

Cumulative Climate Vulnerability at Subsidized Housing Sites in the United States: The Case of Choice Neighborhoods Initiatives

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Abstract

Climate change is intensifying environmental risks in American cities, with hazards often concentrated in communities with the least capacity to prepare for and recover from them, including residents of subsidized housing. Yet little is known about how socioeconomic disadvantage, chronic disease burden, and climate hazard exposure intersect at subsidized housing sites nationally. This study examined this intersection using the Choice Neighborhoods Initiative (CNI), a federal redevelopment program spanning 36 implementation sites across 32 metropolitan areas. We constructed a composite Climate Vulnerability Index (CVI) from 21 indicators at the census-tract level, standardized within each metropolitan area. We conducted three analyses: a paired comparison testing whether CNI tracts differ from non-CNI tracts in the same metropolitan area, cluster analysis to identify climate hazard typologies across CNI sites, and spatial cluster analysis to assess geographic concentration of vulnerability. CNI tracts showed significantly higher vulnerability than non-CNI tracts across all domains, with the largest effects for socioeconomic vulnerability and chronic disease burden, and a smaller effect for climate hazard exposure. Three climate hazard typologies emerged: a lower-hazard group comprising most CNI sites, a higher flood-and-heat-risk group, and a higher wildfire-exposure group. CNI tracts were also disproportionately embedded in spatially concentrated high-vulnerability clusters extending beyond project boundaries. These findings suggest that cumulative vulnerability at subsidized housing sites is driven primarily by social and health disadvantage rather than hazard exposure alone, and that climate resilience investment must address underlying socioeconomic and health conditions alongside physical hazard mitigation to meaningfully improve urban sustainability and equity outcomes.

Introduction

Climate change is reshaping the geography of environmental risks in US cities, with the burden of hazards like extreme heat, flooding, and poor air quality falling often on neighborhoods with the least capacity to prepare for and recover from them (Cohen et al., 2023; Cutter et al., 2003; Declet-Barreto et al., 2025). Subsidized housing often sits at the center of this inequity: millions of low-income residents—disproportionately Black, Latino, elderly, and people with disabilities (NLIHC, 2026)—live in aging subsidized housing in neighborhoods shaped by generations of disinvestment (Goetz, 2011; Rothstein, 2018). As climate hazards intensify, this convergence of socioeconomic and health vulnerability may further entrench inequities in subsidized housing communities (Li et al., 2025; Potter and Godshall, 2024). However, the degree to which socioeconomic disadvantage, health burden, and climate hazard exposure intersect at subsidized housing sites remains understudied, leaving climate resilience investment without an evidence base for targeting.

The Choice Neighborhoods Initiative (CNI), administered by the U.S. Department of Housing and Urban Development (HUD), is the federal government's effort to transform severely distressed subsidized housing developments and their surrounding neighborhoods (The Urban Institute, 2013). Launched in 2010 as the successor to HOPE VI, CNI provides substantial implementation grants—often exceeding \$30 million per site (HUD, 2024)—to support comprehensive neighborhood redevelopment, including housing rehabilitation, wraparound social services, and community infrastructure investment. Between 2010 and 2020, CNI designated 36 implementation sites across 32 metropolitan areas in the continental United States. CNI sites constitute a unique portfolio for studying concentrated disadvantage and climate risk: they were selected for revitalization need, span diverse climate regions, and represent concrete targets for resilience investment.

A growing body of research has documented the environmental burdens faced by residents of subsidized housing. Gabbe and Pierce (2020) found subsidized housing in California concentrated in the hottest, most at-risk census tracts, while Gabbe and colleagues (2020) found it disproportionately located in lower wildfire-risk areas. Chakraborty and colleagues (2026) carried out the first nationwide study of cumulative environmental burdens in public housing in the United States, found residents overrepresented in tracts with elevated PM_{2.5}, with the most severe disparities among Black, Latino, disabled, and extremely low-income households—building on Morello-Frosch and colleagues (2011) foundational framing of cumulative environmental burden as the overlap of social vulnerability and hazard exposure. Efforts to synthesize these dimensions have turned to composite indices which integrates demographic, economic, residential, and health measures (Alnajjar et al., 2026; Roberts et al., 2025; Uong et al., 2023), an approach that simultaneously captures hazard exposure, socioeconomic deprivation, and health burden. Existing research, however, has not examined major climate hazards alongside social and health vulnerability for subsidized housing sites in the United States. The CNI portfolio therefore offers a unique opportunity to examine compounding climate vulnerability at scale within a defined federal housing program.

Building on the cumulative disadvantage theory (Dannefer, 2003; DiPrete and Eirich, 2006) and its application to compounding neighborhood disadvantage (Massey and Denton, 1993; Reid et al., 2009; Rufat et al., 2015; Sampson et al., 2002; Wilson, 2012) and environmental health burden (Jiang et al., 2016; Liu et al., 2024; Theall et al., 2012), we address three research questions:

RQ1. Do CNI sites exhibit higher cumulative climate vulnerability than surrounding non-CNI tracts in the same metropolitan areas?

RQ2. What distinct climate hazard typologies characterize CNI sites?

RQ3. Is vulnerability spatially concentrated and embedded within broader corridors of neighborhood disadvantage?

Data and Methods

We constructed a composite Climate Vulnerability Index (CVI) at the census-tract level to characterize cumulative climate vulnerability at CNI sites. We then applied three complementary analytic strategies aligned with our research questions: a paired-comparison design to test whether CNI tracts are more vulnerable than their metropolitan counterparts (**RQ1**), K-means cluster analysis to identify distinct climate hazard typologies across CNI sites (**RQ2**), and Local Indicators of Spatial Association (LISA) analysis to assess whether CNI tracts are disproportionately embedded in spatially concentrated high-vulnerability clusters (**RQ3**).

CNI Site and Tract Identification

CNI site boundaries were obtained from the HUD Open Data Site. We classified census tracts as CNI or non-CNI using population-weighted tract centroids from the U.S. Census Bureau's Centers of Population files: a tract was designated as a CNI tract if its population-weighted centroid fell within a CNI site polygon. For two CNI sites whose target-area boundaries were too small to contain any population-weighted centroid (Omaha, NE and Seattle, WA), we instead assigned the nearest population-weighted centroid by Euclidean distance. A tract was designated as a non-CNI comparison tract if it fell within the same Core-Based Statistical Area (CBSA) as a CNI tract but its centroid did not fall within any CNI site polygon.

CVI Construction

The CVI comprises 21 indicators organized into three domains: socioeconomic vulnerability, chronic disease burden, and climate hazard exposure (Table 1).

The socioeconomic vulnerability domain includes 12 indicators drawn from the American Community Survey (ACS) 2019 5-year estimates and CDC PLACES 2024: poverty rate, median household income (reverse-coded), share of renter-occupied households, share of population under age 18, share of population aged 65 and older, civilian unemployment rate, vacant housing unit rate, share of adults with any disability, food insecurity, housing insecurity, lack of reliable transportation, and utility shutoff threat.

The chronic disease burden domain includes 5 tract-level age-adjusted prevalence estimates from CDC PLACES 2024: current asthma, diagnosed diabetes, high blood pressure, coronary heart disease, and obesity.

The climate hazard exposure domain includes 4 indicators drawn from multiple sources: the 5-year average (2015–2019) number of extreme heat days, computed from gridMET gridded meteorological data (Abatzoglou, 2013); annual average PM2.5 concentration ($\mu\text{g}/\text{m}^3$), obtained from the AHRQ Social Determinants of Health database (AHRQ, 2026); the annualized frequency of wildfire events, obtained from the FEMA National Risk Index (Zuzak et al., 2022); and the percentage of tract area with moderate-to-high flood risk, obtained from the FEMA National Flood Hazard Layer (FEMA, n.d.).

Within each domain, all indicators were standardized to z-scores using the mean and standard deviation of all tracts within the same CBSA, so that vulnerability is measured relative to local metropolitan context rather than to the national distribution. Median household income was reverse-coded prior to standardization so that, across all 21 indicators, higher z-scores consistently indicate greater vulnerability. Standardized indicators were averaged within each domain to produce three domain scores, and the composite CVI was computed as the equal-weighted mean of the three domain scores. Higher CVI values therefore reflect greater cumulative vulnerability across socioeconomic, health, and climate dimensions simultaneously.

Paired Comparison: CNI vs. Non-CNI Tracts

To test whether CNI tracts exhibit systematically higher vulnerability than surrounding non-CNI tracts within the same metropolitan area (**RQ1**), we used a paired-comparison design at the CBSA level. For each of the 32 CBSAs containing at least one CNI tract and at least one non-CNI tract, we computed the mean composite CVI and the mean of each domain score separately for CNI and non-CNI tracts, yielding one matched pair of observations per CBSA. We then tested whether the within-CBSA difference (CNI mean – non-CNI mean) was significantly greater than zero across the 32 paired observations, using two complementary tests: a one-sided, one-sample t-test on the vector of paired differences, and a one-sided Wilcoxon signed-rank test, which relaxes the normality assumption. Effect sizes are reported as Cohen's d, calculated as the mean paired difference divided by its standard deviation across CBSAs. Aggregating to the CBSA level before testing ensures that each metropolitan area contributes one observation regardless of its number of tracts, and controls for metro-level confounders—such as regional cost of living, climate baseline, and housing policy—that could otherwise inflate or mask differences between CNI and non-CNI tracts.

Climate Hazard Typology Identification

To identify distinct climate risk profiles across CNI sites (**RQ2**), we applied K-means cluster analysis to the four disaggregated climate hazard indicators, motivated by the substantial geographic heterogeneity in hazard type across the U.S. (e.g., heat concentrated in the South and Southwest, wildfire in the West, flood risk along coastal and riverine corridors). The unit of analysis was the CNI site ($n = 36$). Site-level values were computed as the mean of each climate indicator across all census tracts within a project's CNI target-area footprint, then standardized to zero mean and unit variance across sites prior to clustering, so that differences in measurement units and variance did not dominate the Euclidean distance metric.

The optimal number of clusters was selected using two complementary criteria evaluated for $k = 2$ through $k = 8$: the within-cluster sum of squares (elbow method) and the mean silhouette score, which ranges from -1 to 1 and reflects cluster cohesion relative to separation. The k maximizing the silhouette score was retained as the final solution. To ensure a stable solution, K-means was run with 100 random initializations and a maximum of 1,000 iterations per run, retaining the lowest-inertia solution. Resulting cluster profiles were characterized using radar charts of standardized cluster centroids across the four hazard axes.

LISA Analysis

To test whether CNI tracts are disproportionately embedded in spatially concentrated high-vulnerability clusters (**RQ3**), we computed LISA (Anselin, 1995) for the composite CVI and each of the three domain scores. Spatial weights were constructed using queen contiguity and row-standardized; weights matrices

were built independently within each CBSA to prevent spurious spatial associations between geographically separate metropolitan areas. Local Moran's I statistics and pseudo-p-values were estimated via conditional permutation inference (999 permutations, fixed random seed for reproducibility). At $\alpha = 0.05$, tracts were classified into one of five spatial regimes: High-High (HH; above-mean value surrounded by above-mean neighbors), Low-Low (LL), High-Low (HL), Low-High (LH), or Not Significant (NS).

We focused on the HH classification, which identifies tracts embedded in spatially contiguous concentrations of high vulnerability—i.e., vulnerability that extends beyond the tract's own borders into its neighborhood context. We used Pearson's chi-square test to compare the proportion of CNI versus non-CNI tracts classified as HH, separately for each vulnerability score, and report Cramér's V as a measure of effect size. At the site level, we computed the proportion of each grantee's CNI tracts classified as HH on each vulnerability score, and identified multi-domain HH tracts—those classified as HH on two or more of the three domain scores simultaneously—as indicators of the most severe cumulative spatial disadvantage. Finally, we generated LISA choropleth maps for all CNI projects, displaying quadrant classifications across all four vulnerability scores within the full CBSA, with CNI target-area boundaries overlaid.

Results

CNI Sites Exhibit Substantially Higher Cumulative Climate Vulnerability

The paired comparison analysis shows that CNI tracts are more vulnerable than non-CNI tracts in the same metropolitan areas across all four vulnerability scores (Figure 1, Table 2, Supplementary Figure S1). The composite CVI was significantly higher in CNI tracts across all 32 CBSA pairs (mean difference = 0.92, Cohen's $d = 2.45$, $p < 0.001$ by both one-sided t-test and Wilcoxon signed-rank test), indicating a large and consistent vulnerability gap.

[Insert Figure 1 Here]

[Insert Table 2 Here]

The socioeconomic vulnerability domain showed the largest absolute mean difference (mean difference = 1.45, Cohen's $d = 2.62$, $p < 0.001$), reflecting the deep concentration of poverty, unemployment, and housing instability within CNI target areas. The chronic disease burden domain also showed a substantial and statistically significant mean difference (mean difference = 1.26, Cohen's $d = 1.96$, $p < 0.001$ across 31 CBSA pairs with available data), consistent with the well-documented health burden in disinvested urban neighborhoods (Mujahid et al., 2023; Plascak et al., 2022). The climate hazard exposure domain, while statistically significant, showed a considerably smaller effect size (mean difference = 0.07, Cohen's $d = 0.32$, $p = 0.040$). One plausible explanation for this pattern is the geographic nature of climate hazards: within a given metropolitan area, climate hazard exposure tends to be relatively uniform, such that CNI and non-CNI tracts face broadly similar climate conditions. The meaningful variation in climate hazard exposure operates primarily at the cross-metropolitan scale. The subsequent k-means cluster analysis captures this heterogeneity in climate exposure vulnerability.

CNI Sites Exhibit Distinct Climate Hazard Typologies

K-means cluster analysis of the four disaggregated hazard indicators across 36 CNI sites identified three distinct climate risk profiles (Figure 2 and Table 3). The three-cluster solution was selected based on both criteria: $k = 3$ produced the largest marginal reduction in within-cluster sum of squares ($\Delta = 30.5$) and the highest mean silhouette score (0.569), with a pronounced drop at $k = 4$ (0.361), jointly supporting a three-cluster solution (Supplementary Figure S2).

[Insert Figure 2 Here]

[Insert Table 3 Here]

The majority of CNI sites ($n = 31$) were classified into a Lower Hazard Exposure typology, characterized by relatively low scores across all four hazard dimensions. Despite their lower aggregate hazard exposure, these sites carry a substantial combined burden of socioeconomic and chronic disease disadvantage documented above, underscoring that cumulative climate vulnerability at most CNI sites is driven primarily by social and health conditions rather than climate hazard exposures.

The second cluster, Higher Flood and Heat Risk, was comprised by CNI sites in Phoenix (AZ), New Orleans (LA), and Tulsa (OK). These sites combine extreme heat (23–135 annual extreme heat days) with near-total flood zone coverage (99–100% of area at moderate-to-high flood risk), a compounding hazard profile likely to amplify demands on physical infrastructure and limit residents' capacity for emergency evacuation or post-disaster recovery.

The third cluster, Higher Wildfire Exposure, included sites in Sacramento (CA) and Fort Myers (FL), distinguished by a higher annualized wildfire frequency compared with other CNI sites. The NRI's annualized frequency for wildfire is derived from USFS probabilistic wildfire risk datasets (Short et al., 2020) and represents a modeled annual burn probability per census tract. The mean wildfire frequency for this cluster (0.001) falls at approximately the 96th percentile of the 32-metro tract distribution — roughly 100 times the median tract value — and produced a standardized score of +3.2 across sites, the single largest z-score on any hazard indicator in the cluster solution. This represents a statistically distinctive and largely absent hazard dimension for the broader CNI portfolio.

CNI Sites Locate Disproportionately in Spatially Concentrated High-Vulnerability Clusters

LISA analysis revealed that CNI tracts are not merely elevated in vulnerability — they are situated within spatially concentrated areas of high vulnerability (Figure 3). Across all three vulnerability scores (socioeconomic, chronic disease burden, and climate hazard exposure), CNI tracts were significantly more likely than non-CNI tracts to be classified as HH spatial clusters (all $p < 0.001$ by chi-square test; Table S1).

[Insert Figure 3 Here]

The disparity was most pronounced for socioeconomic vulnerability: 86.4% of CNI tracts fell within HH clusters, compared to 16.7% of non-CNI tracts ($\chi^2 = 368.66$, Cramér's $V = 0.141$). Chronic disease burden followed a similar pattern (54.1% vs. 17.2%; $\chi^2 = 99.78$). Climate hazard exposure showed the smallest but still significant disparity (31.8% vs. 15.7%; $\chi^2 = 20.21$).

At the site level, the share of CNI tracts classified as HH varied substantially across projects and domains, with 16 sites showing 100% of their CNI tracts in multi-domain HH clusters and three sites showing 0% (Figure 4). Multi-domain HH designation—classification as HH in two or more vulnerability domains simultaneously—was concentrated among a subset of sites, identifying locations where cumulative spatial disadvantage is more concentrated. LISA choropleth maps for selected CNI projects illustrate how CNI target areas sit within broader neighborhood corridors of compounding vulnerability rather than as isolated pockets of distress (Figure 5).

[Insert Figure 4 Here]

[Insert Figure 5 Here]

Discussion & Conclusion

This study provides the first national-scale assessment of cumulative climate vulnerability at CNI sites, integrating socioeconomic vulnerability, chronic disease burden, and climate hazard exposure into a composite index and examining spatial concentration using LISA methods. We find that the vulnerability gap between CNI and non-CNI tracts exists across all domains. The large effect sizes for socioeconomic vulnerability and chronic disease burden indicate that CNI sites are characterized by concentrated disadvantage. The comparatively modest effect for climate hazard exposure reflects the geographic logic of climate hazards: within a metropolitan area, heat, flood, and wildfire risks tend to be relatively uniformly distributed, such that CNI and non-CNI tracts face broadly similar biophysical conditions. This asymmetry carries an important policy implication: targeting community resilience investments solely on climate hazard exposure would systematically overlook areas with high socioeconomic vulnerability and a high burden of chronic disease. Limited adaptive capacity may increase the potential harms of even modest exposure to hazards.

Climate hazard exposure varies across CNI sites. Most sites face modest aggregate hazard exposure, but a subset—particularly those in Phoenix (AZ), New Orleans (LA), and Tulsa (OK)—face a compounding hazard environment in which extreme heat and near-total flood zone coverage interact with the same concentrated socioeconomic and health disadvantage present across the broader CNI portfolio. These Higher Flood and Heat Risk sites may need targeted investment in physical infrastructure upgrades, green stormwater management, and cooling centers as components of any redevelopment plan. The Higher Wildfire Risk cluster suggests that CNI redevelopment in Sacramento (CA) and Fort Myers (FL) may benefit from proactive capacity building through emergency preparedness planning, resident education, and investment in community infrastructure—before wildfire risk intensifies further.

The LISA analysis shows that the cumulative climate vulnerability is spatially embedded beyond the CNI project boundary. Over 86% of CNI tracts are embedded in socioeconomically vulnerable HH clusters, compared to fewer than 17% of non-CNI tracts, across all tracts in the sample. This means the disadvantages faced by CNI residents are not confined to the site boundaries. These neighborhoods sit in corridors of compounding disadvantage that extend into adjacent tracts, constrain access to nearby resources, and limit the effectiveness of site-bound interventions. This spatial embeddedness is consistent with the prediction of cumulative disadvantage theory that disadvantage compounds across dimensions and contexts rather than remaining localized (DiPrete and Eirich, 2006). From a policy standpoint, it suggests that CNI redevelopment strategies limited to the site footprint may be insufficient; durable improvements in resident wellbeing may require coordinated investment across the broader neighborhood catchment.

Several limitations should be noted. First, the CVI is constructed from cross-sectional data, which may not fully capture more recent shifts in climate hazard exposure or socioeconomic conditions accelerated by the COVID-19 pandemic. Second, the CBSA-level standardization of indicators controls for regional differences in absolute levels of disadvantage but prevents direct comparison of CVI values across metropolitan areas. Third, the sample of 36 CNI implementation grantees, while representing the complete federal portfolio for 2010–2020, is modest in size, which limits statistical power for subgroup analyses and typology characterization.

These findings may inform the design and targeting of place-based subsidized housing programs. The evidence that virtually all CNI sites—regardless of their climate hazard typology—sit within deeply disadvantaged socioeconomic and health contexts suggests that climate resilience planning for subsidized housing cannot be decoupled from investments in economic security, healthcare access, and neighborhood infrastructure. A resilience framework that addresses only physical hazard exposure while leaving underlying social and health vulnerability unaddressed is unlikely to reduce the actual harm that climate events produce for these residents. Conversely, social investment without attention to the compounding role of hazard exposure—particularly in areas with higher flood and heat risk—may improve baseline wellbeing while leaving residents newly exposed to conditions that erode those gains.

Future research should examine how CNI redevelopment investments, once implemented, alter the cumulative vulnerability profile of target tracts over time—and whether observed improvements reflect genuine reductions in resident risk or simply the displacement of low-income households into other vulnerable neighborhoods, transferring rather than resolving disadvantage. Qualitative and participatory research is also needed to understand how residents themselves perceive, prioritize, and navigate the interacting dimensions of climate vulnerability, as community knowledge and lived experience are essential inputs to resilience planning that aggregate indices cannot capture (Crenshaw et al., 2025). Nevertheless, this study offers a necessary baseline for

understanding where and how climate vulnerability is concentrated within subsidized housing landscapes, and it underscores the need for resilience investments that address both the place-based hazards and the structural determinants of disadvantage that compound them.

Declarations

Author Contribution

Y.W., Y.-T.P., C.F., L.U., and R.R. conceived and designed the study. Y.W. conducted the investigation, performed the formal analysis, developed the methodology, and prepared the figures. Y.W., Y.-T.P., and A.A.P.S. curated the data. C.F., L.U., and R.R. acquired funding for the project. All authors contributed to writing the original draft and reviewed and edited the manuscript.

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Data Availability

This study uses publicly available data from the U.S. Census Bureau's American Community Survey, CDC PLACES, the FEMA National Risk Index and National Flood Hazard Layer, gridMET, the AHRQ Social Determinants of Health Database, and HUD Open Data. The processed datasets and analysis code generated for this study are available from the corresponding author upon reasonable request.

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Tables

Table 1. Variable Selection for the Composite Climate Vulnerability Index (CVI).

Domain	Variable	Source
Socioeconomic Vulnerability	Pct of people in poverty	2015-2019 ACS (Schroeder et al., 2025)
	Median household income ^a	
	Pct of renter households	
	Pct of people under 18 years	
	Pct of people 65 years and above	
	Pct of civilian labor force unemployed	
	Pct of vacant housing units	
	Pct of adults with disability	CDC PLACES, 2024 Release (Greenlund et al., 2022)
	Pct of adults who experienced food insecurity in the past 12 months	
	Pct of adults who experienced housing insecurity in the past 12 months	
	Pct of adults who lacked reliable transportation for daily living in the past 12 months	
	Pct of adults who faced a utility shutoff threat in the past 12 months	
Chronic Disease Burden	Pct of adults with asthma	
	Pct of adults with diabetes	
	Pct of adults with high blood pressure	
	Pct of adults with coronary heart disease	
	Pct of adults with obesity	
Climate Hazard Exposure	Average annual number of extreme heat days, 2015-2019	gridMET (Abatzoglou, 2013)
	Average PM2.5 concentration in µg/m3, 2019	AHRQ Social Determinants of Health Database (AHRQ, 2026)
	Average annualized frequency of wildfires, 2021	FEMA National Risk Index (Zuzak et al., 2022)
	Percentage of area with moderate-to-high flood risk	FEMA National Flood Hazard Layer (FEMA, n.d.)

Notes:

Pct = Percentage.

^a We inverted the median household income variable to ensure that lower incomes translate directly into higher climate vulnerability.

Table 2. Paired Comparison Results (CNI vs. Non-CNI within the Same Metropolitan Area).

Score	N pairs	Mean diff (CNI vs. non-CNI)	Cohen's d	t statistic	p (t-test, one-sided)	W statistic	p (Wilcoxon, one-sided)
Composite CVI	32	0.9184	2.45	13.858	<0.001	528	<0.001
Socioeconomic vulnerability	32	1.4517	2.619	14.816	<0.001	528	<0.001
Chronic Disease Burden	31	1.2554	1.957	10.895	<0.001	494	<0.001
Climate Hazard Exposure	32	0.0705	0.318	1.798	0.0409	355	0.0454

Table 3. Climate Typology across CNI sites.

CNI Site Name	City	State	Climate Typology	Extreme Heat Days	PM2.5 Concentration
Edison-Eastlake Community	Phoenix	AZ	Higher Flood & Heat Risks	134.800	9.435
Eastern Bayview	San Francisco	CA	Lower Hazard Exposure	0.900	7.928
River District-Railyards	Sacramento	CA	Higher Wildfire Exposure	41.600	7.700
Sun Valley	Denver	CO	Lower Hazard Exposure	12.800	7.430
South Norwalk	Norwalk	CT	Lower Hazard Exposure	0.400	6.500
Central Park-Ybor	Tampa	FL	Lower Hazard Exposure	3.400	8.600
Edison Avenue-Dunbar	Fort Myers	FL	Higher Wildfire Exposure	2.600	7.830
Atlanta University Center-Ashview Heights-Vine City	Atlanta	GA	Lower Hazard Exposure	6.200	9.677
Woodlawn	Chicago	IL	Lower Hazard Exposure	0.000	9.273
Russell	Louisville	KY	Lower Hazard Exposure	3.400	9.217
Iberville-Treme	New Orleans	LA	Higher Flood & Heat Risks	7.400	8.954
Allendale-Ledbetter Heights-West Edge	Shreveport	LA	Lower Hazard Exposure	39.920	8.440
Ardenwood Village	Baton Rouge	LA	Lower Hazard Exposure	14.000	8.660
Whittier-Roxbury	Boston	MA	Lower Hazard Exposure	2.400	5.975
Dorchester	Boston	MA	Lower Hazard Exposure	2.000	5.700
Perkins-Somerset-Oldtown	Baltimore	MD	Lower Hazard Exposure	4.300	8.550
Tree Streets	Lewiston	ME	Lower Hazard Exposure	0.000	4.900
South Flint	Flint	MI	Lower Hazard Exposure	0.000	7.287
Greater Corktown	Detroit	MI	Lower Hazard Exposure	0.200	8.783
Near North Side	St Louis	MO	Lower Hazard Exposure	5.450	9.525
Paseo Gateway	Kansas City	MO	Lower Hazard Exposure	8.800	8.000
North 30th Street	Omaha	NE	Lower Hazard Exposure	4.600	7.100
Mt. Ephraim South Corridor	Camden	NJ	Lower Hazard Exposure	3.700	7.600
Cramer Hill	Camden	NJ	Lower Hazard Exposure	3.300	8.040
Avondale	Cincinnati	OH	Lower Hazard Exposure	0.000	9.125
Buckeye-Woodhill	Cleveland	OH	Lower Hazard Exposure	0.000	7.850
Near East Side	Columbus	OH	Lower Hazard Exposure	0.000	8.280
Eugene Field	Tulsa	OK	Higher Flood & Heat Risks	23.200	8.500
Larimer-East Liberty	Pittsburgh	PA	Lower Hazard Exposure	0.000	9.250
North Central Philadelphia	Philadelphia	PA	Lower Hazard Exposure	2.700	7.530
South City	Memphis	TN	Lower Hazard Exposure	10.600	8.550
Eastside	San Antonio	TX	Lower Hazard Exposure	68.800	8.475
St. Paul's Area	Norfolk	VA	Lower Hazard Exposure	3.400	6.232
Marshall-Ridley	Newport News	VA	Lower Hazard Exposure	3.000	7.400
Yesler	Seattle	WA	Lower Hazard Exposure	0.200	6.700
Westlawn	Milwaukee	WI	Lower Hazard Exposure	0.000	7.210

Figures

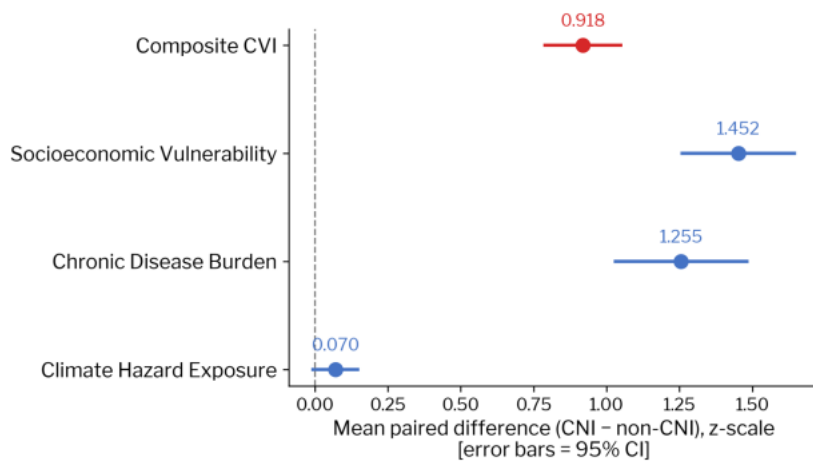


Figure 1

The Vulnerability Gap: CNI vs. non-CNI Tracts within Same Metropolitan Area.

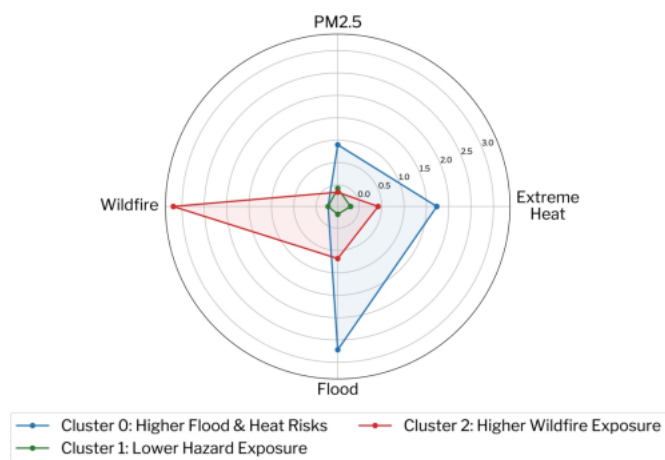


Figure 2

CNI Site Climate Hazard Typologies.

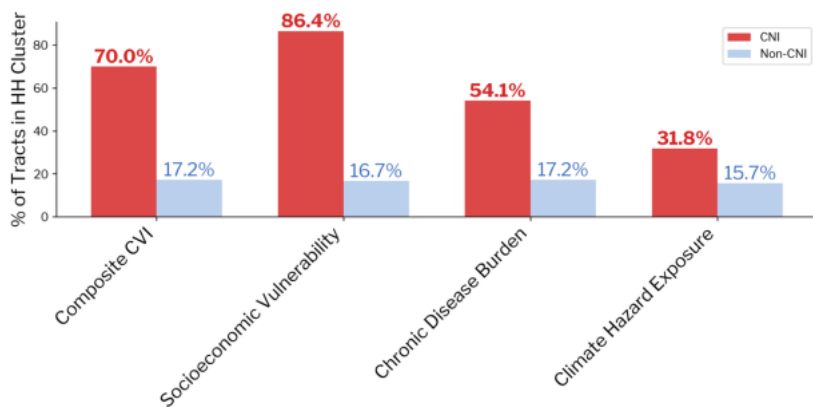


Figure 3

CNI vs. non-CNI tracts in High-High (HH) Cumulative Climate Vulnerability Clusters.

Edison-Eastlake Community, Phoenix, AZ	100	50	100	100
Allendale-Ledbetter Heights-West Edge, Shreveport, LA	100	100	0	100
Yesler, Seattle, WA	100	0	100	100
Marshall-Ridley, Newport News, VA	100	100	0	100
Eastside, San Antonio, TX	100	100	0	100
Mt. Ephraim South Corridor, Camden, NJ	100	100	50	100
Cramer Hill, Camden, NJ	100	100	100	100
North 30th Street, Omaha, NE	100	100	0	100
Near North Side, St Louis, MO	100	75	75	100
Paseo Gateway, Kansas City, MO	100	100	100	100
Dorchester, Boston, MA	100	100	0	100
Westlawn, Milwaukee, WI	100	100	0	100
River District-Railyards, Sacramento, CA	100	0	100	100
Sun Valley, Denver, CO	100	0	100	100
Russell, Louisville, KY	100	100	100	100
Edison Avenue-Dunbar, Fort Myers, FL	100	100	0	100
Atlanta University Center-Ashview Heights-Vine City, Atlanta, GA	86	0	86	86
South Flint, Flint, MI	89	56	44	78
Avondale, Cincinnati, OH	100	75	0	75
St. Paul's Area, Norfolk, VA	100	50	25	75
Eastern Bayview, San Francisco, CA	75	75	0	75
Greater Corktown, Detroit, MI	67	33	67	67
Woodlawn, Chicago, IL	82	64	18	64
Larimer-East Liberty, Pittsburgh, PA	50	50	0	50
North Central Philadelphia, Philadelphia, PA	100	50	0	50
Ardenwood Village, Baton Rouge, LA	50	50	0	50
Whittier-Roxbury, Boston, MA	100	50	0	50
Central Park-Ybor, Tampa, FL	50	50	0	50
Perkins-Somerset-Oldtown, Baltimore, MD	50	0	100	50
Buckeye-Woodhill, Cleveland, OH	100	50	0	50
Tree Streets, Lewiston, ME	100	33	33	33
Iberville-Treme, New Orleans, LA	78	0	22	22
Near East Side, Columbus, OH	67	0	0	0
Eugene Field, Tulsa, OK	0	0	0	0
South City, Memphis, TN	100	0	0	0
South Norwalk, Norwalk, CT	0	0	0	0
	Socioeconomic Vulnerability	Chronic Disease Burden	Climate Hazard Exposure	Multi-Domain HH (≥2)

Figure 4

Share of CNI Tracts in High-High (HH) Spatial Clusters (%) by Site and Vulnerability Domain. HH identifies tracts that score high on vulnerability and are surrounded by other high-scoring tracts — indicating spatially concentrated, embedded disadvantage rather than isolated distress. A multi-domain HH designation refers to classified HH on ≥2 of the three vulnerability domains simultaneously, identifying tracts embedded in the deepest form of cumulative spatial disadvantage.

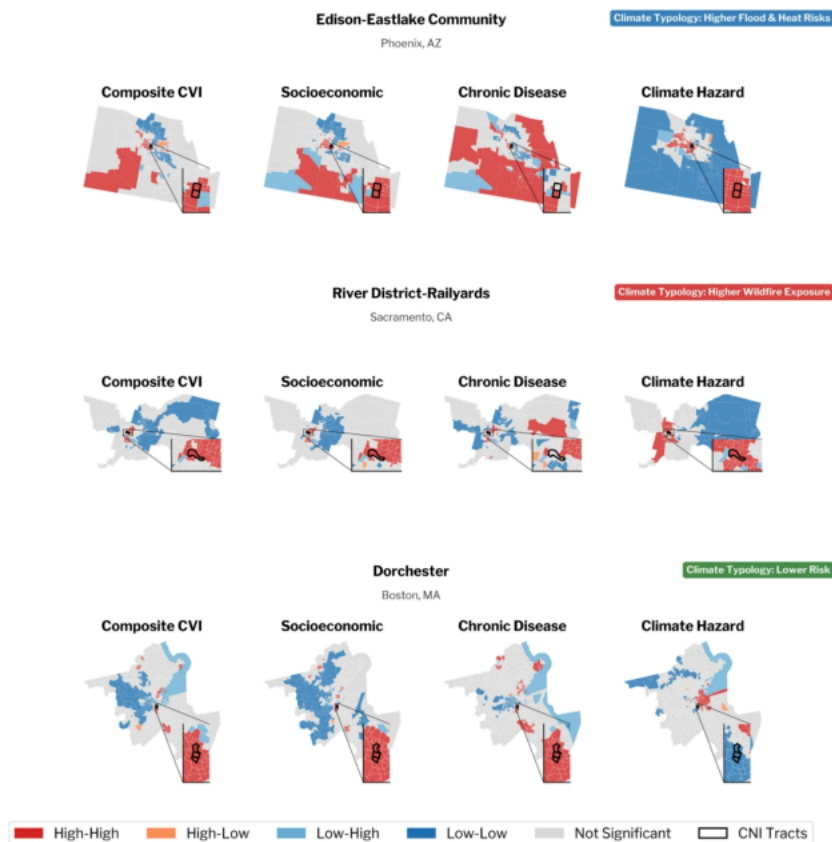


Figure 5

LISA Maps for Selected CNI Projects.

Supplementary Files

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