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The land cover paradox: Characteristics of blue- and green spaces within and beyond high-risk suicide clusters☆,☆☆

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ABSTRACT

Purpose: Urban suicide rates are rising, with disproportionate impacts on communities of color. While social determinants of suicide are well-established, the role of overlapping social, natural, and built environments remains underexamined.

Methods: We integrated National Land Cover Database (NLCD) data on developed open space, tree canopy, blue space, and a novel measure of land cover diversity with indicators of tree and park equity, built environment features, and socioeconomic vulnerability. Bayesian spatial Poisson models were used to estimate associations between these socioenvironmental variables and suicide risk at the Census Block Group (CBG) level in Chicago. We also identified and compared spatial clusters of high and low suicide risk using Local Moran's I.

Results: Blue space and developed, open spaces were associated with reduced suicide risk, with estimated decreases of 17.9 % and 15.1 %, respectively. In contrast, greater land cover diversity was associated with a 32.1 % increase in suicide risk. Suicide risk exhibited spatial structuring, with nearly half of the total variance explained by between-CBG differences ($\gamma = 0.4971$). Although spatial variability was modest ($\sigma S = 0.0214$), suicide deaths were significantly clustered, with 261 spatial clusters identified—59 high-risk and 202 low-risk ($p < 0.05$). Socioenvironmental characteristics differed significantly across cluster types, indicating that place-based exposures intersect with population-level vulnerabilities to shape suicide risk.

Conclusions: The findings reveal that the mental health impacts of environmental features are context-dependent and spatially patterned. While access to green and blue space may offer protective effects, these benefits are not uniformly experienced across urban neighborhoods. Suicide prevention efforts should consider not only individual and socioeconomic risk factors, but also spatial disparities in environmental quality and neighborhood-level disadvantage.

1. Introduction

In the U.S., suicide rates have risen by 30 % since 1999, underscoring their urgency as a public health crisis (Beghi et al., 2021; Mukherjee & Wei, 2021a). Although rural areas have historically experienced higher suicide rates, recent evidence points to growing urban suicide disparity, particularly in major cities such as Chicago, where rates have disproportionately increased among minoritized communities (Mukherjee &

☆ This study was a retrospective analysis of publicly available, deidentified data. Therefore, it meets the criteria for non-human subjects research, and institutional board approval was not required.

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Wei, 2021b; Steelesmith et al., 2019). Between 2015 and 2021, the suicide rate for Black residents in Chicago's South and West Side neighborhoods nearly doubled, rising from 7.7 to 14.6 per 100,000 (Goodwill & Baccile, 2024). Concurrently, increasing urbanization and infrastructure expansion have replaced natural landscapes with impervious surfaces and fragmented development, increasing exposure to environmental stressors, such as excessive noise, heat, and social isolation (Olsen et al., 2019; Percudani et al., 2024), and reducing access to restorative natural environments. Environmental stressors have been linked to reduced subjective well-being, lower quality of life, and heightened mental health problems (Fan et al., 2011; Tyrväinen et al., 2014; Yadav et al., 2025), whereas green space, such as parks and tree cover, has been associated with improvements in these outcomes. Together, these dynamics may contribute to the increased suicide risk observed in recent years.

While most suicide research has emphasized social and economic determinants, comparatively fewer studies have examined how features of the natural (e.g., vegetation, water, and open space) and built environment (e.g., roads, buildings, and transit) influence mental health and suicide risk (Nguyen et al., 2021; Percudani et al., 2024). Among studies that do examine the natural environment, the focus is often limited to discrete land use features, such as park accessibility (Lawrence et al., 2022), park availability (Noseworthy et al., 2023), or the proportion of tree canopy cover (Lee et al., 2023) within a given area. These studies consistently show that urban greenery is associated with better psychological outcomes and reduced mental distress (Alcock et al., 2014; Maas et al., 2006; Mitchell & Popham, 2008; Nutsford et al., 2013; South et al., 2018). Studies of blue spaces, or outdoor water environments such as rivers, lakes, and coastal areas, show a similar association with improved mental health and psychosocial well-being (Banyard et al., 2025).

Despite the increasing recognition of the mental health benefits provided by green and blue spaces, the broader characteristics of land cover have been significantly understudied within the context of suicide research. Land use refers to the functional designation of space (e.g., residential, industrial), whereas land cover encompasses the physical surface features, such as vegetation, impervious surfaces, water, and pavement, that shape the environmental context in which individuals reside. Within this framework, land cover diversity, or the range of land cover types in a specific area, can indicate either ecological richness and access to restorative environments or environmental fragmentation and disorder, influenced by broader social and planning conditions. Growing evidence suggests that land cover — the amount, distribution, and configuration of both green and blue space, as well as overall land cover diversity—may also play a critical, albeit indirect, role in shaping mental health outcomes and suicide vulnerability. In urban and suburban contexts, high land cover diversity has been linked to reduced walkability, increased car dependency, and limited public transit access (Momeni & Antipova, 2022a), all of which have been associated with poor mental health and increased suicide risk (Adams et al., 2015; Baobeid et al., 2021; Lachapelle et al., 2011; Makram et al., 2025; Ceñido et al., 2019; Zumelzu & Herrmann-Lunecke, 2021).

While land use and land cover are interconnected, land cover more accurately represents the physical surfaces that individuals actually experience. This provides insight into the arrangement of natural and constructed environments, which in turn affects walkability, the level of exposure to environmental stressors, and access to open spaces. However, to date, no research has explored whether the protective effects of environmental exposure rely not only on the existence of green or blue spaces, but also on their composition, spatial layout, and accessibility within the surrounding landscape. To address these gaps, this study investigates whether features of the natural and built environment—including land cover diversity, tree canopy coverage, park accessibility, and green and blue spaces—are associated with suicide mortality at the neighborhood level in Chicago. We further assess whether spatial patterns in suicide risk reflect underlying inequities in exposure to protective versus harmful environmental conditions. By integrating detailed land cover data with spatial modeling approaches, this study contributes to a growing literature linking ecological characteristics to mental health and suicide, while advancing understanding of how urban form and environmental inequity shape spatial vulnerability to suicide.

1.1. Spatio-demographic and socioenvironmental factors associated with suicide risk

Psychiatric disorders, including major depression and anxiety, are among the strongest individual-level risk factors for suicide (Bachmann, 2018; Batterham et al., 2013). Individual risk factors, however, are compounded by sociodemographic and social stressors, including race/ethnicity, gender identity, and physical health conditions (Bachmann, 2018; Barboza et al., 2016; GBD 2015 Mortality and Causes of Death Collaborators, 2016 Mortality and Causes of Death; Johns, 2020). Additional risk factors include housing insecurity (Houle & Light, 2014; Montgomery et al., 2024), financial hardship and job stress (Milner et al., 2013), involvement with the criminal legal system (Bravo et al., 2024; Cook, 2012), relationship breakdowns (Kposowa, 2003; Stack & Scourfield, 2015), alcohol misuse (Brady, 2006; Rizk et al., 2021), and childhood trauma (Barboza-Salerno & Meshelemiah, 2024). Cumulative exposure to neighborhood stressors, including socioeconomic deprivation, high population density, and limited access to health-promoting environments, has also been linked to elevated psychological distress and increased suicide risk (Fan et al., 2011; Fedina et al., 2019; Matthews & Yang, 2010).

Beyond individual and relational factors, specific features of the social, built, and natural environment contribute to poor mental health (Chipman et al., 2024; Tsai et al., 2018) and suicide risk (Runkle et al., 2023; Carleton, 2017; Vaz et al., 2020). For example, studies have shown that municipalities with greater tree canopy coverage and better park access tend to have lower suicide rates (Helbich et al., 2018; Lee et al., 2024). The proposed mechanisms include the role of green space in promoting social cohesion, reducing noise and air pollution, and enhancing neighborhood conditions such as property values (Donovan & Butry, 2010; Wolch et al., 2014). However, access to green space is often unevenly distributed, with disadvantaged urban neighborhoods experiencing the least availability and poorest quality (Heo & Bell, 2023). This spatial inequity in green infrastructure contributes to the emergence of suicide "hotspots"—areas where environmental and social disadvantage intersect to elevate risk (Mukherjee & Wei, 2021a; Vaz et al., 2020). In such contexts, limited park access and fragmented green space reduce opportunities for physical activity, recreation, and social interaction, thereby increasing vulnerability to mental health challenges (Bolanis et al., 2024; Kim & Sung, 2022). Similarly, while blue spaces have been associated with improved mental well-being (Banyard et al., 2025), their relationship to suicide remains less clearly established (Smith et al., 2021).

Several studies suggest that heterogeneous or mixed landscapes can confer mental health benefits, but the findings remain mixed. For instance, greater land cover diversity has been associated with reduced risk of health conditions known to be associated with increased suicide risk, such as chronic illness and asthma (Nguyen et al., 2021; Shim et al., 2023; Zhang et al., 2019). Also, some studies report that mixed-use development enhances social cohesion and accessibility, thereby reducing depression and suicide (Wei et al., 2024). On the other hand, some argue that dense, overcrowded housing near or within mixed-use environments is associated with greater odds of anxiety, stress, and sensory overload, especially for younger individuals, individuals who identify as female, individuals living in poverty, or when the overall infrastructure is poorly integrated (Chan et al., 2021).

"Equigenic environments" promote equitable access to natural spaces, which helps mitigate suicide risk across socioeconomic groups (Olsen et al., 2019). These environments ensure that all individuals, regardless of their socioeconomic status, can benefit from the health advantages provided by green spaces. A growing body of research, however, shows that the health benefits of green space vary by age, gender, and the type and structure of vegetation present in the surrounding environment. Formal green spaces—such as forests and greenways—have been linked to lower risks of sudden, unexpected deaths and chronic conditions, including cardiovascular disease and psychological distress, while informal vegetation types, like grasslands or isolated tree canopies, often show weaker or inconsistent effects (Wu et al., 2018). Studies also suggest that the relationship between green space and health is not uniform across populations: shrubs and grass may be more beneficial than trees for certain groups, while non-native or allergenic plant species in low-diversity areas may increase the risk of asthma and allergies. Similar variation is seen in physical health outcomes such as body mass index (BMI), where land cover type matters more for younger adults than older adults (Sander et al., 2017), and in respiratory outcomes, where greater land cover diversity is associated with lower asthma risk, an effect moderated by vegetation nativity and biodiversity (Alcock et al., 2017).

While much of this research focuses on general health or self-reported mental health outcomes, fewer studies have examined how green space influences suicide, particularly suicide mortality. A growing number of international studies suggest that the protective effect of green space on suicide varies based on ecological composition, urbanicity, and demographic context. For example, park-based trees and grass were linked to improved well-being among older adults in Switzerland (Bahr, 2024), and studies in Japan and Belgium found that green space was associated with lower suicide mortality, but only for certain age and gender groups and within specific urban settings (Jiang et al., 2021; Mendoza et al., 2023). In large cities, park density was associated with lower suicide rates among adult females and younger and older males, while in smaller cities, park coverage was protective for older women (Jiang et al., 2021). In contrast, in rural areas, woodland, but not parks, was associated with lower suicide risk, and only among middle-aged and older men (Jiang et al., 2021). These findings suggest that the structure, type, and distribution of green space, in addition to the broader social and ecological context, play critical roles in determining mental health outcomes. Despite these advances, few studies have examined land cover composition and diversity as multidimensional ecological exposures that may shape suicide risk. Most existing research relies on self-reported mental health outcomes and tends to focus on anxiety (Chan et al., 2021; Hartley et al., 2021), stress (Nguemeni Tiako et al., 2021; Tyrväinen et al., 2014), or suicide attempts (Lee et al., 2023), with relatively few addressing suicide mortality directly (but see, Asri et al., 2022; Helbich et al., 2020, 2020; Jiang et al., 2021; Mendoza et al., 2023). Additionally, limited studies assess the spatial distribution and arrangement of various land cover types, such as tree canopy, green and blue spaces, and land cover diversity, while considering aspects of the built environment and social and health-related vulnerabilities.

1.2. Present study

While prior research has emphasized the importance of context and population needs in shaping the relationship between blue or green space and suicide risk, this study asks a distinct but complementary question: Is variation in land cover types—and how evenly those types are distributed—associated with suicide risk, independent of green and blue space coverage? To our knowledge, no previous studies have applied a land cover diversity metric, such as Simpson's Diversity Index (SDI), to assess suicide risk, making the expected direction of its association uncertain. On the one hand, higher land cover diversity could indicate a mix of vegetation, open space, and built surfaces that support mental health through greater environmental variety, walkability, and visual interest. On the other hand, high diversity may reflect fragmented or disordered land use patterns, such as abrupt transitions between industrial, commercial, and residential zones, that contribute to stress, environmental inequality, or social disruption. Therefore, our land cover diversity metric captures the fragmented and heterogeneous imprint of urbanization across neighborhoods, which may correspond to uneven exposures to beneficial or harmful environmental features. Given spatial heterogeneity in both built and natural environments, a spatial analytical perspective is necessary to identify geographic disparities in suicide risk. To this end, we applied Bayesian spatial statistical models and disease mapping techniques to examine patterns of suicide mortality across Cook County, Illinois. This study contributes a novel application of remote sensing data to measure ecological diversity and assess how physical, social, and environmental characteristics jointly shape suicide risk in a large, socioeconomically diverse urban region. We address the following research questions: 1) Does suicide risk show a significant pattern of spatial variation within Cook County? and 2) What measured characteristics of the physical, social, natural, and built environment tend to explain patterns of suicide risk in this diverse urban setting?

2. Methods

2.1. Study area

Cook County, Illinois, is characterized by a diverse land cover that includes heavily urbanized areas with significant impervious surfaces, suburban regions with more green space, and natural areas such as forests, wetlands, and water bodies. Cook County, the most populous county in Illinois and the second in the United States, has a population exceeding 5 million residents (U.S. Census Bureau, 2023). The county encompasses the city of Chicago, known for its dense urban core and numerous suburban municipalities. This diversity in land use and population density creates a complex socio-environmental landscape. Cook County also has a rich cultural and ethnic diversity, with significant Latine, African American, and Asian communities (U.S. Census Bureau, 2023). The county's economic activities are varied, including major industrial zones, commercial centers, and residential neighborhoods. Additionally, in certain areas, Cook County faces environmental challenges, including pollution and limited green space, which impact residents' mental and physical health (Cook County Public, 2024).

2.2. Description of data sources

We analyzed all data using 2020 U.S. Census geographies at the census block group (CBG) level. In 2020, Cook County, Illinois, comprised approximately 4002 CBGs. However, due to restrictions based on population size and missing covariate data, our full analytic sample was limited to 3705 block groups. We conducted the analysis using QGIS 3.34 and R 4.3.2.

All data used in this study are publicly accessible via open data portals (Supplementary Table 1). The Cook County Medical Examiner's Office provided data on suicides, consisting of individual records of reported suicides from January 1, 2023, through December 31, 2024. While suicide data were available for more extended periods, some green space variables, such as the Tree Equity Score, were only available for the specified two-year period. Consequently, this period corresponds temporally with the duration of observation for the predictors of interest.

Land cover variables were sourced from the 2023 National Land Cover Database (NLCD) and tree canopy cover data from the United States Geological Survey (USGS). We selected an area of 5052 km^2 with the following land cover categories identified using the NLCD Viewer tool (Supplementary Appendix, Fig. 1): forest, grassland, urban, water, and barren land. The extracted data includes the percentage of each category within the selected area, which helps understand the distribution of land cover types.

The Transit Equity Dashboard (TED; Klumpenhouwer et al., 2021) provided multiple measures of neighborhood-level access to the built environment. This dashboard integrates data from publicly available

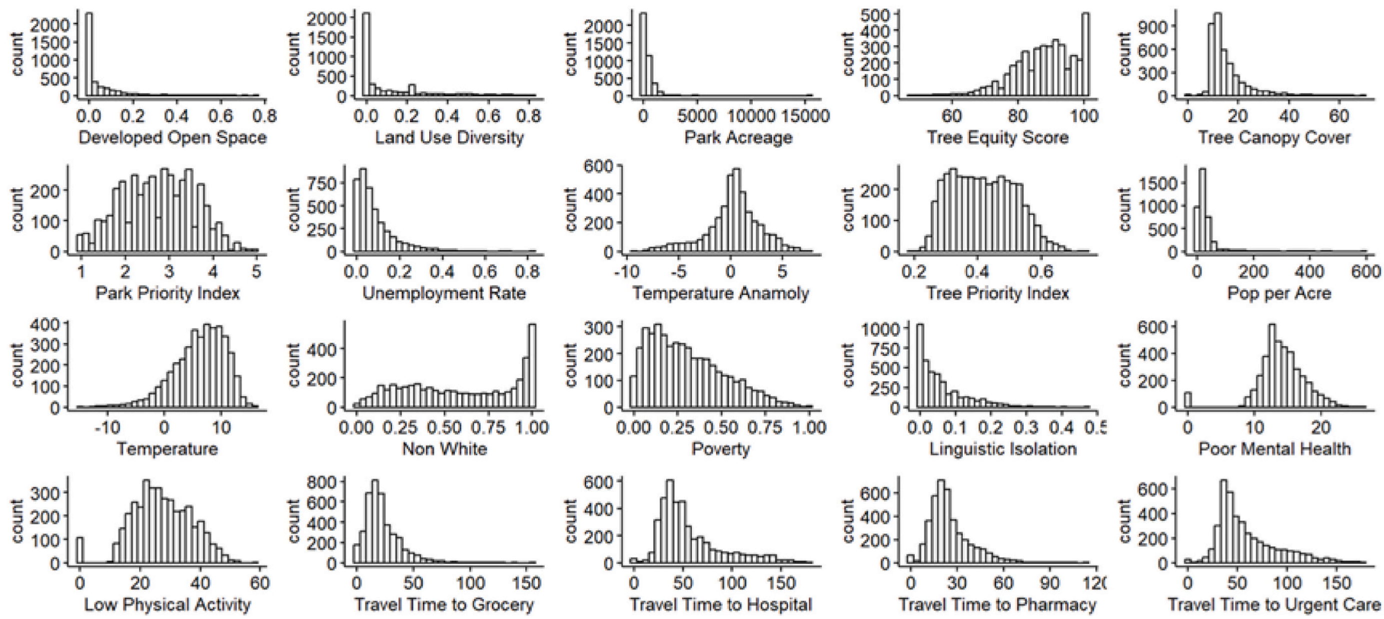

Fig. 1. Density Distribution of Socioeconomic, Environmental, and Health Variables. The figure displays histograms representing the distribution of various socioeconomic (e.g., poverty, non-White, linguistic isolation, unemployment rate, population per acre), environmental (e.g., open spaces, land use diversity, park priority, temperature anomaly, tree priority, travel times), and health-related variables (poor mental health, low physical activity) used in this study.

sources, including U.S. Census demographic information and transit agency performance metrics, to evaluate how effectively transit systems connect neighborhoods to essential services such as jobs, healthcare facilities, and pharmacies.

We downloaded the Tree Equity database from American Forests, which developed the Tree Equity Score (TES) to measure the need for tree canopy coverage in small areas (Campbell et al., 2022; Grant et al., 2024). TES calculates a neighborhood's tree canopy goal and compares it to its existing tree canopy coverage. The tree canopy goal derives from natural biome baselines (e.g., forest: 40 %, grassland: 20 %, desert: 15 %) and adjusts for factors such as building density. The tree canopy cover data come from a pre-aggregated Google high-resolution tree canopy dataset sourced from Google Environmental Insights Explorer.

Park access data were obtained from the Trust for Public Land's (TPL) ParkServe and ParkScore databases (see Lee et al., 2025; Robertson-Wilson et al., 2024), which together provide comprehensive, nationally standardized park availability, access, and equity measures. The ParkServe database, compiled between 2016 and 2018, contains data for over 145,000 parks across the United States, with boundaries verified through combined municipal GIS data, satellite imagery, and public access confirmation via city websites and Google Street View.

We extracted several measures from the 2019–2022 American Community Survey, including the number of people in each CBG, the percentage of people below the poverty line, median home value, homeownership rates, the percentage of non-White people, unemployment rates, and linguistic isolation at the CBG level. Supplementary Table 1 lists all variables used in this study.

2.3. Variables

2.3.1. Dependent variables

The Cook County Medical Examiner (ME) provides spatially referenced information about all individuals who died by suicide in Cook County and were under the medical Examiner's jurisdiction. Regardless of the cause of death, the medical examiner categorized all fatalities as intentional self-harm.

2.3.2. Independent variables

The ME data contained race, ethnic origin, age, sex at birth, primary cause, manner of death, location, and residence of death. Two variables capturing the decedent's race and ethnic origin were recorded into a single variable to capture racial and ethnic identity.

Built Environment and Service Accessibility. We used data from the Transit Center's Equity Dashboard (https://dashboard.transitcenter.org) to incorporate several built environment accessibility measures: job accessibility, defined as the number of jobs reachable within a 30-min public transit trip; travel times to the third-nearest pharmacy, hospital, grocery store, and urgent care facility. Following prior work (Farber et al., 2014; H. Liu, Rahman, & Karner, 2023), we used the third-nearest amenity to capture a broader range of feasible options beyond the closest location. All travel time estimates were based on weekday morning trips between 7:00 a.m. and 9:00 a.m. on March 27, 2023, and rely on General Transit Feed Specification (GTFS) data that incorporate walking access, transfer times, and wait times. For full technical documentation, see Klumpenhouwer et al. (2021) and the Equity Dashboard https://dashboard.transitcenter.org/about.

Natural Environment and Land Cover. The National Land Cover Database (NLCD) contains 27 detailed land cover classes (see Supplementary Appendix), including open space, developed areas, forested land, grassland, wetlands, water, and barren land. Raster images were obtained from the Multi-Resolution Land Characteristics (MRLC) Consortium and reclassified into broader land cover categories using the Raster Calculator tool in QGIS. For simplification, we grouped low-to medium-intensity developed areas into one category and combined deciduous, evergreen, and mixed forests into a single "forested" category. We retained "*Developed Open Space*" (impervious cover (IC) < 20 %) and "*Water*" (i.e., Blue Space) as distinct land cover types due to their hypothesized relevance to mental health and suicide risk (modeled as separate predictors. After reclassification, raster files were converted to vector format using the "Raster to Polygon" tool in QGIS, enabling the delineation of land cover areas within census block group (CBG) boundaries. The reclassified land cover data were then spatially joined to CBGs, and the Zonal Statistics tool was used to calculate the proportion of each land cover type present in each CBG.

To quantify landscape diversity, we calculated *Simpson's Diversity Index (SDI),* a widely used measure of land cover heterogeneity (Comer & Greene, 2015a; Kudas et al., 2024; Momeni & Antipova, 2022b; Papa et al., 2011) to reflect the conceptualization of urban areas as "spatially heterogeneous and temporally dynamic mosaics" (Pickett et al., 2017), and included it as a separate predictor in our models. SDI measures landscape diversity by considering the relative abundance of different land cover classes, giving more weight to common types so that very small land cover classes do not significantly affect the overall diversity score. (Fang et al., 2023). The index was derived by first computing the proportion of each land use category within each CBG, followed by applying the formula $D = 1 - \sum p_i^2,$ where p_i represents the proportion of land use in category i relative to the total land area for a given CBG. The index ranges from 0 (indicating a single dominant land cover type) to 1 (indicating an even distribution of land cover types).

Tree Cover and Tree Equity Score. Tree Canopy Cover (TCC), derived from the NLCD database, represents the percentage of land covered by tree canopy per census tract. The Tree Priority Index was obtained from American Forests and reflects a composite measure designed to prioritize neighborhoods for tree planting based on seven equally weighted indicators including health burden (e.g., asthma rates and cardiovascular risk), exposure to surface Urban Heat Island (UHI) intensity, unemployment rate, income levels, population density, and race/ethnicity-composition (American Forests, n.d.). We incorporated the Tree Equity Score (TES) to evaluate whether urban neighborhoods have sufficient tree canopy to support environmental health and climate resilience, in line with the local population's needs. TES is based on the percentage of Tree Canopy Cover in a given area: $CC\ (\%) = {A_T}/{A_L}, \times 100$, where CC = Canopy Cover, A_L is the land area of the block group, not including the water area, and A_T is the tree canopy cover in the area. The Gap Score (GS) represents the difference between the current tree canopy and an equity-adjusted tree canopy goal for a given area (e.g., neighborhood or census tract). The *TES* is then calculated by multiplying the gap score by an index, E, for prioritizing neighborhoods with the greatest need for tree planting: $TES = 100(1 - GAP_{score} \times E)$. Scores range from 0 to 100, with higher scores reflecting greater equity. The data also includes a *Tree Priority* index, which measures the self-reported prevalence of poor mental health, poor physical health, asthma, and heart disease in an equally weighted index. A higher Tree Priority Index score indicates a greater urgency for tree planting to achieve tree equity.

Park Priority and Accessibility. Park access was measured using 10-min walk service areas, calculated as a half-mile network distance from each park's public access point, using Esri's StreetMap Premium. This tool accounts for spatial impediment barriers such as highways or train tracks. These service areas were used to generate access statistics, including the number of people within walking distance of a park, disaggregated by race/ethnicity, income, and age, based on U.S. CBG data provided by Esri. An indicator variable is provided to identify block group portions outside this 10-min walk zone. To address equity in park distribution, we incorporated the Park Priority Index, which categorizes all areas outside a 10-min walk as 'very high,' 'high,' or 'moderate' priority for new parks. This index is based on six equally weighted factors: population density, density of low-income households, density of people of color, community health (based on poor mental health and physical inactivity from Centers for Disease Control and Prevention, 2024), urban heat island intensity (from 2023 Landsat 8), and pollution burden (from 2023 EPA EJScreen). These six factors are normalized within each city and averaged to produce a composite score Park Priority score, with relative rankings assigned within each CBG to identify areas with the greatest need for green space investment. Additionally, to capture regional park access beyond walkability, we used TED's measure of park accessibility, defined as the total acreage of parks reachable within a 30-min public transit trip during weekday morning hours.

Effect Modification by Socioeconomic Context. Given that the protective effects of green and blue space may vary by socioeconomic context, we test whether neighborhood-level disadvantage moderates their association with suicide risk. Prior research suggests that green space benefits are more substantial in socioeconomically vulnerable areas (Lee et al., 2023), but such effects may also be influenced by land use fragmentation or diversity. We included a series of interaction terms between land cover diversity and key environmental, demographic, and socioeconomic variables to explore these dynamics. These included interactions between land cover diversity and: open space, blue space, tree canopy, tree equity score, and park priority (capturing natural and built environmental features); as well as interactions with median home value, health burden, percent people of color, and percent in poverty (capturing structural and social disadvantage).

This research utilized a de-identified, publicly accessible database and was exempt from the Institutional Review Board (IRB) review.

2.4. Statistical approach

For the descriptive statistical analysis, the dataset was stratified by year before calculating summary statistics for age, gender, race/ethnicity, place of residence, and manner of death. Each suicide was assigned to its corresponding CBG through aggregation. We then converted the suicide data to a spatial object, with latitude and longitude as the coordinate reference system (CRS). The CRS was transformed to match the geographic data for Cook County, Illinois, which uses the NAD 1983 StatePlane Illinois East (EPSG: 3435) projection.

A binary indicator variable was created to assess whether the location of death matched the place of residence at the time of death. We systematically searched the primary cause of death using regular expressions to organize it into predefined categories based on keyword matching using the *stringr* package. For instance, deaths associated with terms like hanging, asphyxia, or strangulation were categorized as Hanging/Asphyxia. Similar categorizations were made for causes such as drug overdose, drowning, gunshot wounds, blunt force trauma, and other injuries. The ME classifies deaths using the International Classification of Diseases (ICD) codes from X60 to X84, which cover various methods of intentional self-harm.

Poisson models are typically used for count data, such as the number of suicides in census tracts. In contrast, Negative Binomial and Zero-Inflated models are commonly used when count data exhibit over-dispersion—that is, when the variance substantially exceeds the mean—or in cases where there are more zero counts than expected under standard count distributions. Therefore, we began by assessing over-dispersion and zero inflation in the suicide count data. The over-dispersion ratio, calculated as the deviance divided by the residual degrees of freedom, was 0.70, indicating underdispersion. Additionally, the proportion of zero counts did not exceed expectations under the Poisson distribution. Given that these findings confirm the suitability of the Poisson model, we proceeded accordingly. Variance inflation factors (VIFs) were computed for each model to account for multicollinearity between predictors. These values helped identify and address highly correlated variables that could distort the regression estimates. A correlation matrix was also computed for a subset of predictor variables to explore potential relationships. A correlation plot was created to visualize the strength of these associations (see Supplementary Appendix Fig. 2).

For models incorporating spatial dependencies, the study utilized the spatial autocorrelation measure Moran's I to test for clustering in the residuals of the regression models. The local Moran's I was computed to identify regions with significant clusters of high or low suicide rates, which were mapped and visually examined for spatial patterns. A Bayesian hierarchical model was also fit using the Integrated Nested Laplace Approximation (INLA) method. Let y_i represent the observed suicide counts in area i, where $i = 1, \ldots, n$, with n being the number of spatial regions. The observed suicide counts y_i are modeled as follows:

$$y_i \sim \text{Poisson}(\lambda_i) \tag{1}$$

where λ_i represents the expected suicide count in area i. The log of the expected count λ_i is modeled as follows:

$$\log(\lambda_i) = \mathbf{x}_i^\top \boldsymbol{\beta} + u_i + v_i, \qquad (2)$$

$\mathbf{x}_i^\top$ is a transposed ($\top$) vector of covariates for area i.

$\boldsymbol{\beta}$ is a vector of regression coefficients (fixed effects).

u_i is the spatially structured random effect with an intrinsic conditional autoregressive (ICAR) prior.

v_i is the spatially unstructured random effect with a Gaussian prior.

The spatially structured random effect u_i is specified using an ICAR prior: $u_i \Big| u_{-i} \sim \text{Normal}\left(\frac{1}{N_i}\sum_{j\in\delta_i} u_j, \frac{\sigma_u^2}{N_i}\right)$; δ_i is the set of neighbors for region i; N_i is the number of neighbors for region i; σ_u^2 is the variance parameter for the ICAR random effect. The precision for the fixed effects was assigned a Gaussian distribution with mean zero and precision 0.001, i.e., $\boldsymbol{\beta} \sim \text{Normal}(0, 0.001)$. The precision of the random effects v_i and the spatial random effects u_i are assigned Gamma priors: $\sigma_v^2 \sim \text{Gamma}(1, 0.001)$, $\sigma_u^2 \sim \text{Gamma}(1, 0.001)$, corresponding to a weakly informative prior (Barboza-Salerno et al., 2025; Lemoine, 2019; Yankey et al., 2021). Spatial dependence was incorporated by specifying an intrinsic conditional autoregressive (ICAR) structure. The ICAR model was built on the adjacency of areas defined by their spatial contiguity, allowing for spatial smoothing of suicide counts to account for unobserved heterogeneity in neighboring regions. The model included spatial and non-spatial components, with different priors for each. The spatial component utilized a random effect for each area, accounting for the geographic structure of the data.

We developed a series of Bayesian spatial Poisson models, starting with a null model and progressing to a fully adjusted model that included social and environmental covariates (e.g., housing conditions, unemployment, heat anomalies, and temperature) to assess their impact on suicide rates across regions. Model performance was assessed using the Deviance Information Criterion (DIC) and Watanabe-Akaike Information Criterion (WAIC), with lower values indicating better fit. After identifying the best-fitting model, we tested whether the associations between environmental features (e.g., green space, park priority, land cover diversity) and suicide risk varied by neighborhood-level structural vulnerability. Interaction terms with poverty and racial/ethnic composition were added individually to the final model, estimated using INLA with structured and unstructured random effects (BYM specification). Interactions were considered statistically meaningful if their 95 % credible intervals excluded zero.

Bayesian model results were summarized by reporting both fixed and random effects. To aid interpretation, estimated fixed effects were exponentiated to produce posterior relative risks and scaled per 100,000 population. The proportion of variance explained by the spatial component was calculated as the ratio of the spatial variance to the unstructured variance (Lawson & Lee, 2017; Moraga et al., 2021). To identify areas of elevated suicide risk, we calculated exceedance probabilities from the final Bayesian hierarchical spatial model. CBGs were classified as high-risk if the posterior probability of a relative risk (RR) greater than 1 exceeded 0.8. Exceedance probabilities—representing the probability that a region's modeled risk exceeds a specified threshold—were computed using fitted values to identify areas of elevated suicide risk. Thresholds were set at 1.0, 1.25, and 1.5 to capture regions with increasingly higher relative risk. We computed Local Moran's I to identify areas with similar values that cluster spatially (e.g., high-high or low-low clusters). Unlike exceedance probabilities, which quantify model-derived risk, Local Moran's I captures purely spatial patterns in the distribution of suicide events. These two approaches provide complementary perspectives—exceedance probabilities reflect statistically significant modeled risk, while Local Moran's I detects empirically clustered patterns, making it possible to differentiate between structurally elevated risk and spatial contagion or diffusion effects. Both methods were used in tandem to compare model-based high-risk areas with clusters of spatial dependence.

To examine whether spatial clusters of elevated suicide risk were associated with distinct socio-environmental profiles, we used Local Moran's I to classify census block groups (CBGs) into three mutually exclusive categories based on spatial autocorrelation patterns: (1) High-High clusters, defined as areas with high suicide rates surrounded by similarly high-risk areas; (2) Low-Low clusters, defined as areas with low suicide rates surrounded by similarly low-risk areas; and (3) No Spatial Autocorrelation, referring to areas that did not exhibit statistically significant clustering. We then compared the distribution of scaled predictor variables across these groups using Kruskal–Wallis rank-sum tests, reporting group means and standard deviations to assess whether cluster types differed in their socio-environmental characteristics.

3. Results

3.1. Descriptive results

During the study period, a total of 903 suicides were reported across Cook County between 2023-24. Table 1 compares demographic and incident characteristics for individuals who died by suicide in 2023 (N = 508) and 2024 (N = 395). Sex distribution was similar across both years, with males comprising the majority (77 % in 2023 and 79 % in 2024) of all deaths. Most individuals who died by suicide were non-Latine White (59 % in 2023 and 61 % in 2024), followed by non-Latine Black (20 % in 2023 and 17 % in 2024) and Latine (15 % in 2023 and 16 % in 2024) individuals. The mean age at death was 46 years in both 2023 and 2024. Gunshot or firearm-related causes were the most common manner of death, accounting for 38 % in 2023 and increasing to 44 % in 2024. Hanging or asphyxia was the second most prevalent cause, representing 32 % in 2023 and 29 % in 2024. Other notable causes included drug/toxicity (12 % in 2023 and 11 % in 2024) and jump/falls (7.5 % in 2023 and 6.8 % in 2024). Sharp object incidents increased slightly from 3.3 % in 2023 to 5.3 % in 2024, while other causes remained relatively rare. Four in every five (80 %) deaths took place in the city where the decedent lived.

Table 1

Descriptive statistics of individuals who died by suicide.

Characteristic	2023, N = 508	2024, N = 395	p-value[b]
Sex at birth[b]			0.4
Female	115 (23 %)	81 (21 %)	
Male	393 (77 %)	314 (79 %)	
Race/Ethnicity[c]			0.3
Am. Indian	***	***	
Asian	22 (4.3 %)	21 (5.3 %)	
Black	102 (20 %)	69 (17 %)	
Latine	78 (15 %)	64 (16 %)	
Other	***		
Unknown	***		
White	300 (59 %)	240 (61 %)	
Age[a]	46 (19)	46 (18)	0.6
Primary Cause[c]			
Blunt Force Injury	26 (5.1 %)	11 (2.8 %)	
Drowning	***	***	
Drugs/Toxicity	60 (12 %)	45 (11 %)	
Electrocution	***		
Gunshot/Firearm	192 (38 %)	172 (44 %)	
Hanging/Asphyxia	162 (32 %)	113 (29 %)	
Immolation	***		
Jump/Falls	38 (7.5 %)	27 (6.8 %)	
Other	***	***	
Sharp Object	17 (3.3 %)	21 (5.3 %)	
Location of Death is the same as Residence	412 (81 %)	317 (80 %)	0.7

[a] n (%); Mean (SD).

[b] Pearson's Chi-squared test was used for categorical variables.

[c] Fisher's exact test was used for variables with fewer than 10 cases, and the Wilcoxon rank sum test was applied for continuous variables. Cells with fewer than 10 cases are suppressed for statistical accuracy. The *p*-values correspond to differences across years (2023 vs. 2024), not across variables.

Table 2
Descriptive Statistics of Socioenvironmental Correlates of Suicide used in this study.

Variable	N	N = 4,001[a]
NCLD Land Cover - Open Space	3791	0.00 (0.00, 0.05)
NCLD Water	4001	
Missing		210 (5.2 %)
False		3342 (84 %)
True		449 (11 %)
Developed, Open Space	4001	
Missing		210 (5.2 %)
False		1903 (48 %)
True		1888 (47 %)
Transportation Access	4001	
False		798 (20 %)
True		
Park Access (15-min walk)	3915	
False		
True		697 (18 %)
Land Cover Diversity	4001	0.01 (0.00, 0.18)
Park Acreage within a 30-min drive time	4001	191 (82, 430)
Tree Equity Score	3999	89 (82, 95)
NCLD Tree Canopy Cover (%)	4001	13 (11, 17)
Park Priority Index	3915	2.75 (2.08, 3.42)
Unemployment Rate	3999	0.05 (0.02, 0.11)
Urban Heat Index (UHI)	3915	0.40 (−0.90, 1.67)
Heat Anomaly	3999	0.41 (0.33, 0.50)
Pop/Acre	3915	18 (10, 34)
Urban Heat Index (UHI)	3999	6.8 (3.5, 9.6)
Non-White (%)	3999	0.60 (0.30, 0.93)
Poverty (%)	3999	0.27 (0.13, 0.44)
Linguistic Isolation	3999	0.04 (0.01, 0.09)
Health Burden	3999	0.31 (0.24, 0.40)
Job Access within a 30-min drive time	4001	143,277 (35,104, 864,804)
Travel time to the third nearest grocery store	4001	19 (12, 29)
Travel time to the third nearest hospital	4001	47 (34, 69)
Travel time to the third nearest Pharmacy	4001	22 (16, 31)
Travel time to the third nearest Urgent Care	4001	50 (38, 74)
Median Home Value	3991	276,900 (201,200, 394,400)

[a] Median (IQR); n (%).

Table 2 provides insights into the environmental, built, social, and health characteristics across CBGs. Regarding land cover, water was present in 84 % of CBGs, 48 % of CBGs had open space, and 5.2 % of CBGs were classified as undeveloped. Land cover diversity showed a median of 1 % (IQR: 0.00 %–18 %), while tree canopy cover had a median of 13 % (IQR: 11 %–17 %). Land use characteristics revealed that 20 % of CBGs had a highway present, while 18 % of the population resided more than a 10-min walk from a park. Park acreage accessible within a 30-min drive had a median of 191 acres (IQR: 82–430). Built environment measures included a median Tree Equity Score of 89 (IQR: 82–95) and a Park Priority Index of 2.75 (IQR: 2.08–3.42). Travel times to essential services varied, with medians of 19 min (IQR: 12–29) to the third closest grocery store, 47 min (IQR: 34–69) to a hospital, 22 min (IQR: 16–31) to a pharmacy, and 50 min (IQR: 38–74) to urgent care. Population density had a median of 18 people per acre (IQR: 10–34). Health burden indicators included a median heat index anomaly of 0.40 (IQR: −0.90–1.67), a median of 13.9 % reporting poor mental health (IQR: 12.3 %–16.0 %), and 27 % with low physical activity (IQR: 21 %–34 %). The median temperature was 6.8 °C (IQR: 3.5°C–9.6 °C). Social characteristics showed a median of 60 % non-White residents (IQR: 30 %–93 %), 27 % of residents living in poverty (IQR: 13 %–44 %), and 4 % experiencing linguistic isolation (IQR: 1 %–9 %). The unemployment rate had a median of 5 % (IQR: 2 %–11 %). Supplementary Fig. 2 shows the correlation between the variables.

3.2. Bayesian spatial model results

3.2.1 Model fit. Table 3 shows the model fit parameters: Deviance Information Criterion (DIC), the number of parameters (nP), the

Table 3
Model fit parameters.

	DIC	nP	WAIC	Marginal log-Likelihood
Model 0: Unstructured Heterogeneity (null model)	4002.75	1.02	4003.09	−2002.96
Model 1: Convolution (null model)	3981.88	63.84	3988.17	−554.40
Model 2: Convolution + social factors	3979.17	18.62	3980.67	−577.44
Model 3: Convolution + social factors + health factors	3977.99	23.94	3980.75	−593.72
Model 4: Convolution + social factors + health factors + built environment	3963.58	26.15	3966.54	−633.76
Model 5: Convolution + social factors + health factors + built environment + land cover	**3956.93**	**30.09**	**3960.34**	**−650.98**
Model 6: Convolution + social factors + land cover + land use	3958.98	32.88	3963.74	−667.66

Note. Model 5 is the most suitable model and has been chosen for additional analysis.

Watanabe-Akaike Information Criterion (WAIC), and the marginal log-likelihood values for each model. Lower values of DIC and WAIC indicate better model fit, while marginal log-likelihood reflects the model's explanatory power, with more negative values suggesting better performance. The unstructured heterogeneity (null model) had the poorest fit (DIC = 4002.75, WAIC = 4003.09), serving as the baseline. Adding a convolution structure to model the spatial structure significantly improved the model (DIC = 3981.88, WAIC = 3988.17). Incrementally adding social factors, health factors, and built environment further reduced the DIC and WAIC, with the "Convolution + social factors + health factors + built environment + land cover" model achieving the lowest DIC (3956.93) and WAIC (3960.34). This suggests that including these variables accounts for a significant portion of the variability in the data. However, adding the built environment variables to this model slightly increased (DIC = 3958.98, WAIC = 3963.74), suggesting that the additional complexity did not improve model performance. Thus, the optimal model is Model 5, the "Convolution + social factors + health factors + built environment + land cover" model, as it achieves the best balance of fit and complexity, with the lowest DIC and WAIC and substantial explanatory power reflected by its marginal log-likelihood (−650.98). Therefore, Model 5 was chosen for additional analysis below. An analysis of VIF scores indicated that while specific measures (such as land cover diversity burden and Open Space) exhibited strong pairwise correlations, their VIF scores, which assess multivariate multicollinearity, ranged from low to moderate. (≤ 5; see Table 4). In any event, VIF rules of thumb should be interpreted in context. In our Bayesian model, credible intervals remained sufficiently narrow and estimates remained stable, suggesting that multicollinearity did not bias the results or obscure significant effects (O'brien, 2007). Therefore, all variables in the final model represent related but distinct dimensions.

3.2.2 Bayesian model. Table 4 presents results from Model 5, which was identified as the best-fitting model based on the fit statistics shown in Table 3. Table 4 shows that the Bayesian hierarchical regression models identified several significant predictors of suicide risk, including both protective and risk factors. A predictor is considered meaningful if its credible interval (crI) does not include 1, indicating a strong association with suicide risk. The unadjusted null model estimated an average suicide rate of 7.75 deaths per 100,000 persons per year (95 % CrI: 7.22–8.33). In the fully adjusted model (Model 5), protective factors included Developed Open Space (Posterior Rate Ratio [PRR]: 0.849, CrI: 0.721–0.999) and Blue Space (PRR: 0.528, CrI: 0.371–0.753), both of which were associated with a lower suicide risk. Tree Priority indices were also associated with reduced risk (PRR: 0.588, CrI: 0.453–0.763.

Table 4
Results of Bayesian hierarchical regression models (Model 5 in Table 3) for suicides.

	Posterior Mean (β)	Posterior Rate Ratio exp (β) (crI)	% Change in Odds	VIF
Intercept				
Developed, Open Space	−0.163	0.849 (0.721, 0.999)	−15.040	2.62
Land Cover Diversity	0.278	1.320 (1.089, 1.599)	32.048	5.00
Blue Space	−0.637	0.528 (0.371, 0.753)	−47.112	1.92
Tree Equity Score[a]	−0.076	0.926 (0.825, 1.040)	−7.318	1.55
Park Priority Index[a]	−0.100	0.904 (0.804, 1.017)	−9.516	1.53
Tree Priority Index	−0.531	0.588 (0.453, 0.763)	−41.198	3.98
Median Home Value	−0.171	0.842 (0.729, 0.974)	−15.717	1.80
Health Burden	0.300	1.349 (1.096, 1.663)	34.985	4.27
σ_S	0.0214			
σ_ε	0.0217			
γ	0.4971			

Notes. The analysis controls for the following variables measured at the census tract level: % of persons who live outside of a 10-min walk from a park, the presence of a highway, the number of park acres accessible from a 30 min drive, population per acre, number of jobs accessible from a 60 min drive, number of pharmacies accessible from a 60 min drive, number of urgent care facilities accessible from a 60 min drive, unemployment rate, linguistic isolation, % owner occupied housing, temperature anomalies.
σ_S = spatial effects; σ_ε = residual or unexplained variance due to unmeasured spatial factors; γ = spatial random effect; VIF = Variance Inflation Factor.
Notes. CrI = credible interval. Variables with 95 % CrIs that exclude 1 are considered statistically significant at traditional levels ($p < 0.05$).
σ_S = spatial variability; σ_ε = residual variability; γ = the proportion of variation in suicides attributed to spatial clustering. % change in odds calculated as (Exp (β) - 1) × 100.
[a] Variables with 90 % CrIs excluding 1 are denoted as marginally significant.

The Tree Equity Score (PRR: 0.926, CrI: 0.825–1.040) and Park Priority (PRR: 0.904, CrI: 0.804–1.017) see Table 4). exhibited negative trends that were marginally significant. While not reaching conventional levels of significance, these associations are important given the directionality and theoretical backing. Median Home Value had a protective effect, with a 15.7 % reduction in suicide odds (PRR: 0.842, CrI: 0.729–0.974). Conversely, certain factors were associated with increased suicide risk. Land Cover Diversity was positively associated with increased suicide odds, with a 32.05 % increase in suicide risk for each unit increase in the land cover mix (PRR: 1.32, 95 % CrI: 1.089–1.599). Additionally, the level of health burden within the census block group (CBG) was linked to a 34.98 % increase in odds (PRR: 1.349, crI: 1.096, 1.663).

After selecting the final model, we evaluated twenty-five interaction terms to test whether environmental factors influenced suicide risk differently by poverty levels or racial/ethnic composition. Results indicated that poverty moderated the effect of park priority on suicide risk (β = −0.122; 95 % CrI: [−0.205, −0.038]; DIC = 3950.25), and that land cover diversity moderated the associations between both developed open space (β = 0.131; 95 % CrI: [0.054, 0.208]; DIC = 3947.89) and park priority (β = −0.104; 95 % CrI: [−0.167, −0.041]; DIC = 3944.11) on suicide risk.

The spatial random effects exhibited strong spatial autocorrelation, with a high precision estimate (2180.62), indicating significant clustering of suicide risk across census block groups (CBGs). In the baseline model without covariates, approximately **49.71 %** of the total variance in suicide risk was attributable to the spatially structured random effects ($\gamma = 0.4971$), confirming that suicide risk is spatially patterned. However, in the fully adjusted model that included environmental and demographic predictors, the spatial variance component dropped substantially ($\sigma_S^2 = 0.0214$), indicating that absolute differences in suicide risk across CBGs became much smaller after accounting for neighborhood-level exposures. This suggests that environmental and sociodemographic factors largely explain the observed spatial clustering in suicide risk. At the same time, the low residual error variance ($\sigma_\varepsilon = 0.0217$) indicates that most of the variation in suicide risk is captured by the model; hence, the model effectively accounts for spatial heterogeneity. Fig. 2 shows the posterior distribution of the most significant fixed effects. We calculated exceedance probabilities associated with relative risks (RR) greater than 1, 1.25, and 1.5 (Fig. 3), identifying N = 58, 38, and 26 high-risk areas, respectively.

Results showed that 38.1 % of suicides occurred in high-risk CBGs (95 % CrI: 11.4 %–61.9 %) defined as a CBG where the posterior probability of RR exceeding the county average was ≥0.8. In contrast, only 3.1 % of suicides occurred in low-risk CBGs, where the posterior probability of RR being below the county average was also ≥0.8 (95 % CrI: 0.3 %–25.4 %). This indicates that suicides were over twelve times more likely to occur in high-risk areas than in low-risk ones, demonstrating a clear spatial concentration of suicide mortality.

To determine whether suicides were spatially clustered and to examine the conditions surrounding those deaths, we conducted a Local Moran's I analysis. Each suicide death was linked to the census block group (CBG) where it occurred, and that CBG was classified using Local Moran's I as either a high-high cluster (high suicide count surrounded by high-count areas), a low-low cluster (low count surrounded by low-count areas), or an area with no significant spatial pattern. This enabled us to associate each victim with the socio-environmental characteristics of their neighborhood and analyze how these contextual factors varied across different types of spatial clusters.

Moran's I confirmed the presence of statistically significant spatial autocorrelation in suicide risk across the county, indicating spatial clustering of similarly high values. Fig. 4A highlights this heterogeneity by showing the spatial distribution of three different suicide cluster types represented by a different color [red: High-High (N = 59), blue: Low-Low (N = 202), and gray: Non-clustered areas (N = 3740)]. The clusters are statistically significant ($p < 0.05$), and the non-clustered areas are not statistically significant (Fig. 4B). The high-high clusters represent high-risk areas where suicide risk is concentrated. The low-low areas are regions of low risk. As shown by Fig. 4, the primary spatial pattern observed was that high-high suicide clusters were often located adjacent to or near low-low clusters, indicating stark local contrasts in suicide risk in areas deemed a high risk cluster. We focus on the four most significant high-risk clusters below.

Cluster 1 centers around Downtown Chicago, or 'the Loop,' and is characterized by highly developed urban areas, green spaces, and diverse land cover types, including commercial, residential, and recreational spaces. This area, while socially vulnerable, has high transportation and job access. Cluster 2 encompasses the O'Hare Airport area, which includes industrial, commercial, and residential uses, as well as significant transportation infrastructure and open spaces such as parks and vacant land. Cluster 3 encompasses the Chicago Ridge and Oak Lawn areas, characterized by suburban residential neighborhoods, commercial centers, and green spaces. The eastern part of this cluster includes the Sag Valley, which is rich in natural features, including forests, wetlands, and water bodies, in contrast to the suburban developments nearby. Cluster 4 surrounds Orland Park, a suburban area featuring a mix of residential, commercial, and recreational spaces and notable green spaces, parks, and wetlands. Supplementary Figs. 3–6 provide detailed maps of these clusters.

3.2.3. Characteristics of individuals who died by suicide by socio-environmental characteristics. The findings from the Local Moran's I spatial clusters—High-High, Low-Low, and Other—highlight distinct socio-environmental and individual-level patterns associated with suicide risk (Table 5). In the High-High clusters, where significant spatial clustering of elevated suicide rates was detected, suicides occurred predominantly among Non-Latine White individuals (72 %) and males

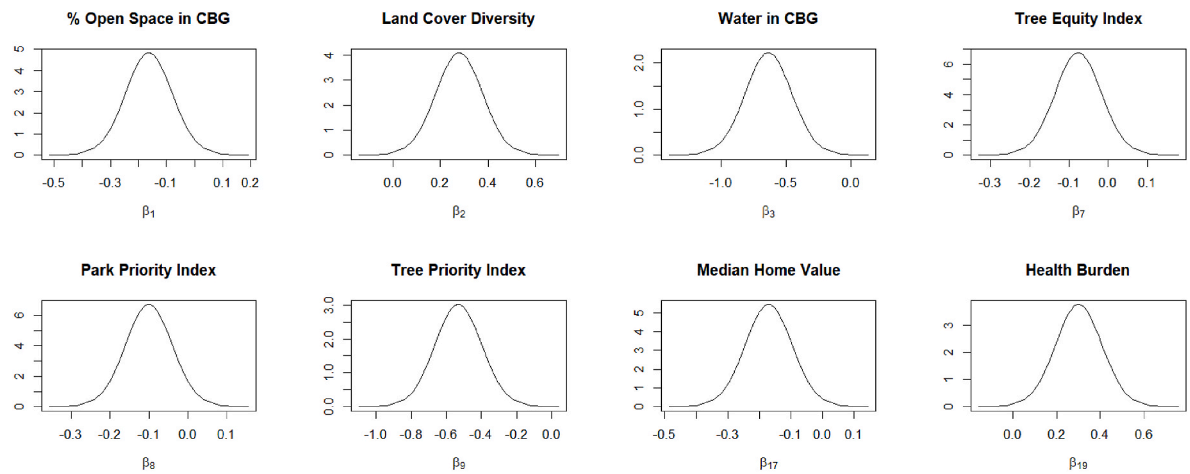

Fig. 2. Posterior distributions of fixed effects.

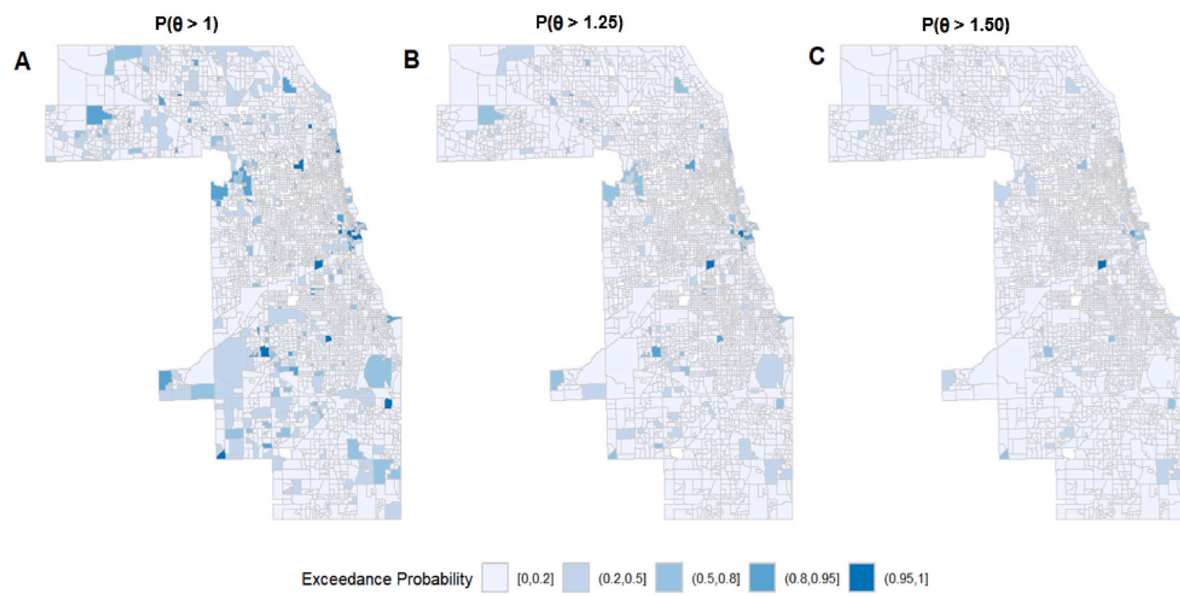

Fig. 3. Exceedance probabilities associated with A) theta = 1, B) theta = 1.25, and C) theta = 1.50 greater risk of suicide relative to the whole county with the highest probability shaded dark blue.

(67 %). This cluster had the lowest representation of Non-Latine Black (9.3 %) and Latine (5.3 %) individuals compared to the Other group, where 20 % were Non-Latine Black and 17 % Latine ($p = 0.002$). Individuals in these clusters were also more likely to die by jumping or falling (23 %), a method significantly more common here than in the Other areas (5.9 %, $p < 0.001$). Additionally, drug/toxicity-related suicides were more prevalent (21 %) in High-High clusters, compared to 11 % in the Other group.

Neighborhoods within the High-High clusters (N = 75) exhibited more favorable built and natural environmental characteristics, including greater park acreage (median = 443 acres) and higher park priority index scores (median = 3.17), both statistically significant when compared to Other areas ($p < 0.001$ and $p = 0.004$, respectively). These areas also had lower unemployment rates and heat anomalies ($p < 0.001$), and greater job accessibility, with a median of over 839,000 jobs accessible within 60 min, far surpassing access levels in Other and Low-Low clusters ($p < 0.001$). Land cover diversity, which reflects the degree of heterogeneity in surface types such as vegetation, impervious surfaces, and water, varied slightly across suicide clusters but was not a statistically significant differentiator ($p = 0.8$). Individuals who died by suicide in High-High clusters lived in areas with the broadest range of land cover diversity (median = 0.03, IQR: 0.00–0.34), while those in Low-Low and Other areas had more constrained distributions (Low-Low: median = 0.03, IQR: 0.01–0.11; Other: median = 0.01, IQR: 0.00–0.21). These findings suggest that individuals in High-High areas were more likely to live in neighborhoods characterized by a mix of land uses or fragmented surface types. The inset map in Fig. 4, labeled 1–4, shows land use patterns within the cluster, with red indicating highly developed areas, green indicating open, developed spaces, and blue indicating bodies of water.

In contrast, the Low-Low clusters (N = 7) represent areas with significantly low suicide rates and spatial clustering. The few suicides in Low-Low clusters were also predominantly among Non-Latine White males, with hanging/asphyxia (57 %) and firearm use (43 %) as the most common causes. These areas had significantly lower park acreage (median = 23 acres) and park priority index (1.83) than High-High clusters. Despite lower health burdens and more favorable housing metrics, including higher homeownership (median = 77 %) and median house values (median = \$259,400)—individuals in Low-Low areas experienced higher temperatures, higher poverty rates (median = 27 %), and greater tree planting need (tree priority index = 0.45), suggesting they may still face environmental disadvantages ($p < 0.001$).

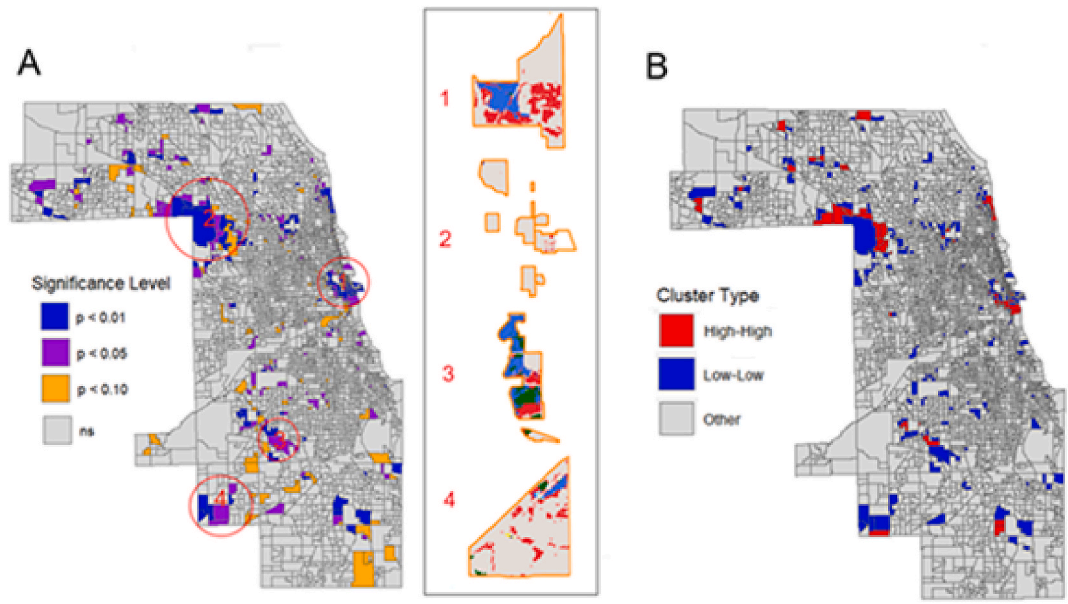

Fig. 4. Spatial clustering of suicide risk across Chicago.

The Other areas, which accounted for the majority of suicide deaths (N = 752), exhibited more racially diverse profiles, with higher proportions of Non-Latine Black (20 %) and Latine (17 %) decedents. Firearms were the most common cause of death in these areas (42 %), followed by hanging/asphyxia (31 %). Neighborhood conditions in the Other group were more heterogeneous. These areas had higher unemployment (6 %), greater heat exposure, and higher health burdens ($p < 0.001$). Additionally, the non-clustered areas had lower park acreage, fewer jobs accessible, and more limited access to services such as healthcare and groceries.

4. Discussion

This study identified several environmental, demographic, and socioeconomic characteristics associated with both the relative risk of suicide in neighborhoods compared to Cook County and high-risk suicide clusters, defined as areas with high suicide counts surrounded by similarly high-risk areas. Our findings mostly align with previous studies on suicide risk, particularly regarding the protective role of blue (Banyard et al., 2025; Smith et al., 2021; White et al., 2020) and green spaces (Bolanis et al., 2024; Lee et al., 2024) and the exacerbating impact of economic strain and health burden (Marlow et al., 2021; Milner et al., 2013; Nafilyan et al., 2022). However, this study adds to the existing literature in multiple ways. First, whereas our analysis revealed that green and blue spaces were protective factors associated with reducing suicide *risk*, after controlling for green and blue space, as well as other confounding factors, the odds of suicide were found to increase along with land cover diversity: each one unit increase in land cover diversity resulted in a 32.05 % increase in suicide risk. Second, we found that socio-environmental factors, such as health burdens and housing wealth, play significant roles in influencing suicide risk, further highlighting the importance of considering the overall health and economic burden of neighborhoods as factors in suicide prevention. Third, our results show substantial spatial dependencies, indicating that spatial factors across the county influence the geographic clustering of suicide risk. Specifically, nearly 38 % of suicides occurred in high-risk CBG, and almost 1 in 10 victims of suicide died in a high-risk cluster defined as an area of high risk surrounded by other high-risk areas. Based on these findings, we were able to distinguish between regions with elevated suicide risk due to structural vulnerabilities and areas identified as spatial clusters of suicide events, which may point to behavioral contagion or localized dynamics. We will now discuss these findings in detail.

Our model-based estimate of the crude suicide rate, averaged across all geographic units, was 7.75 deaths per 100,000 population, which is consistent with published reports (Cook County Department of Public Health, 2020). While most individuals who died by suicide were non-Latine White, non-Latine Black individuals accounted for one in five cases, based on medical examiner data. Further, following past research identifying sex differences in suicide rates (Carretta et al., 2023), males accounted for the majority of suicide fatalities in both 2023 (77 %) and 2024 (80 %), highlighting the stability of this trend. The most frequent causes of death include hanging/asphyxia, gunshot wounds, and jumps/falls, typically taking place in residential or public areas, such as open spaces. Most individuals died within the same ZIP code where they lived, suggesting that local environmental conditions shape suicide risk for those who are most vulnerable.

Consistent with prior research, we found that green and blue spaces are protective against suicide risk at the county level, while social and health-related vulnerabilities increase risk(Feng et al., 2025; S. Liu, Rahman, & Karner, 2023). These results align with previous studies demonstrating that open spaces, such as parks, lawns, and minimally developed areas with less than 20 % impervious surfaces, provide important mental health benefits, particularly in urban and suburban settings (Bolanis et al., 2024; Lee et al., 2023; Steelesmith et al., 2019; White et al., 2020). Although green and blue spaces were generally associated with reduced suicide risk, land cover diversity emerged as a risk factor after adjusting for these variables. The unexpected positive link between land cover diversity and suicide risk requires an interpretation that accounts for both the measure's definition and Chicago's highly developed urban landscape, where land cover diversity might indicate fragmentation instead of ecological health richness. Operationalized using Simpson's Diversity Index and derived from the NLCD, land cover diversity measures the heterogeneity and evenness of land cover types, such as developed surfaces, vegetation, and water, within a given area. Importantly, this metric reflects the configuration and mix of land cover, rather than the absolute presence or quality of green space alone (Comer & Greene, 2015b). Because the effects of green and blue space were already partialed out of the model, the observed association with land cover diversity likely captures complex and potentially disruptive land use patterns, such as abrupt transitions between residential, commercial, and industrial zones. In a densely built city like

Table 5
Characteristics of individuals who died by suicide, stratified by local Moran's I cluster classification.

Characteristic	High-High, N = 75[a]	Low-Low, N = 7[a]	Non-clustered areas, N = 752[a]	p-value[b]
Sex at Birth				0.023
Female	25 (33 %)	2 (29 %)	153 (20 %)	
Male	50 (67 %)	5 (71 %)	599 (80 %)	
Race/Ethnicity				0.002
Non-Latine Am. Indian	0 (0 %)	0 (0 %)	1 (0.1 %)	
Non-Latine Asian	10 (13 %)	0 (0 %)	31 (4.1 %)	
Non-Latine Black	7 (9.3 %)	0 (0 %)	151 (20 %)	
Latine	4 (5.3 %)	1 (14 %)	128 (17 %)	
Other	0 (0 %)	0 (0 %)	4 (0.5 %)	
Unknown	0 (0 %)	0 (0 %)	1 (0.1 %)	
Non-Latine White	54 (72 %)	6 (86 %)	436 (58 %)	
Age	39 (29, 54)	45 (27, 53)	46 (31, 60)	0.2
Cause of Death				<0.001
Blunt Force Injury	1 (1.3 %)	0 (0 %)	32 (4.3 %)	
Drowning	1 (1.3 %)	0 (0 %)	7 (0.9 %)	
Drugs/Toxicity	16 (21 %)	0 (0 %)	80 (11 %)	
Electrocution	0 (0 %)	0 (0 %)	1 (0.1 %)	
Gunshot/Firearm	17 (23 %)	3 (43 %)	315 (42 %)	
Hanging/ Asphyxia	21 (28 %)	4 (57 %)	236 (31 %)	
Immolation	0 (0 %)	0 (0 %)	2 (0.3 %)	
Jump/Falls	17 (23 %)	0 (0 %)	44 (5.9 %)	
Other	0 (0 %)	0 (0 %)	1 (0.1 %)	
Sharp Object	2 (2.7 %)	0 (0 %)	34 (4.5 %)	
Developed, Open Space	0.00 (0.00, 0.05)	0.01 (0.01, 0.04)	0.00 (0.00, 0.07)	0.7
Land Cover Diversity	0.03 (0.00, 0.34)	0.03 (0.01, 0.11)	0.01 (0.00, 0.21)	0.8
Park Acreage within a 30-min drive time	443 (187, 1086)	23 (14, 437)	224 (87, 516)	<0.001
Tree Equity Score	90 (82, 94)	78 (77, 85)	88 (82, 95)	0.2
NCLD Tree Canopy Cover (%)	14 (9, 18)	12 (11, 14)	14 (11, 19)	0.3
Park Priority Index	3.17 (2.42, 3.50)	1.83 (1.79, 2.38)	2.75 (2.17, 3.33)	0.004
Unemployment Rate	0.04 (0.00, 0.06)	0.03 (0.03, 0.29)	0.06 (0.02, 0.10)	<0.001
Heat Anomaly	−1.7 (−5.1, 0.2)	0.7 (−0.3, 1.1)	0.4 (−0.9, 1.6)	<0.001
Tree Priority Index	0.31 (0.28, 0.36)	0.45 (0.38, 0.47)	0.39 (0.33, 0.47)	<0.001
Pop/Acre	47 (11, 82)	10 (7, 16)	17 (9, 32)	<0.001
Urban Heat Index (UHI)	3.9 (1.3, 7.1)	11.1 (4.9, 11.9)	6.5 (2.4, 9.3)	<0.001
Non-White (%)	0.32 (0.20, 0.44)	0.45 (0.21, 0.48)	0.52 (0.27, 0.85)	<0.001
Poverty (%)	0.15 (0.09, 0.23)	0.27 (0.26, 0.34)	0.25 (0.14, 0.41)	<0.001
Linguistic Isolation	0.04 (0.02, 0.08)	0.14 (0.03, 0.16)	0.04 (0.01, 0.10)	0.2
Health Burden	0.21 (0.15, 0.32)	0.31 (0.28, 0.32)	0.30 (0.23, 0.39)	<0.001
Job Access within a 30-min drive time	4001	71,980 (59,477, 111,165)	104,854 (24,271, 832,080)	<0.001
Travel time to the third nearest grocery store	14 (8, 34)	9 (5, 35)	19 (12, 32)	0.026
Travel time to the third nearest hospital	31 (21, 78)	61 (58, 67)	50 (35, 77)	<0.001
Travel time to the third nearest Pharmacy	15 (7, 28)	21 (20, 24)	23 (17, 35)	<0.001
Travel time to the third nearest Urgent Care	44 (19, 73)	60 (57, 65)	53 (39, 81)	<0.001
Owner Occupied Housing (%)	0.56 (0.29, 0.77)	0.77 (0.66, 0.91)	0.62 (0.41, 0.83)	0.032
Median Home Value	379,800 (273,300, 610,450)	259,400 (247,550, 294,250)	275,950 (208,250, 389,275)	<0.001

Notes.
[a] n (%); Median (IQR).
[b] Fisher's exact test; Fisher's Exact Test for Count Data with simulated p-value (based on 2000 replicates); Kruskal-Wallis rank sum test.

Chicago, higher land cover diversity may signal urban fragmentation, which can undermine community cohesion, elevate environmental stressors (e.g., traffic, noise, pollution), and contribute to psychological distress and social fragmentation (Bolanis et al., 2024; Lee et al., 2023; Steelesmith et al., 2019; White et al., 2020). This interpretation is supported by prior studies, which demonstrate that not all green spaces equally enhance mental well-being. For example, Tsai et al. (2018) found that dispersed green areas and forest edge contrast were associated with reduced mental distress, while other green space configurations had no effect or were linked to greater distress. Similarly, land cover diversity has been used as a proxy for environmental biodiversity. However, in urban contexts, it may instead reflect land use discontinuity and social fragmentation, especially in areas with low vegetation cover and dense development (Chipman, Shi, Gilbert-Diamond, et al., 2024).

Several significant interactions that emerged from the full model further nuanced the main effects. Specifically, we found that the association between park priority and suicide risk was moderated by poverty, such that the impact of poverty on suicide was larger in areas with greater need for park infrastructure. This finding supports environmental justice theories, suggesting that the absence of accessible green space may exacerbate the mental health consequences of economic deprivation, and park investment in high-poverty neighborhoods may have a protective effect. This result contrasts with prior studies showing that the mental health benefits of green space, including tree canopy cover, are sometimes weaker in more disadvantaged areas, possibly due to barriers such as poor quality, lack of safety, or limited usability of green infrastructure (Lee et al., 2023). Instead, our findings align with a growing body of work arguing that access to green space can be most impactful for those facing structural disadvantage when it is meaningful, equitable, and integrated into the community context. We also observed that the association between land cover diversity and suicide risk was stronger in areas with more developed, open spaces. This suggests that fragmented or mixed landscapes may become more detrimental when restorative green features are insufficient. In contrast, land cover diversity appeared to serve a compensatory protective function in areas with high park priority, suggesting that in the absence of formal parks, heterogeneous landscapes with informal or residual green elements may still offer some mental health benefits. These findings highlight that environmental features do not operate uniformly across different social and spatial contexts; rather, their impacts on mental health are shaped by broader structural inequalities, the quality and usability of green spaces, and the landscape configuration in which they are embedded.

We found substantial geographical variation in residual suicide risk. The spatial effect suggested that suicide rates are clustered, with neighboring areas exhibiting similar rates due to shared regional characteristics or environmental factors. The residual variance highlights unexplained variations in suicide risk that the model's predictors do not fully account for, suggesting additional influencing factors. The spatial random effect shows significant spatial dependencies in the model, indicating that spatial factors meaningfully impact overall suicide risk. These findings emphasize the need for region-specific interventions and resource allocation, suggesting that targeting high-risk areas could be more effective than one-size-fits-all approaches.

To shed insight into the possible contextual mechanisms, we used Local Moran's I to identify high-risk cluster areas, allowing us to distinguish between model-estimated structural risk and observed spatial clustering. While exceedance probabilities captured CBGs with significantly elevated modeled suicide risk, Moran's I revealed patterns of spatial dependence. In this regard, it is important to distinguish between factors that increase the overall relative risk of suicide across the county and the areas of localized suicide clusters, which are identified by an examination of spatial autocorrelation in the data. The presence of statistically significant suicide clusters does not necessarily mean that the highest-risk areas are those with the most disadvantaged conditions. Instead, suicide locations are shaped by behavioral mechanisms that influence suicide risk in addition to social and environmental factors. Even in areas with relatively small absolute differences in risk levels, spatial dependence plays a key role in shaping suicide patterns.

The individuals who died by suicide and the neighborhood environments in which they lived—classified by Moran's I-defined clusters—were consistent with the spatial patterns identified in the Bayesian model. About 10 % of those who died by suicide lived in High-High clusters, which are areas marked by statistically significant concentrations of suicides. These clusters were situated in neighborhoods with lower poverty levels, fewer residents of color, greater land cover diversity, more open space, higher tree canopy coverage, and lower health burdens. At first glance, these characteristics may seem contradictory, as they deviate from traditional indicators of structural disadvantage. However, this paradox aligns with previous research on the spatial dependencies of suicide risk, indicating that environmental factors do not exert uniform effects across different contexts; rather, their influence is shaped by social and cultural dynamics at local levels. For instance, individuals in Low-Low clusters, which have consistently low suicide rates, lived in neighborhoods with high housing values and economic stability, although some environmental vulnerabilities were still present. Moreover, most suicides occurred in non-clustered ("Other") areas, characterized by greater racial and economic disadvantage, higher health burdens, and limited access to green infrastructure. These findings closely match the Bayesian model, which identified structural disadvantage and environmental stressors as key drivers of suicide risk.

Together, this suggests that environmental features, like green spaces, may not always serve as protective buffers and can interact with sociodemographic factors in complex ways. Overall, these results underscore the importance of considering ecological features, such as green and blue spaces, in relation to broader socio-environmental and structural contexts. We further analyzed four of the high-risk suicide clusters to examine the broader socioenvironmental context. One cluster was identified as the area encompassing Chicago Ridge and Oak Lawn, where impervious surfaces, vegetated areas, and water features are interspersed, corresponding to the underlying land use mixes of moderate-density housing, commercial corridors, and industrial sites. Similarly, areas surrounding O'Hare Airport, another identified cluster, have a mix of residential, commercial, transportation infrastructure, and open spaces. Finally, the Loop in downtown Chicago, another high-risk cluster, is marked by dense urban development, high impervious surfaces, and proximity to Lake Michigan to the east. The location of these clusters is consistent with prior studies that link fragmented land use, such as the mix of industrial, residential, and commercial zones, to increased suicide risk, particularly in socioeconomically vulnerable neighborhoods in Chicago's East and West Sides, areas characterized by industrial pollution, concentrated poverty, and limited green space (Evans, 2023; Molitor & White, 2024). It is plausible that green spaces provide psychological benefits in some communities, while remaining underutilized or inaccessible in others. If true, green or open spaces do not directly lower suicide risk; their influence is dependent on broader structural and behavioral contexts. Behavioral mechanisms—such as social contagion, place-based stigma, or access to and utilization of behavioral health care—may interact with environmental features to create clustering, even in neighborhoods that appear advantaged.

Further support for this interpretation comes from the significant interaction between poverty and park priority, where the protective effect of green infrastructure was most substantial in high-poverty areas. Similarly, interactions between land cover diversity and environmental features, such as developed open space and park priority, suggest that the mental health impact of landscape features depends on the social and spatial context in which they appear. For example, land cover diversity was associated with increased suicide risk in more built-up environments but showed a protective effect in park-deprived areas. These interactions highlight that spatial risk is not solely driven by structural disadvantage, but by the interplay between urban form, environmental configuration, and demographic vulnerability. Together, these findings reinforce the need to interpret suicide patterns through both structural and spatial lenses, where social fragmentation, spatial disorganization, and unmeasured community-level dynamics may drive localized suicide risk, even in places with apparent material advantage.

4.1. *Environmental justice policy implications*

Our findings suggest that from a policy perspective, intervention strategies should adopt a multiprong approach. First, systemic investments in environmental equity, such as tree planting, park development, and reducing environmental stressors, such as affordable housing, are crucial for mitigating structural risk (Branas et al., 2018; Brown et al., 2015; Yadav et al., 2025; Zou, 2017). Second, localized interventions, including crisis hotline signage, enhanced community mental health outreach, and restricting access to common suicide sites, may effectively address risk in spatially clustered areas where contagion or social transmission could be at play.

These study findings carry significant implications for public health policies aimed at tackling the spatial and socio-environmental disparities associated with suicide risk, particularly in urban settings. For instance, high noise pollution levels and fragmented land use near airports, as evident in land cover patterns characterized by extensive impervious surfaces interspersed with vegetation, can contribute to environmental stress, thereby exacerbating mental health issues. Pairing noise reduction strategies with green buffer zones, such as tree-lined sound barriers or expanded parks, might replicate the positive impact that urban parks had as effective 'green buffer zones' during the COVID-19 pandemic (Gunnell et al., 2020; Xie et al., 2020), helping to alleviate environmental stress while fostering mental well-being (Van Renterghem et al., 2012).

Policies should also integrate targeted crisis intervention programs, like signage and crisis phones, which have proven effective in reducing suicide rates (Cox et al., 2013). An example of such an initiative is 'Operation Disrupt,' a suicide prevention program in the Chicago area launched following the suicide of a United Airlines executive in 2021. This initiative installs green signs with crisis hotline information in forest preserves. Expanding programs like Operation Disrupt to additional vulnerable locations could enhance public health and environmental justice strategies.

Moreover, combining mitigation efforts with urban greening projects, such as developing shaded pedestrian areas or improving park access, can simultaneously address multiple risk factors. Specifically, transforming vacant lots into community parks, gardens, or recreational spaces can encourage social cohesion and enhance mental health outcomes. Research shows that even minor improvements, like cleaning up neglected lots and introducing inviting features, can significantly decrease environmental stress and improve perceptions of safety (Wolch et al., 2014).

Crucially, our findings suggest that housing stability and health burden (measured by both mental *and* physical health) are significant predictors of suicide risk, highlighting the need for structural interventions extending beyond environmental design. Public policies focusing on expanding access to affordable, stable, and high-quality housing could alleviate the chronic stress associated with housing insecurity and economic instability, particularly in marginalized neighborhoods. Addressing health burdens requires targeted investments in behavioral health services, such as mobile mental health units, community clinics, and wellness hubs, in underserved areas. A 2020 report from the Cook County Department of Public Health noted that only 12.4 percent of residents accessed mental health assistance that year (Cook County Department of Public Health, 2020). Integrating housing, health, and environmental strategies into a coordinated policy response can effectively tackle various suicide risk dimensions. For instance, ensuring affordable housing is co-located with parks, clinics, and reliable transit options could synergistically affect mental well-being while promoting environmental and health equity goals.

4.2. *Strengths & limitations*

This study offers several important contributions to the emerging literature on environmental determinants of suicide. Combining high-resolution spatial data with Bayesian hierarchical modeling, we identified complex relationships between neighborhood conditions and suicide risk at the census block group level, revealing how spatial patterns in environmental exposure and structural disadvantage jointly shape vulnerability. The integration of exceedance probabilities and Moran's I clustering allowed us to distinguish between elevated model-based risk and observed spatial clustering of suicides, linking each to the broader socioenvironmental context in which suicides occurred.

Despite these contributions, this study is not without limitations. A key limitation of this study is that it focuses exclusively on suicide mortality, which represents a less prevalent indicator of poor mental health compared to suicide attempts. As such, the findings may not capture the broader spectrum of suicidal behavior or underlying mental health distress in the population. Also, the cross-sectional design limits our ability to make causal inferences about the relationship between environmental exposures and suicide mortality. Longitudinal data would help clarify temporal dynamics and better account for changes in neighborhood conditions or individual life course factors. Second, because our analysis relied on aggregate data at the census block group level, findings may be subject to ecological fallacy, in which group-level associations do not necessarily reflect individual-level processes. This limitation is significant for understanding behavioral mechanisms, such as contagion, mental health trajectories, or access to behavioral healthcare, none of which are captured here.

While including detailed geospatial data is a strength, the accuracy and completeness of spatial predictors, such as tree canopy, impervious surfaces, or park boundaries, depend on the availability and consistency of administrative and satellite data. Temporal misalignment across data sources may also affect the validity of measured exposures. Furthermore, generalizability is limited by the unique demographic and structural characteristics of Cook County, a racially and economically diverse but densely urbanized setting. The extent to which these findings apply to more rural or less spatially fragmented areas remains uncertain.

Notably, sex- and racial/ethnic-specific differences emerged in the environmental characteristics of neighborhoods where individuals died by suicide. Women were more likely than men to live in areas with greater park acreage, lower health burden, lower racial diversity, and higher median home values. These differences may point to sociodemographic mechanisms of suicide risk, including differential exposure to the built environment or variations in mobility, isolation, or vulnerability to contagion effects. However, we lacked data on how individuals experienced or navigated their environments, which limited our ability to interpret these differences. Future work should consider mobility patterns and time spent in green or built spaces, especially given prior findings that transportation inequalities and caregiving roles shape women's environmental exposure.

While our Moran's I analysis cannot confirm interpersonal contagion, it did identify significant clusters of suicides that exceeded what would be expected by chance. These patterns necessitate further research into the interpersonal, temporal, or institutional factors that may drive clustering independently of structural disadvantage, factors that are not currently considered in our models. An analysis of contagion requires both space and time; therefore, integrating more fine-grained temporal data can help uncover the broader social dynamics not captured by structural indicators alone.

Finally, although our model controls for access to green and blue spaces, the land cover diversity index reflects broader patterns of landscape complexity, rather than direct access or quality. As such, it may conflate protective features, such as dispersed tree cover or water bodies, with risk-enhancing ones, including fragmented development or proximity to industrial zones. Given the unique characteristics of Cook County, the index may be capturing areas with irregular land use configurations, including green buffers adjacent to impervious surfaces or neighborhoods transitioning between residential and commercial functions. While this offers a valuable proxy for urban form, it does not isolate specific land use types that may affect mental health differently. Future research should link spatial land cover patterns with explicit land use designations (e.g., residential, industrial, recreational) to better isolate environmental stressors from protective features. Future research should continue to explore the role of land cover diversity in suicide risk and related outcomes, such as stress, life satisfaction, and mental health service use. Studies should compare different diversity measures (e.g., Shannon's Index), use longitudinal designs, and examine rural, suburban, and urban areas to better understand how different spatial configurations of the environment contribute to risk. By clarifying the mechanisms through which fragmented or heterogeneous environments impact mental health, this research can inform targeted prevention strategies that consider both the physical and social structures of neighborhoods.

5. Conclusion

Revitalizing blue- and green spaces, particularly in underserved neighborhoods, represents an important aspect of suicide prevention. However, the impact of green infrastructure alone is insufficient without consideration of the broader sociodemographic and environmental context. Such targeted, evidence-based public health and urban planning interventions can address spatial and socio-environmental disparities to create healthier, more equitable communities.

CRediT authorship contribution statement

Gia E. Barboza-Salerno: Writing – review & editing, Writing – original draft, Visualization, Supervision, Software, Resources, Project administration, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Amy Watson-Grace:** Writing – review & editing, Writing – original draft, Conceptualization. **Karla Shockley-McCarthy:** Writing – review & editing, Writing – original draft, Supervision, Conceptualization. **Taylor Harrington:** Writing – review & editing. **Keith Warren:** Writing – review & editing, Supervision, Conceptualization. **Danielle Steelesmith:** Writing – review & editing, Validation, Conceptualization.

Declaration of competing interest

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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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.ssmph.2025.101820.

Panel (A) shows the statistical significance of spatial autocorrelation in suicide rates across census block groups, as identified by Local Moran's I. Colored areas indicate levels of statistical significance ($p < 0.01$ in dark blue, $p < 0.05$ in purple, $p < 0.10$ in orange), while gray areas are not statistically significant. Red circles highlight clusters of interest discussed in the text. Panel (B) displays cluster types based on the direction and intensity of spatial association: **High-High** clusters (red) represent areas with high suicide rates surrounded by similarly high-rate neighbors, while **Low-Low** clusters (blue) are areas with low suicide rates surrounded by other low-rate areas. Gray areas labeled "Other" indicate census block groups with no significant spatial autocorrelation. The inset map (center) provides a zoomed view of key regions by land use (labeled 1–4) referenced in the manuscript.

Data availability

Links to all data used in the study are noted within the manuscript

References

Adams, M. A., Todd, M., Kurka, J., Conway, T. L., Cain, K. L., Frank, L. D., & Sallis, J. F. (2015). Patterns of walkability, transit, and recreation environment for physical activity. *American Journal of Preventive Medicine, 49*, 878–887.

Alcock, I., White, M., Cherrie, M., Wheeler, B., Taylor, J., McInnes, R., Im Kampe, E. O., Vardoulakis, S., Sarran, C., & Soyiri, I. (2017). Land cover and air pollution are associated with asthma hospitalisations: A cross-sectional study. *Environment International, 109*, 29–41.

Alcock, I., White, M. P., Wheeler, B. W., Fleming, L. E., & Depledge, M. H. (2014). Longitudinal effects on mental health of moving to greener and less green urban areas. *Environmental Science & Technology, 48*, 1247–1255. https://doi.org/10.1021/es403688w

Zumelzu, A., & Herrmann-Lunecke, M. G. (2021). Mental well-being and the influence of place: conceptual approaches for the built environment for planning healthy and walkable cities. *Sustainability, 13*(11), 6395.

American Forests, n.d. Methods & data: Tree equity score.

Asri, A. K., Tsai, H.-J., Wong, P.-Y., Lee, H.-Y., Pan, W.-C., Guo, Y.-L., Wu, C.-S., Su, H.-J., Wu, C.-D., & Spengler, J. D. (2022). Examining the benefits of greenness on reducing suicide mortality rate: A global ecological study. *Frontiers in Public Health, 10*, Article 902480.

Bachmann, S. (2018). Epidemiology of suicide and the psychiatric perspective. *International Journal of Environmental Research and Public Health, 15*, 1425. https://doi.org/10.3390/ijerph15071425

Bahr, S. (2024). The relationship between urban greenery, mixed land use and life satisfaction: An examination using remote sensing data and deep learning. *Landscape and Urban Planning, 251*, Article 105174. https://doi.org/10.1016/j.landurbplan.2024.105174

Banyard, V., Rousseau, D., Shockley McCarthy, K., Stavola, J., Xu, Y., & Hamby, S. (2025). *Community-level characteristics associated with resilience after adversity: A scoping review of research in urban locales* (Vol. 26, pp. 356–372). Trauma Violence Abuse. https://doi.org/10.1177/15248380241309374

Baobeid, A., Koç, M., & Al-Ghamdi, S. G. (2021). Walkability and its relationships with health, sustainability, and livability: Elements of physical environment and evaluation frameworks. *Front. Built Environ., 7*, Article 721218.

Barboza, G. E., Dominguez, S., & Chace, E. (2016). Physical victimization, gender identity and suicide risk among transgender men and women. *Prev. Med. Rep., 4*, 385–390. https://doi.org/10.1016/j.pmedr.2016.08.003

Barboza-Salerno, G., Liebhard, B., Duhaney, S., & Harrington, T. (2025). Redlining, reinvestment, and racial segregation: A bayesian spatial analysis of mortgage lending trajectories and firearm-related violence. *Inj. Epidemiol., 12*, 23. https://doi.org/10.1186/s40621-025-00579-9

Barboza-Salerno, G. E., & Meshelemiah, J. C. (2024). Associations between early child adversity and lifetime suicide attempts among gender diverse individuals: A moderated mediation. *Child Abuse & Neglect, 149*, Article 106705.

Batterham, P. J., Christensen, H., & Calear, A. L. (2013). Anxiety symptoms as precursors of major depression and suicidal ideation: Research article: Anxiety preceding depression and suicidal ideation. *Depress. Anxiety n/a-n/a*. https://doi.org/10.1002/da.22066

Beghi, M., Butera, E., Cerri, C. G., Cornaggia, C. M., Febbo, F., Mollica, A., Berardino, G., Piscitelli, D., Resta, E., Logroscino, G., Daniele, A., Altamura, M., Bellomo, A., Panza, F., & Lozupone, M. (2021). Suicidal behaviour in older age: A systematic review of risk factors associated to suicide attempts and completed suicides. *Neuroscience & Biobehavioral Reviews, 127*, 193–211. https://doi.org/10.1016/j.neubiorev.2021.04.011

Bolanis, D., Vergunst, F., Mavoa, S., Schmelefske, E., Khoury, B., Turecki, G., Orri, M., & Geoffroy, M.-C. (2024). Association between greenspace exposure and suicide-related outcomes across the lifespan: A systematic review. *The Science of the Total Environment, 906*, Article 167451. https://doi.org/10.1016/j.scitotenv.2023.167451

Brady, J. (2006). The association between alcohol misuse and suicidal behaviour. *Alcohol and Alcoholism, 41*, 473–478.

Branas, C. C., South, E., Kondo, M. C., Hohl, B. C., Bourgois, P., Wiebe, D. J., & MacDonald, J. M. (2018). Citywide cluster randomized trial to restore blighted vacant land and its effects on violence, crime, and fear. *Proceedings of the National Academy of Sciences, 115*, 2946–2951. https://doi.org/10.1073/pnas.1718503115

Bravo, L. G., Meza, J., Schiff, S. J., Ahmed, C., Elliot, T., La Charite, J., & Choi, K. (2024). Parental legal system involvement, positive childhood experiences, and suicide risk. *Pediatrics, 153*.

Brown, B., Rutherford, P., & Crawford, P. (2015). The role of noise in clinical environments with particular reference to mental health care: A narrative review. *International Journal of Nursing Studies, 52*, 1514–1524.

Carleton, T. A. (2017). Crop-damaging temperatures increase suicide rates in India. *Proc. Natl. Acad. Sci., 114*(33), 8746–8751.

Carretta, R. F., McKee, S. A., & Rhee, T. G. (2023). Gender differences in risks of suicide and suicidal behaviors in the USA: A narrative review. *Current Psychiatry Reports, 25*, 809–824.

Cen̄ido, J. F., Freeman, C., & Bazargan-Hejazi, S. (2019). Environmental interventions for physical and mental health: challenges and opportunities for Greater Los Angeles. *Int. J. Environ. Res. Pub. Health, 16*(12), 2180.

Centers for Disease Control and Prevention. (2024). *PLACES: Local Data for Better Health, Census Tract Data 2023 release*. Centers for Disease Control and Prevention. https://data.cdc.gov/500-Cities-Places/PLACES-Local-Data-for-Better-Health-Census-Tract-D/em5e-5hvn/data.

Chan, S. M., Wong, H., Chung, R. Y., & Au-Yeung, T. C. (2021). Association of living density with anxiety and stress: A cross-sectional population study in Hong Kong. *Health and Social Care in the Community, 29*, 1019–1029. https://doi.org/10.1111/hsc.13136

Chipman, J. W., Shi, X., Gilbert-Diamond, D., Khatchikian, C., Baker, E. R., Nieuwenhuijsen, M., & Karagas, M. R. (2024). Greenspace and land cover diversity during pregnancy in a rural region, and associations with birth outcomes. *GeoHealth, 8*, Article e2023GH000905. https://doi.org/10.1029/2023GH000905

Chipman, J. W., Shi, X., Gilbert-Diamond, D., Khatchikian, C., Baker, E. R., Nieuwenhuijsen, M., & Karagas, M. R. (2024). Greenspace and land cover diversity during pregnancy in a rural region, and associations with birth outcomes. *Geohealth, 8*(1), Article e2023GH000905.

Comer, D., & Greene, J. S. (2015a). The development and application of a land use diversity index for Oklahoma City, OK. *Applied Geography, 60*, 46–57.

Comer, D., & Greene, J. S. (2015b). The development and application of a land use diversity index for Oklahoma City, OK. *Applied Geography, 60*, 46–57. https://doi.org/10.1016/j.apgeog.2015.02.015

Cook, T. B. (2012). Assessing legal strains and risk of suicide using archived court data. Suicide life. Threat. *Beyond Behavior, 42*, 495–506. https://doi.org/10.1111/j.1943-278X.2012.00107.x

Cook County Department of Public Health. (2020). *Epi data request: Suicide* [excel spreadsheet].

Cook County Public, Health. (2024). *Cook County environmental justice survey report*. Cook County Department of Public Health. https://www.cookcountyil.gov/news/cook-county-releases-results-environmental-justice-survey.

Cox, G. R., Owens, C., Robinson, J., Nicholas, A., Lockley, A., Williamson, M., Cheung, Y. T. D., & Pirkis, J. (2013). Interventions to reduce suicides at suicide hotspots: A systematic review. *BMC Public Health, 13*, 214. https://doi.org/10.1186/1471-2458-13-214

Donovan, G. H., & Butry, D. T. (2010). Trees in the city: Valuing street trees in Portland, Oregon. *Landscape and Urban Planning, 94*, 77–83.

Evans, M. (2023). These South and West Side neighborhoods have been hardest hit by pollution. https://blockclubchicago.org/2023/09/18/these-south-and-west-side-neighborhoods-have-been-hardest-hit-by-pollution-study-shows/.

Fan, Y., Das, K. V., & Chen, Q. (2011). Neighborhood green, social support, physical activity, and stress: Assessing the cumulative impact. *Health & Place, 17*, 1202–1211.

Fang, F., Greenlee, A. J., He, Y., & Eutsler, E. (2023). Evaluating the quality of street trees in Washington, DC: Implications for environmental justice. *Urban Forestry and Urban Greening, 85*, Article 127947.

Farber, S., Morang, M. Z., & Widener, M. J. (2014). Temporal variability in transit-based accessibility to supermarkets. *Applied Geography, 53*, 149–159. https://doi.org/10.1016/j.apgeog.2014.06.012

Fedina, L., Mushonga, D. R., Bessaha, M. L., Jun, H.-J., Narita, Z., & DeVylder, J. (2019). Moderating effects of perceived neighborhood factors on intimate partner violence, psychological distress, and suicide risk. *Journal of Interpersonal Violence, 36*, 10546–10563.

Feng, T.-J., Hu, W., Shen, Z.-Z., Wang, J.-N., Liu, B.-P., & Jia, C.-X. (2025). Associations of green and blue space and the natural environment with suicidal ideation: The role of psychiatric disorders. *Environmental Research, 269*, Article 120861.

GBD 2015 Mortality and Causes of Death Collaborators. (2016). Global, regional, and national life expectancy, all-cause mortality, and cause-specific mortality for 249 causes of death, 1980-2015: A systematic analysis for the global burden of disease study 2015. *Lancet Lond. Engl., 388*, 1459–1544. https://doi.org/10.1016/S0140-6736(16)31012-1

Goodwill, J. R., & Baccile, R. (2024). Suicide methods and trends across race/ethnicity, age, and sex groups in Chicago, Illinois, 2015–2021. *American Journal of Public Health, 114*, 319–328.

Gunnell, D., Appleby, L., Arensman, E., Hawton, K., John, A., Kapur, N., Khan, M., O'Connor, R. C., Pirkis, J., & Caine, E. D. (2020). Suicide risk and prevention during the COVID-19 pandemic. *The Lancet Psychiatry, 7*, 468–471.

Hartley, K., Perazzo, J., Brokamp, C., Gillespie, G. L., Cecil, K. M., LeMasters, G., Yolton, K., & Ryan, P. (2021). Residential surrounding greenness and self-reported symptoms of anxiety and depression in adolescents. *Environmental Research, 194*, Article 110628.

Helbich, M., De Beurs, D., Kwan, M.-P., O'Connor, R. C., & Groenewegen, P. P. (2018). Natural environments and suicide mortality in The Netherlands: A cross-sectional, ecological study. *The Lancet Planetary Health, 2*, e134–e139.

Helbich, M., O'Connor, R. C., Nieuwenhuijsen, M., & Hagedoorn, P. (2020). Greenery exposure and suicide mortality later in life: A longitudinal register-based case-control study. *Environment International, 143*, Article 105982.

Heo, S., & Bell, M. L. (2023). Investigation on urban greenspace in relation to sociodemographic factors and health inequity based on different greenspace metrics in 3 US urban communities. *Journal of Exposure Science and Environmental Epidemiology, 33*, 218–228.

Houle, J. N., & Light, M. T. (2014). The home foreclosure crisis and rising suicide rates, 2005 to 2010. *American Journal of Public Health, 104*, 1073–1079. https://doi.org/10.2105/AJPH.2013.301774

Jiang, W., Stickley, A., & Ueda, M. (2021). Green space and suicide mortality in Japan: An ecological study. *Social Science & Medicine, 282*, Article 114137.

Johns, M. M. (2020). Trends in violence victimization and suicide risk by sexual identity among high school students — youth risk behavior Survey. https://doi.org/10.15585/mmwr.su6901a3.

Kim, U. R., & Sung, H. (2022). Urban parks as a potential mitigator of suicide rates resulting from global pandemics: Empirical evidence from past experiences in Seoul, Korea. *Cities, 127*, 103725.

Klumpenhouwer, W., Allen, J., Li, L., Liu, R., Robinson, M., Da Silva, D., … Buchanan, M. (2021). A comprehensive transit accessibility and equity dashboard. *Univ. Vt. Transp. Res. Cent.*. https://doi.org/10.32866/001c.25224

Kposowa, A. J. (2003). Divorce and suicide risk. *Journal of Epidemiology & Community Health, 57*, 993–993.

Kudas, D., Wnęk, A., Hudecová, L., & Fencik, R. (2024). Spatial diversity changes in land use and land cover mix in central European capitals and their commuting zones from 2006 to 2018. *Sustainability, 16*, 2224.

Lachapelle, U., Frank, L., Saelens, B. E., Sallis, J. F., & Conway, T. L. (2011). Commuting by public transit and physical activity: Where you live, where you work, and how you get there. *Journal of Physical Activity and Health, 8*, S72–S82.

Lawrence, B. C., Kheyfets, A., Carvalho, K., Dhaurali, S., Kiani, M., Moky, A., & Amutah-Onukagha, N. (2022). *The impact of psychosocial stress on maternal health outcomes: A multi-state prams 8 (2016-2018) analysis 15*.

Lawson, A., & Lee, D. (2017). Bayesian disease mapping for public health. In *Handbook of statistics* (pp. 443–481). Elsevier. https://doi.org/10.1016/bs.host.2017.05.001.

Lee, H.-Y., Chang, H.-T., Herianto, S., Wu, C.-S., Liu, W.-Y., Yu, C.-P., Pan, W.-C., & Wu, C.-D. (2024). Do greenness and landscape indices for greenspace correlate with suicide ratio? *Landscape and Urban Planning, 242*, Article 104935. https://doi.org/10.1016/j.landurbplan.2023.104935

Lee, L. H., Haque, A., Cui, J., Smith, A., Mancus, G., Yi, N., & Yuen, H. K. (2025). Examining the indirect effect of park size on community health via crime risk in Alabama: A cross-sectional mediation model. *Health & Place, 92*, Article 103423.

Lee, S., Lee, R. J., & Scherr, S. (2023). How tree canopy cover can reduce urban suicide attempts: A geospatial analysis of the moderating role of area deprivation. *Landscape and Urban Planning, 230*, Article 104606.

Lemoine, N. P. (2019). Moving beyond noninformative priors: Why and how to choose weakly informative priors in bayesian analyses. *Oikos, 128*, 912–928. https://doi.org/10.1111/oik.05985

Liu, H., Rahman, M., & Karner, A. (2023). Bus network redesigns and public transit equity analysis: Evaluating system-wide changes in Richmond, Virginia. *Travel Behav. Soc., 31*, 151–165.

Maas, J., Verheij, R. A., Groenewegen, P. P., Vries, S. de, & Spreeuwenberg, P. (2006). Green space, urbanity, and health: How strong is the relation? *Journal of Epidemiology & Community Health, 60*, 587–592. https://doi.org/10.1136/jech.2005.043125

Makram, O.M., Pan, A., Parekh, T., Maddock, J.E., & Kash, B. (2025). Exploring the relationship between neighborhood walkability and mental health: a study of urban areas in Texas. Heliyon.

Marlow, N. M., Xie, Z., Tanner, R., Jo, A., & Kirby, A. V. (2021). Association between disability and suicide-related outcomes among U.S. Adults. *American Journal of Preventive Medicine, 61*, 852–862. https://doi.org/10.1016/j.amepre.2021.05.035

Matthews, S. A., & Yang, T.-C. (2010). Exploring the role of the built and social neighborhood environment in moderating stress and health. *Annals of Behavioral Medicine, 39*, 170–183.

Mendoza, H., Rodriguez-Loureiro, L., Gadeyne, S., Lefebvre, W., Vanpoucke, C., & Casas, L. (2023). Urban green spaces and suicide mortality in Belgium (2001–2011): A census-based longitudinal study. *Environmental Research, 216*, Article 114517.

Milner, A., Page, A., & LaMontagne, A. D. (2013). Long-term unemployment and suicide: A systematic review and meta-analysis. *PLoS One, 8*, Article e51333.

Mitchell, R., & Popham, F. (2008). Effect of exposure to natural environment on health inequalities: An observational population study. *Lancet, 372*, 1655–1660.

Molitor, D., & White, C. (2024). Do cities mitigate or exacerbate environmental damages to health? *Regional Science and Urban Economics, 107*, Article 103973.

Momeni, E., & Antipova, A. (2022a). A micro-level analysis of commuting and urban land using the Simpson's index and socio-demographic factors. *Applied Geography, 145*, Article 102755. https://doi.org/10.1016/j.apgeog.2022.102755

Momeni, E., & Antipova, A. (2022b). A micro-level analysis of commuting and urban land using the Simpson's index and socio-demographic factors. *Applied Geography, 145*, Article 102755.

Montgomery, A. E., Blosnich, J. R., deRussy, A., Richman, J. S., Dichter, M. E., & True, G. (2024). Association between services to address adverse social determinants of health and suicide mortality among veterans with indicators of housing instability, unemployment, and justice involvement. *Archives of Suicide Research, 28*, 860–876. https://doi.org/10.1080/13811118.2023.2244534

Moraga, P., Dean, C., Inoue, J., Morawiecki, P., Noureen, S. R., & Wang, F. (2021). Bayesian spatial modelling of geostatistical data using INLA and spde methods: A case study predicting malaria risk in Mozambique. *Spat. Spatio-Temporal Epidemiol., 39*, Article 100440. https://doi.org/10.1016/j.sste.2021.100440

Mukherjee, S., & Wei, Z. (2021a). Suicide disparities across metropolitan areas in the us: A comparative assessment of socio-environmental factors using a data-driven predictive approach. *PLoS One, 16*, Article e0258824. https://doi.org/10.1371/journal.pone.0258824

Mukherjee, S., & Wei, Z. (2021b). Suicide disparities across metropolitan areas in the us: A comparative assessment of socio-environmental factors using a data-driven predictive approach. *PLoS One, 16*, Article e0258824. https://doi.org/10.1371/journal.pone.0258824

Nafilyan, V., Morgan, J., Mais, D., Sleeman, K. E., Butt, A., Ward, I., Tucker, J., Appleby, L., & Glickman, M. (2022). Risk of suicide after diagnosis of severe physical health conditions: A retrospective cohort study of 47 million people. *Lancet Reg. Health - Eur., 25*, Article 100562. https://doi.org/10.1016/j.lanepe.2022.100562

Nguemeni Tiako, M. J., South, E., Shannon, M. M., McCarthy, C., Meisel, Z. F., Elovitz, M. A., & Burris, H. H. (2021). Urban residential tree canopy and perceived stress among pregnant women. *Environmental Research, 201*, Article 111620. https://doi.org/10.1016/j.envres.2021.111620

Nguyen, P.-Y., Astell-Burt, T., Rahimi-Ardabili, H., & Feng, X. (2021). Green space quality and health: A systematic review. *International Journal of Environmental Research and Public Health, 18*, Article 11028.

Noseworthy, M., Peddie, L., Buckler, E. J., Park, F., Pham, M., Pratt, S., Singh, A., Puterman, E., & Liu-Ambrose, T. (2023). The effects of outdoor versus indoor exercise on psychological health, physical health, and physical activity behaviour: A systematic review of longitudinal trials. *International Journal of Environmental Research and Public Health, 20*, 1669. https://doi.org/10.3390/ijerph20031669

Nutsford, D., Pearson, A. L., & Kingham, S. (2013). An ecological study investigating the association between access to urban green space and mental health. *Public Health, 127*, 1005–1011.

O'brien, R. M. (2007). A caution regarding rules of thumb for variance inflation factors. *Quality and Quantity, 41*, 673–690. https://doi.org/10.1007/s11135-006-9018-6

Olsen, J. R., Nicholls, N., & Mitchell, R. (2019). Are urban landscapes associated with reported life satisfaction and inequalities in life satisfaction at the city level? A cross-sectional study of 66 European cities. *Social Science & Medicine, 226*, 263–274. https://doi.org/10.1016/j.socscimed.2019.03.009

Papa, G. L., Palermo, V., & Dazzi, C. (2011). Is land-use change a cause of loss of pedodiversity? The case of the mazzarrone study area, sicily. *Geomorphology, 135*, 332–342.

Percudani, M., Porcellana, M., Di Bernardo, I., & Morganti, C. (2024). Urbanization and mental health. In A. Fiorillo, & S. De Giorgi (Eds.), *Social determinants of mental health, sustainable development goals series* (pp. 279–296). Nature Switzerland, Cham: Springer. https://doi.org/10.1007/978-3-031-70165-8_18.

Pickett, S. T. A., Cadenasso, M. L., Rosi-Marshall, E. J., Belt, K. T., Groffman, P. M., Grove, J. M., Irwin, E. G., Kaushal, S. S., LaDeau, S. L., Nilon, C. H., Swan, C. M., & Warren, P. S. (2017). Dynamic heterogeneity: A framework to promote ecological integration and hypothesis generation in urban systems. *Urban Ecosystems, 20*, 1–14. https://doi.org/10.1007/s11252-016-0574-9

Rizk, M. M., Herzog, S., Dugad, S., & Stanley, B. (2021). Suicide risk and addiction: The impact of alcohol and opioid use disorders. *Curr. Addict. Rep., 8*, 194–207. https://doi.org/10.1007/s40429-021-00361-z

Robertson-Wilson, J., Rodden-Aubut, S., Tracey, J., Miller, M., & Lapid, H. (2024). Parkrun across the pond: examining location and event characteristics in Canada and the United States of America. *Leisure/Loisir, 48*, 371–392. https://doi.org/10.1080/14927713.2023.2187866

Runkle, J. R., Harden, S., Hart, L., Moreno, C., Michael, K., & Sugg, M. M. (2023). Socioenvironmental drivers of adolescent suicide in the United States: A scoping review. *J. Rural Ment. Health, 47*, 65–80. https://doi.org/10.1037/rmh0000208

Sander, H. A., Ghosh, D., & Hodson, C. B. (2017). Varying age-gender associations between body mass index and urban greenspace. *Urban For. Urban Green., Special feature:TURFGRASS, 26*, 1–10. https://doi.org/10.1016/j.ufug.2017.05.016

Shim, E.-J., Ha, H., Kim, B., Kim, S. M., Moon, J. Y., Hwang, J. H., & Hahm, B.-J. (2023). The multi-dimensional assessment of suicide risk in chronic illness-20 (MASC-20): Development and validation. *General Hospital Psychiatry, 83*, 140–147.

Smith, N., Georgiou, M., King, A. C., Tieges, Z., Webb, S., & Chastin, S. (2021). Urban blue spaces and human health: A systematic review and meta-analysis of quantitative studies. *Cities, 119*, Article 103413. https://doi.org/10.1016/j.cities.2021.103413

South, E. C., Hohl, B. C., Kondo, M. C., MacDonald, J. M., & Branas, C. C. (2018). Effect of greening vacant land on mental health of community-dwelling adults: A cluster randomized trial. *JAMA Network Open, 1*, Article e180298.

Stack, S., & Scourfield, J. (2015). Recency of divorce, depression, and suicide risk. *Journal of Family Issues, 36*, 695–715. https://doi.org/10.1177/0192513X13494824

Steelesmith, D. L., Fontanella, C. A., Campo, J. V., Bridge, J. A., Warren, K. L., & Root, E. D. (2019). Contextual factors associated with county-level suicide rates in the United States. *JAMA Network Open, 2*. https://doi.org/10.1001/jamanetworkopen.2019.10936

Tsai, W.-L., McHale, M. R., Jennings, V., Marquet, O., Hipp, J. A., Leung, Y.-F., & Floyd, M. F. (2018). Relationships between characteristics of urban green land cover and mental health in US metropolitan areas. *International Journal of Environmental Research and Public Health, 15*, 340.

Tyrväinen, L., Ojala, A., Korpela, K., Lanki, T., Tsunetsugu, Y., & Kagawa, T. (2014). The influence of urban green environments on stress relief measures: A field experiment. *Journal of Environmental Psychology, 38*, 1–9.

Van Renterghem, T., Botteldooren, D., & Verheyen, K. (2012). Road traffic noise shielding by vegetation belts of limited depth. *Journal of Sound and Vibration, 331*, 2404–2425.

Vaz, E., Shaker, R. R., & Cusimano, M. D. (2020). A geographical exploration of environmental and land use characteristics of suicide in the greater Toronto area. *Psych. Res., 287*, 112790.

Wei, Y. D., Wang, Y., Curtis, D. S., Shin, S., & Wen, M. (2024). Built environment, natural environment, and mental health. *GeoHealth, 8*, Article e2024GH001047. https://doi.org/10.1029/2024GH001047

White, M. P., Elliott, L. R., Gascon, M., Roberts, B., & Fleming, L. E. (2020). Blue space, health and well-being: A narrative overview and synthesis of potential benefits. *Environmental Research, 191*, Article 110169. https://doi.org/10.1016/j.envres.2020.110169

Wolch, J. R., Byrne, J., & Newell, J. P. (2014). Urban green space, public health, and environmental justice: The challenge of making cities 'just green enough. *Landscape and Urban Planning, 125*, 234–244.

Wu, J., Rappazzo, K. M., Simpson Jr, R. J., Joodi, G., Pursell, I. W., Mounsey, J. P., Cascio, W. E., & Jackson, L. E. (2018). Exploring links between greenspace and sudden unexpected death: A spatial analysis. *Environment International, 113*, 114–121.

Xie, J., Luo, S., Furuya, K., & Sun, D. (2020). Urban parks as green buffers during the COVID-19 pandemic. *Sustainability, 12*, 6751.

Yadav, D., Garg, N., Gautam, C., Agarwal, R., & Yadav, S. (2025). Noise pollution: The silent intruder to health and well-being. In N. Garg, C. Gautam, S. Rab, M. Wan, R. Agarwal, & S. Yadav (Eds.), *Handbook of vibroacoustics, noise and harshness* (pp. 1185–1203). Singapore: Springer Nature Singapore. https://doi.org/10.1007/978-981-97-8100-3_63.

Yankey, O., Amegbor, P. M., & Lee, J. (2021). The effect of sociodemographic factors on the risk of poor mental health in akron (Ohio): A bayesian hierarchical spatial analysis. *Spat. Spatio-Temporal Epidemiol., 38*, Article 100438.

Zhang, Y., Cheng, J., Li, Y., He, R., Choudhry, A. A., Jiang, J., Pan, P., Su, X., & Hu, C. (2019). Suicidality among patients with asthma: A systematic review and meta-analysis. *Journal of Affective Disorders, 256*, 594–603.

Zou, E. (2017). *Wind turbine syndrome: The impact of wind farms on suicide*. Mimeo.

U.S. Census Bureau. (2023). QuickFacts: Cook County, Illinois [Data set]. U.S. Department of Commerce. https://www.census.gov/quickfacts/cookcountyillinois.