces fire risk, but increased dryness does not proportionally increase it, at least as perceived by the housing market.

Table 5: Repeat Sales Regression Results

	Dependent Variable: Log(Sales Price)						
	CRI_{365}	FD	SI	$REC_{>90}$	$REC_{>99}$	$DEC_{<10}$	$DEC_{<1}$
Index	-0.021***	-0.057***	-0.019	-0.003***	-0.007***	0.000	-0.005**
	(0.003)	(0.017)	(0.012)	(0.000)	(0.002)	(0.000)	(0.002)
Index × Fire Risk	0.013***	0.078***	0.052***	0.002***	0.010***	-0.001**	-0.004
	(0.003)	(0.014)	(0.012)	(0.000)	(0.001)	(0.000)	(0.003)
Fire Risk × Year	-0.005***	-0.004***	-0.005***	-0.005***	-0.004***	-0.005***	-0.005***
	(0.002)	(0.001)	(0.002)	(0.002)	(0.001)	(0.002)	(0.002)
Num. Obs.	180,044	180,044	180,044	180,044	180,044	180,044	180,044
R^2	0.880	0.881	0.880	0.881	0.881	0.880	0.880
Adj. R^2	0.804	0.804	0.804	0.804	0.804	0.804	0.804
Property FE	Y	Y	Y	Y	Y	Y	Y
Year-month FE	Y	Y	Y	Y	Y	Y	Y
Census Time Trend	Y	Y	Y	Y	Y	Y	Y

Note: Significance levels: *** p<0.01, ** p<0.05, * p<0.1. Two-way clustered standard errors in parentheses. This table presents repeat sales regression results with various rainfall measures. CRI_{360} (Cumulative Rainfall Index, 360-day), FD (Fractional Deviation), SI (Shock Index), REC (Rain Event Count), and DEC (Dry Event Count) capture different aspects of precipitation patterns. Subscripts for REC and DEC indicate percentile thresholds, with both measures calculated based on a 365-day lookback period.

Our repeat sales model corroborates the hedonic model findings while addressing potential omitted variable bias through its control of time-invariant property characteristics. The coefficients for rainfall indices remain notably consistent between both models. For instance, a one standard deviation increase in CRI corresponds to a 2.1% decrease in property values (p<0.05) in low fire risk areas, closely matching the 1.9% effect observed in the hedonic model. Similarly, the fire risk-mitigating benefits of rainfall persist with properties in high-risk areas showing only a 0.8% depreciation following precipitation. Properties in fire risk areas face an annual price appreciation penalty of 0.5%, indicating an accumulating long-term cost to being in these risk zones.

Collectively, our findings in the hedonic and repeat sales model indicate that while rainfall generally decreases property values, this negative effect is substantially moderated in fire-prone areas. The divergence suggests that housing markets capitalize the protective function of rainfall against fire hazards in vulnerable areas.

7 Discussion and Conclusion

The relationship between precipitation and fire risk operates through multiple channels that may have countervailing effects on property values. Drought conditions enhance fire risk by increasing the availability of combustible fuel (Westerling et al., 2006; Lima et al., 2018; Puxley et al., 2024). Conversely, periods of excessive precipitation can promote vegetation growth that subsequently becomes potential fire fuel under dry conditions (Volkova et al., 2019; Hernández Ayala et al., 2021). However, wet conditions may also reduce fire risk through several mechanisms: maintaining higher soil moisture that reduces ignition probability (Abatzoglou and Williams, 2016), limiting the accumulation of dry fine fuels (Van Blerk et al., 2021), and altering vegetation moisture content. These mitigating effects have been documented across diverse ecosystems, from tropical regions (Spracklen et al., 2012) to urban-wildland interfaces (Sakai et al., 2004).

Our empirical findings suggest that real estate markets place significant value on the fire-mitigating effects of precipitation in high-risk areas. The attenuation of rainfall's negative price effect in fire-prone zones indicates that buyers pay attention to these complex ecological relationships in their property valuations. The moderation effect is not sensitive to how we quantify rainfall, is robust to alternative regression specifications, and is consistent when using alternative fire risk measures, including both designated risk zones and actual fire occurrences. Such market behavior parallels documented responses to other natural hazards where risk perceptions drive price dynamics (Bin and Landry, 2013; Hallstrom and Smith, 2005).

The magnitude of these effects is economically significant. While a one unit increase in cumulative rainfall index (which is equivalent to a one standard deviation increase in precipitation) reduces property values by 1.9% in low-fire-risk areas, this negative effect decreases to 0.8% in high-risk areas. This difference suggests that markets assign substantial value to precipitation's potential role in fire risk mitigation. Similarly, each additional day of extreme rainfall (above the 99th percentile) reduces values by 0.8% in low-risk areas but only 0.2% in high-risk areas.

Our findings have three key implications. First, there is value in further research examining if real estate markets process compound climate risks correctly. While our results show that markets incorporate precipitation-fire risk relationships into property values, these price responses occur in a context of evolving ecological understanding (Westerling et al., 2006; Abatzoglou and Williams, 2016). As precipitation patterns become more variable, public education and disclosure requirements could help markets better reflect emerging scientific evidence.

Second, the heterogeneous impact of precipitation across fire risk zones suggests the need for spatially targeted adaptation strategies. While our findings show that markets already differentiate between high and low-fire-risk areas, the growing threat of climate change may warrant additional policy consideration. Local governments might evaluate building codes or land management requirements in high-risk areas to complement market-based responses.

Third, our results inform ongoing debates about climate adaptation in spatially granular contexts. Hawaii's diverse microclimates and varying exposure to fire risk create valuable variation for studying climate-property value relationships. The substantial price discounts we document in fire risk areas (8-15%) suggest a significant market valuation of fire risk, with potential implications for public investment in risk mitigation infrastructure extending beyond Hawaii's unique context.

Several promising directions for future research emerge from our analysis. While we document how markets process climate risks in Hawaii's setting, investigating whether similar patterns exist in other regions would illuminate the broader applicability of our findings. Studies could examine how major events like the 2023 Lahaina fire influence market responses to precipitation in fire risk areas, and how variations in risk communication affect market pricing of compound climate risks. Such analyses would extend our understanding beyond single climate hazards to better capture the interactions between multiple environmental risks.

In conclusion, our findings reveal that markets actively price both precipitation and fire risks through measurable effects on property values. The observed price patterns suggest that buyers weigh precipitation's role in fire risk when valuing properties, contributing to a growing literature on how real estate markets price compound climate risks. As communities worldwide confront intersecting environmental hazards, understanding these market responses becomes increasingly relevant for policy design.

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A Appendix

Our fire risk designation is based on wildfire risk zones established in the mid-2000s, with boundaries remaining constant from data collection in 2006-2007 to the end of our sample period in 2019. While research shows that home buyers respond to such risk designations (Donovan et al., 2007), figure A1 reveals that actual wildfire occurrences do not perfectly align with these established risk zones. To validate our findings, we complement our analysis using a time-varying fire index based on actual wildfire occurrences, rather than relying solely on the time-invariant risk ratings.

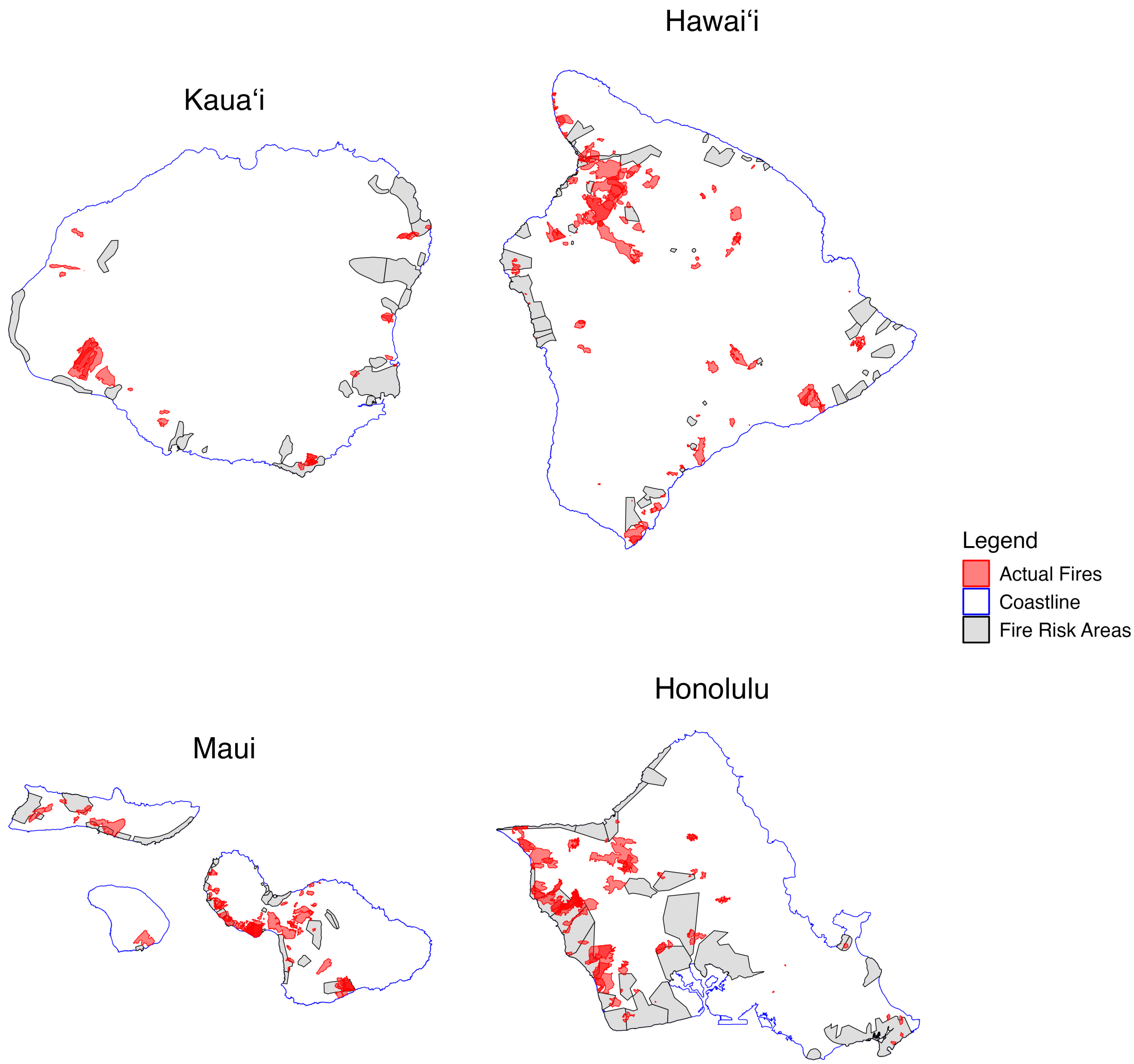

Figure A1: Actual Fire Occurrences and Fire Risk Areas

We obtain the wildfire occurrence data from the Pacific Fire Exchange website. The dataset primarily focuses on fires equal to or larger than 20 hectares (50 acres) and integrates multiple data sources including ground-based GPS-mapped fire perimeters from the Hawaii Wildfire Management Organization, National Park Service records from Hawaii Volcanoes National Park, US Geological Survey's Monitoring Trends in Burn Severity satellite data (2002-2011), and the Army Natural Resource Program-Oahu. Additional fires were mapped by the University of Hawaii's Department of Natural Resources and Environmental Management using LANDSAT and Sentinel-2 satellite imagery. The state had a total of 310 wildfires between 2000-2019, with an average size of 796 acres.

Existing literature typically employs either the size and proximity of the nearest fire (Holmes et al., 2008; Stetler et al., 2010) or considers the number and average size of fires within a set distance from properties (Hansen and Naughton, 2013; Xu and van Kooten, 2013), finding significant impacts on property values. However, using these attributes individually can overlook the non-linear relationships between fire exposure and property values, potentially missing relevant fire characteristics. To circumvent these issues, we construct a transaction-specific index following Shi et al. (2022). This measure integrates all major aspects of wildfire exposure; fire sizes, distances to fires, and the number of fires. Specifically, for each property transaction i at time t, we calculate:

$$\text{fireindex}_{it} = \sum_{k} \frac{\text{size}_{kt}^{\alpha}}{\exp(\text{distance}_{kt})} \tag{9}$$

where size_{kt} represents the size of fire k in acres, distance_{kt} indicates the proximity in km from the property to the centroid of fire k, and α is a diminishing parameter estimated using a grid search method that minimizes the sum of squared errors. This specification allows for nonlinear impacts of fire size while accounting for spatial decay in the fire's influence through the exponential distance term.

Following (Shi et al., 2022), we use wildfires occurring between three years and 60 days before the sale date to construct the fire index. The lower limit of 60 days is selected because the decision to purchase a property is often made around two months before the official recording date, as commonly noted in hedonic studies (Loomis, 2004; Mueller et al., 2009). The upper limit of three years is informed by literature indicating that initial high price discounts due to wildfire risk tend to diminish over a 2–3-year period (McCoy and Walsh, 2018). We further restrict our analysis to wildfires within 10 km of the property [4]. Prior studies indicate that wildfires beyond 20 km generally do not significantly affect property values (Stetler, 2008; Stetler et al., 2010), which has led to 20 km being a standard search radius in previous research (Shi et al., 2022). However, we adopt a 10 km radius, as the geographic area in our study is generally smaller than those examined in these earlier works.

We employ the conventional grid search method, which exhaustively searches through a manually spec-

[4]We calculate distances from the center of each property to the centroid of each fire polygon, reflecting the assumption that a fire's impact emanates from its center.

ified subset of possible values for α (Dufour and Neves, 2019; Shi et al., 2022). Specifically, we calculate the fire index for values of α between $[-2, 2]$ in increments of 0.1 and estimate our models accordingly. The value that minimizes the sum of squared residuals (SSR) serves as the estimate for α. Previous studies suggest that α should be relatively small, likely within the range of 0 to 1, indicating a diminishing marginal impact of fire size on property values (Xu and van Kooten, 2013; Shi et al., 2022). In this context, our estimate of $\alpha = 0.2$ aligns well with existing literature.

Table A1 presents summary statistics for the newly added fire-related variables, using the same sample as the previously analyzed dataset. Overall, 43% of transactions in the sample had some level of wildfire exposure. The mean fire index value of 0.41 and median of 0 suggest that most of these properties had low fire exposure. The maximum fire index value of 18 highlights that certain properties were situated in significantly high-risk zones.

Table A1: Summary Statistics for Fire Index Sample (2000-2019)

	Mean	**Median**	**Sd**	**Min.**	**Max.**
Fire Index	0.41	0	1.1	0	18
Fire Index > 0	0.43	0	0.5	0	1

Note: Descriptive statistics for the fire index sample for the four islands of Maui, Kaua'i, Honolulu, and Hawai'i. The variable "Fire Index > 0" is a dummy, equal to 1 if the fire index for a transaction is positive. N = 268,406.

We now estimate our main hedonic specification using the time-varying fire index measure as opposed to the fire risk designation. Table A2 reinforces our core findings while providing additional robustness. The results continue to demonstrate the dual negative effects of both rainfall and wildfire risk on property values. More importantly, they substantiate our primary hypothesis regarding rainfall's moderating effect on wildfire risk.

Specifically, in areas considered safe from fires, a one unit higher CRI, representing one standard deviation higher rainfall at a particular location, corresponds to a 1.5% decrease in property values. However, for properties in fire-prone areas that experienced rainfall, this negative effect is reduced to approximately 1%. This pattern, observed across both static and dynamic measures of fire risk, provides robust evidence for our central finding: rainfall significantly mitigates the negative impact of being in a fire-prone area. We also find some support ($p < 0.1$) that each additional dry day further reduces property values in areas at risk of wildfire.

We also examine correlations among key variables to assess the extent of dependence between our fire risk and precipitation measures (Figure A2). The fire risk zone indicator correlates positively with our dynamic fire exposure index, suggesting consistency between designated risk areas and actual fire patterns. Precipitation measures exhibit expected correlations with each other but show minimal correlation with either fire risk measure, supporting the identification of interaction effects in our main analysis.

Next, we show that our results are not sensitive to the choice of lookback period before the property

Table A2: Hedonic Regression Results with Fire Index

	Dependent Variable: Log(Sales Price)						
	CRI_{365}	FD	SI	$REC_{>90}$	$REC_{>99}$	$DEC_{<10}$	$DEC_{<1}$
Index	-0.015***	-0.019**	-0.001	-0.002***	-0.003*	-0.001***	-0.006***
	(0.003)	(0.011)	(0.009)	(0.000)	(0.001)	(0.000)	(0.001)
Fire Index	-0.011***	-0.011***	-0.011***	-0.034***	-0.021***	-0.022***	-0.011***
	(0.003)	(0.003)	(0.003)	(0.005)	(0.004)	(0.004)	(0.003)
Index × Fire Index	0.006***	0.018***	0.013***	0.001***	0.003***	-0.001***	-0.003*
	(0.001)	(0.004)	(0.003)	(0.000)	(0.001)	(0.000)	(0.002)
House Age	-0.004***	-0.004***	-0.004***	-0.004***	-0.004***	-0.004***	-0.004***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Living Area (1000 sq. ft.)	0.252***	0.252***	0.252***	0.252***	0.252***	0.252***	0.252***
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
Bedrooms	0.030***	0.030***	0.030***	0.030***	0.030***	0.030***	0.030***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
SFR	0.202***	0.202***	0.202***	0.202***	0.202***	0.202***	0.202***
	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)
Avg. Slope	0.005***	0.005***	0.005***	0.005***	0.005***	0.005***	0.005***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Num. Obs.	268,406	268,406	268,406	268,406	268,406	268,406	268,406
R^2	0.728	0.728	0.728	0.728	0.728	0.728	0.728
Adj. R^2	0.716	0.716	0.716	0.716	0.716	0.716	0.716
Census FE	Y	Y	Y	Y	Y	Y	Y
Year-month FE	Y	Y	Y	Y	Y	Y	Y

Note: Significance levels: *** p<0.01, ** p<0.05, * p<0.1. Two-way clustered standard errors in parentheses. This table presents hedonic regression results with various rainfall measures. CRI_{365} (Cumulative Rainfall Index, 365-day), FD (Fractional Deviation), SI (Shock Index), REC (Rain Event Count), and DEC (Dry Event Count) capture different aspects of precipitation patterns. Subscripts for REC and DEC indicate percentile thresholds, with both measures calculated based on a 365-day lookback period.

transaction. We consider the alternative construction of the cumulative rainfall index with lookbacks of 90 and 180 days respectively. We also consider the impact of Rain and Dry Event counts based on various percentile thresholds. Table A3, A4, and A5 report these results.

The Cumulative Rain Index (CRI) captures broad precipitation patterns over 90, 180, and 365 day lookbacks, comparing them to either fixed historical (1990-1999) or dynamic (prior decade) baselines. Table A6 reports fixed baseline results. Both CRI and Fire Risk coefficients maintain similar magnitudes and statistical significance across specifications.[5] However, the interaction effects between CRI and fire risk are muted under fixed baseline, particularly for the shorter 90 and 180-day lookback periods. This suggests buyers emphasize recent weather trends over historical patterns when assessing climate risks. While FD and SI measures show

[5]Under the fixed baseline specification, the CRI coefficients were consistently negative: -1.9% (365-day), -1.5% (180-day), and -1.0% (90-day), with all coefficients significant at 1% level. In dynamic baseline, these are -1.7%, -1.1%, and -0.7%, respectively, significant at either 1% or 5% level. In both cases, Fire Risk coefficient is approximately -0.8%, significant at 5% level (see Tables 4 & A3).

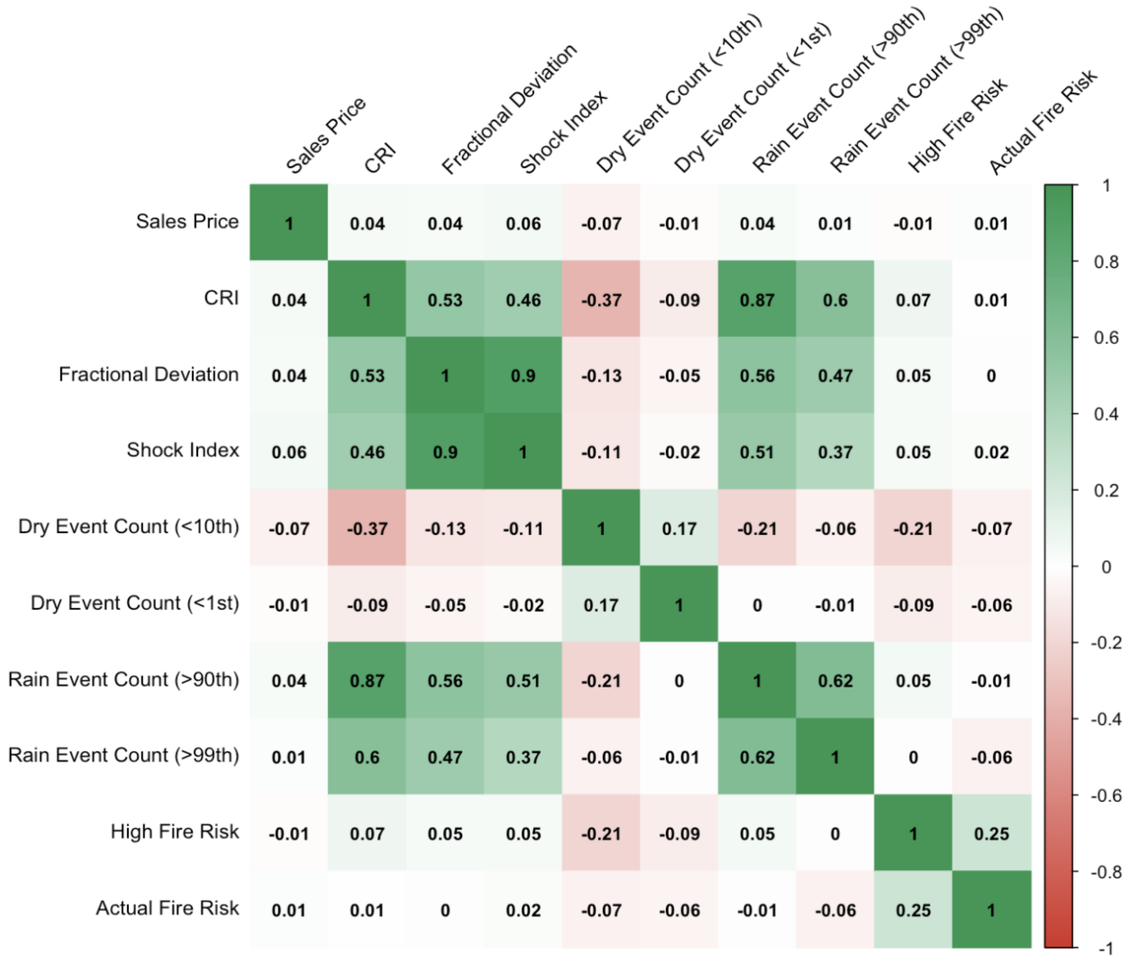

Figure A2: Correlation Matrix

Note: Lookback period is 365 days where applicable.

stronger fire risk mitigation effects even when anchored to the same historical 1990-1999 period, this could be due to markets viewing sharp monthly rainfall deviations as more effective at temporarily reducing fire risk than smooth cumulative patterns.

Table A3: Hedonic Regression Results with Different Lookbacks for CRI

	Dependent Variable: Log(Sales Price)			
Lookback Days	180	90	180	90
CRI	-0.015***	-0.010***	-0.010***	-0.007**
	(0.004)	(0.004)	(0.003)	(0.003)
Fire Risk	-0.084**	-0.083**		
	(0.038)	(0.038)		
CRI × Fire Risk	0.010***	0.007***		
	(0.002)	(0.003)		
Fire Index			-0.011***	-0.011***
			(0.003)	(0.003)
CRI × Fire Index			0.005***	0.003***
			(0.001)	(0.001)
House Age	-0.004***	-0.004***	-0.004***	-0.004***
	(0.000)	(0.000)	(0.000)	(0.000)
Living Area (1000 sq. ft.)	0.252***	0.252***	0.252***	0.252***
	(0.006)	(0.006)	(0.006)	(0.006)
Bedrooms	0.030***	0.030***	0.030***	0.030***
	(0.003)	(0.003)	(0.003)	(0.003)
SFR	0.201***	0.201***	0.200***	0.200***
	(0.009)	(0.009)	(0.009)	(0.009)
Avg. Slope	0.005***	0.005***	0.005***	0.005***
	(0.001)	(0.001)	(0.001)	(0.001)
Num. Obs.	268,406	268,406	268,406	268,406
R^2	0.728	0.728	0.728	0.728
Adj. R^2	0.716	0.716	0.716	0.716
Census FE	Y	Y	Y	Y
Year-month FE	Y	Y	Y	Y

Note: Significance levels: *** $p<0.01$, ** $p<0.05$, * $p<0.1$. Two-way clustered standard errors are in parentheses. This table presents hedonic regression results using different lookback periods for the Cumulative Rainfall Index, incorporating both static and dynamic fire risk measures.

Table A4: Hedonic Regression Results with Different Lookbacks for REC

	Dependent Variable: Log(Sales Price)						
	365 Days	180 Days			90 Days		
	REC_{95}	REC_{99}	REC_{95}	REC_{90}	REC_{99}	REC_{95}	REC_{90}
Index	-0.005***	-0.006***	-0.004***	-0.003***	-0.002	-0.004***	-0.003***
	(0.001)	(0.002)	(0.001)	(0.000)	(0.002)	(0.001)	(0.001)
Index × Fire Risk	0.003***	0.010***	0.003***	0.002***	0.009***	0.003***	0.002***
	(0.000)	(0.001)	(0.001)	(0.000)	(0.002)	(0.001)	(0.001)
Fire Risk	-0.147***	-0.106***	-0.113***	-0.112***	-0.093**	-0.098**	-0.099***
	(0.039)	(0.038)	(0.038)	(0.038)	(0.038)	(0.038)	(0.038)
House Age	-0.004***	-0.004***	-0.004***	-0.004***	-0.004***	-0.004***	-0.004***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Living Area (1000 sq. ft.)	0.252***	0.252***	0.252***	0.252***	0.252***	0.252***	0.252***
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
Bedrooms	0.030***	0.030***	0.030***	0.030***	0.030***	0.030***	0.030***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
SFR	0.202***	0.201***	0.201***	0.202***	0.201***	0.201***	0.202***
	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)
Avg. Slope	0.005***	0.005***	0.005***	0.005***	0.005***	0.005***	0.005***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Num. Obs.	268,406	268,406	268,406	268,406	268,406	268,406	268,406
R^2	0.729	0.728	0.728	0.728	0.728	0.728	0.728
Adj. R^2	0.716	0.716	0.716	0.716	0.716	0.716	0.716
Census FE	Y	Y	Y	Y	Y	Y	Y
Year-month FE	Y	Y	Y	Y	Y	Y	Y

Note: Significance levels: *** $p<0.01$, ** $p<0.05$, * $p<0.1$. Two-way clustered standard errors in parentheses. REC (Rain Event Count) variables are partitioned by lookback periods (365, 180, 90 days) and percentile thresholds (99, 95, 90).

Table A5: Hedonic Regression Results with Different Lookbacks for DEC

	Dependent Variable: Log(Sales Price)						
	365 Days	180 Days			90 Days		
	DEC_5	DEC_{10}	DEC_5	DEC_1	DEC_{10}	DEC_5	DEC_1
Index	-0.001*	0.000	0.000	-0.004**	0.001	0.000	-0.006**
	(0.000)	(0.000)	(0.001)	(0.002)	(0.001)	(0.001)	(0.002)
Index × Fire Risk	0.000	-0.001*	-0.001	0.001	0.000	0.000	0.004
	(0.000)	(0.000)	(0.001)	(0.003)	(0.001)	(0.001)	(0.003)
Fire Risk	-0.080**	-0.073**	-0.078**	-0.083**	-0.081**	-0.083**	-0.083**
	(0.039)	(0.038)	(0.038)	(0.038)	(0.039)	(0.038)	(0.038)
House Age	-0.004***	-0.004***	-0.004***	-0.004***	-0.004***	-0.004***	-0.004***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Living Area (1000 sq. ft.)	0.252***	0.252***	0.252***	0.252***	0.252***	0.252***	0.252***
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
Bedrooms	0.030***	0.030***	0.030***	0.030***	0.030***	0.030***	0.030***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
SFR	0.202***	0.202***	0.202***	0.202***	0.202***	0.202***	0.202***
	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)
Avg. Slope	0.005***	0.005***	0.005***	0.005***	0.005***	0.005***	0.005***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Num. Obs.	268,406	268,406	268,406	268,406	268,406	268,406	268,406
R^2	0.728	0.728	0.728	0.728	0.728	0.728	0.728
Adj. R^2	0.716	0.716	0.716	0.716	0.716	0.716	0.716
Census FE	Y	Y	Y	Y	Y	Y	Y
Year-month FE	Y	Y	Y	Y	Y	Y	Y

Note: Significance levels: *** p<0.01, ** p<0.05, * p<0.1. Two-way clustered standard errors in parentheses. DEC (Dry Event Count) variables are partitioned by lookback periods (365, 180, 90 days) and percentile thresholds (10, 5, 1).

Table A6: Hedonic Regression Results with Different Lookbacks for CRI (1990-1999 base)

	Dependent Variable: Log(Sales Price)		
Lookback Days	365	180	90
CRI	-0.017***	-0.011***	-0.007**
	(0.003)	(0.004)	(0.004)
Fire Risk	-0.080**	-0.082**	-0.082**
	(0.038)	(0.038)	(0.038)
CRI × Fire Risk	0.006**	0.004	0.002
	(0.003)	(0.003)	(0.003)
House Age	-0.004***	-0.004***	-0.004***
	(0.000)	(0.000)	(0.000)
Living Area (1000 sq. ft.)	0.252***	0.252***	0.252***
	(0.006)	(0.006)	(0.006)
Bedrooms	0.030***	0.030***	0.030***
	(0.003)	(0.003)	(0.003)
SFR	0.201***	0.201***	0.201***
	(0.009)	(0.009)	(0.009)
Avg. Slope	0.005***	0.005***	0.005***
	(0.001)	(0.001)	(0.001)
Num. Obs.	268,406	268,406	268,406
R^2	0.728	0.728	0.728
Adj. R^2	0.716	0.716	0.716
Census FE	Y	Y	Y
Year-month FE	Y	Y	Y

Note: Significance levels: *** p<0.01, ** p<0.05, * p<0.1. Two-way clustered standard errors (by Census Tract and year-month) are in parentheses. This table presents hedonic regression results using different lookback periods (365, 180, and 90 days) for the Cumulative Rainfall Index, where each period's rainfall is compared to the same calendar days in the fixed base period of 1990-1999.