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Development of a community severance index for urban areas in the United States: A case study in New York City

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Abstract

Background and aims: Traffic-related exposures, such as air pollution and noise, have a detrimental impact on human health, especially in urban areas. However, there remains a critical research and knowledge gap in understanding the impact of community severance, a measure of the physical separation imposed by road infrastructure and motorized road traffic, limiting access to goods, services, or social connections, breaking down the social fabric and potentially also adversely impacting health. We aimed to robustly quantify a community severance metric in urban settings exemplified by its characterization in New York City (NYC).

Methods: We used geospatial location data and dimensionality reduction techniques to capture NYC community severance variation. We employed principal component pursuit, a pattern recognition algorithm, combined with factor analysis as a novel method to estimate the Community Severance Index. We used public data for the year 2019 at census block group (CBG) level on road infrastructure, road traffic activity, and pedestrian infrastructure. As a demonstrative application of the Community Severance Index, we investigated the association between community severance and traffic collisions, as a proxy for road safety, in 2019 in NYC at CBG level.

Results: Our data revealed one multidimensional factor related to community severance explaining 74% of the data variation. In adjusted analyses, traffic collisions in general, and specifically those involving pedestrians or cyclists, were nonlinearly associated with an increasing level of Community Severance Index in NYC.

Conclusion: We developed a high spatial-resolution Community Severance Index for NYC using data available nationwide, making it feasible for replication in other cities across the United States. Our findings suggest that increases in the Community Severance Index across CBG may be

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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.

Appendix A. Supplementary material
Supplementary data associated with this article can be found, in the online version, at https://doi.org/10.1016/j.envint.2024.108526.

linked to increases in traffic collisions in NYC. The Community Severance Index, which provides a novel traffic-related exposure, may be used to inform equitable urban policies that mitigate health risks and enhance well-being.

1. Introduction

Road transport-related infrastructure and motorized traffic can have substantial impacts on everyday life and human health in cities, where the density of both circulating vehicles and population is also large (Rahman et al., 2021). In the United States (US), for example, road transport and traffic congestion have been on the rise in cities in recent decades (Schrank et al., 2021), and people living in neighborhoods with lower socioeconomic status tend to live closer to high traffic-volume roads, increasing their risk of adverse health effects (Tian et al., 2013). Road transport has been linked to detrimental health outcomes through air pollution and noise, among other health-relevant pathways (Glazener et al., 2021). For instance, a systematic review indicated consistent associations between long-term exposure to traffic-related air pollution and all-cause, lung cancer, and circulatory mortality (Boogaard et al., 2022). Also, a systematic review and meta-analysis reported an association between traffic-related air pollution and increased risk of asthma development in childhood (Khreis et al., 2017).

Proximity to busy roads has also been associated with having smaller social networks (Boniface et al., 2015), restrictions in children’s outdoor play (Lambert et al., 2019), and diminished social and motor skills for 5-year-old children (Evans, 2006). Additionally, residents on streets with higher traffic volume interact less with their neighbors relative to those living on less congested streets (Appleyard and Lintell, 1972). Road infrastructure and traffic may sever communities, leading to negative health outcomes either on their own or in combination with other traffic-related factors, such as traffic-related air pollution. Community severance measures the ”cumulative negative impact of the presence of transport infrastructure or motorised traffic on the perceptions, behavior, and well-being of people who use the surrounding areas or need to make trips along or across that infrastructure or traffic” (Mindell et al., 2017; Anciaes, 2015). Community severance may be a relevant indicator for better understanding the mechanisms through which road infrastructure and traffic can lead to poor health outcomes. However, scientific evidence on the role of community severance on human health remains scarce (Glazener et al., 2021).

Community severance (Fig. 1) may impact individuals’ health and their access to goods, services, and personal networks (Mindell et al., 2017). Community severance can increase as a result of road safety concerns, discouraging walking and limiting social contact between residents in high-traffic areas. For example, Anciaes and Bradbury (2022) reviewed the scientific literature on community severance in African cities reporting that perception of lower traffic safety for pedestrians was associated with reduced propensity to walk (−31%) in Yaoundé, Cameroon (Zogo et al., 2017) and lower levels of physical activity in Maiduguri, Nigeria (Oyeyemi et al., 2012). Similar findings were also observed in South African urban centers (Malambo et al., 2017). In addition, Higgsmith et al. (2022) identified an association between community severance and poor self-rated health in a survey-based study in Great Britain. Consequently, community severance can be associated with insufficient physical activity, reduced social networks, stress, and overall reduced independence and access to and ease of mobility, thereby increasing morbidity and premature mortality (Glazener et al., 2021).

To date, however, studies of community severance have focused on qualitative, survey-based assessments within limited spatial domains, typically encompassing only a few streets (Mindell et al., 2017). For instance, pattern recognition algorithms, like principal component analysis, have been used to identify a community severance indicator based on survey data (Higgsmith et al., 2022). Nonetheless, no community severance indicator has been developed at the city level that can be used for public health analyses; a robust metric that represents a consistent index across a variety of urban neighborhoods is lacking. This index of community severance is a critically needed tool for environmental epidemiology, urban and transportation planning, among other applications. It can facilitate the development of targeted policy interventions aimed at mitigating the adverse health effects of intra-city transportation infrastructure and can be used to assess the health implications of existing infrastructure.

Here, we develop a novel Community Severance Index based on conceptually-related urban spatial features using pattern recognition over New York City (NYC), US. We apply a robust and well-established method for data dimensionality reduction and pattern recognition in computer vision applications, named principal component pursuit, which has been adapted to suit environmental health applications (Gibson et al., 2022). Finally, we apply the newly developed Community Severance Index to estimate the association between community severance and traffic collisions, a proxy for road safety in NYC.

To our knowledge, this is the first time that community severance has been estimated at the city level using pattern recognition on urban spatial data. Similar approaches have been previously used to construct standardized indices of other neighborhood-level characteristics, e.g., the area deprivation index (Messer et al., 2006) and the National Walkability Index (US-EPA, 2021a).

2. Methods

2.1. Area and period of study

We carried out the investigation at the census block group (CBG) level across the entire NYC (N = 6,301, average population 1339 inhabitants, average surface area 0.13 km^2). We chose NYC because it is a large and dense urban area with a diverse representation of neighborhoods. We chose CBGs, which are smaller than census tracts and larger than census blocks, as the unit of analysis to provide a basis to compare community severance across communities. Additionally, CBG is used as the unit of analysis on a set of publicly available data products to summarize several built environment variables for every CBG in the US on the Smart Location Database from the US Environmental Protection Agency (US-EPA, 2021b). For instance, Smart Location Database variables are applied to develop the National Walkability Index (US-EPA, 2021a), which is a relevant resource for this work. We selected the year 2019 as the reference because (1) extensive data were available, and (2) it is representative of current urban infrastructure characteristics and road traffic activity.

2.2. Selection of urban spatial variables

We used detailed data on urban spatial features related to community severance at the CBG level (Table 1) as described below. We chose the data sources and data categories following a literature review on the topic, according to which road infrastructure, road traffic activity, and pedestrian infrastructure were identified as essential categories for estimating community severance (Anciaes and do Nascimento, 2022; Higgsmith et al., 2022). We chose datasets available nationwide to allow the feasibility and potential transferability of the Community Severance Index to other cities in the US.

2.2.1. Road infrastructure—We included 13 variables in this category to represent the presence of road infrastructure and its surrogates.

Proximity to roads.: This distance-based indicator represents a measure of how close a CBG is to a specific road type. The effect of community severance has been linked to the proximity to road infrastructure, with more intensity near busy traffic areas (Anciaes et al., 2016; Mindell et al., 2017). Also, distance to roads is typically used as a measure to assess traffic-related exposure (e.g., air pollution (Amini et al., 2022)). We use data from OpenStreetMap (OSM, 2017) and Bureau of Transportation Statistics (US Department of Transportation) (US-DOT BTS, 2023) to obtain georeferenced roads (i.e., six variables including major, minor, and residential roads) following the categorization used by Larkin et al. (2017) and Bureau of Transportation Statistics (i.e., three variables for major roads classified as Interstate, Principal Arterial - Other Freeways and Expressways, and Principal Arterial - Other) as identified by the Freight Analysis Framework Version 5 created for 2017 as reference year (US-DOT BTS, 2023). We first estimated the euclidean distance from each CBG centroid to each road type and then transformed it into a proximity measure, by changing its direction and normalizing it to range between 0 and 1 using the following equation:

$$\text{proximity}_{\text{cr}} = \frac{\max(\text{dist}_{\text{r}}) - \text{dist}_{\text{cr}}}{\max(\text{dist}_{\text{r}})} \tag{1}$$

where c is the CBG centroid, and r is road type. $proximity_{cr}$ increases with shorter distances from the CBG centroid to closest road ($dist_{cr}$) and ranges from 0 to 1 because it is divided by the maximal distance from any CBG in the city to this specific road type.

Road traffic network.: Urban space prioritizing road traffic flow may increase pedestrian delays (i.e., time spent waiting to cross roads), contributing to community severance (Glazener et al., 2021; Anciaes et al., 2016). We included road network density and road traffic intersection density per square mile from the US-EPA Smart Location Database (US-EPA, 2021b) for each CBG in the Community Severance Index input data. These indicators are based on auto-oriented infrastructure such as highways, where high speed (e.g., ⩾55 mph) is allowed or where four or more lanes of travel are devoted to a single direction.

Barrier factor.: Road infrastructure may sever communities by intersecting potential flows of pedestrians and other active mobility forms. We developed an indicator to estimate to what extent paths at a walkable distance between CBGs are blocked by major roads. We considered the CBG walkable area as the circular buffer centered at the CBG centroid with a radius of 0.5 miles. We considered a walking distance of 0.5 miles because it represents the median for walking trips among US residents as reported by Yang and Diez-Roux (2012) using data from the 2009 National Household Travel Survey. We used a straight line as a proxy for walkable paths between each CBG centroid and the surrounding CBGs centroids within the walkable area. We then identified if any major road segments crossed each of the lines linking the CBG of interest to other CBGs within the walkable area. We estimated the combined barrier effect caused by the set of major road segments crossing the CBG as the percentage of blocked paths. Anciaes and do Nascimento (2022) developed a similar indicator to assess the barrier effect of roads for trips between buildings in Praia (Cape Verde). Our two barrier factor variables are based on publicly available data on major roads from two road infrastructure sources, OpenStreetMap and Freight Analysis Framework Version 5 from Bureau of Transportation Statistics. Major road segments from OpenStreetMap followed the categorization used by Larkin et al. (2017) including motorways, motorway links, trunks, trunk links, primary and secondary roads and links. Major roads from Bureau of Transportation Statistics (US-DOT) included those classified as Interstate, Principal Arterial - Other Freeways and Expressways, and Principal Arterial - Other. The two data sources for major roads contain complementary information. They were, thus, treated independently, and they were used as individual input variables in the estimation of the Community Severance Index.

2.2.2. Road traffic activity—

Community severance may increase with increasing road traffic activity, including volume and speed (Anciaes et al., 2016). We included three variables related to this category.

Annual Average Daily traffic.: We added two datasets on annual average daily traffic from two different sources: point-based traffic counts from ESRI (ESRI, 2022) and annual average daily traffic provided on the Highway Performance Monitoring System by Federal Highway Administration for 2019 at the road segment level for major roads (FHWA, 2023). In both cases, we applied ordinary kriging (Wackernagel, 2003) to interpolate annual average daily traffic estimates from their original spatial data type to CBG centroids. The estimated annual average daily traffic at the CBG centroids represent the annual average traffic from both methods at that CBG.

Traffic annual CO_2 emissions.: We used CO_2 emissions from road traffic as a proxy for vehicle miles traveled, vehicle types, and speed. The Database of Road Transportation Emissions (DARTE) provides annual average CO_2 emissions for 1980–2017 aggregated as total emissions in kilograms CO_2 per year for each CBG (Gately et al., 2019). DARTE combines the roadway-level vehicle miles traveled from Highway Performance Monitoring System (FHWA, 2023) with vehicle-specific emissions factors. We normalized 2017 total CBG estimates by dividing it by the CBG area in square meters (Gately et al., 2019).

2.2.3. Pedestrian infrastructure—Pedestrian infrastructure including sidewalks, crosswalks, and intersections may enhance the walking experience (Mitropoulos et al., 2023) buffering community severance. We included three variables in this category.

Pedestrian network.: We used two built-environment variables that are available for every CBG in the US from the Smart Location Database (US-EPA, 2021b). We included pedestrian network density and street intersection density (i.e., weighted to emphasize pedestrian and bicycle travel connectivity and leave out automobile-oriented intersections that include major highways or other facilities that exclude pedestrian crossings) per square mile (US-EPA, 2021b). Higher intersection density is correlated with enhanced walking trips (Zeng et al., 2023).

National Walkability Index.: US-EPA released the National Walkability Index in 2021 providing walkability scores based on indicators from the Smart Location Database that can affect the propensity of walk trips (US-EPA, 2021a). The National Walkability Index dataset is available at the CBG level and ranks each CBG relative to all other CBGs in the US. The National Walkability Index is based on street intersection density, proximity to transit stops, and diversity of land uses. Each CBG is first ranked based on each input variable, and these ranked scores are combined in an index that weighs them assigning equal weights to each of the three main categories. Similar indices have been developed in other countries (Dhanani et al., 2017). For a more detailed description of the index we refer to US-EPA (2021a).

2.3. Covariates for analyses

In this work, we used total motor vehicle collisions per CBG in NYC as a proxy for road safety and examined the association between the estimated Community Severance Index and road safety. In addition to community severance, levels of motor vehicle collisions per CBG may also depend on population density (LaScala et al., 2004) and socioeconomic status (Morency et al., 2012). We considered CBG population density—obtained from the American Community Surveys (2015–2019)—and socioeconomic status, as represented by the Area Deprivation Index (Kind and Buckingham, 2018), as potential confounders, as these variables may spatially correlate with motor vehicle collisions, as well as the Community Severance Index.

2.4. Construction of the Community Severance Index

To identify common patterns in the high-dimensional spatial dataset described above, we applied principal component pursuit (Candès et al., 2011). Principal component pursuit is a pattern recognition algorithm that was originally developed for computer vision and video surveillance applications and recently adapted to model environmental mixtures (Gibson et al., 2022; Tao et al., 2023). Principal component pursuit decomposes a high-dimensional data matrix into a low-rank matrix that identifies consistent patterns while reducing data dimensionality, and a sparse matrix, which identifies unique values in the original data matrix unexplained by the common patterns. Principal component pursuit depends on a minimal set of assumptions, can handle missing data, and is robust to noisy data (Candès et al., 2011). The sparse matrix estimation ensures statistical robustness to major outliers in the pattern identification process (Candès et al., 2011; Gibson et al., 2022). Patterns identified by principal component pursuit are more robust to noise and incomplete data than those identified using traditional pattern identification methods, such as principal component analysis, because patterns in the low-rank matrix are not influenced by events captured by the sparse matrix. In a recent simulation study (Gibson et al., 2022), principal component pursuit identified the true number of patterns in all simulations, while principal component analysis did so only in 32% of the simulations. In general, principal component pursuit outperformed principal component analysis in most simulated scenarios (Gibson et al., 2022).

The rank of a matrix helps to govern the structure of the data, representing the maximal number of linearly independent columns or rows in the matrix. This way, a principal component pursuit-identified rank can be thought of as the number of inherent latent patterns within the input dataset. To identify the optimal rank we applied a cross-validated grid search across different combinations of plausible rank values, i.e., from 1 to 5, to cover a wide range of potential patterns.

We considered as optimal the rank minimizing the relative error, while recovering the low-rank matrix and the sparse matrix (i.e., with enough sparsity; at least 1%). The optimal rank was then subsequently considered as the input for the principal component pursuit rank when calculating the low-rank matrix for recognizing the patterns in the spatial input data.

Once we obtained the low-rank matrix from principal component pursuit, we applied factor analysis to extract interpretable patterns. We tested both orthogonal and oblique rotation solutions. We considered the rank of the low-rank matrix as the number of factors in the factor analysis.

We used the factor analysis-estimated scores of the factor explaining most of the commonly shared variance in the data as the Community Severance Index; we extracted the scores of that factor and assessed the spatial distribution of community severance across NYC and the association between community severance and road safety.

2.4.1. Validation of Community Severance Index—

Community Severance, and consequently the Community Severance Index developed in this work, does not have direct validation measures, i.e., there is no quantitative “ground truth”. We used visual inspection of geographic maps and personal experience of NYC neighborhoods to compare the Community Severance Index with what we expected. Prior studies that developed urban indices that also did not have direct validation measures have assessed associations between the newly created index and related outcomes. For instance, Cerin et al. (2006) and Rundle et al. (2019) examined the association between walkability indexes and walking data. Here, we assessed the association between community severance and road safety in NYC.

2.5. Community severance and road safety in NYC

Road safety concerns, which may discourage walking and limit social contact between residents, are likely high in areas with high levels of community severance (Glazener et al., 2021; Boniface et al., 2015). In this work, we investigated the association between the estimated Community Severance Index and road safety, using motor vehicle collisions as a proxy for road safety.

Vehicle collisions data were obtained through the NYC Open Data Portal (NYC Open Data, 2022) from police reports, which register collisions when someone is injured or killed, or where there is at least $1000 worth of damage. Data consist of information on each collision, including location, time, and number of people injured or killed. In this work, we focused on all 2019 collisions, consistently with the Community Severance Index. Individual georeferenced collisions were assigned to CBGs and aggregated to annual counts to form the outcome of interest. We used the total annual counts of collisions as the outcome, instead of using rates (e.g., collisions per vehicle miles traveled), because we assumed that road safety concerns in a block group equally increase with each collision.

We investigated the association between the number of collisions and Community Severance Index in a CBG (i.e., normalized scores of the Community Severance Index ranging from 0 to 1). We ran a negative binomial generalized additive model (GAM) to estimate the association of interest, adjusting for the covariates described in Section 2.3. To allow for nonlinear associations in the exposure–response function, we used natural cubic splines with two degrees of freedom (based on the Akaike information criterion; AIC).

2.6. Sensitivity analyses

For sensitivity analyses, we estimated the Community Severance Index using principal component pursuit combined with factor analysis adding as an input a variable representing the ratio of the area of sidewalks (Rhoads et al., 2021) over the area of roads (NYC Open Data, 2022) within walkable distance (0.5 miles) of each CBG centroid. We also included two datasets related to crossings from NYC Open Data (NYC Open Data, 2022): enhanced crossings and accessible pedestrian signals in NYC. Enhanced crossings are intended to provide a safe place for crossing the street when there is no traffic signal. Accessible pedestrian signals are installed to ease crossing the street to visually impaired people or those who have low vision. These variables are excluded from the main analysis as both sidewalk and crossing data are not available nationwide.

We also reran the models linking Community Severance Index and vehicle collisions additionally adjusting for the National Walkability Index per CBG. We also reran the models additionally adjusting for the annual average daily traffic from ESRI per CBG. We repeated analyses using the vehicle collisions data restricting to instances with pedestrians or cyclist involved (i.e., injured or killed). Lastly, we used a flexible function of space that adjusts for spatial correlation among CBGs to assess the robustness of our results to spatial dependence in vehicle collisions. We added a two-dimensional term for the coordinates (latitude and longitude) of each CBG centroid using a tensor product in the model.

All statistical analyses were performed using the R Statistical Software, version 4.2.2 (R Core Team, 2022). All data and code are available at https://github.com/jaime-benavides/community_severance_nyc.

3. Results

3.1. Distribution of urban spatial variables

Distributional characteristics of the spatial variables across CBGs in NYC are presented in Table 2. Fig. 2 illustrates the spatial distribution of the barrier factor for the Bureau of Transportation Statistics (US-DOT) major roads (Section 2.2.1), as an example of the variables used as inputs to estimate community severance in NYC.

The correlation coefficients between the spatial variables selected to build the Community Severance Index in the raw data matrix are presented in Fig. 3a. Road infrastructure and road traffic activity variables were positively correlated (correlations ranged between 0.1 and 0.7), with the exception of small local roads. The correlations between variables falling within these two data categories and pedestrian infrastructure variables ranged between −0.1 and 0.2, being mostly negative.

3.2. Patterns of urban spatial variables

The estimated optimal rank (i.e., the number of patterns) in the low-rank data matrix after cross-validation was two. Fig. 3b depicts the low-rank correlation matrix alongside the correlation matrix of the raw data (Fig. 3a). Principal component pursuit removed sparse values and residual noise that cannot be explained by the main patterns in the data, highlighting the correlations between spatial variables in the dataset (Fig. 3b). To characterize underlying patterns, we ran factor analysis on the low-rank matrix, using its rank as the number of factors.

Fig. 4 depicts the loadings of the factor that explained most of the commonly shared variance of the low-rank matrix (74%) (Table S1). This profile is characterized by road traffic infrastructure and road traffic activity loading in the same direction, Cand pedestrian infrastructure variables loading in the opposite direction. We used this profile as the ommunity Severance Index in this work because of its agreement with the hypothesized concept of community severance and because of the high proportion of variance explained in the low-rank matrix. The factor loadings from the other profile, which explained 26% of the variance, are shown in Supplementary Figure S1 and the direction of associations in the loadings is inverted with respect to the Community Severance Index.

Fig. 5 depicts the normalized scores of the Community Severance Index ordered by quartiles in NYC at CBG–level. The Community Severance Index values vary considerably across the city showing higher values near highly trafficked areas.

Fig. 6 shows the final correlations between the estimated Community Severance Index and the raw input variables. The barrier factor was the variable most correlated to the estimated index.

3.3. Association between community severance and road safety

We found evidence that the Community Severance Index for CBGs was associated with increases in the annual number of vehicle collisions in NYC. The non-linear associations between Community Severance Index and vehicle collisions followed an upward trend, with collisions increasing with increasing Community Severance Index (Fig. 7). The trend was steeper for Community Severance Index above 0.5.

3.4. Sensitivity analyses

When considering the ratio of sidewalks to roads, enhanced crossings, and accessible pedestrian signals in the Community Severance Index estimation, we found similar results compared with the main analysis (Figure S2). When rerunning analyses for the association between the Community Severance Index and vehicle collisions incorporating the National Walkability Index per CBG as a covariate, the association became more pronounced, with a steeper upward trend (Figure S3). When rerunning analyses incorporating the annual average daily traffic per CBG as a covariate, the association remained similar, with a more moderate trend at lower levels of Community Severance Index (below 0.5) which became steeper for Community Severance Index above 0.5 (Figure S4). When restricting analyses to consider as collisions only those with pedestrians or cyclists involved, we found similar overall results but the upward trend was not as steep (Figures S5 and S6). Also, our results were robust to incorporating a term accounting for potential spatial autocorrelation (Figure S7).

4. Discussion

We constructed a Community Severance Index, a pattern recognition factor-based index that uses 19 road infrastructure, road traffic activity, and pedestrian infrastructure indicators at the CBG level. The Community Severance Index quantifies the influence of transportation infrastructure and motorized traffic that divides places and people, in turn severing communities. It measures community severance on a particular census-based urban region in the US, as demonstrated in this article through its estimation for NYC. The input variables at CBG level were either directly drawn from the US-EPA built environment open data collection or derived using data available nationwide.

The present study, to our knowledge, is the first to characterize community severance at the city level using spatial data analysis. Most studies to date have estimated community severance over spatial domains of just a few streets (Mindell et al., 2017) and using survey data (Higgsmith et al., 2022). These local studies may inform urban design in specific areas. Nonetheless, city-level estimates may provide a broader view for identification of areas that require intervention and used as the exposure of interest in subsequent health studies.

As traffic-related emissions are decreasing (McDuffie et al., 2020) and the electrification of the vehicle fleet is increasing (Bui et al., 2021), characterizing the potential role of community severance on human health becomes increasingly critical. Some of the traffic-related environmental issues (e.g., air pollution) may be reduced, but not eliminated, by technological advancements such as vehicle electrification (Peters et al., 2020). However, community severance will likely remain unchanged without further interventions explicitly aiming to reduce it or even become higher with increasingly higher volume vehicles (Tyndall, 2021). Understanding the potential health impacts of community severance may help clarify the influence of traffic and road infrastructure on human health beyond traffic-related environmental exposures.

Community severance may have implications for environmental justice. Historically in the US, financial and political support has prioritized highways instead of public transit systems, despite stark racial/ethnic differences in car (mostly White) vs. public transit (predominantly non-White) usage (Bhat and Naumann, 2013; McKenzie, 2013). Moreover, many of these urban highways were built either severing disadvantaged Black communities or segregating them from other communities. For example, the Major Deegan Boulevard was built in 1937–1939 in an environmental justice area in the South Bronx in NYC (New York City, 2023). This project was originally conceived both as a congestion-relief and slum-clearance project (New York Times, 1939). The areas surrounding this road infrastructure fall within the highest quartile of Community Severance Index estimated in this work. The Community Severance Index may also have implications for policy design and impact evaluations. For instance, in the busy traffic areas of midtown and downtown Manhattan the level of community severance is high (i.e., 2nd to 4th quartiles). The anticipated congestion pricing scheme in NYC is set to impose fees on motor vehicles within the area, expected to reduce the total number of trips (Baghestani et al., 2020). Consequently, it will potentially reduce community severance in the congestion pricing zone.

At the city level, Anciaes and do Nascimento (2022) estimated a barrier factor from road infrastructure in Praia (Cape Verde) representing limited accessibility to neighboring areas. They found that the barrier factor disproportionately decreased walking accessibility to individuals aged 65 + as well as those with very low socioeconomic status. Their barrier factor estimate is similar to the barrier factor developed in this work as one of the input variables for the Community Severance Index estimation (Fig. 2). Indeed, the barrier factor was the input most highly correlated with the estimated Community Severance Index (Fig. 6) and can be an informative proxy for community severance when other relevant information is lacking. In our case, it is used to represent limited accessibility to neighboring CBGs. However, our work also integrated data on proximity to road infrastructure, traffic activity, and pedestrian infrastructure to build a comprehensive index based on spatial analysis at the city level. In addition, we carefully chose data available nationwide to make this work extensible to other cities in the US.

As an application of the Community Severance Index, we estimated associations between this index and road safety using the annual number of motor vehicle collisions in NYC in 2019 as a proxy. We found that increases in the Community Severance Index in a CBG were associated with an increasing amount of motor vehicle collisions, in general, as well as for collisions in which either pedestrians or cyclist were injured or killed. Other recent works assessed how aspects of the built environment are associated with the distribution of motor vehicle collisions in cities. In the US, roadway fatalities declined for the period 1980–2010, followed by a plateau in 2010s and an increase in 2020 and 2021 (US-DOT, 2023). It is crucial to understand which factors contribute to this rise. For road infrastructure characteristics, pedestrian–vehicle collision increased with the number of lanes and road width in NYC (Ukkusuri et al., 2012). Also, increasing levels of road density were associated with increasing passenger transport fatalities (Moeinaddini et al., 2014). For road traffic activity, limiting speeds (e.g., 20 mph) in specific zones has been effective in reducing collisions and injuries from motor vehicle collisions (Cairns et al., 2014). Traffic safety levels may also influence the chosen transportation mode. Typically, shifts to lower levels of safety can make people choose to drive a car instead of cycling or walking in their day-by-day trips (van Eldijk et al., 2022). The Community Severance Index developed here for NYC includes the variables investigated by the above-mentioned studies, along with others that may also be linked to traffic collisions. Our finding offer evidence on the composite influence of these factors on increasing motor vehicle collisions, impacting both the general population and specifically pedestrians and cyclists. Thus, the novel Community Severance Index may be used for detecting areas that require improvements to increase road safety and reduce the number of traffic collisions.

Our study has several limitations. First, no prior Community Severance Index estimates exist to validate ours, since no physical measurements for community severance have been developed. To address this limitation, we visually inspected the results and examined associations with vehicle collisions using it as a proxy for safety concerns related to road traffic. Another limitation is that community severance may change over time (e.g., increase of traffic intensity) and we used 2019 as the basis for the estimation of the Community Severance Index, using annual average values of variables changing over time, such as traffic intensity. Future studies could extend this approach to estimate a Community Severance Index changing over time. Furthermore, the index does not directly consider data on the presence and quality of crossings as nationwide data are not available to build a reliable set of variables representing crossings. However, we included street intersection density, also considered in the Walkability Index, that leaves out automobile-oriented intersections including major highways or other facilities that exclude pedestrian crossings. Another limitation is that some input variables were based on the centroids of CBGs, omitting the fact that in some cases the population could be concentrated in a small part of the CBG. Nonetheless, the average CBG area is quite small; we, thus, expect that any potential resulting error is likely negligible. In our analysis, we used a 0.5-mi radius (2 km^2 surface) around the CBG centroids to build circular buffers and capture an area of potential walking trips. Given the small area of NYC CBGs, we expect that this radius is sufficient for the Community Severance Index estimation. If other studies aim to estimate this index in larger area units, longer radii should be considered. Additionally, the index does not integrate information on the presence and quality of sidewalks as nationwide data was not available to build a set of variables representing sidewalks. However, we find that pedestrian infrastructure variables used in this work (e.g., the National Walkability Index) (US-EPA, 2021a) provide a robust basis for the estimation of this index. Also, we assessed the sensitivity to including as input a ratio of sidewalks to roads, enhanced crossings, and accessible pedestrian signals in NYC finding similar results. Another aspect of importance for community severance in US cities may be the increasing physical volume of vehicles linked to the increasing presence of Sport Utility Vehicles in US roads (Tyndall, 2021). In this work, we used traffic CO_2 emissions as a proxy for vehicle type, miles traveled and speed, partially addressing this limitation.

Our work focused on NYC, but the methodology may be replicable in other US cities, where the input data are available. The next step is to extend the Community Severance Index to provide values nationwide at CBG level and investigate potential associations with socioeconomic status and health outcomes.

5. Conclusions

The presence of road infrastructure and road traffic may influence human health in cities, beyond most studied exposures such as air pollution and noise. Community severance provides a conceptual construct that can be used as a basis to assess health impacts of this imposed physical separation. In this study, we rigorously quantified a Community Severance Index for urban environments, with a specific focus on its detailed characterization at a high spatial resolution within NYC. We showed that increases in the Community Severance Index across CBG may be linked to increases in the number of motor vehicle collisions in NYC, both in general and specific for collisions when either a pedestrian or a cyclist is injured or killed. The Community Severance Index can provide urban health scientists and practitioners with a complementary perspective to other traffic-related exposures to investigate neighborhood environments and help guide equitable urban policies that mitigate health risks and enhance community cohesion and overall well-being.

Supplementary Material

Refer to Web version on PubMed Central for supplementary material.

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Data availability

Data will be made available on request.

List of abbreviations:

AADT	Annual Average Daily Traffic
AIC	Akaike information criterion
BTS	Bureau of Transportation Statistics
US-DOT	US Department of Transportation
CBG	Census Block Group
DARTE	Database of Road Transportation Emissions
FHWA	Federal Highway Administration
GAM	Generalized Additive Model
NYC	New York City
OSM	OpenStreetMap
US-EPA	US Environmental Protection Agency

US	United States

References

Amini H, Danesh-Yazdi M, Di Q, Requia W, Wei Y, Abu-Awad Y, Shi L, Franklin M, Kang C-M, Wolfson J, James P, Habre R, Zhu Q, Apte J, Andersen Z, Xing X, Hultquist C, Kloog I, Dominici F, Koutrakis P, Schwartz J, 2022. Hyperlocal super-learned PM2.5 components across the contiguous US. ResearchSquare. 10.21203/rs.3.rs-1745433/v1.

Anciaes P, Bradbury A, 2022. Community Severance in Urban Africa. In Acheampong C, Lucas RA, Poku-Boansi K, Uzondu M, editor, Transport and Mobility Futures in Urban Africa, chapter Community, pages 111–127. Springer, the urban edition, 2022. ISBN 978-3-031-17327-1. 10.1007/978-3-031-17327-1_8. URL https://doi.org/10.1007/978-3-031-17327-1_8.

Anciaes P, Boniface S, Dhanani A, Mindell JS, Groce N, 2016. Urban transport and community severance: Linking research and policy to link people and places. J. Transp. Health 3 (3), 268–277. 10.1016/j.jth.2016.07.006. ISSN 22141405.

Anciaes P, do Nascimento JM, 2022. Road traffic reduces pedestrian accessibility – Quantifying the size and distribution of barrier effects in an African city. J. Transp. Health 27 (October), 101522. 10.1016/j.jth.2022.101522. ISSN 22141405.

Anciaes P, Jones P, Mindell JS, 2016. Community severance: where is it found and at what cost? Transport Reviews 36 (3), 293–317. 10.1080/01441647.2015.1077286. ISSN 14645327.

Appleyard D, Lintell M, 1972. The environmental quality of city streets: the residents ' viewpoint. J. Am. Inst. Planners 38 (2), 84–101.

Baghestani A, Tayarani M, Allahviranloo M, Gao HO, 2020. Evaluating the traffic and emissions impacts of congestion pricing in New York city. Sustainability (Switzerland) 12 (9), 1–16. 10.3390/su12093655. ISSN 20711050.

Bhat G, Naumann RB, 2013. Travel-related behaviors, opinions, and concerns of U.S. adult drivers by race/ethnicity, 2010. J. Safety Res. 47, 93–97. 10.1016/j.jsr.2013.09.001. ISSN 00224375. [PubMed: 24237875]

Boniface S, Scantlebury R, Watkins SJ, Mindell JS, 2015. Health implications of transport: Evidence of effects of transport on social interactions. J. Transp. Health 2 (3), 441–446. 10.1016/j.jth.2015.05.005. ISSN 22141405.

Boogaard H, Patton AP, Atkinson RW, Brook JR, Chang HH, Crouse DL, Fussell JC, Hoek G, Hoffmann B, Kappeler R, Kutlar Joss M, Ondras M, Sagiv SK, Samoli E, Shaikh R, Smargiassi A, Szpiro AA, Van Vliet EDS, Vienneau D, Weuve J, Lurmann FW, Forastiere F, 2022. Long-term exposure to traffic-related air pollution and selected health outcomes: A systematic review and meta-analysis. Environ. Int. 164 (April), 107262. 10.1016/j.envint.2022.107262. ISSN 18736750. [PubMed: 35569389]

Bui A, Slowik P, Lutsey N, 2021. Evaluating electric vehicle market growth across U. S. cities. International Council on Clean Transportation. Technical report.

Cairns J, Warren J, Garthwaite K, Greig G, Bambra C, 2014. Go slow: An umbrella review of the effects of 20 mph zones and limits on health and health inequalities. J. Public Health (United Kingdom) 37 (3), 515–520. 10.1093/pubmed/fdu067. ISSN 17413850.

Candès EJ, Li X, Ma Y, Wright J, 2011. Robust principal component analysis? J. ACM 58 (3). 10.1145/1970392.1970395. ISSN 00045411.

Cerin E, Saelens BE, Sallis JF, Frank LD, 2006. Neighborhood environment walkability scale: Validity and development of a short form. Med. Sci. Sports Exerc. 38 (9), 1682–1691. 10.1249/01.mss.0000227639.83607.4d. ISSN 01959131. [PubMed: 16960531]

Dhanani A, Tarkhanyan L, Vaughan L, 2017. Estimating pedestrian demand for active transport evaluation and planning. Transport. Res. Part A: Policy Pract. 103, 54–69. 10.1016/j.tra.2017.05.020.

Anciaes P Street mobility and network accessibility: What do we mean by " community severance "? Technical report, UCL, 2015. URL https://www.ucl.ac.uk/epidemiology-health-care/sites/epidemiology-health-care/files/Anciaes_ucl_streetmobility_pape r04.pdf.

ESRI. The USA Traffic Counts from Kalibrate's TrafficMetrix for the United States, 2022. https://www.arcgis.com/home/item.html? id=70507a8779a2470b89c6a8c90394d68e.

Evans GW, 2006. Child development and the physical environment. Annu. Rev. Psychol. 57, 423–451. 10.1146/annurev.psych.57.102904.190057.ISSN 00664308. [PubMed: 16318602]

FHWA. Highway Performance Monitoring System (HPMS), 2023. https://www.fhwa.dot.gov/policyinformation/hpms.cfm.

Gately C, Hutyra LR, and Wing IS DARTE Annual On-road CO2. Technical report, ORNL DAAC, Oak Ridge, Tennessee, USA, 2019. URL https://daac.ornl.gov/CMS/guides/CMS_DARTE_V2.html.

Gibson EA, Zhang J, Yan J, Chillrud L, Benavides J, Nunez Y, Herbstman JB, Goldsmith J, Wright J, Kioumourtzoglou M-A, 2022. Principal Component Pursuit for Pattern Identification in Environmental Mixtures. Environ. Health Perspect. 130 (11), 1–10. 10.1289/EHP10479.

Glazener A, Sanchez K, Ramani T, Zietsman J, Nieuwenhuijsen MJ, Mindell JS, Fox M, Khreis H, 2021. Fourteen pathways between urban transportation and health: a conceptual model and literature review. Transp. Health 21 (June 2021), 101070. 10.1016/j.jth.2021.101070. ISSN 2214–1405.

Higgsmith M, Stockton J, Anciaes P, Scholes S, Mindell JS, 2022. Community severance and health – A novel approach to measuring community severance and examining its impact on the health of adults in Great Britain. J. Transp. Health 25 (April), 101368. 10.1016/j.jth.2022.101368. ISSN 22141405.

Khreis H, Kelly C, Tate J, Parslow R, Lucas K, Nieuwenhuijsen M, 2017. Exposure to traffic-related air pollution and risk of development of childhood asthma: A systematic review and meta-analysis. Environ. Int. 100, 1–31. 10.1016/j.envint.2016.11.012. ISSN 18736750. [PubMed: 27881237]

Kind AJH, Buckingham WR, 2018. Making neighborhood-disadvantage metrics accessible – the neighborhood atlas. New Direct. Eval. 378 (26), 2456–2458. 10.1056/NEJMp1802313.Making.

Lambert A, Vlaar J, Herrington S, Brussoni M, 2019. What is the relationship between the neighbourhood built environment and time spent in outdoor play? A systematic review. Int. J. Environ. Res. Public Health 16 (20). 10.3390/ijerph16203840. ISSN 16604601.

Larkin A, Geddes JA, Martin RV, Xiao Q, Liu Y, Marshall JD, Brauer M, Hystad P, 2017. Global Land Use Regression Model for Nitrogen Dioxide Air Pollution. Environ. Sci. Technol. 51 (12), 6957–6964. 10.1021/acs.est.7b01148. ISSN 15205851. [PubMed: 28520422]

LaScala EA, Gruenewald PJ, Johnson FW, 2004. An ecological study of the locations of schools and child pedestrian injury collisions. Accid. Anal. Prev. 36 (4), 569–576. 10.1016/S0001-4575(03)00063-0. ISSN 00014575. [PubMed: 15094409]

Malambo P, Kengne AP, Lambert EV, De Villers A, Puoane T, 2017. Association between perceived built environmental attributes and physical activity among adults in South Africa. BMC Public Health 17 (1). 10.1186/s12889-017-4128-8. ISSN 14712458.

McDuffie EE, Smith SJ, O'Rourke P, Tibrewal K, Venkataraman C, Marais EA, Zheng B, Crippa M, Brauer M, Martin RV, 2020. A global anthropogenic emission inventory of atmospheric pollutants from sector- And fuel-specific sources (1970–2017): An application of the Community Emissions Data System (CEDS). Earth Syst. Sci. Data 12 (4), 3413–3442. 10.5194/essd-12-3413-2020. ISSN 18663516.

Messer LC, Laraia BA, Kaufman JS, Eyster J, Holzman C, Culhane J, Elo I, Burke JG, O'Campo P, 2006. The development of a standardized neighborhood deprivation index. Journal of Urban Health 83 (6), 1041–1062. 10.1007/s11524-006-9094-x. ISSN 10993460. [PubMed: 17031568]

Mindell JS, Anciaes P, Dhanani A, Stockton J, Jones P, Haklay M, Groce N, Scholes S, Vaughan L, 2017. Using triangulation to assess a suite of tools to measure community severance. J. Transp. Geogr. 60, 119–129. 10.1016/j.jtrangeo.2017.02.013. ISSN 09666923.

Mitropoulos L, Karolemeas C, Ts igdinos S, Vassi A, Bakogiannis E, 2023.A composite index for assessing accessibility in urban areas: A case study in Central Athens. Greece. Journal of Transport Geography 108 (March), 103566. 10.1016/j.jtrangeo.2023.103566. ISSN 09666923.

Moeinaddini M, Asadi-Shekari Z, Shah MZ, 2014. The relationship between urban street networks and the number of transport fatalities at the city level. Saf. Sci. 62, 114–120. 10.1016/j.ssci.2013.08.015. ISSN 09257535.

Morency P, Gauvin L, Plante C, Fournier M, Morency C, 2012. Neighborhood social inequalities in road traffic injuries: The influence of traffic volume and road design. Am. J. Public Health 102 (6), 1112–1119. 10.2105/AJPH.2011.300528. ISSN 00900036. [PubMed: 22515869]

McKenzie BS, 2013. Neighborhood Access to Transit by Race, Ethnicity, and Poverty in Portland, OR. City and Community, 12(2):134–155. 10.1111/cico.12022. ISSN 15356841.

New York City. NYC Open Data, 2022. URL https://opendata.cityofnewyork.us/.

New York City. New York City Climate Policy and Programs, 2021. Environmental Justice in New York City, 2023. URL https://climate.cityofnewyork.us/topic/environmental-justice/.

New York Times. Bridge approach in Bronx is ready: Road leading to Triborough span officially opened by the mayor, Apr 1939.

OSM. Planet dump retrieved from https://planet.osm.org. https://www.openstreetmap.org, 2017.

Oyeyemi AL, Adegoke BO, Sallis JF, Oyeyemi AY, De Bourdeaudhuij I, 2012. Perceived crime and traffic safety is related to physical activity among adults in Nigeria. BMC Public Health 12 (1). 10.1186/1471-2458-12-294. ISSN 14712458.

Peters DR, Schnell JL, Kinney PL, Naik V, Horton DE, 2020. Public Health and Climate Benefits and Trade-Offs of U.S. Vehicle Electrification. GeoHealth 4 (10). 10.1029/2020GH000275. ISSN 24711403.

R Core Team, 2022. R: A Language and Environment for Statistical Computing. R Foundation for Statistical Computing, Vienna, Austria.

Rahman MM, Najaf P, Fields MG, Thill JC, 2021. Traffic congestion and its urban scale factors: Empirical evidence from American urban areas. Int. J. Sustain. Transport. 1–16. 10.1080/15568318.2021.1885085. ISSN 15568334.

Rhoads D, Solé-Ribalta A, González MC, Borge-Holthoefer J, 2021. A sustainable strategy for Open Streets in (post)pandemic cities. Communications Physics 4 (1), 1–12. 10.1038/s42005-021-00688-z. ISSN 23993650.

Rundle AG, Chen Y., Quinn JW, Rahai N, Bartley K, Mooney SJ, Bader MD, Zeleniuch-Jacquotte A, Lovasi GS, Neckerman KM, 2019. Development of a Neighborhood Walkability Index for Studying Neighborhood Physical Activity Contexts in Communities across the U.S. over the Past Three Decades. Journal of Urban Health 96 (4), 583–590. 10.1007/s11524-019-00370-4. ISSN 14682869. [PubMed: 31214976]

Schrank DL, Albert Eisele B,L, Lomax T, 2021. Urban Mobility Report. Mobility Division - Texas A&M University. Technical report.

Tao RH, Chillrud LG, Nunez Y, Rowland ST, Boehme AK, Yan J, Goldsmith J, Wright J, Kioumourtzoglou MA, 2023. Applying principal component pursuit to investigate the association between source-specific fine particulate matter and myocardial infarction hospitalizations in New York City. Environmental Epidemiology 7 (2), E243. 10.1097/EE9.0000000000000243. ISSN 24747882. [PubMed: 37064426]

Tian N, Xue J, Barzyk TM, 2013. Evaluating socioeconomic and racial differences in traffic-related metrics in the United States using a GIS approach. Journal of Exposure Science and Environmental Epidemiology 23 (2), 215–222. 10.1038/jes.2012.83. ISSN 15590631. [PubMed: 22872311]

Tyndall J, 2021. Pedestrian deaths and large vehicles. Economics of Transportation 26–27 (July), 100219. 10.1016/j.ecotra.2021.100219. ISSN 22120122.

Ukkusuri S, Miranda-Moreno LF, Ramadurai G, Isa-Tavarez J, 2012. The role of built environment on pedestrian crash frequency. Saf. Sci. 50 (4), 1141–1151. 10.1016/j.ssci.2011.09.012. ISSN 09257535.

US-DOT BTS. Freight Analysis Framework, 2023. https://www.bts.gov/faf.

US-EPA. National Walkability Index: Methodology and User Guide. Technical Report June, U.S. Environmental Protection Agency, 2021a. URL www.epa.gov/smartgrowth.

US-EPA. Smart Location Database Technical Documentation and User Guide, Version 3.0. Technical Report June, U.S. Environmental Protection Agency, 2021b. URL https://www.epa.gov/sites/default/files/2021-06/documents/epa_sld_3.0_technicaldocumentationuserguide_may2021.pdf.

US-DOT, 2023. The Roadway Safety Problem. https://www.transportation.gov/NRSS/SafetyProblem.

van Eldijk J, Gil J, Marcus L, 2022. Disentangling barrier effects of transport infrastructure: synthesising research for the practice of impact assessment. Eur. Transp. Res. Rev. 14 (1), 1–19. 10.1186/s12544-021-00517-y. ISSN 18668887.

Wackernagel H, 2003. Ordinary kriging. In: Multivariate geostatistics. Springer, pp. 79–88. 10.1007/978-3-662-05294-5_11.

Yang Y, Diez-Roux AV, 2012. Walking Distance by Trip Purpose and Population Subgroups Yong. Am. J. Prev. Med. 43 (1), 11–19. 10.1016/j.amepre.2012.03.015. [PubMed: 22704740]

Zeng Q, Bao X, Dewancker BJ, 2023. Association between built environment on transport and recreational walking in Japan: the case of Kitakyushu. City Built Environ. 1–14. 10.1007/s44213-023-00011-2. ISSN 2435–7936.

Zogo VO, Epo BN, Meli CN, 2017. La marche à pied dans les métropoles africaines: Le cas de Yaoundé (Walking in African metropolises: the case of Yaoundé). Cahiers Scientifiques Du Transport 72, 143–159.

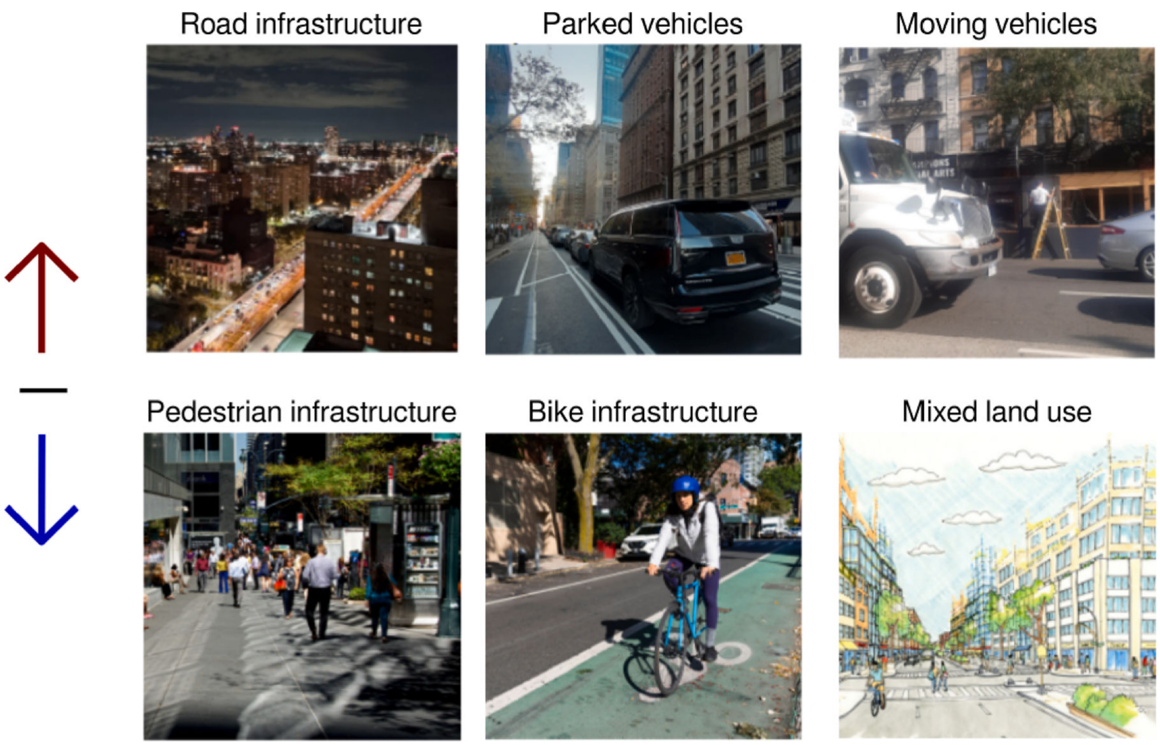

Fig. 1.
Community severance increases with physical presence of road infrastructure, parked and moving vehicles (top row); decreases with more relative presence of pedestrian and bike infrastructure and increased mixed land-uses (bottom row).

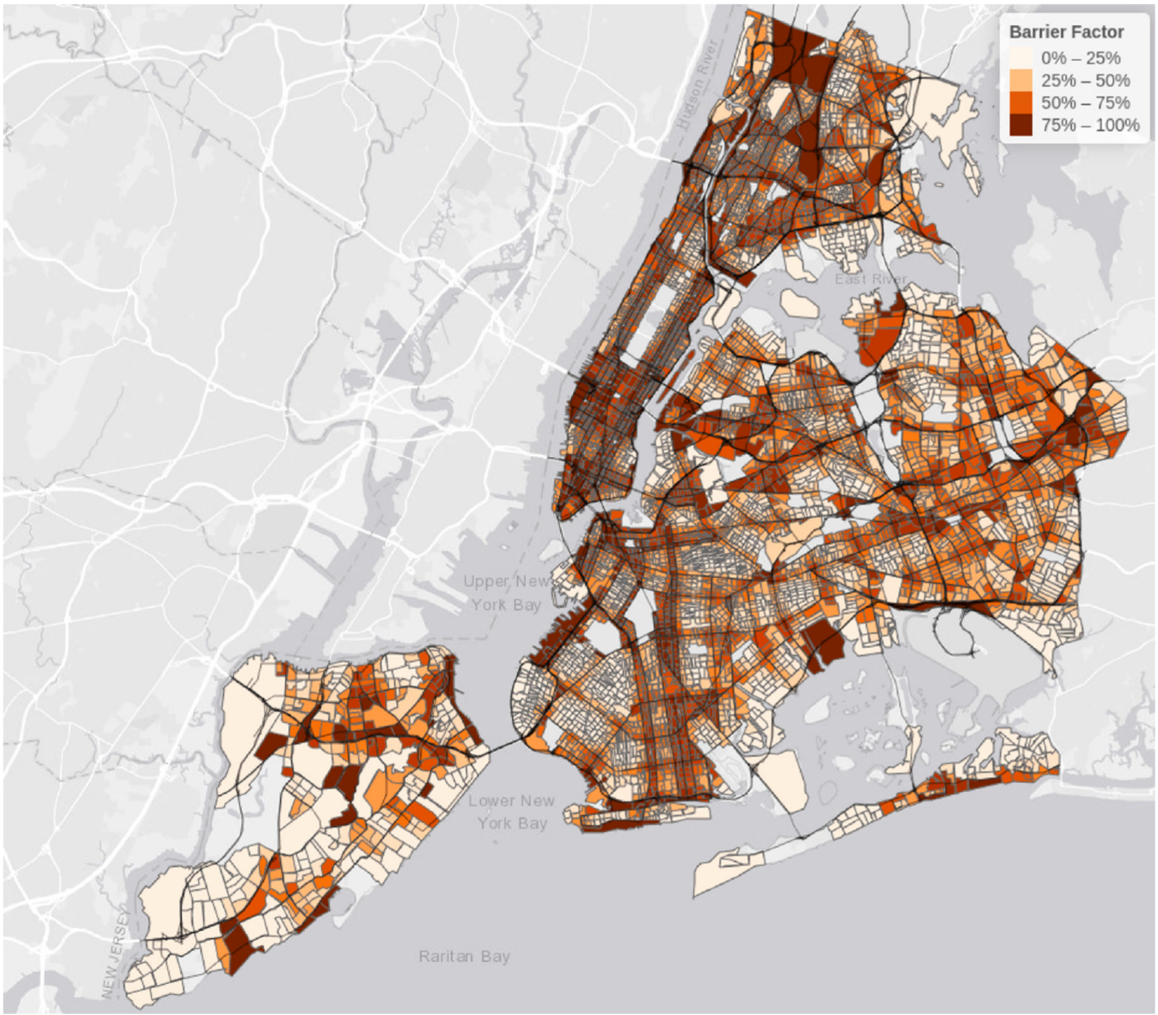

Fig. 2.

Spatial distribution of barrier factor using major roads (Interstate, Principal Arterial - Other Freeways and Expressways, and Principal Arterial - Other) from Bureau of Transportation Statistics (BTS, US Department of Transportation) (US-DOT BTS, 2023) as input. Values of barrier factor are ordered from lower to higher on a color scale that divides CBGs into four equal-sized groups.

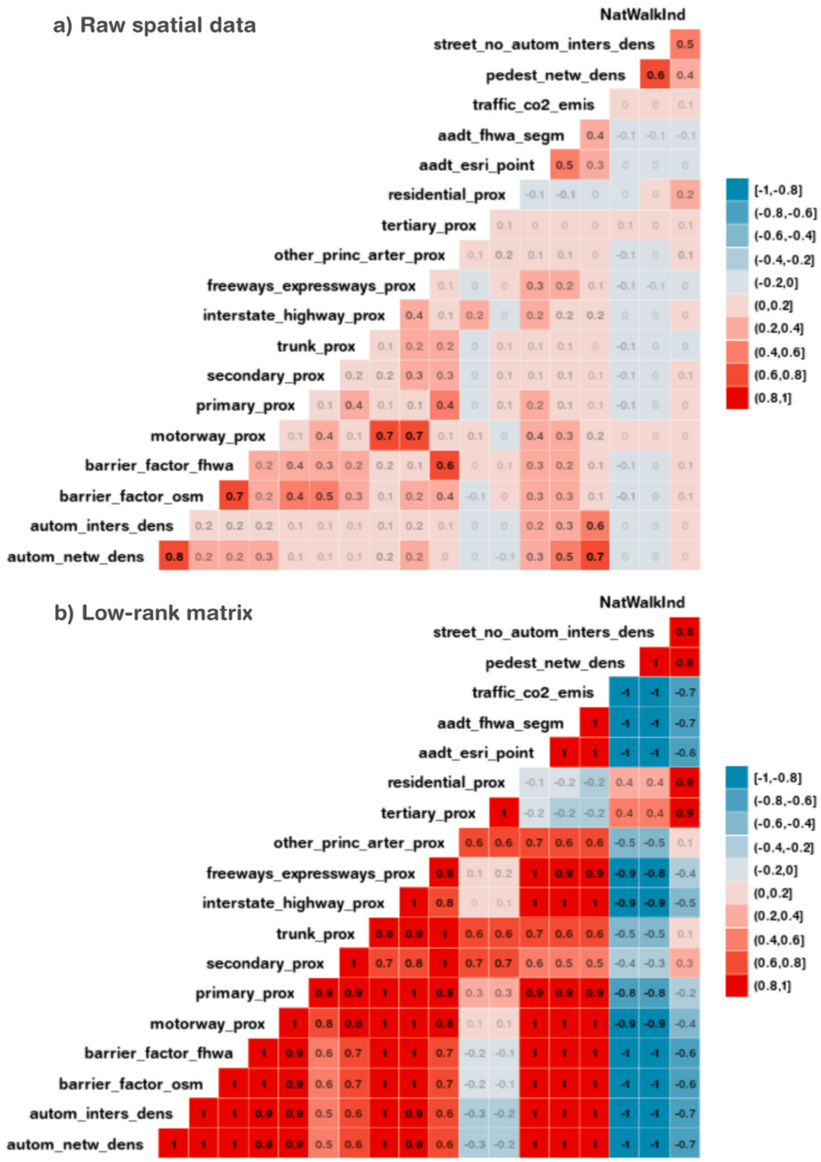

Fig. 3.

Pearson correlation coefficients among the 19 spatial variables at census block group (CBG) level using 2019 as reference year: (a) raw data matrix; (b) low-rank structure estimated by principal component pursuit. dens means density and prox, proximity, emis means emissions. For complete names of variables refer to Table 2.

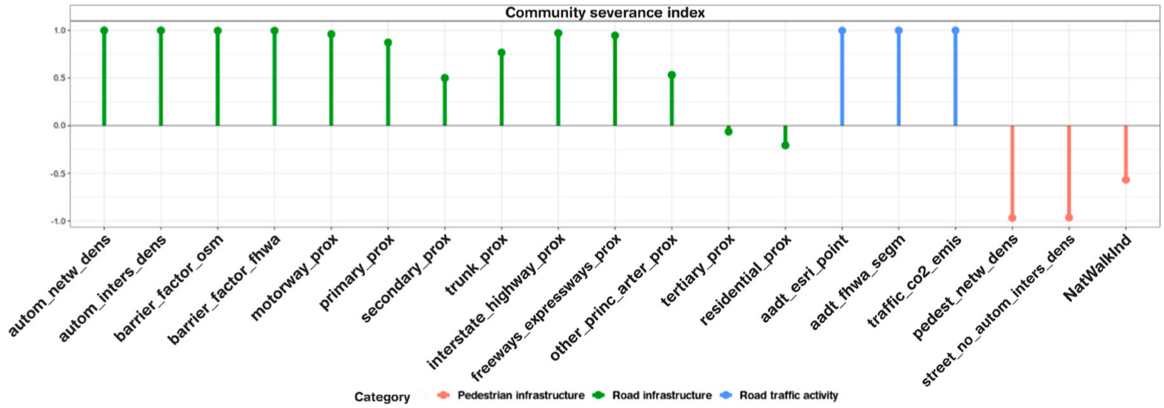

Fig. 4.

Factor loadings for the main pattern of road and pedestrian infrastructure, and road traffic activity. This factor, which we interpreted as the Community Severance Index, documents high levels of road traffic activity and road infrastructure variables and low levels of pedestrian infrastructure variables. For complete names of variables refer to Table 2.

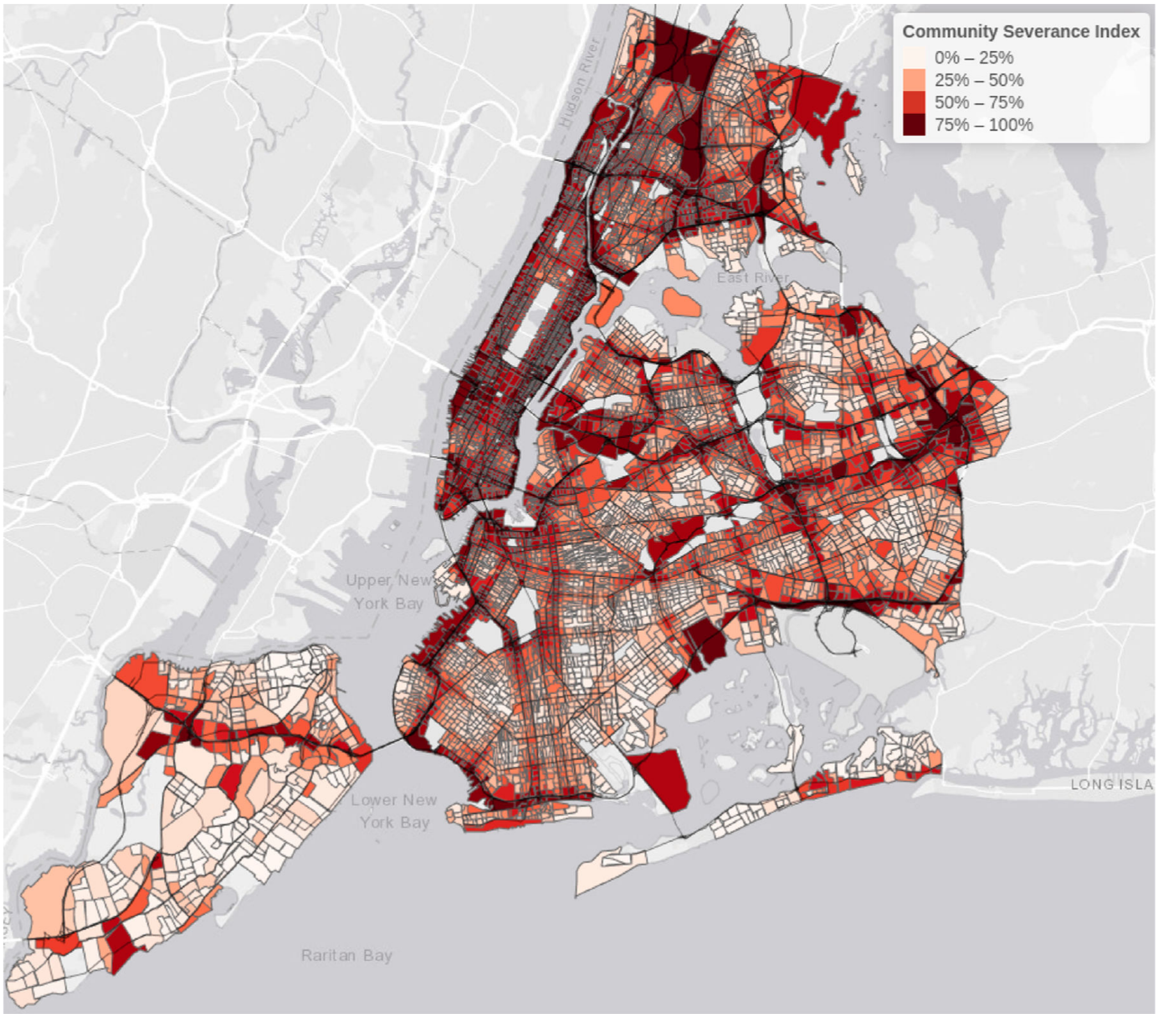

Fig. 5.

CBG-level Community Severance Index for NYC estimated using principal component pursuit and factor analysis. Values of Community Severance Index are ordered from lower to higher on a color scale that divides CBGs into four equal-sized groups.

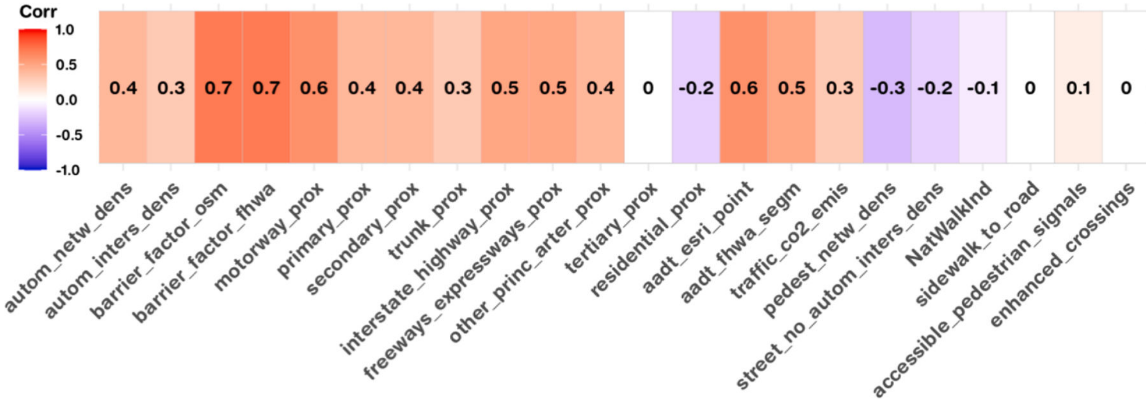

Fig. 6.

Pearson correlation coefficients among the 22 spatial variables at census block group (CBG) used in this study and the Community Severance Index. *dens means density and prox, proximity, emis means emissions. For complete names of variables refer to Table 2..

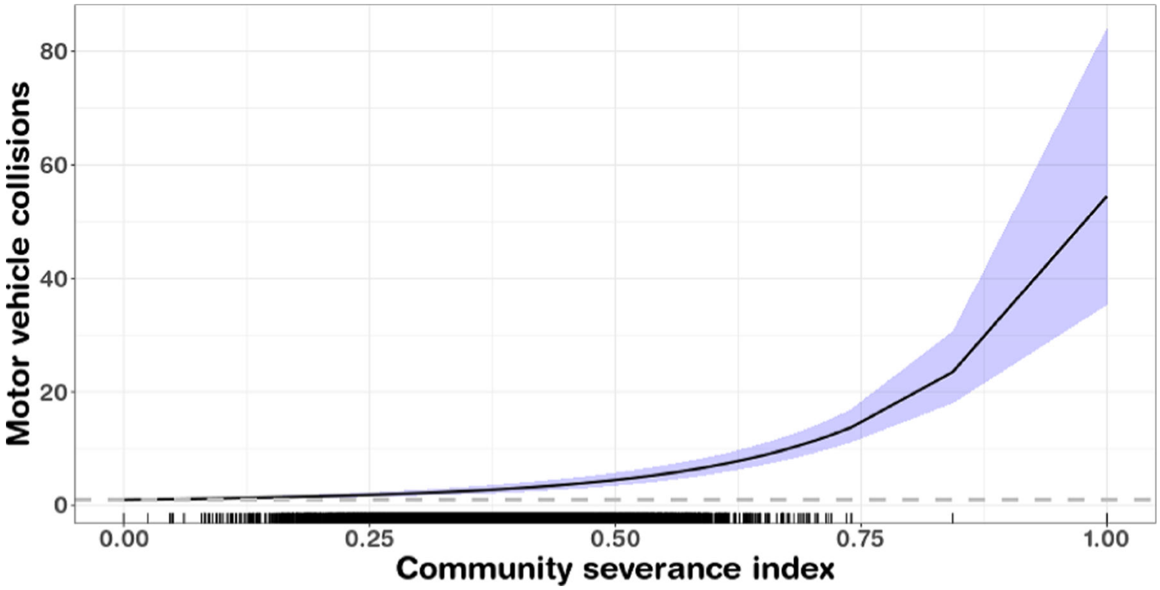

Fig. 7.

Estimates for the association between normalized scores of the Community Severance Index and number of vehicle collisions in a census block group. Models were adjusted for population density and Area Deprivation Index.

Table 1

Summary table of urban spatial features by category and their sources used in this study for NYC (2019).

Category	Subcategory	Source	Number of variables
Road infrastructure	Proximity to roads	OSM and BTS	9
	Road traffic network	US-EPA	2
	Barrier Factor	OSM and BTS	2
Road traffic activity	Annual Average Daily traffic	FHWA and ESRI	2
	Traffic annual CO_2 emissions	DARTE	1
Pedestrian infrastructure	Pedestrian network	US-EPA	2
	National Walkability Index	US-EPA	1

* OpenStreetMap (OSM). Bureau of Transportation Statistics (BTS, US Department of Transportation). Federal Highway Administration (FHWA). US Environmental Protection Agency (US-EPA). Environmental Systems Research Institute (ESRI). Database of Road Transportation Emissions (DARTE).

Table 2

Characteristics of spatial variables (N = 6,301). Distribution quartiles are presented as the 25th, 50th, and 75th percentiles.

Variable	Mean	SD	Min	Pctl. 25	Pctl. 50	Pctl. 75	Max
National Walkability Index	13.8	2.7	1	12.2	14	15.7	20
Street intersection density (no autom.)	119.86	120.41	0	57.24	107.58	162.1	5289.52
Pedestrian network density	13.12	9.88	0	5.77	11.34	19.44	121.29
Traffic CO_2 emissions *	11.71	48.5	0	1.45	2.13	3.36	1964.55
AADT FHWA	11501.9	12641.1	0	4616.3	7615.9	12757.9	133216.6
AADT ESRI	13210.8	7107.2	2803.5	8214.5	11367.6	15918.6	61974.6
Residential roads proximity	0.98	0.04	0	0.97	0.98	1	1
Tertiary roads proximity	0.85	0.14	0	0.79	0.91	0.96	1
Principal arterial - other proximity	0.93	0.07	0	0.91	0.95	0.97	1
Freeways Expressways proximity	0.83	0.13	0	0.77	0.86	0.92	1
Interstate highway proximity	0.77	0.19	0	0.68	0.82	0.91	1
Trunk roads proximity	0.86	0.12	0	0.83	0.89	0.94	1
Secondary roads proximity	0.95	0.07	0	0.95	0.97	0.99	1
Primary roads proximity	0.87	0.14	0	0.82	0.91	0.96	1
Motorways proximity	0.84	0.14	0	0.79	0.88	0.94	1
Barrier factor FHWA-BTS	52.0	26.3	0	34.3	53.3	72.2	100
Barrier factor OSM	58.5	28.7	0	38.7	61.5	82.9	100
Automobile intersection density	6.34	29.11	0	0	0	0	742.21
Automobile network density	1.78	5.68	0	0	0	0	107.99

* The variable Traffic CO_2 emissions has 1.1% of missing data.

SD is standard deviation. Annual Average Daily Traffic (AADT). Federal Highway Administration (FHWA). Environmental Systems Research Institute (ESRI). OpenStreetMap (OSM).

Bureau of Transportation Statistics (BTS, US Department of Transportation).