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ORIGINAL ARTICLE

Historical Redlining and Community-Reported Housing Quality: A Spatial Analysis

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Abstract Historical redlining, a racially discriminatory practice implemented by the US government in the 1930s, has been associated with present-day environmental outcomes. However, there is limited research examining the relationship between historical redlining and contemporary housing quality. The objective of the present study was to investigate the relationship between historical redlining and contemporary housing quality in Atlanta, Georgia. Spatial patterns of housing code violation complaints from 2015 to 2019 were examined using point-pattern and spatial cluster analyses. We used Bayesian hierarchical models, accounting for spatial autocorrelation, to estimate associations between historical redlining and housing complaints, after adjusting for contemporary neighborhood characteristics, such as poverty, median structure age, vacant and renter-occupied properties, and residential racial segregation. A total of 48,626 housing code violation complaints were reported during the study period, including 6531 complaints deemed "hazardous." Historical redlining was a statistically significant predictor of housing complaints. We observed a 167% increased risk (IRR = 2.67, 95% confidence interval = 1.49, 4.77) of housing complaints for historically redlined neighborhoods compared to neighborhoods historically graded as "best" or "still desirable," after adjusting for neighborhood characteristics. Redlined neighborhoods also had an increased risk of "hazardous" housing complaints (IRR = 1.94, 95% confidence interval = 1.11, 3.40), after adjusting for contemporary neighborhood characteristics. Historically redlined neighborhoods exhibited disproportionately higher rates of housing code violation complaints. Spatial analysis of housing code violation complaints can provide insights into housing quality and inform interventions targeted at addressing the environmental legacy of structural racism.

Keywords Environmental justice · Spatial analysis · Housing · Structural racism · Redlining

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Introduction

Poor housing conditions have been associated with a range of adverse health impacts [1, 2]. Poor ventilation and exposure to hazards such as mold, dampness, and pests increase the risk for incidence, morbidity, mortality, and exacerbation of asthma and other respiratory conditions, while household exposure to lead and radon can lead to a range of respiratory problems, including lung cancer [3–5]. In addition to adverse physical health consequences, poor housing conditions can have an impact on mental health. Living in overcrowded or unstable housing situations can contribute to stress, anxiety, and depression [6–9]. Furthermore, exposure to lead can cause neurological damage, which can contribute to behavioral and cognitive problems, particularly among children [10, 11].

In the United States (USA), housing quality is a social determinant of health that may be driven by structural racism. Structural racism encompasses the ways in which racial discrimination is embedded in the policies, institutions, and structures of society, leading to systematic disadvantages for racial and ethnic minoritized groups [12–14]. Unlike individual acts of prejudice or discrimination, structural racism is a broader system of power that shapes opportunities and outcomes based on race. The legacy of structural racism in the US has resulted in a long history of housing discrimination, perpetuating segregation and inequality in housing [15].

One key aspect of the relationship between structural racism and housing discrimination is the legacy of redlining. Redlining is the practice of denying access to credit, insurance, and other financial services based on the racial makeup of a neighborhood. In the 1930s, the US government-created Home Owners' Loan Corporation (HOLC) engaged in redlining practices through the creation of residential maps, intending to guide mortgage industry lenders [16]. HOLC maps were color-coded to indicate perceived mortgage investment risk. Red zones, or "redlined" neighborhoods, were labeled as "undesirable" or "lower grade." HOLC's assessments incorporated housing conditions, class, and racial/ethnic composition, adversely affecting Black and immigrant populations, and designating certain neighborhoods as "hazardous" based on their racial makeup [16]. This practice effectively contributed to low levels of neighborhood investments, excluded communities of color from homeownership in certain neighborhoods, and created racially segregated neighborhoods that are still pervasive in U.S. cities [16, 17].

Historical redlining has contributed to the concentration of poverty and lack of investment in communities of color in the U.S. [18, 19]. Individuals and families living in segregated neighborhoods with limited resources and opportunities are more likely to face significant health disparities due to a lack of access to quality healthcare and other health-promoting resources [14, 20]. They are also more likely to experience disparate exposures to multiple environmental health hazards [21]. Historically redlined neighborhoods were often located near highways, airports, and industrial zones, which are all significant sources of air pollution. Furthermore, recent studies have documented associations between historical redlining and elevated exposure to air pollution in low-income and minoritized communities [22–24]. Historical redlining has also been associated with a lack of green spaces and tree cover in these communities, further exacerbating the effects of air pollution [22, 25, 26].

Although there is significant evidence that historical redlining has played a role in shaping the environmental health of U.S. communities, most of these studies have focused on outdoor environmental factors such as air quality and the built environment. To our knowledge, few studies have focused on the potential relationships of historical redlining on contemporary housing conditions. To address this gap in knowledge, this study examined associations between historical redlining and contemporary (2015–2019) housing code violation complaints in Atlanta, GA, USA. We hypothesized that (1) historically redlined communities have higher neighborhood exposure to housing code complaints and (2) the association between historically redlined communities and neighborhood exposure to housing code complaints persists after adjusting for contemporary racial residential segregation and other known area-level risk factors for housing code violations (e.g., renter occupancy and low-income) [27].

Methods

Study Setting

This study was performed within the city boundaries of Atlanta, Georgia. The 1938 HOLC neighborhood grade scoring (Fig. 1) marked a clear north–south demarcation between desirable (A and B) and undesirable (C and D) neighborhoods in Atlanta. Modern-day Atlanta is racially diverse city, with 41% of residents identifying as white and 48% identifying Black or African American [28]. Nevertheless, Atlanta remains segregated along racial lines [29]. The average number of housing units in Atlanta during the study period was 185,182 [28].

Data Sources

Housing Code Complaints

We assessed all community-reported housing code violation complaints filed between 2015 and 2019 with the City of Atlanta's Code Enforcement Section. The Code Enforcement Section is responsible for inspecting residential properties that are reported to be in violation of Atlanta's housing Code [30]. Residents can file complaints through several channels, including in-person, by mail, by phone, by fax, by email, or by area survey of officers in the field. Common housing code violations include property maintenance issues, landscaping issues, flooding issues, the accumulation of trash and garbage, units not supplied with water or adequate heat, rodent infestations, inoperative vehicles, open/vacant structures and lots, and other deficiencies which may render properties unsafe to its occupants or the general public [30].

For the current analysis, complaint records were obtained through a search of the City of Atlanta's publicly available Code Enforcement database [31]. Each complaint record included the date the complaint was received, the address of the property, a text description of the complaint, and a binary officer-assigned "Short Notes" category (Property Maintenance or Highly Hazardous). The database included a total of 49,339 complaints from 2015 to 2019, 6570 of which were determined by Code Enforcement officers as "Hazardous" Complaints.

Geocoding of Housing Code Complaints

Housing code complaints were geocoded using the Nominatim geocoding service in the "tidygeocoder" package. We were unable to render coordinates for 4067 property addresses. These 4067 addresses were geocoded using Google's Geocoding API in the "ggmap" package, and manually reviewed by two study authors. It should be noted that street names were changed due to Atlanta's effort to rename streets

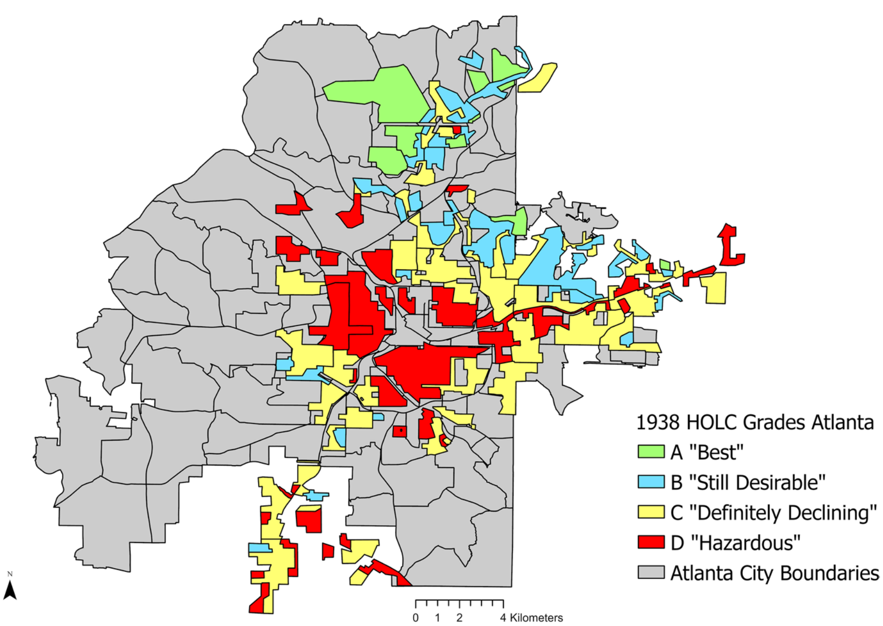

Fig. 1 The 1938 HOLC neighborhood grades overlaid on census tracts in the city boundaries of modern-day Atlanta

that were named in honor of the Civil War-era Confederacy [32]. The Code Enforcement database address and Google API-derived address were input into three mapping services to identify discrepancies: Google Maps, Apple Maps, and Map Quest. The complaints remained in the analytical sample if the address was identified in at least two of the three mapping services. A handful of complaints were for properties that were located outside of the city limits of Atlanta, leaving a remaining total of 48,626 (98.6%) and 6531 Hazardous (99.4%) geocoded complaints in the analytical sample.

Spatial Data

Census-tract polygon files were obtained from the US Census Bureau. Within ArcGIS, the tabulate intersection tool was used to compute the percent of area intersection between the U.S. Census tract shapefile and clipped shapefile of Atlanta's administrative boundaries. Census tracts that did not have an intersection percentage of over 50% were removed from our dataset, resulting in 38 census tracts (intersection percentage range from 0.000061% to 42.23%) removed for failing to meet our spatial intersection criteria. This resulted in a total of 126 census tracts within Atlanta's administrative boundaries.

Historical Redlining

HOLC maps do not align with contemporary census tract boundaries. To address this spatial misalignment, we utilized a historical redlining score created by Meier and Mitchell to link 2010 census tract boundaries to HOLC maps [33]. Briefly, the historical redlining score for each census tract was determined by summing the proportion of HOLC grades multiplied by a weighting factor based on area within the census tract. Scores were then reclassified into four equal intervals, ranging from 1 (lowest degree of redlining) to 4 (highest degree of redlining). For census tracts that did not have any overlap with HOLC-graded neighborhoods, we assigned these tracts a value of 5 to indicate these neighborhoods were *not* a part of the HOLC grading scheme. For the purposes of our redlining analyses, the two lowest redlining scores were collapsed to create three categories of historical redlining: low (scores 1–2), medium (score = 3), and high (score = 4).

Contemporary Segregation, Socio-Environmental, and Housing Characteristics

A census tract-level index of contemporary racial segregation, determined from 2010 census data, was obtained from the Othering and Belonging Institute [34]. This segregation index was selected due to its statistical rigor and policy relevance [35]. Census tract-level socio-environmental (number of people living below the poverty line, the proportion of non-white people) and housing (median age of home, proportion of renter-occupied homes, proportion of vacant homes) data were obtained from the US Census Bureau's American Community Survey [28].

All the datasets were joined to an Atlanta administrative boundary shapefile. ArcGIS Pro (3.0.0) and R (version 4.2.2) were used for data management and analysis.

Statistical Analyses

Spatial Analyses

For each census tract, we calculated and mapped the rates of total and hazardous complaints per 1000 households from 2015 to 2019. Spatial analysis was performed for each outcome variable (total or hazardous complaints).

Kernel Density Estimation KDE was used to identify hotspots of total and hazardous complaints. KDE was performed with the Spatial Analyst Tool in ArcGIS Pro 3.0.0 using the quadratic kernel function described by Silverman [35]. The KDE formula is expressed as

$$f(x,y) = \frac{1}{nh^2}\sum_{i=1}^{n} K\left(\frac{d_i}{h}\right)$$

where $f(x,y)$ is the density estimate at the location (x,y), n is the number of complaints (total or hazardous), h is the bandwidth or the kernel size, k is the kernel function, and d_{i} is the distance between the location (x,y) and the location of the i^{th} observation.

Spatial Autocorrelation To assess spatial clustering patterns for rates of both complaint types, we performed global and local cluster analysis for spatial autocorrelation using the Spatial Analyst tool. Global Moran's I was used to measure the overall clustering pattern of total and hazardous complaints in the city of Atlanta. The calculation of the Global Moran's I statistic is as follows [36, 37]:

$$I = \frac{N \sum_{ij} W_{ij}(\overline{\overline{X}_i - \overline{X}})(\overline{\overline{X}_j - \overline{X}})}{\sum_{ij} W_{ij} \sum_i (\overline{\overline{X}_i - \overline{X}})^2}$$

where N is the number of census tracts, X_i is the outcome (total or hazardous complaints) at the location i, $\overline{X}$ is the mean value of the outcome (total or hazardous complaints) in the study, and W_{ij} is the elements of a spatial lag operator W (spatial weights of matrix W).

Local Moran's I was calculated using the spatial queen's contingency matrix. The calculation of the local Moran's I statistic is as follows [38]:

$$I_i = Z_i \sum W_{ij} Z_j$$

where I_i is the statistic for a census tract I, Z_i is the difference between the risk of a housing complaint (total or hazardous) at I and the mean risk of type housing complaints for Atlanta, Z_j is the difference between the risk of a housing complaint (total or hazardous) at j and the mean risk of type housing complaints for Atlanta, and W_{ij} is the weight matrix for a queen contingency matrix that considers neighbors that share a common border.

Hierarchical Spatial Regression Analysis

Due to exploratory analysis determining spatial clustering of environmental health hazard complaints, a multilevel spatial Bayesian Poisson regression model was selected to determine the global statistical significance of spatial predictor variables. Spatially structured and random effects were implemented through a Besag-York-Mollie (BYM) model to account for spatial autocorrelation of code violations [39, 40]. Integrated nested Laplace approximation (INLA) was used to fit the multilevel model, with a queen's adjacency matrix for spatial error terms. This was conducted using the "R-INLA" package [41]. The equation for this model is:

$$log(\lambda_i) = \alpha + \beta * x_i + u_i + v_i$$

where $log(\lambda_i)$ represents the log expected count data at location i, α represents intercept term, β represents the coefficient associated with covariate x_i, u_i represents the spatially structured effect, and v_i represents the random (unstructured) effect term [42, 43].

A directed acyclic graph (DAG) was used to identify potential covariates (see Supplementary data). Variables included in our analysis are tract-level values that include rates of total or hazardous complaints, proportions of vacant homes, proportion of renter occupied homes, median age of homes, proportion of the population in poverty, historical segregation score based on HOLC grade, contemporary segregation score, and proportion non-white. The variables proportion non-white and segregation scores were grouped into tertiles (low, medium, high) to deal with possible non-linearity and assess variables' impacts in a way that is more comparable and understandable to community stakeholders. Analysis was conducted for both highly total and hazardous environmental health complaints.

Results

Spatial Patterns of Housing Code Complaints

There were 48,626 total complaints made to Atlanta's Code Enforcement Section from 2015 to 2019, of which a total of 6531 complaints were assigned as "hazardous." Global Moran's I results showed significant tract-level spatial clustering for total (Z-score 10.75; $p<0.0001$) and hazardous (Z-score 9.16; $p<0.0001$) complaints. Evidence of local positive clustering for total and hazardous complaints is seen in Fig. 2A and B. Clusters of high total and hazardous complaints have substantial overlap with HOLC grade C and D neighborhoods. Clusters of low numbers of complaints per household were present in Northern Atlanta, overlapping the majority of HOLC grade A and B neighborhoods (Fig. 2A and B).

KDE suggests six possible hotspots in Southeast and Southwest Atlanta (Fig. 2C) for total complaints. A similar yet stronger spatial pattern is seen in the density of hazardous complaint with seven hotspots and the density being more pronounced in color gradation with a wider spread (Fig. 2D). The bulk of hotspots observed for total and hazardous complaints overlap with HOLC grade C and D neighborhoods.

Associations Between Historical Redlining, Contemporary Segregation, and Housing Code Complaints

We observed significantly positive incidence rate ratios (IRR) for redlined neighborhoods, higher segregation score, median age of structure, and proportion non-white for census tracts in Atlanta (Table 1). When compared with A- and B-graded neighborhoods, we observed a 68% (95% CI 1%, 179%) and 167% (49%, 377%) increased risk of reported housing complaints for C-graded and D-graded neighborhoods, respectively. For segregation score categories, only the highest tertile for modern day segregation score has a significant increase in housing complaints, with a 80% (6%, 208%) increase in risk moderate and highest proportion non-white has a 102% (16%, 252%) and 152% (23%, 414%) increased risk of a reported complaint when compared to lowest proportion non-white tertile.

For hazardous complaints, there were positive, statistically significant associations with total number of renters and vacancies, median age of structure, "hazardous" HOLC grade neighborhoods and the two upper tertials of proportion non-white reported hazardous complaints (Table 2). When compared to A- and B-graded neighborhoods, only D-graded

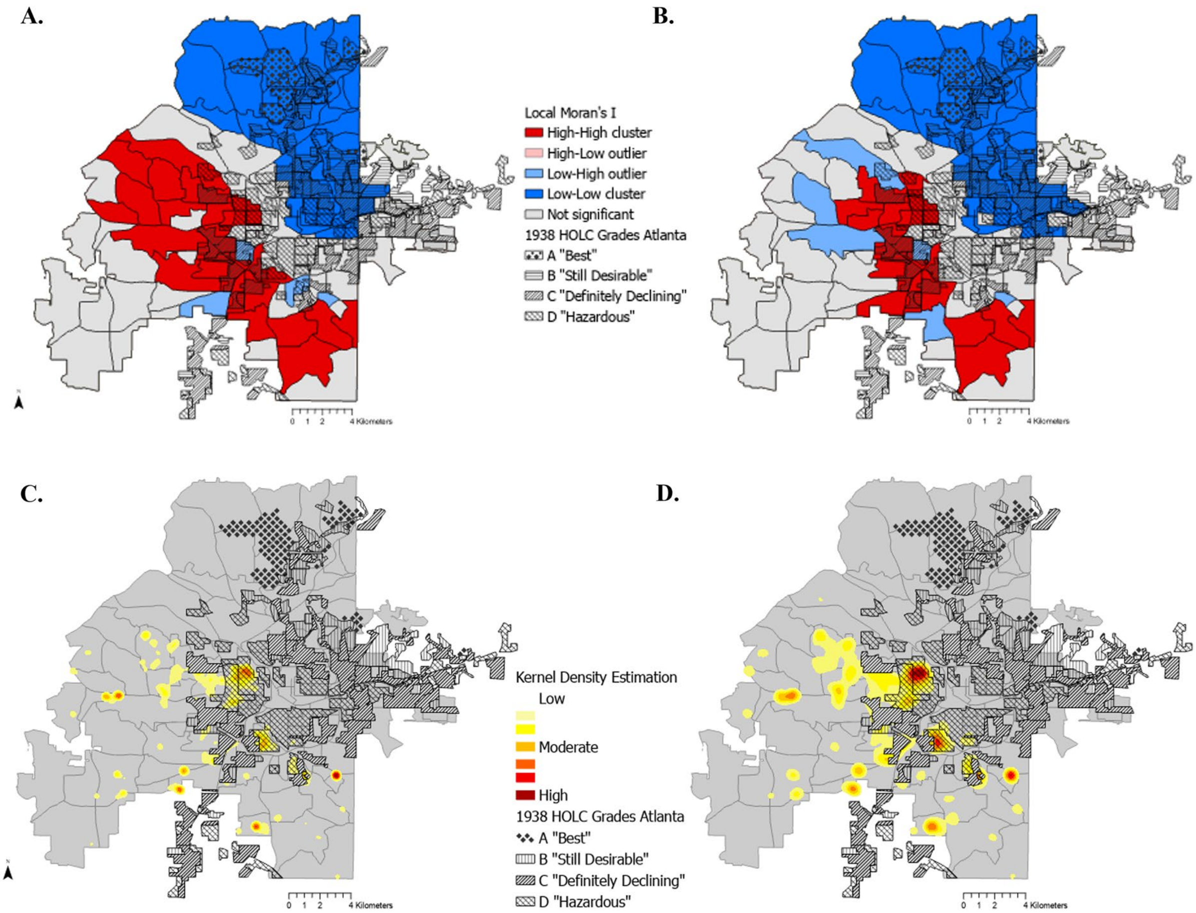

Fig. 2 Results from a Local Moran's I analysis using a queen's contingency matrix for total complaints (**A**) and hazardous complaint rates (per 1000 households) (**B**). Clusters of high numbers (hotspots) are shown in red while low number clusters (coldspots) are in blue. Point pattern analysis results from a kernel density estimation for total (**C**) and hazardous (**D**) complaints shown in increasing gradients from yellow to red

Table 1 Crude and adjusted regression coefficients from the spatial hierarchical model for total complaints

Model covariates	Crude			Adjusted		
	β	Cr *I* (95%)		β	Cr *I* (95%)	
Social environmental covariates						
Historical redlining score (categories)						
Low (A–B)	Ref			Ref		
Moderate (C)	**3.81**	**1.72–8.42**	*	**1.68**	**1.01–2.79**	*
High (D)	**5.49**	**2.50–12.04**	*	**2.67**	**1.49–4.77**	*
No HOLC grade assigned	**5.60**	**2.67–11.75**	*	1.57	0.92–2.69	
Present-day segregation index tertiles						
Low [0.0157, 0.17]	Ref			Ref		
Moderate [0.17, 0.602]	**1.89**	**1.16–3.08**	*	1.32	0.93–1.87	
High [0.602, 0.963]	**6.43**	**3.94–10.48**	*	**1.80**	**1.06–3.08**	*
Proportion non-white tertiles						
Low [0.0329, 0.387]	Ref			Ref		
Moderate [0.387, 0.916]	**3.51**	**2.30–5.35**	*	**2.02**	**1.16–3.52**	*
High [0.916, 1.0]	**10.09**	**6.61–15.38**	*	**2.52**	**1.23–5.14**	*
Poverty proportion tertiles						
Low [0.0155, 0.126]	Ref			Ref		
Moderate [0.126, 0.307]	**3.88**	**2.35–6.40**	*	0.89	0.53–1.49	
High [0.307, 0.807]	**5.36**	**3.24–8.83**	*	0.57	0.30–1.06	
Housing covariates						
Proportion renter-occupied homes	**1.85**	**1.49–2.29**	*	**1.50**	**1.21–1.87**	*
Proportion vacant homes	**1.94**	**1.57–2.41**	*	**1.43**	**1.22–1.69**	*
Median age of structure	**1.83**	**1.47–2.28**	*	**1.78**	**1.51–2.09**	*

*Statistical significance at the $p < 0.05$ level

Bold values denote statistical significance at the $p < 0.05$ level

neighborhoods were associated with a 94% (11%, 240%) increased risk of housing complaints. Though positive, we do not observe a significant association between current segregation score and risk of hazardous complaints. Conversely, there was a 91% (14%, 220%) increase in risk for moderate and a 143% (26%, 368%) increase in risk for the highest proportion of non-white tertiles compared to the lowest proportion of non-white tertile.

Discussion

This study examined spatial patterns of housing code complaints using community-reported data from Atlanta, GA, in 2015–2019. Geographical variation in housing complaints was identified throughout the study period, with spatial clusters observed in the southern and western regions of Atlanta. As hypothesized, historical redlining is significantly associated with higher neighborhood exposure to housing complaints; we observed an increased incidence of reported housing complaints for neighborhoods scored as C or D compared with those scored as A or B. Further examination of the subset of complaints classified as "hazardous" revealed similar associations between historical redlining and neighborhood exposure to housing complaints. Notably, these associations persisted after adjusting for contemporary socio-environmental factors such as residential segregation, illustrating the long-lasting consequences and environmental legacy of historical redlining.

Our study builds on previous research highlighting the environmental impact of historical redlining in the USA [22–26]. To our knowledge, our study is the first to consider the role of both historical redlining and contemporary residential segregation in the spatial distribution of housing complaints. Analyses of both historical redlining maps and contemporary neighborhood socio-environmental factors offered

Table 2 Crude and adjusted regression coefficients from the spatial hierarchical model for hazardous complaints

Model covariates	Crude			Adjusted		
	β	Cr *I* (95%)		β	Cr *I* (95%)	
Social environmental covariates						
Historical redlining score (categories)						
Low (A–B)	Ref			Ref		
Moderate (C)	**3.72**	**1.58–8.79**	*	1.40	0.85–2.28	
High (D)	**6.30**	**2.69–14.75**	*	**1.94**	**1.11–3.40**	*
No HOLC grade assigned	**6.06**	**2.72–13.52**	*	1.26	0.75–2.10	
Present-day segregation index tertiles						
Low [0.0157, 0.17]	Ref			Ref		
Moderate [0.17, 0.602]	**2.00**	**1.19–3.35**	*	1.31	0.94–1.83	
High [0.602, 0.963]	**7.54**	**4.51–12.60**	*	1.53	0.94–2.51	
Proportion non-white tertiles						
Low [0.0329, 0.387]	Ref			Ref		
Moderate [0.387, 0.916]	**4.46**	**2.89–6.87**	*	**1.91**	**1.14–3.20**	*
High [0.916, 1.0]	**13.32**	**8.69–20.45**	*	**2.43**	**1.26–4.68**	*
Poverty proportion tertiles						
Low [0.0155, 0.126]	Ref			Ref		
Moderate [0.126, 0.307]	**4.46**	**2.83–7.57**	*	0.96	0.59–1.56	
High [0.307, 0.807]	**8.71**	**5.31–14.26**	*	0.77	0.43–1.38	
Housing covariates						
Proportion renter-occupied homes	**2.08**	**1.67–2.60**	*	**1.66**	**1.36–2.02**	*
Proportion vacant homes	**2.37**	**1.93–2.92**	*	**1.76**	**1.51–2.05**	*
Median age of structure	**1.77**	**1.40–2.26**	*	**1.62**	**1.39–1.90**	*

*Statistical significance at the $p < 0.05$ level

Bold values denote statistical significance at the $p < 0.05$ level

unique advantages for studying spatial associations between residential segregation and housing complaints. In addition to redlining and structural age, we identified contemporary neighborhood factors, such as racial residential segregation and vacant- and renter-occupied housing, that were associated with greater rates of housing complaints. Further, while previous studies have found that racially minoritized groups are more likely to live in poorer quality housing compared to their white counterparts [1, 44–46], our study results provided valuable insights on the potential long-term impacts of redlining practices on housing quality. For example, in our analyses of "hazardous" reported complaints, we found significant association with historical redlining, but not contemporary residential segregation, highlighting the value of leveraging historical context to interpret contemporary environmental patterns.

In the 1930s, the HOLC redlined neighborhoods with predominantly minoritized populations were labeled as "high risk," resulting in disinvestment and limited access to financial resources. Neighborhood disinvestment manifests in various forms, and one indicator might be the prevalence of housing code complaints. These complaints not only point to potential physical deterioration but might also reflect broader economic and social disparities within a community. Moreover, housing code violations may have a detrimental effect on property values, potentially exacerbating a cycle of disinvestment. As property values decrease, homeowners in low-income areas may find it difficult to access loans or investments, limiting their ability to fund necessary repairs and improvements [47]. These factors contribute to a cycle of disinvestment that can lay the groundwork for present-day disparities in community-reported housing conditions.

Examining community-reported housing data offers insights into the quality and safety of housing in a neighborhood. Patterns of housing complaints can expose potential hazards that have implications for resident health and well-being, such as structural deficiencies, mold, and pest infestations. Prior research suggests that housing code violations are associated with negative health and safety impacts. These studies have primarily relied on administrative health data as well as self-reported health data [48–52]. For example, in a study of asthmatic children hospitalized in Cincinnati, OH, USA, higher densities of housing code violations were associated with increased emergency department use [48]. Another study conducted in Boston, Massachusetts, which utilized tenant reports, revealed an association between housing violations and the incidence of asthma triggers, further noting an escalation in trigger incidence concomitant with increasing racial diversity in neighborhood demographics [46]. A study of renter-reported data from Arkansas, USA, reported associations between housing complaints and health, with increased stress, breathing problems, and headaches being the more reported health problems [52]. Nevertheless, major gaps remain in our understanding of the relationships between housing quality and early clinical and biological indicators of disease. There are also gaps in understanding the relationship between housing quality and disease management. Integrating community-reported data with clinical and biological data will inform future work and enhance the capacity to understand and address the health impacts of poor housing quality. This work will also assist in assessing the health impacts of sustainable building standards and programs.

Addressing housing complaints is not only essential for ensuring safe and habitable living conditions, but also for promoting public health and reducing health disparities [1, 2, 53–55]. One key way community-reported housing complaint data can inform policy decisions is by helping policymakers identify priority areas for intervention or potential "bad actor" landlords with a pattern of complaints across properties. By analyzing patterns and clusters of reported violations, policymakers can pinpoint neighborhoods or specific housing issues that require immediate attention. For example, if a particular community consistently reports issues related to lead paint, this information can guide policies and programs focused on lead abatement and prevention. Community-reported data can also inform effective resource allocation. By identifying neighborhoods with higher concentrations of violations, policymakers can target interventions where they are most needed. This targeted approach ensures that limited resources, whether financial or human, are directed toward addressing specific issues, maximizing the impact of interventions.

Disparities in reported violations, such as the neighborhood disparities we observed in the current study, may indicate underlying issues related to socioeconomic factors, racial discrimination, and/or neglect. For example, an analysis of housing code enforcement data from the City of Chicago found differential enforcement decisions by inspectors based on area-level income, poverty, and the type of landlord ownership of rental units [27]. To address these issues, policymakers can collaborate with public health and community partners to develop targeted strategies to rectify these disparities, foster more equitable housing conditions, and address housing-related health risks. Finally, while analyzing trends and identifying recurring issues can inform policy decisions and advocacy, efforts should be made to ensure that housing code-enforcement measures are not selectively applied in ways that further reinforce discrimination against disadvantaged low-income tenants and property owners [56, 57]. This approach aligns with principles of environmental justice, ensuring that all communities have fair and equitable treatment with respect to safe and healthy living environments [58].

Limitations

Our research leverages publicly available, community-reported housing data, which presents some limitations. Analyzing housing complaints may have underestimated the burden of housing hazards, particularly in low-income neighborhoods, where individuals may have competing demands that supersede filing a complaint [59–61]. Although there is substantial evidence suggesting that low-income and racially marginalized residents are more likely to encounter substandard housing conditions than high-income residents [62], there might be significant barriers preventing these groups of residents from reporting these issues, such as fear of retaliation, lack of awareness of reporting mechanisms, and concerns about repercussions. This potential underreporting could have biased our estimates either away from or toward the null. Our study was also limited by its cross-sectional analysis of a singular city. However, this work is a critical first step in demonstrating the potential utility of this publicly available, community-reported data. For example, the HOLC drew maps for over 200 US cities [16]. In addition to evaluating associations between historical redlining and validated complaints, time to resolution, and complaint enforcements across multiple US cities, future analyses are planned to examine the utility of housing complaint data in predicting health outcomes.

Conclusion

Community-reported housing complaint data is a powerful tool for examining the environmental legacy of redlining and neighborhood disinvestment. Further investigation and analysis will be critical for evaluating associations with health outcomes and developing targeted interventions and policies to address housing disparities.

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Data Availability The data presented in this study are available from the corresponding author on reasonable request.

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