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Elevation Effectiveness and Equity Across Flood Zones: A 30-Year Cost-Effectiveness Analysis in Post-Katrina Louisiana

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Abstract

Federal flood mitigation programs are designed to allocate resources efficiently, but whether these investments produce equitable outcomes remains unclear. We examine the 30-year cost effectiveness of federally funded home elevation following Hurricanes Katrina and Rita across 123 coastal Louisiana census tracts, using flood depth data, building attributes, federal funding records, and tract level demographics. Flood risk is measured as average annual loss (AAL), and mitigation performance is evaluated using percentage risk reduction and benefit cost ratio (BCR).

Flood risk is highly concentrated in frequently flooded areas. AAL in ≥10 year zones is about ten times higher than in ≥200 year zones. Elevation performs differently across these regimes. In high frequency zones, it reduces risk by about 95%, while in low frequency zones, where extreme floods can exceed practical elevation heights, risk reduction drops to about 53%. Populations are unevenly distributed across these regimes. White populations are overrepresented in higher frequency zones, while Non-white populations are more common in lower frequency zones. BCR outcomes differ significantly by tract racial composition with 68% of cost effective projects (BCR ≥ 1) located in white majority tracts.

Property level analysis shows that flood zone exposure is the dominant driver of avoided losses, while the association with tract racial composition is small and not significant at conventional thresholds ($\beta = -0.35$, $p = 0.07$). Disparities therefore arise primarily from the geographic distribution of populations across flood regimes rather than from within zone differences in performance. Equity weighted evaluation could justify additional investment in moderate BCR communities but cannot overcome the physical limits of elevation in low frequency zones.

Keywords

Flood mitigation, home elevation, cost-effectiveness, flood adaptation, social vulnerability

1. Introduction

1.1 Overview

Flooding is the nation's most expensive natural hazard (Srivastava et al., 2025). The United States continues to experience frequent and costly flood damage that imposes persistent and unequal burdens across communities (NCEI, 2024). In response, home elevation has become one of the most widely implemented structural flood mitigation strategies. Raising the first-floor height above the 100-year flood elevation (ASCE, 2005; 2014) can substantially reduce flood risk, and billions of dollars have been invested in elevating flood-prone homes, particularly following major disasters (FEMA, 2024; Mobley et al., 2020).

However, the effectiveness of elevation is not uniform. It depends on a fundamental physical condition: whether the elevated structure remains above flood depths during an event (Al Assi et al., 2024). This condition is more likely to be satisfied in high-frequency flood zones, where flood depths are generally moderate and predictable, than in low-frequency zones, where rare but extreme floods may exceed standard elevation heights (Ward et al., 2011). As a result, the same elevation investment can produce very different levels of risk reduction depending on the flood regime in which it is applied, even when allocation is based on risk and cost-effectiveness considerations (Zarekarizi et al., 2020). Although prior studies consistently show that elevation is cost-effective in high-risk floodplains (Al Assi 2023b; Gnan et al., 2022; FEMA, 2021a, 2021b, 2022), far less attention has been given to how elevation effectiveness varies systematically across return periods or whether risk-based investment performs equally well across the full range of flood exposure.

The economic benefit of home elevation is typically estimated using average annual loss (AAL) assessment, which quantifies expected damage aggregated across all flood events and weighted by their probability of occurrence (Al Assi et al., 2023a; Bowers et al., 2022; Hallegatte et al., 2013). AAL enables comparison of economic risk across the full spectrum of flood frequencies from frequent, lower-return-period events to rare, high-return-period catastrophes. However, this aggregate measure obscures how different flood frequencies contribute to risk. Properties exposed to more frequent flooding (e.g., 10-year events) experience moderate damage every few years. While individual events cause moderate damage, their cumulative effect produces substantial long-term losses (Ward et al., 2011). Properties exposed to less frequent flooding (e.g., 200-year events) face a different pattern: rare catastrophic floods that can devastate a home in a single event yet contribute less to AAL simply because they happen so infrequently (Wing et al., 2018; Olsen et al., 2015). While AAL is a useful planning metric (Montgomery & Kunreuther, 2018; Taghi Nezhad Bilandi, 2018), it obscures how risk is generated and how mitigation strategies perform under different flood regimes. Although flood frequency exists on a continuum, evaluating elevation effectiveness requires comparing performance across zones defined by return-period ranges.

Differential effectiveness across frequencies would have limited equity implications if populations were evenly distributed across flood zones. In practice, however, flooding does not affect all communities equally. Extensive research shows that communities with higher proportions of racial and ethnic minorities face disproportionate flood impacts (Emrich et al., 2019; Linscott et al., 2022; Seong et al., 2021; Ueland & Warf, 2006). In the southeastern United States, Black populations have been found to experience heightened flood exposure linked to

historical patterns of racism and segregation. Similar disparities have been documented among Hispanic and Latino populations in states such as Washington (Messager et al., 2021) and Georgia (Selsor et al., 2023). Hurricane Katrina remains a stark illustration of these inequities (CRS, 2005). In Louisiana, the storm disproportionately affected low-income and minority communities through higher mortality rates, greater property losses, longer displacement periods, and slower recovery trajectories (Elliott & Pais, 2006; Fussell et al., 2010). Studies documented significant racial disparities in federal assistance distribution, with predominantly Black neighborhoods receiving less aid relative to damage severity (Masozera et al., 2007). Given these well-documented racial and ethnic disparities across multiple facets of Hurricane Katrina's impact and recovery in Louisiana, an important question emerges: *do similar patterns exist in the cost-effectiveness of federally funded elevation investments?*

If mitigation strategies perform differently across flood regimes, and if socially vulnerable populations are unevenly distributed across those regimes, then unequal protection may emerge even in the absence of inequitable allocation decisions. Structural inequities may arise not only from who receives mitigation funding, but from how effectively the chosen strategy reduces risk under differing hazard conditions.

Using federally funded elevation projects implemented after Hurricanes Katrina and Rita in coastal Louisiana, we examine how the effectiveness of home elevation varies across flood regimes and across the communities exposed to them. We frame this question through the Intergovernmental Panel on Climate Change (IPCC) risk framework (Alegría et al., 2024), treating outcomes as the product of interacting components: hazard (flood depth and frequency), exposure (where elevated properties are located), vulnerability (the racial and socioeconomic composition of recipient communities), and response (the elevation strategy itself). This framing allows us to move beyond average cost-effectiveness to examine where, for whom, and under what flood conditions elevation delivers protection.

Three features distinguish our analysis. First, we evaluate elevation effectiveness over a 30-year horizon at the property level, long enough to capture cumulative benefits across the full distribution of flood return periods rather than relying on event-based or short-horizon assessments. Second, we connect physical mitigation effectiveness directly to the racial composition of recipient communities by combining property-level benefit-cost ratios with tract-level demographic data, and we break down the resulting disparities into two distinct sources: differences across flood zones, driven by where racial groups are located relative to the physical conditions under which elevation succeeds or fails, and differences within zones, which would indicate that similarly exposed Non-white and white communities receive different levels of protection. Third, we apply equity-weighted benefit-cost analysis as a counterfactual evaluation criterion to test whether alternative valuation frameworks would shift investments toward currently underserved communities. This approach helps us determine whether observed racial disparities in elevation outcomes are mainly a function of where people live, differences within similar conditions, or a combination of both, each of which has different implications for policy.

1.2 Research Gap, Motivation, and Objective

Despite extensive research on flood risk, mitigation policy, and environmental justice, important questions remain unanswered. While mitigation effectiveness is typically assessed using

aggregated risk metrics such as AAL, we do not know whether elevation performs equally across moderate versus extreme flood regimes over long time horizons. Similarly, although environmental justice research has documented disparities in exposure and funding access, it remains unclear whether the magnitude of risk reduction varies across demographic groups after mitigation is implemented. This distinction matters because equity in allocation does not necessarily translate to equity in protection. Finally, despite recent research for equity-weighted benefit-cost analysis, empirical evidence of how these frameworks would alter real-world mitigation decisions remains limited.

To address these gaps, we examine the interaction between flood regime, mitigation effectiveness, and demographic composition using federally funded elevation projects in coastal Louisiana:
(1) How do flood risk and the cost-effectiveness of elevation mitigation investments vary across flood return periods?
(2) Do racial disparities in elevation cost-effectiveness reflect differences in where Non-white and white populations are located across flood zones with different physical effectiveness, or differences in mitigation outcomes among similarly exposed properties?
(3) How would equity-weighted evaluation criteria alter cost-effectiveness outcomes for different populations?

2. Data

This study examines federally funded home elevations following Hurricanes Katrina and Rita (Figure 1) through FEMA's Hazard Mitigation Grant Program (HMGP) and HUD's Community Development Block Grant - Disaster Recovery (CDBG-DR). We focus on these programs because (1) this represents the largest federal elevation program in U.S. history, (2) sufficient time has elapsed to assess 30-year cost-effectiveness using FEMA's standard evaluation horizon, and (3) post-mitigation outcomes can be verified through observable elevation heights.

The mitigation efforts were supported by the Louisiana Governor’s Office of Homeland Security and Emergency Preparedness (GOHSEP) via the Road Home Program. The analysis specifically examines 123 census tracts. The study area is located in southern Louisiana, a low-lying coastal region highly vulnerable to flooding due to its proximity to the Gulf of Mexico and extensive network of rivers, bayous, and wetlands. This region experiences frequent hurricanes and tropical storms, which contribute to recurrent flooding, particularly in urbanized areas with high population densities. These 123 tracts represent those with complete data across all analysis variables, flood depth, building attributes, investment records, and demographic characteristics.

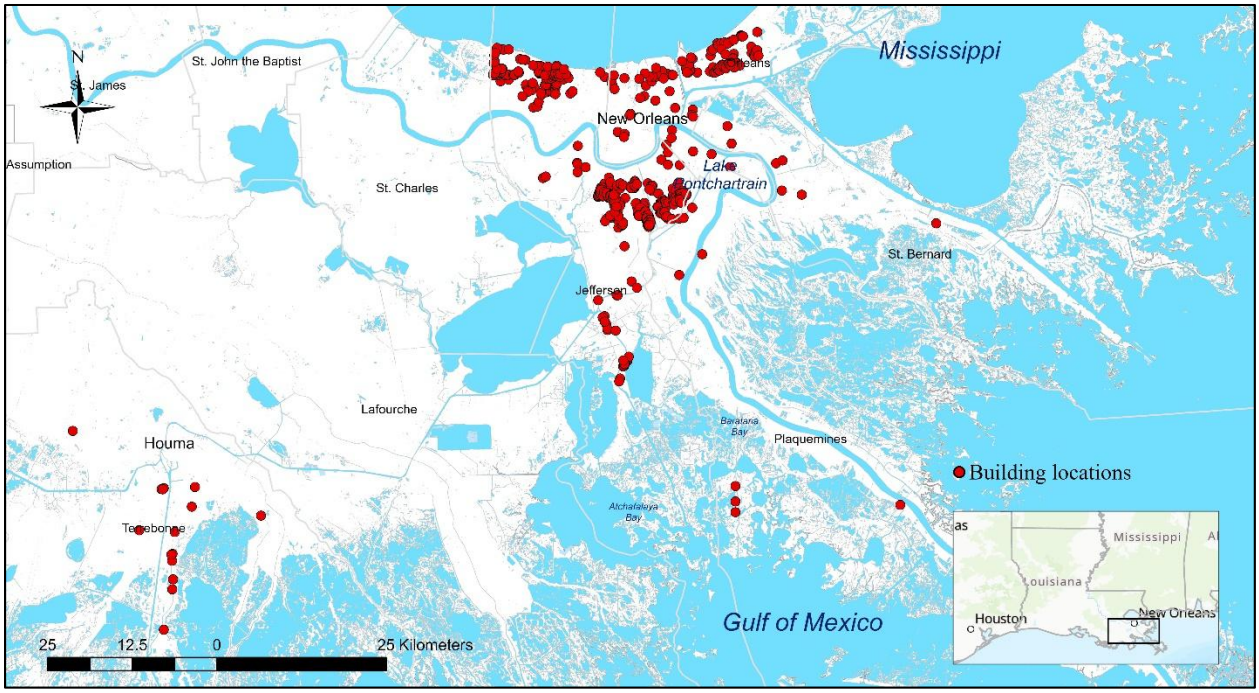

Figure 1. *Elevated buildings in Southern Louisiana.*

Four main types of data (Table 1) are required to conduct this analysis: flood depths, building attributes, demographic characteristics, and investment size. For flood depths, we used high-resolution data (10 x 10 m) for return periods of 5, 10, 20, 50, 100, 200, 500, and 1,000 years. The data were sourced from Fathom, a global flood hazard dataset provider (Bates et al., 2021). While Fathom models have shown a good agreement with real-world conditions and improved in many areas, many limitations have been noted. According to Schubert et al. (2024), nationwide flood models such as Fathom are less accurate in urban regions, especially in identifying complex stormwater drainage systems and pluvial flooding. This indicates the importance of refined models that accurately represent urban drainage infrastructure. Devitt et al. (2021) described that the Fathom regionalized flood frequency analysis (RFFA) method overpredicted the 100-year flood magnitude, which showed overestimation in 83% of the evaluated gauges, and 73% of them were overpredicted by more than 100%.

Table 1. *Analysis of variables and sources for flood risk assessment*

Data set	Variables	Source
Flood depth grids	Return periods of 5, 10, 20, 50, 100, 200, 500, and 1,000 years	Fathom
Depth Damage Function	Building and Content Loss	United States Army Corps of Engineers (USACE) 2000
Building attributes	Lat/Long	National Structure Inventory
	Occupancy type	
	Area	
	Number of stories	
	Basement existent	
	Structure Value	
	First-floor elevation before elevation	U.S. Department of Housing and Urban Development (HUD, 2012).
	First-floor elevation after elevation	Google Earth
Elevation investment	Eligible total project cost	Louisiana Governor's Office of Homeland Security and Emergency Preparedness
Population characteristics	Proportions of Hispanic, Asian, Native American, Black, Nonwhite, and renter populations; poverty rate	US Census Bureau

We extracted building attributes from the National Structure Inventory (NSI; 2025) of the U.S. Army Corps of Engineers. NSI represents every structure in the study area as a point and includes information on building characteristics such as occupancy type, first-floor elevation (FFE), number of stories, area, foundation type (e.g., crawl space or slab-on-grade), and whether the home has a basement. While the NSI provides data on FFE, the research team found it outdated and verified FFE measurements using Google Earth. For homes with crawl space foundations, the pre-mitigation FFE was determined to be 1.5 feet, and for slab-on-grade homes, it was 0.5 feet, following the guidelines of the U.S. Department of Housing and Urban Development (HUD, 2012). Post-mitigation FFE measurements were similarly verified through Google Earth imagery by measuring the visible distance from ground level to the bottom of the elevated structure.

We measured investment size as the cost of elevating homes in the selected study area, as determined by GOHSEP. HMGP funds typically cover 75% of this cost, while the Road Home Program covers the remaining 25%, ensuring homeowners meet HMGP's requirement for matching funds (Turnham et al. 2011).

We collected population data from the 2021-2025 American Community Survey (ACS) of the US Census Bureau (2025), at the census tract level. Census tracts are commonly used in socio-economic geospatial research to delineate small, statistically relevant areas. Variables include race/ethnicity, median income per capita, poverty rates, employment status, housing type, and the percentage of renters within these tracts. Because the distribution of flood exposure and mitigation benefits may vary with demographic composition, understanding how the study area compares to broader populations provides context for interpreting results.

In this study, we focus on race/ethnicity, poverty rate, and renter status. These variables aren't arbitrary; each captures a distinct dimension of vulnerability that research consistently links to flood outcomes. Race reflects structural disadvantages beyond economics, including historical patterns of residential segregation that shaped where communities live relative to flood hazards (Campbell, 2023). Poverty captures economic constraints that limit recovery capacity and mitigation access. Renter status matters because renters have less control over property-level decisions like elevation and face higher displacement risk (Wilson et al., 2021).

Table 2 compares the demographic composition of the study area with that of Louisiana and the national averages. The study area has a higher proportion of Black residents (53%) compared to Louisiana (31%) and the U.S. (13.7%), reflecting the demographic characteristics of the study area communities disproportionately impacted by Hurricanes Katrina and Rita.

Table 2. *Racial and ethnic composition (%) of the study area, Louisiana, and the United States*

	Study Area	LA	USA
Asian	3.7	1.8	6.0
Black	53.0	31.2	14.0
Hispanic	7.8	6.9	18.7
Native	0.5	1.0	1.0
White	35.0	56.0	58.0

3. Methodology

This section presents the methodology used to analyze flood risk and elevation cost-effectiveness across flood frequencies and demographic groups. We quantified flood risk in terms of AAL, using a computational framework to conduct the analysis at the building level and characterized demographic composition at the census tract level, matching the scale at which federal programs allocate mitigation resources. To examine how flood exposure varied among flood-vulnerable populations, we analyzed flood exposure among socially vulnerable populations by evaluating critical demographic indicators, showing insights into the distribution of federal elevation investments and risk mitigation outcomes across diverse groups. We then evaluated cost-effectiveness using BCR over a 30-year time horizon, applied chi-square analysis to test whether BCR outcomes differ significantly by racial composition, and conducted sensitivity tests using continuous demographic variables and quintile-based comparisons to ensure findings are robust to classification choices. We explored equity-weighted BCR to examine how alternative evaluation criteria might alter cost-effectiveness outcomes. Finally, we assessed the financial impact of elevation mitigation by examining both the size of federal elevation investments and the percent reduction in AAL across different flood return periods.

3.1 AAL across Return Periods

We evaluated flood risk across multiple return periods, utilizing the computational framework developed by Al Assi et al. (2023a). This framework evaluated flood risk in terms of AAL at both the individual building and aggregated levels, considering building structure, contents, and use risk. It addresses key limitations of existing loss models that rely only on available data, such as the Hazus Flood Model (FEMA, 2013), by applying a refined numerical integration method that considers the risk across the full range of probabilities. It enhances building-specific risk estimation by overcoming the generalization issues present in macro- and meso-scale assessments. Furthermore, this method minimizes errors associated with piecewise and log-linear

extrapolation techniques, providing a more precise evaluation of long-return-period floods and their financial impacts (Gnan et al., 2022).

AAL is defined as the integral of the loss curve as a function of flood probability, where P_{min} represents the lowest exceedance probability value and P_{max} the highest exceedance probability value (Eq.1).

$$AAL = \int_{\mathrm{P\ min}}^{\mathrm{Pmax}} L(P)dP \quad (1)$$

$L(P)$ includes losses that are proportional to the replacement cost value (Kodavatiganti et al. 2023) of the building, its contents, and loss of use (duration the structure is out of service). The trapezoidal Riemann sum is used to aggregate the product results across all possible probabilities to compute the AAL (Eq.2).

We used the USACE Generic Depth-Damage Functions (USACE, 2000) to relate flood depth above the structure to building losses and contents losses. These functions are based on generic residential data collected between 1996 and 2000 and are widely used in federal benefit-cost analysis. Although more recent USACE (2006) functions incorporate flood duration and foundation type, the 2000 generic functions were selected here because they require only the input data consistently available across our 123-tract sample.

$$AAL = \sum_{n=1}^{N} \left\{ [P_{n+1} - P_n] * \frac{[L_n + L_{n+1}]}{2} \right\} \quad (2)$$

Gumbel distribution parameters (location u and scale a) were estimated for each property individually, using the four Fathom-derived depth–frequency pairs (10-, 50-, 100-, and 200-year return periods). Parameters were obtained by least-squares fit on the Gumbel reduced-variate transform. Properties for which all four Fathom depths were zero (i.e., not exposed at any modeled return period) were excluded from AAL computation.

The two-parameter Gumbel extreme value distribution used to model P for the expected flood depths because it is known to be better suited for smaller sample sizes in extreme value analysis (Cunnane, 1989; Onen & Bagatur, 2017). The cumulative distribution function (CDF) of Gumbel extreme value is shown in Eq. 3, where p represents the annual probability of non-exceedance. The complement of the CDF is shown in Eq. 4, which represents P of a potential flood event with depth above the ground (d).

$$CDF = p = exp\left[-exp\left(-\left(\frac{d-u}{a}\right)\right)\right] \quad (3)$$

$$P = 1 - exp\left[-exp\left(-\left(\frac{d-u}{a}\right)\right)\right] \quad (4)$$

We subsequently determined the portion of the AAL that arises from these probabilities in relation to the overall AAL (Eq. 5). This analysis showed the impact of varying return periods on flood risk in the study area. This was conducted by categorizing the return periods into five groups based on flood frequency and risk: Return periods less than or equal to 10 years (higher frequency, lower severity); return periods between 10 and 50 years; return periods between 50

and 100 years; return periods between 100 and 200 years; return periods exceeding 200 years (lower frequency, higher severity).

$$\%\ of\ AAL\ attributed\ to\ specific\ return\ period = \frac{\sum AAL\ from\ such\ return\ period}{Total\ AAL} \quad (5)$$

3.2 Variation in Elevation Investment Size and Avoided Average Annual Loss (ΔAAL) across Flood Return Periods

To address the question, *"How does the cost-effectiveness of federal elevation mitigation investments vary across different flood return periods?" w*e assessed how investment size and avoided risk change as flood risk severity increases in areas prone to flooding with different return periods. We analyzed the variation in investment size and avoided AAL across areas flooded at return periods greater than 10, 50, 100, and 200 years. This provides a clearer picture of how efficiently federal funds are being utilized to reduce flood risk, particularly in areas with varying flood probabilities, by comparing the avoided AAL to the size of federal investments.

Investment represents the cost of implementing flood elevation measures through federal assistance. The investment size ranged between $40,000 and $180,000, capturing the financial input required for mitigation efforts. Avoided AAL (ΔAAL) quantifies the economic benefit of flood mitigation by measuring the reduction in annual average potential losses due to home elevation. This metric was used to calculate the economic benefits achieved by elevating homes. To quantify the avoided AAL as a result of these flood mitigation measures, ΔAAL was computed as the difference between the AAL before and after the home elevation for each individual property (Eq.6).

$$\Delta AAL = AAL_{\ before\ mitigation} - AAL_{\ after\ mitigation} \quad (6)$$

The data were represented by flood return periods (≥10, ≥50, ≥100, and ≥200 years) to capture how both investment size and avoided AAL vary across different flood risk levels. Descriptive statistics were used to present the distribution and variability of investment size and avoided AAL across the different return periods and provide insights into the median, upper, and lower quartiles, and any outliers. To examine whether elevation is equally effective across flood zones, we calculated percentage risk reduction as:

$$\%\ \text{Risk Reduction} = \frac{\Delta AAL}{AAL\ before\ mitigation} \times 100 \quad (7)$$

This metric isolated mitigation effectiveness from baseline risk differences, addressing whether lower avoided AAL in certain zones reflects reduced effectiveness or simply lower pre-mitigation risk. Also, we presented the mean values of investment size and risk reduction percentage for each flood return period to help identify the trends and assess whether larger investments yield higher returns in terms of avoided AAL or if diminishing returns are observed as flood return periods increase.

3.3 Population exposure across Return Periods

To explore the distribution of impacted populations across different areas subjected to different flood exposure, we analyzed the population percentages for each demographic and socio-economic group across the different return periods. The analysis focused on highlighting how

different groups are exposed to varying flood return periods. We conducted a detailed census tract-level analysis to examine how flood risk impacts various socio-economic groups, incorporating key demographic factors such as race/ethnicity, poverty rate, and renter status. These variables are critical indicators of flood-vulnerable populations, as they often correlate with significant barriers to accessing recovery resources and contribute to prolonged recovery times following flood events (Wilson et al., 2021). Furthermore, we presented the distribution of federal elevation investment and avoided AAL across different socio-economic groups.

For that, we considered the area flooded at return periods of more than 10-, 50-, 100-, and 200-years. Census tract-level variables included racial composition, with proportions of Hispanic, Asian, Native American, and Black populations. Additionally, we considered three core socio-economic factors: poverty rate, minority status (Non-white populations), and renter percentage. For a deeper understanding of how different populations are impacted by flooding events of varying magnitudes, we examined the medians, upper and lower quartiles, and overall distribution patterns of the demographic and socio-economic variables, identifying trends in population vulnerability across flood-prone regions.

To compare the proportion of each group exposed to flooding against their overall representation in the study area's population, we computed disproportionality ratios (Eq. 8) for populations exposed to flood events at several return periods.

$$\text{Disproportionality Ratio} = \frac{(\%\ \text{of group in flood zone})}{(\%\ \text{of group in study area})} \tag{8}$$

A ratio greater than 1.0 indicates overrepresentation in flood-prone areas, while a ratio less than 1.0 indicates underrepresentation (National Center for Pyramid Model Innovations, 2021). This, therefore, helped us identify whether individual groups are over- or underrepresented within flood-affected areas relative to their population share.

3.4 Benefit-Cost Ratio (BCR) Analysis and Equity-Weighted Evaluation

To evaluate the cost-effectiveness of home elevation investments, we calculated the Benefit-Cost Ratio (BCR) for individual properties over a 30-year time horizon using Eq. 9.

$$BCR_{DPV_{T_i}} = \frac{\Delta AAL_{DPV_{T_i}}}{C_i} \tag{9}$$

Where $\Delta AAL_{DPV_{T_i}}$ is the discounted present value of the avoided AAL accumulated over the 30-years, and C_i is the cost of the home elevation investment. We utilized 7% discount rate consistent with current FEMA Benefit-Cost Analysis guidance (FEMA, 2009) to compute all relevant benefits of home elevation to the present value, accumulated across 30-year time horizons. BCR values were categorized into three tiers: low efficiency (BCR $\leq$ 0.5), moderate efficiency (0.5 < BCR $\leq$ 1), and high efficiency (BCR > 1).

To examine the relationship between elevation effectiveness and tract racial composition, we use three complementary approaches. First, we conduct a Chi-square test of independence to assess whether BCR categories differ by tract racial majority. Second, we use Spearman rank

correlation to test for a consistent relationship between tract Non-white share and property-level BCR. Third, we estimate ordinary least squares (OLS) models at the property level to evaluate this relationship while accounting for other factors.

In the regression analysis, the dependent variable is the log of avoided AAL. We use avoided AAL rather than BCR because BCR depends directly on investment cost, whereas avoided AAL more directly reflects the physical effectiveness of elevation. The model includes the proportion of Non-white residents in the tract, the log of elevation investment cost, and indicators of flood-zone exposure. Flood-zone exposure is represented using quartiles of pre-mitigation property-level AAL, which capture differences in underlying depth and frequency conditions at each location. Standard errors are clustered at the census tract level to account for similarities among properties within the same tract. To further assess the role of flood-zone exposure, we also estimate a model that includes only the zone indicators and report its R^2 alongside the full specification.

To explore how alternative evaluation frameworks might address potential disparity, we applied equity-weighted benefit-cost analysis (EWBCA) following the framework proposed by Lockwood et al. (2024). The EWBCR was calculated as:

$$EWBCR = BCR \times (1 + proportion\ Non-white) \quad (10)$$

This specification applies a linear weighting scheme that increases the relative value of investments in communities with higher Non-white populations, reflecting the social value of directing resources toward historically underserved groups. The approach is implemented as a sensitivity analysis rather than a prescriptive framework; it relies on a simplified functional form and a single demographic dimension, both of which are discussed as limitations.

To evaluate implications for decision-making, the conventional cost-effectiveness threshold (BCR = 1.0) was applied to the equity-weighted metric. This allows identification of investments that would be classified as cost-effective under equity-adjusted evaluation but not under standard efficiency-based criteria.

3.5 Limitations

Our methodology has some notable limitations. First, flood depth data from Fathom models have known uncertainties, particularly in urban areas with complex drainage systems (Schubert et al., 2024). Second, our study examines 123 census tracts in Louisiana, representing communities disproportionately impacted by Hurricanes Katrina and Rita. The study area has higher Non-white representation than national averages; findings may be most generalizable to communities with similar demographic and flood risk characteristics.

Third, our analysis uses AAL and BCR to assess elevation effectiveness, following FEMA's standard methodology for evaluating mitigation projects. These metrics have well-recognized limitations. AAL doesn't capture indirect losses like health impacts, business disruption, or psychological costs that may disproportionately affect vulnerable populations. BCR and AAL calculations are value-driven, meaning results reflect property values as much as physical performance. We use percentage risk reduction (Equation 7) to isolate mitigation effectiveness from baseline risk differences across flood zones which show whether elevation works

differently in high-frequency versus low-frequency areas independent of absolute risk magnitude. Our primary findings focus on how elevation effectiveness varies with flood frequency while acknowledging that economic metrics may be influenced by differences in property values across communities.

Fourth, we apply a 7% real discount rate consistent with FEMA's Benefit-Cost Analysis Reference Guide (FEMA, 2009), but acknowledge that this rate is higher than the 3% rate now recommended by OMB Circular A-4 (2023) for regulatory analyses and the lower social discount rates (often 2%) increasingly used in climate-adaptation economics (Drupp et al., 2018). Because the discount rate enters the BCR calculation as a uniform present-value factor across all properties, lower rates would scale all BCR values upward proportionally without altering the relative ordering of zones or the racial disparity in cost-effectiveness, both of which are driven by physical effectiveness differences that are independent of the discount rate. However, the share of investments classified as cost-effective (BCR $\geq$ 1) would shift upward at lower rates, particularly for moderate-BCR projects that fall just below the threshold at 7%. This effect strengthens the case for equity-weighted evaluation discussed in Section 5.3.

Fifth, we assign demographic characteristics at the census tract level while analyzing individual property mitigation. While this creates potential for ecological fallacy, this approach is both methodologically appropriate and policy relevant. This is methodologically appropriate because (1) our research question addresses community-level patterns in mitigation distribution, not individual household disparities, and (2) federal programs target resources geographically, making tract-level analysis policy-relevant. Tract-level analysis is standard in environmental justice research for examining structural resource distribution patterns.

Finally, post-mitigation FFE measurements were verified through Google Earth imagery, introducing potential measurement uncertainty.

4. Results

4.1 AAL across Return Periods

We begin by addressing research question 1 on the variation of flood risk and mitigation effectiveness across return periods. Figure 2a shows the mean of AAL as a proportion of replacement cost value for areas subjected to flooding at return periods of $\geq$10, $\geq$50, $\geq$100, and $\geq$200 years. Areas subjected to flood events $\geq$10 are prone to both frequent flooding with less damage and rare events with severe damage (Merz et al., 2009). In contrast, areas subjected to flood events $\geq$200 are affected only by rare events with severe damage (Merz et al., 2009). The figure shows that regions within the $\geq$10-year return period have the highest mean AAL. Specifically, the AAL for areas exposed to floods with a $\geq$10-year return period is notably higher than for other zones, reaching 13% of replacement cost value compared to 1.3% in areas subject to the $\geq$200-year return period. Because areas in the $\geq$10-year zone are exposed to the full spectrum of flood events including frequent, moderate-severity events as well as rare, high-severity ones, we decomposed the AAL for these areas to identify which flood frequencies contribute most to total risk.

In Figure 2b, the proportion of AAL contributed by flood events at different return periods in areas flooded at $\geq$10 and $\geq$50-year return periods are analyzed. The breakdown shows that 38%

of the total AAL is attributed to flood events within the [10, 50] return period, which suggests that areas experiencing floods within this range of return periods (Annual Exceedance Probability (AEP) of 2-10%) show the largest contribution of the total losses. Conversely, the AAL from less frequent flood events, such as those in the (100, 200] and ≥200 return periods, are significantly smaller, at 9% and 12%, respectively.

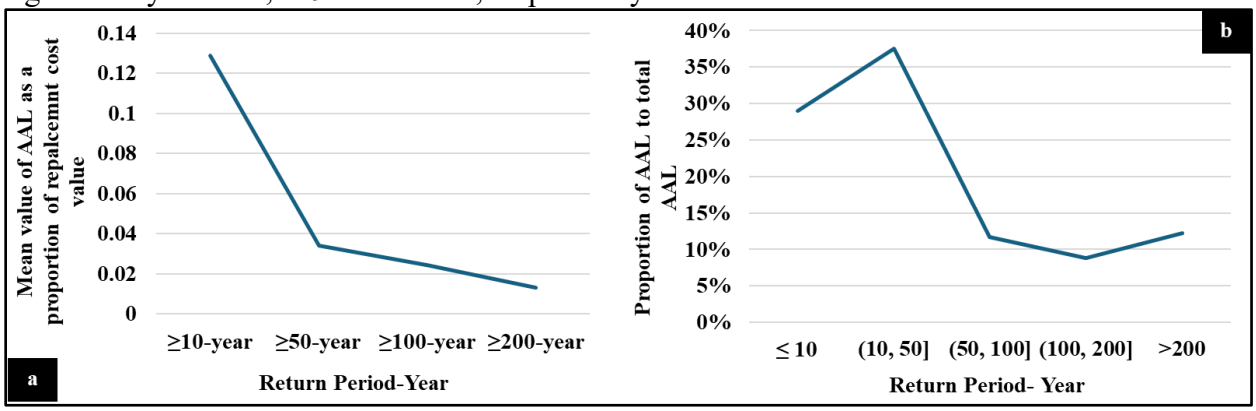

Figure 2. *Distribution of average annual loss (AAL) across return periods. (a) Mean AAL normalized by replacement cost for increasing return period thresholds. (b) Fractional contribution of AAL by return period intervals*

4.2 Elevation Investment and Avoided AAL across Return Periods

Figure 3a shows descriptive statistics through boxplots for both elevation investment size and avoided AAL across areas subjected to flood risks at return periods of greater than 10, 50, 100, and 200 years. The figure shows disparities in response capacity and adaptation effectiveness, as reflected in the size of elevation investments and avoided AAL. For areas with high-risk impacts, particularly those with flood return periods greater than 10 years (Figure 2a), the results show the highest avoided AAL at moderate investment levels. However, as the return periods increase to 50, 100, and 200 years, the avoided AAL decline, despite investments remaining stable or even slightly increasing. For areas with return periods of 200 years or more, the investment size ranges from approximately $40,000 to $180,000, with several notable outliers. Despite higher investments, the avoided AAL for these properties is notably lower, with scatter points concentrated toward the lower end of the spectrum.

To examine whether elevation is equally effective across flood zones, we further analyzed the risk reduction percentage against mean investment (Figure 3b). Investment levels remain relatively stable across zones, ranging from $129,000 to $145,000. However, risk reduction outcomes vary substantially. In ≥10-year zones, elevation achieves 95% risk reduction. Effectiveness remains high through ≥100-year zones (92-95%). In ≥200-year zones, however, risk reduction drops sharply to 53%.

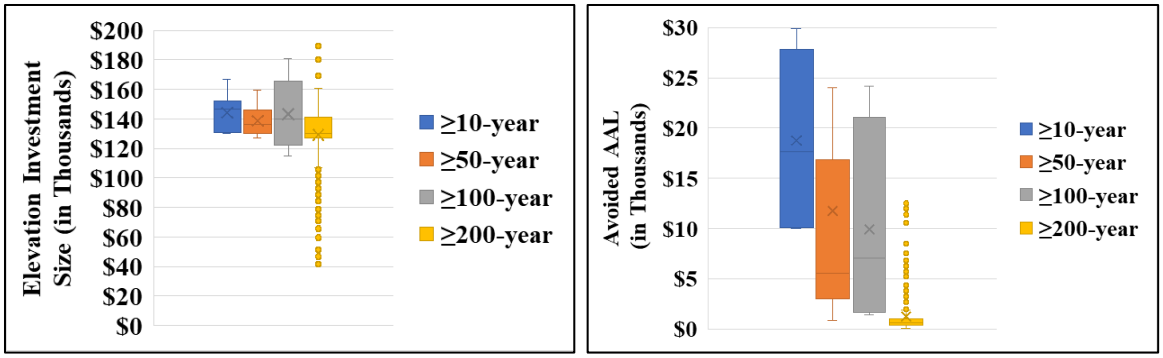

Figure 3a. *Descriptive statistics of elevation investment level and avoided AAL across flood return*

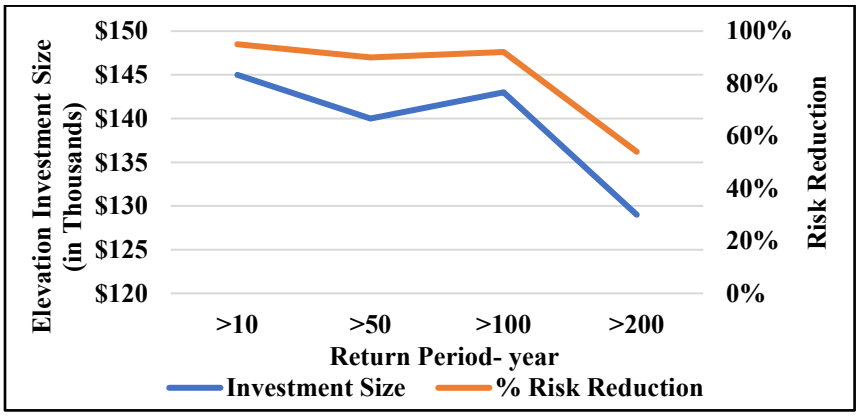

Figure 3b. *Mean value of elevation investment size and risk reduction percentage across flood return periods*

4.3 Population exposure across Return Periods

We now examine how population exposure varies across flood zones (research question 2). This assessment, in conjunction with Figures 2a and 2b, shows how demographic composition relates to flood risk patterns. Figure 4a illustrates the distribution of the population in relation to flood exposure at various return periods. The white population percentage is consistently highest in areas flooded at a return period of ≥10 years (Figure 4a), with the mean value increasing until peaking in areas flooded at the ≥100-year return period (Figure 4b). In contrast, the Black population percentage is lower in areas flooded at the ≥10-year return period, but this percentage increases, reaching its highest levels in areas flooded at return periods exceeding 200 years. The percent Native American population is highest in areas flooded at return periods ≥10 and ≥50, while it decreases across ≥100. The Hispanic population decreases slightly across the first two thresholds, before rising again at ≥100. The Asian population percentage is the lowest across all return periods, with minimal variation in exposure.

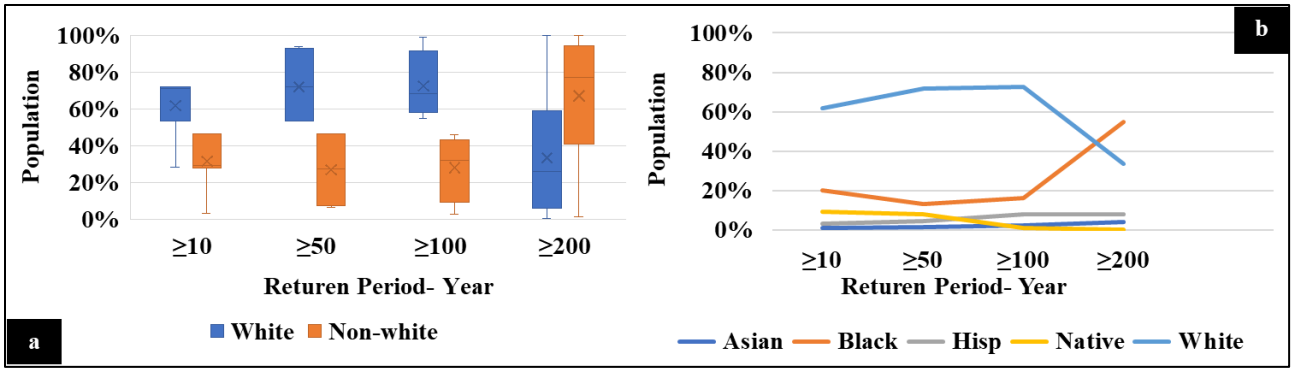

Figure 4. *Distribution of population exposure across return period thresholds by race/ethnicity. (a) Percentage distribution of White and Non-White populations across return period thresholds. (b) Percentage distribution of population by race/ethnicity across return period thresholds.*

Figure 5 provides the percentage distribution of Non-white populations, renters, and those living in poverty across flood-prone areas with return periods of ≥10, ≥50, ≥100, and ≥200 years. Across all return periods, the percentage of Non-white populations is consistently higher compared to renters and those in poverty, with the median values and variability being larger. The percentage of renters shows a notably higher exposure to flood risks in zones with a return period of ≥200 years compared to other areas. In contrast, households living in poverty are more concentrated in areas with frequent flooding, particularly in zones with a return period of ≥10 years, but their percentage decreases in areas with return periods of ≥200 years.

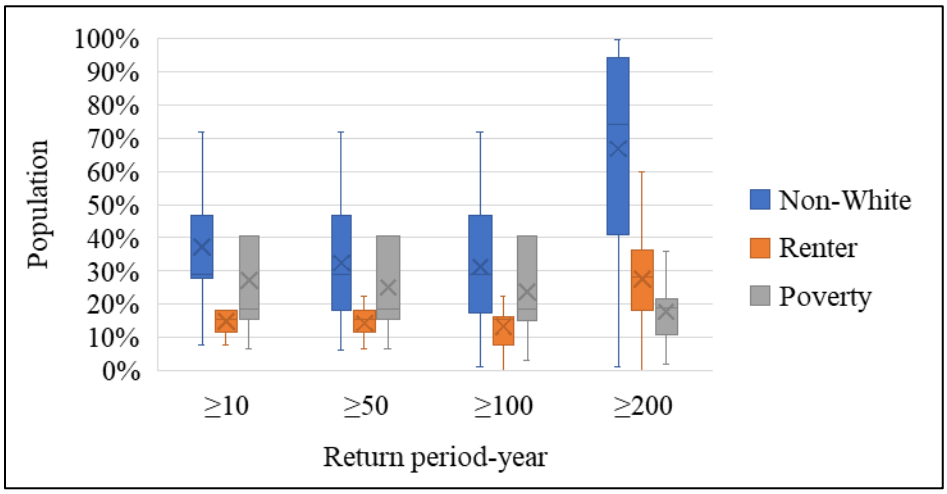

Figure 5. *Distribution of Socio-economic groups in areas exposed to flooding at return periods of ≥10, ≥50, ≥100, and ≥200*

Table 3 presents the disproportionality ratio analysis of flood exposure among various socio-economic groups across different flood return periods. The disproportionality ratios in Table 3 show that white populations are overrepresented in zones flooded at the ≥10-, ≥50-, and ≥100-year return periods (ratios of 1.8, 2.1, and 2.1, respectively), while Non-white populations are underrepresented in these same zones (ratios of 0.5–0.6). This pattern reverses in the ≥200-year zone, where Non-white populations and renters become slightly overrepresented (ratio 1.2) and white populations become underrepresented. Households in poverty follow a pattern similar to

the white population in this sample, with overrepresentation in the more frequently flooded zones (ratios 1.3–1.5) declining toward parity in the ≥200-year zone.

Table 3. *Disproportionality Ratios across return periods*

Return Period-year	Disproportionality Ratio			
	Non-White	White	Renter	Poverty
≥10	0.6	**1.8**	0.6	**1.5**
≥50	0.5	**2.1**	0.5	**1.4**
≥100	0.5	**2.1**	0.5	**1.3**
≥200	**1.2**	0.8	**1.1**	0.9

4.4 Benefit-Cost Ratio (BCR) Analysis and Equity-Weighted Evaluation

For research question 3, we assessed the influence of equity-weighted evaluation criteria on cost-effectiveness outcomes for different populations. Figure 6 presents the mean Non-white and white population shares of tracts receiving elevation investments, grouped by 30-year BCR category. The horizontal reference lines indicate each group's share of the overall study-area population (65% Non-white, 35% white; Table 2), so bars exceeding the reference line indicate overrepresentation relative to the study area as a whole. Two patterns are evident. In tracts receiving low-BCR investments (≤0.5), the mean Non-white population share is 67%, and in moderate-BCR tracts (0.5 < BCR ≤ 1.0) it rises to 72%. Both well above the 65% study-area baseline. In tracts receiving cost-effective investments (BCR > 1.0), the mean white population share is 60%, well above the 35% study-area baseline. Reframed in terms of where investments land using the binary tract classification, 71% of low-BCR investments and 72% of moderate-BCR investments are located in Non-white majority tracts (>50% Non-white), while 72% of cost-effective investments are located in white majority tracts.

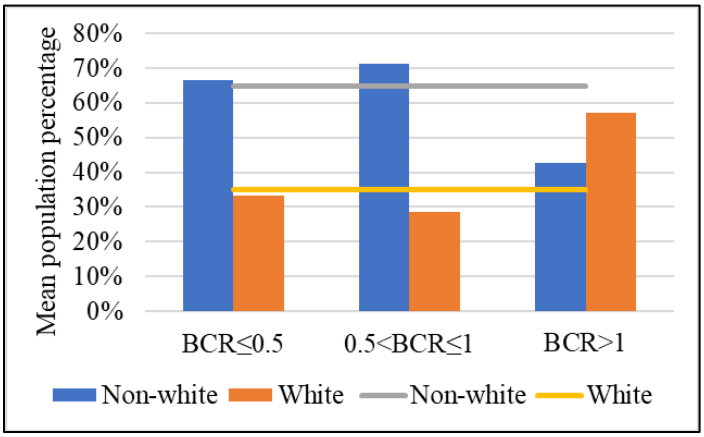

Figure 6. *Mean Non-white and white population shares of tracts receiving elevation investments, grouped by 30-year benefit-cost ratio (BCR) category. Horizontal reference lines indicate each group's share of the overall study-area population.*

We assessed the association between tract racial composition and property-level elevation effectiveness using three approaches: a contingency analysis of BCR categories by tract racial majority, a Spearman rank correlation, and an OLS regression with cluster-robust standard errors

at the tract level. Flood-zone exposure is represented using quartiles of pre-mitigation property-level AAL.

The contingency analysis ($\chi^2 = 20.82$, df = 2, N = 579, $p < 0.001$, Cramér's V = 0.19) shows that the distribution of BCR categories differs significantly between Non-white–majority and white-majority tracts. This difference is not spread evenly across all projects. Instead, it is concentrated at the cost-effective end: only 32% of projects with BCR ≥ 1 are located in Non-white–majority tracts, compared to 68% in white-majority tracts.

By contrast, the Spearman rank correlation between tract Non-white share and property-level BCR is small and not statistically significant ($\rho = 0.03$, $p = 0.50$). These two results are not contradictory. The contingency analysis is picking up a clustering of high-performing projects at the top of the distribution, while the rank correlation looks for a smooth relationship across all observations. Because the disparity in our data appears mainly at the upper end rather than as a gradual trend, it shows up in the contingency test but not in the correlation.

To better understand what is driving this pattern, we estimate a regression of property-level log(avoided AAL) on tract Non-white proportion, flood-zone fixed effects, and log(investment cost) (Table 4). The results show that flood-zone exposure is the main factor shaping elevation effectiveness. Properties in higher-AAL zones generate much larger avoided losses than those in lower-risk zones, and zone fixed effects alone explain 81% of the variation in log(AAL).

Once we account for zone and cost, the relationship between tract racial composition and avoided losses becomes small and only marginally significant ($\beta = -0.35$, $p = 0.07$). We use log(AAL) instead of log(BCR) as the outcome because BCR is tied to cost. Standard errors are clustered at the tract level. These results are consistent with the observed disparities in elevation effectiveness being driven primarily by the geographic distribution of populations across flood-risk zones, rather than by systematic within-zone differences in how effectively elevation reduces risk. The within-zone coefficient on tract Non-white share is negative and approaches conventional significance thresholds ($\beta = -0.35$, $p = 0.07$), so we cannot rule out a small within-zone penalty; with 123 tracts and clustered standard errors, our analysis is best powered to detect across-zone rather than within-zone differences.

Table 4. *Ordinary least squares regression of property-level log(avoided AAL) on tract racial composition, investment cost, and flood-zone exposure.*

Variable	Coefficient	Std. Error	p-value
Non-white proportion	-0.35	0.19	0.071
Log(Investment Cost)	-0.39	0.2	0.058
AAL Quartile 2	0.63	0.03	<0.001 ***
AAL Quartile 3	1.14	0.04	<0.001 ***
AAL Quartile 4	3.03	0.15	<0.001 ***

Further, we explored whether equity-weighted criteria might shift these outcomes. Table 5 shows that investments in the moderate BCR category rose from 0.64 to 1.10, above the standard BCR threshold. Since this category is predominantly Non-white (72%), equity weighting would bring a substantial share of currently excluded communities into the range of justified investments. However, the lowest BCR category (mean 0.08) remains below the threshold even with equity adjustment (EWBCR = 0.13).

Table 5. *Effect of equity weighting on benefit-cost ratios*

BCR Category	Standard BCR (Average value)	Equity Weight	EWBCR
≤ 0.5	0.08	1.67	0.13
0.5 - 1.0	0.64	1.72	**1.1**
> 1.0	3.5	1.40	4.9

5. Discussion

5.1 Elevation is not cost-effective in Low-Frequency Zones

Our analysis shows that flood risk, measured as AAL, is ten times higher in high-frequency zones (≥10-year) than low-frequency zones (≥200-year), reaching 13% versus 1.3% of replacement cost value. This concentration of risk in frequently flooded areas is driven by cumulative impacts—38% of total AAL comes from events in the [10, 50] return period range, while rare events (≥200-year) contribute only 12%. These findings align with Ward et al. (2011), who demonstrated that frequent floods contribute substantially to annual risk despite lower per-event damages. While elevation has advantages, including reducing flood risk to structures, lowering insurance premiums, and eliminating the need to relocate items during floods (Gnan et al., 2024; Friedland et al., 2023), these benefits diminish substantially in low-frequency zones where severe floods exceed elevation heights.

Elevation effectiveness varies dramatically across flood zones. In high-frequency flood zones (areas exposed to ≥10-year flood), our analysis shows that elevation investments are generally more efficient, leading to substantial risk reduction (95%). However, in ≥200-year zones, risk reduction drops sharply to 53%. The likely explanation is that rare but severe flood events produce water depths that overtop elevated structures, a limitation inherent to elevation as a strategy in low-frequency zones. This decline is independent of probability weighting in AAL calculations. The percentage risk-reduction metric isolates mitigation performance from baseline risk differences, confirming that elevation itself performs worse in low-frequency flood zones. This aligns with FEMA (2007) research, which indicates that frequent flooding events can yield significant benefits and lower relative costs, thereby justifying investment in structural measures such as building elevation.

Our analysis also brings to light critical questions about ***the cost-effectiveness of large-scale flood mitigation projects in low-probability, high-impact flood zones.*** Some properties may require significantly higher investments to achieve minimal reductions in risk. Like FEMA's standard BCR methodology, our 30-year evaluation assumes constant flood risk, though climate change and evolving engineering standards increasingly challenge this assumption (Galloway et al., 2024). We do not expect this bias to meaningfully alter our central conclusion regarding the inter-zone effectiveness gap. In low-frequency flood zones, elevation already performs poorly because the most severe events can exceed typical elevation heights; projected increases in flood

depth would further diminish its effectiveness. In contrast, in high-frequency zones where flooding tends to be shallower, modest depth increases may still fall within the range that standard elevation practices can accommodate. Accordingly, the effectiveness gap between zones is likely to widen rather than narrow under plausible climate trajectories. Conducting a formal, climate-conditioned BCR analysis using downscaled flood projections represents an important direction for future research.

For communities in ≥200-year flood zones, this effectiveness gap, and its likely widening under climate change, motivates consideration of adaptive measures such as green infrastructure including property-scale interventions (rain gardens, permeable pavement) and watershed-scale interventions (detention basins, wetland restoration) which may provide more sustainable and cost-effective protection in low-frequency flood zones (Singh et al., 2021).

5.2 Efficient Allocation Produces Racially Disparate Outcomes

Federal flood mitigation programs are designed to follow risk-based efficiency criteria, prioritizing investments where expected losses are highest. Our analysis is restricted to properties that received funding and therefore cannot directly evaluate whether allocation decisions among applicants were biased. A question addressed by other Katrina-focused studies that documented disparities in federal aid distribution, with predominantly Black neighborhoods receiving less assistance relative to damage severity (Masozera et al., 2007), slower return migration and prolonged displacement for minority households (Fussell et al., 2010; Elliott & Pais, 2006), and unequal access to recovery resources (Squires & Hartman, 2006), and administrative and financial barriers to program participation (García et al., 2022). What our analysis demonstrates is complementary: even under the assumption that allocation perfectly followed risk-based criteria, inequitable outcomes still emerge because the mitigation strategy itself performs differently across the flood zones where different populations live.

Our findings suggest that cost-effectiveness is related to the racial composition of tracts, but not in a smooth or gradual way. Instead, the difference shows up mainly at the top of the distribution. Cost-effective projects are more likely to be in White-majority tracts, while lower-performing projects are more evenly spread across communities. This pattern matters because policy decisions are made at that upper end where projects either meet the cost-effectiveness threshold or fall short. As a result, a disparity that may not appear in overall trends becomes important exactly at the point where funding decisions are made.

The regression results help explain why this happens. Once we account for flood-zone exposure, the remaining relationship between tract racial composition and elevation effectiveness becomes small and only marginally significant. The main factor driving avoided losses is the flood zone itself, not who lives in the surrounding tract. In other words, properties in the same zone tend to receive similar levels of protection from elevation. What differs is which communities are more likely to be located in higher- or lower-effective zones. This shifts the focus from how decisions are made within the program to where different populations are located relative to flood risk.

This points to a more structural form of inequity. The difference does not arise from how projects are selected within a given zone, but from how populations are distributed across zones where elevation is more or less effective. Because of this, the disparity would remain even under

a perfectly implemented risk-based allocation process. Addressing it, therefore, requires looking beyond allocation rules alone. It also requires recognizing that elevation is not equally effective everywhere. It depends on the flood conditions and its broader impacts depend on which communities are exposed to those conditions.

The geographic distribution of these populations reflects historical structural inequities. White populations are overrepresented in high-frequency flood zones, while Non-white populations are overrepresented in low-frequency zones. Places with higher proportions of white populations are characterized by higher flood exposure, often located within FEMA's SFHA, where flood protection infrastructure is more prevalent (Pollack et al., 2023). Communities and infrastructure in these areas are constantly at risk of flooding and typically benefit from more robust mitigation, such as federally supported flood insurance programs (Smiley et al., 2022). In contrast, Non-white communities are disproportionately located in zones vulnerable to 200-year floods, classified as FEMA X zones which are not subject to the same regulatory standards and have fewer protections in place (Al Assi et al., 2023c).

The proportion of Non-white communities exposed to severe but less frequent flood events (events that occur outside FEMA's designated SFHA) can be linked to historical factors, such as land use policies, housing affordability, and long-standing socio-economic inequalities (Campbell, 2023; Herreros-Cantis et al., 2020; Maantay & Maroko, 2009). Aligned with empirical evidence highlighting recovery barriers for marginalized groups (Wilson et al., 2021), our analysis shows that Non-white populations are overrepresented in high-poverty and high-renter areas. These populations, often residing in lower property value areas, are underrepresented in high-investment projects and areas with higher risk avoidance benefits. In contrast, white populations are more likely to live in higher-value properties with greater risk reduction potential, receiving investments with higher BCR. The result is that federal investment favors more valuable properties, reinforcing racial inequities in recovery outcomes.

Adding to these structural barriers, García et al. (2022) found that even when elevation is offered through federally funded programs, socially vulnerable populations (e.g., low-income residents, individuals with disabilities) struggle significantly to access and complete elevation projects due to administrative complexity, financial inaccessibility, and logistical challenges.

The result is that risk-based allocation, however well-implemented, produces racially disparate protection in this setting. Even setting aside documented inequities in program access (García et al., 2022; Wilson et al., 2021), the interaction between strategy effectiveness and population geography is sufficient on its own to generate unequal outcomes. This is a form of structural inequity that consistent with the choice of mitigation strategy and the spatial distribution of vulnerable populations, rather than through who receives funding within a given zone, and it is not addressed by reforms that focus only on allocation fairness.

5.3 Equity-Weighted Evaluation as Policy Alternative

Given that efficient risk-based allocation produces racially disparate outcomes, we examined whether equity-weighted evaluation criteria might alter cost-effectiveness determinations. Following Lockwood et al. (2024), we applied equity-weighted benefit-cost analysis that assigns additional value to investments serving disadvantaged communities.

The analysis reveals three distinct outcomes across BCR categories. For high BCR investments (>1.0), equity weighting increases values from 3.5 to 4.9. These projects remain justified under any criteria. For moderate BCR investments (0.5-1.0), equity weighting shifts values from 0.64 to 1.10, crossing the cost-effectiveness threshold. Since this category is 72% Non-white, equity weighting would bring currently excluded communities into the range of justified investments. For low BCR investments (≤0.5), values rise from 0.08 to only 0.13, remaining far below the threshold even with the equity adjustment.

These results carry important policy implications. Equity weighting can address disparities in moderate BCR zones but cannot solve the fundamental problem in low BCR zones: elevation is simply the wrong tool. When a mitigation strategy achieves only 53% risk reduction, no amount of equity weighting makes it effective. This approach addresses project selection, not the underlying geographic and historical factors that produced disparate outcomes. Long-term solutions require addressing inequities in housing, land use, and infrastructure investment that concentrated vulnerable populations in areas where standard mitigation strategies fail. Structural factors such as lower educational attainment, substandard housing, and weak social and economic foundations exacerbate flood vulnerability, although local investments in welfare and public safety can mitigate some of these challenges (Lim & Skidmore, 2019). In the U.S., areas most at risk for flooding exposure and social vulnerability tend to be more concentrated in rural areas of the U.S. South, where there are higher proportions of racial minorities and mobile homes (Tate et al., 2021). Across the globe, socioeconomically disadvantaged populations are more exposed to flood risks, both in high-income nations like Belgium (Poussard et al., 2021) and in rapidly urbanizing areas such as Nigeria (Eseosa Halima & Hiroaki, 2022). For mitigation efforts to effectively address such inequities and benefit all communities, their design should embed social equity at the forefront.

6. Conclusion

This study investigated how flood risk and the 30-year cost-effectiveness of federal elevation mitigation investments change across flood return periods and populations, through analysis of homes funded for elevation mitigation through HMGP and CDBG-DR programs in the aftermath of Hurricanes Katrina and Rita. Our analysis reveals three main findings:

1. Elevation effectiveness varies substantially across flood zones, achieving 95% risk reduction in high-frequency zones (≥10-year) but only 53% in low-frequency zones (≥200-year). This confirms that elevation is fundamentally less effective where severe floods can exceed elevation heights.
2. Property-level regression shows that flood-zone exposure is the dominant driver of variation in avoided losses, while the association with tract Non-white proportion is small and not statistically significant. This indicates that disparities in elevation outcomes are primarily driven by the geographic distribution of populations across flood zones where the strategy performs differently.
3. Equity-weighted benefit-cost analysis shifts moderate BCR investments (0.64 to 1.10) above the cost-effectiveness threshold, demonstrating how alternative evaluation criteria could justify investments in currently excluded communities.

Our analysis does not evaluate whether federal allocation decisions are biased. Addressing that question would require information on applicants, eligibility, and rejected projects, which is beyond the scope of this study and has been examined elsewhere in the literature. Instead, our results highlight an important distinction between efficient allocation and equitable outcomes. A policy can be effective in reducing overall risk while still producing uneven benefits across populations. Even under a fully risk-based allocation process, differences in how elevation performs across flood zones, combined with where populations are located, can lead to unequal levels of protection. In our sample, Non-white populations are more concentrated in areas where elevation provides substantially lower risk reduction compared to high-frequency zones.

These findings suggest a tiered policy approach: continue elevation in high-frequency zones where it is effective; apply equity-weighted criteria in moderate BCR zones to justify investments in underserved communities; and redirect resources in low BCR zones toward alternative strategies such as buyouts, public infrastructure, or insurance subsidies. We note that buyout programs themselves face well-documented equity challenges, including racial disparities in participation and unequal compensation outcomes (Siders, 2019), and would need to be designed with explicit attention to procedural justice

This study makes two contributions that are worth keeping separate. First, we provide empirical evidence that the effectiveness of single strategy mitigation varies systematically with flood frequency. Elevation delivers strong cost effectiveness in high frequency zones and underperforms in low frequency zones, where severe flood depths can exceed practical elevation heights. This reflects a physical limit of elevation itself, and we expect it to generalize to other settings where the strategy is used across a wide range of flood regimes.

Second, we identify a mechanism through which risk-based allocation can produce racially disparate protection even when there is no bias within zones. When a mitigation strategy works better in some flood zones than others, and when racial groups are unevenly distributed across those zones, uniform program design generates unequal outcomes almost by construction. In our study area, this mechanism produces lower protection for Non-white communities because the historical settlement of Black households in coastal southeastern Louisiana concentrated them in lower frequency, higher depth flood zones where elevation does not perform well. The mechanism itself, that variation in strategy effectiveness interacts with the geography of race to produce structural inequity, is general. The specific demographic gradient we observe is not, and the direction and magnitude of similar disparities in other regions will depend on local histories of segregation, settlement, and flood exposure.

This framing places our contribution alongside, but distinct from, prior environmental justice work that has focused on allocation fairness, meaning who receives funding, and access barriers, meaning who is able to complete projects. Both remain important. What our analysis adds is that even after these issues are addressed, structural inequity can still persist through the choice of mitigation strategy itself. Future work should evaluate whether alternative strategies such as buyouts, green infrastructure, and neighborhood scale flood control perform more equitably across heterogeneous flood regimes, and whether equity weighted evaluation criteria, when implemented in practice rather than as a sensitivity analysis, actually shift investments toward underserved communities.

7. Acknowledgments

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8. Data Availability

The flood depth data used in this study were obtained from Fathom under a data use agreement and cannot be redistributed by the authors. Researchers interested in accessing these data should contact Fathom directly. Federal elevation investment records were obtained from the Louisiana Governor's Office of Homeland Security and Emergency Preparedness (GOHSEP) and are available upon request from that office. All other data used in this study, including building attributes from the National Structure Inventory, depth damage functions from USACE, and demographic data from the American Community Survey, are publicly available from the sources cited in the manuscript. Derived data and analysis code supporting the findings of this study are available from the corresponding author upon reasonable request.

9. Author Contributions

Ayat Al Assi: Conceptualization, methodology, formal analysis, investigation, data curation, visualization, writing the original draft, and writing the final draft. Eric Tate: Conceptualization, methodology, review, and editing. Fuad Hasan: Data collection, investigation, review, and editing. Rubayet Bin Mostafiz: Data curation, review, and editing. Carol J. Friedland: Supervision, review, and editing.

10. Conflict of Interest statements

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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