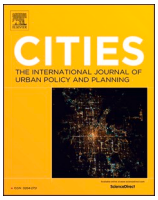
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Changing associations of built environment with usage of urban space due to the COVID-19 pandemic in the United States

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ABSTRACT

This paper aims to analyze how the associations of built environment and usage of urban space changed due to the social restrictions during COVID-19 pandemic in the United States. A total of 57,185 census block groups (CBGs) in 459 cities were analyzed. Built environment elements including road network, green space, and land use associated with usage of urban space (measured by over two billion mobile phone data) before/during COVID-19 were evaluated at both CBG and city level. Our results showed drastic decreases of urban space usage, ranging from 0.25 % to 76.35 %, among cities during COVID-19 social restriction. Specifically, CBG-level road length-node ratio, road intersection index and land use densities contributed less to usage of urban space during COVID-19. Meanwhile, the heterogeneity of city-level road network, commercial, public places, as well as hospitals and health cares exhibited stronger relationship with usage of urban space. The heterogeneity of green space at both CBG and city level showed less associations with usage of urban space during COVID-19. The discrepancies of the built environment effects on usage of urban space between CBG and city level suggest the importance of varying-scale analysis. Future interventions should consider space usages and health inequality from a space-varying perspective for post-pandemic period.

1. Introduction

Usage of urban space is referred as the individual utilization of urban space that supports the basic needs and daily activities (Du, Wang, Mao, & Kang, 2024; Rapoport, 2016). It has been increasingly intertwined with various built environment elements such as road, green space, and land use, and captured the human activities with multiple urban functions (Zhong et al., 2017). The interactions of usage of urban space with built environment could be highlighted regarding the availability of urban facilities at a micro scale such as neighborhoods (Zhong et al., 2017). At a macro scale, the spatial heterogeneity of built environment provides new insights in the special dynamics of usage of urban space in cities (Taubenböck et al., 2014).

However, such interactions between built environment and usage of urban space have been dramatically reshaped by the pandemic of coronavirus disease (COVID-19) since 2019 (Li & Wei, 2023). Lockdown and restricted social distancing policies before vaccinations were widely applied (Chu et al., 2020; Karatayev, Anand, & Bauch, 2020; Kraemer et al., 2020; Pei, Kandula, & Shaman, 2020), which have exhibited changes of socioeconomic conditions and increased people's negative responses to usage of urban space such as public space visits and working places (Bavel et al., 2020; Grantz et al., 2020; Huang et al., 2022; Mishra et al., 2020). Such changes have exhibited challenges on monitoring and evaluating the actual usage of urban space. First, there is a lack of assessment to what extent social restrictions have influenced people's daily space use with various spatial built environment patterns. Second, the effects of social restrictions may vary among places. It highlights the necessity to explore whether different local built environments during social restriction are functionable and manageable to serve human activities. Third, whether the interactions between built environment and urban space usage change based on different spatial scales remains unclear. Examples are the assessment of urban green infrastructures that suggested higher-degree inequality at the neighborhood level (Wu, Wei, Liu, & García, 2023). It revealed the

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0264-2751/© 2024 Elsevier Ltd. All rights are reserved, including those for text and data mining, AI training, and similar technologies.

importance to further distinguish the discrepancies of urban space usage responding to the built environment between neighborhood and city level.

This study aims to fill the research gap and examine the changing association of built environment and usage of urban space due to COVID-19. We formulated the following hypotheses: 1) the social restriction could reduce people's social contact and further change the usage of urban space responding to the built environment; 2) such associations of built environment features and space use vary among different locations and spatial scales. On this basis, this study first measured daily usage of urban space using over two billion records of daily visits from a panel of opted-in mobile device across 459 U.S. cities, which were compared within periods of before COVID-19, pre-social restriction and during social restriction. Second, the spatial variations of the associations between built environment features of road network, green space, and land use and usage of urban space were estimated using a Geographically Weighted Regression (GWR) model. Third, usage of urban space was assessed based on census-block-group (CBG) level and city level separately to distinguish the effects of neighborhood environment and citywide heterogeneity. Findings could provide implications regarding whether an inequality of space usage and health resources has occurred because of potential uneven and clustered distributions of human activities in a varying-scale context.

2. Literature review

2.1. Built environment, usage of urban space, and the influence of COVID-19

Built environment is usually constructed by many elements such as roads and green space for the (re)generation of sense of community, place attachment, as well as urban land use which could provide basic services for inhabitant activities (Newman, Kosonen, & Kenworthy, 2016; Zhao, 2014). The spatial allocations of built environment features can provide multifunctional services for daily usage of urban space, contribute to the diversity of human activities, and enhance physical/social contacts among urban residents with social inclusion (Chen, Hui, Wu, Lang, & Li, 2019). Since the outbreak of COVID-19, increasing attention has been received on the drastic changes of urban space usage with different urban functions. Built environment elements such as road networks and urban green space, as well as many land uses, once providing basic amenities and public transportation to maintain daily needs, livability, and quality of local citizens' lives, have dramatically become the urban features that can affect disease transmission and further changed people's daily usage of urban space (Kwok et al., 2021; Li, Ma, & Zhang, 2021; Mouratidis & Yiannakou, 2022).

A wide range of research has been proposed to analyze such space usage changes along with the effects of built environment. The spatial features of urban road network such as density and centrality and their impacts on the spread of virus during COVID-19 have been assessed (Tang, Lin, Fan, Yu, & Lu, 2022), and a negative relationship between transportation efficiency and COVID-19 infection was revealed (Zhang, Yang, & Yang, 2021). Moreover, as the essential element in urban environment, urban green space has amplified the beneficial effects on physical and mental health (Lusseau & Baillie, 2023; Pan, Bardhan, & Jin, 2021). As social restrictions have limited residents' regular activities, the needs of urban green space for providing places for physical exercise and relaxation have increased (Ugolini et al., 2020). The exposure to urban green space was also beneficial for mental health such as stress relief and alcohol consumption decrease (Jato-Espino, Moscardó, Rodríguez, & Lázaro, 2022; Maury-Mora, Gómez-Villarino, & Varela-Martínez, 2022), emphasizing the importance of green space accessibility. In addition, land use providing various urban functions has reshaped people's contacts. The function configurations such as diversity and accessibility have played a vital role in assessing the COVID-19 prevalence (Huang, Kwan, & Kan, 2021; Yip, Huang, & Liang, 2021).

In summary, the above findings have revealed the close relationship between built environment (i.e., including road network, green space, and land use) and usage of urban space, indicating how such relationships have been changed since COVID-19. However, space-varying patterns of built environment and their changing effects to usage of urban space under the influence of COVID-19 remain unclear.

2.2. Space-varying built environment and the association with usage of urban space

The space-varying patterns of built environment and the connection with usage of urban space could be better evaluated based on two aspects. The first is the spatial distribution of built environment associated with the changing usage of urban space. Regarding such local changes, evidence suggests that high-degree complexity of road network structures exhibits great impact on traffic flows and further changes people's daily activities (Wang, Zhang, Hu, & Zhang, 2022). The heterogeneity of green space, which could distinguish the clustering and dispersal compared to green space occupation, is highly connected with green space proximity, and thus leads to the changes of green space visits and life quality (Chen et al., 2023; Sharifi, Nygaard, & Stone, 2021). Influenced by COVID-19 social restriction, the mediation effects of green space on pandemic fatigue in social distance were also identified (Wu, Lu, & Jiang, 2023). Moreover, the changing densities of urban facilities have been proved to be consistent with urban development in different areas (Xu et al., 2022), which further induced inequalities of space use in terms of resource allocations, physical activities, and mental wellbeing (Hussaini, Farhadi, Pourahmad, & Tondelli, 2023; Ramesh, McBain, Cantor, Stein, & Yu, 2023).

Another aspect is focused on the varying-spatial-scale patterns and effects of heterogeneity of built environment. One question remaining to be further addressed is whether spatiotemporal changes of urban space usage with human activities can be associated with heterogenous built environment features at different levels, such as neighborhood and city level. Specifically, the spatial variability of built environment configurations can be high among micro-level spatial units (e.g., neighborhood level). When these units are aggregated to the macro level (e.g., city level), such micro-level variability from several units can exhibit a heterogeneity of built environment. The heterogeneity of built environment at the macro level may lead to dispersed human activities and unequal space usage in multiple spatial clusters, as the proximity and quality of the access to different places can be varied within this large spatial unit (Sharifi et al., 2021). This further influences the varying usage of urban space across a region.

3. Data and methods

3.1. Study area and data

We collected the 500 largest population cities in the U.S. from the PLACES project (cdc.gov/places/) and further extracted census block groups (CBGs) that was classified as urban area classified by United States Census Bureau from 500 cities. Specifically, CBGs are clusters of census blocks in the U.S. in which each CBG contains between 250 and 550 housing units (United States Bureau of the Census, 1994). We removed cities with less than 20 selected CBGs to minimize the biases of assessing the association between built environment and usage of urban space. As a result, 459 cities with 57,185 CBGs were selected as the study area (Fig. 1, eTable 1 in the supplementary material).

Data sources were summarized in Table 1. The built environment was measured using multisource administrative and environmental data including city and CBG boundaries, road and railway networks, place data, and greenery data. The usage of urban space was quantified by the frequency of place visitation in SafeGraph Patterns data. COVID-19 Stringency Index was adopted to determine periods of social restriction during COVID-19.

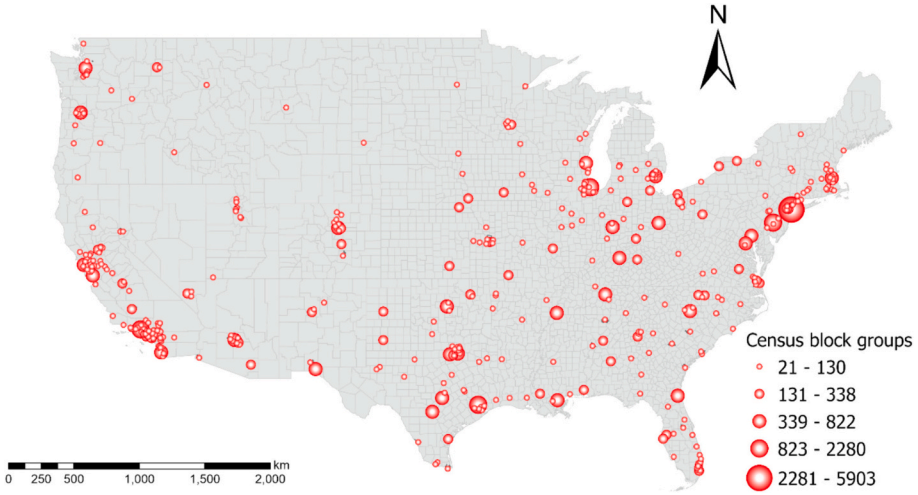


Fig. 1. Distribution of 459 U.S. cities and the number of CBGs.

Table 1
Summary of data sources for measuring built environment, usage of urban space, socioeconomics, and social restriction during COVID-19.

	Dataset	Source agency
Built environment	Cities	Centers for Disease Control and Prevention (data.cdc.gov/500-Cities-Places/500-Cities-City-Boundaries/n44h-hy2j/about_data)
	Urban area	United States Census Bureau (census.gov/cgi-bin/geo/shapefiles/index.php)
	CBGs	
	Road and railway networks	
	Place data	SafeGraph (docs.safegraph.com/docs/places)
	Greenery data	OpenStreetMap (openstreetmap.org)
Usage of urban space	SafeGraph Patterns	SafeGraph (docs.safegraph.com/docs/monthly-patterns)
Socioeconomics	Total population	United States Census Bureau (census.gov/programs-surveys/decennial-census/about/rdo/summary-files.html#P1)
	Total housing units	
COVID-19 social restriction	COVID-19 Stringency Index	Oxford Coronavirus Government Response Tracker project (ourworldindata.org/covid-stringency-index)

3.2. Measuring the usage of urban space

In this study, we collected place-based daily visit records to places in 2019 and 2020 from the SafeGraph Patterns dataset (Table 1) to measure the usage of urban space and compare the space use changes before and during COVID-19 pandemic. The usability and quality of this dataset have been assessed in the previous research (Li, Ning, Jing, & Lessani, 2024; Liang et al., 2022). Specifically, daily visits of a total number of 1,807,564 places in 459 cities were included and over two billion (n = 2,648,248,625) records of daily visits were collected to measure the usage of urban space at the CBG level and city level. We assume that the visit counts to the ith place within the jth CBG/city during the kth month are defined as $\boldsymbol{H}_{i,j}^{k} = \left\{h_{i,j}^{1}, h_{i,j}^{2} \ldots h_{i,j}^{d} \ldots h_{i,j}^{n}\right\}$ where $h_{i,j}^{d}$ indicates the visit counts to the ith place within the jth CBG on the dth day during the kth month, and n refers to the number of days during kth month. Places within the jth CBG/city are defined as $\boldsymbol{P}_j = \left\{p_j^1, p_j^2 \ldots p_j^i \ldots p_j^m\right\}$ in which p_j^i is the ith place within the jth CBG/city and m indicates the total number of places within the CBG/city. On this basis, the usage of urban spaces was quantified as the mean daily visits to places at the CBG and city level within each period, as follows:

$$HC_{j,T} = \sum_{d=1}^{nsum} \sum_{i=p_j^1}^{p_j^m} h_{i,j}^{d} \Big/ D_{sum} \tag{1}$$

where $HC_{j,T}$ refers to the mean daily visits to places within the jth CBG/city during the Tth period. D_{sum} is the total number of days.

3.3. Measurement of built environment

3.3.1. Road network

Road network features are related with the traffic volumes and activity changes. The effectiveness of capturing road distribution patterns to assess transportation-related activities has been supported in previous research (Martín, Ortega, Cuevas-Wizner, Ledda, & De Montis, 2021; Zhao, Wu, Sun, Gao, & Liu, 2016). The quantification of such characteristics varies among different spatial scales. This study applied road and railway networks from the United States Census Bureau (Table 1) to quantify three indicators of road network features.

At the CBG level, length-node ratio is defined as the ratio of road length and road nodes: $LNR_j = L_{sum,j}/N_{sum,j}$, where LNR_j is the length-node ratio within the jth CBG. $L_{sum,j}$ and $N_{sum,j}$ refer to the total length of roads (m) and the number of nodes within the jth CBG.

The other CBG-level indicator, road intersection index, is designed considering the transportation features among neighborhoods, which is defined as

$$RI_j = ND_j{}^{*}\left(1 + EN_{road,j} + EN_{rail,j}\right) \tag{2}$$

where $EN_{road,j}$ and $EN_{rail,j}$ are the edge nodes of roads and railways crossing CBG boundaries of the jth CBG. ND_j refers to the road node density which is calculated as $ND_j = N_{sum,j}/L_{sum,j}(m)$. Specifically, higher values represent higher-degree intersections with neighborhood CBGs.

The city-level indicator, length density range, is calculated as:

$$LDR_j = LD_{max,j} - LD_{min,j} \tag{3}$$

in which LDR_j refers to the length density range of the jth city. $LD_{max,j}$ and $LD_{min,j}$ represent the maximum and the minimum value of road density within the jth city. Specifically, the road density is calculated as the total road length (m) per 100-m search radius of places with daily visits, where the selection of 100-m search radius has been assessed in previous research (Owens et al., 2010). Greater length density ranges indicate higher-degree clustered road while smaller length density ranges are related to homogeneous road distribution.

3.3.2. Green space

We collected greenery data from OpenStreetMap land use layers of data to depict the spatial distribution of green space. The usability and accuracy of OpenStreetMap greenery data have been assessed in previous research (Cui, Malleson, Houlden, & Comber, 2021; Ju, Dronova, & Delclòs-Alió, 2022; Teeuwen, Milias, Bozzon, & Psyllidis, 2024). In this study, we focused on the spatial heterogeneity characteristics that could reflect the accessibility of the green space (Liu, Kwan, & Kan, 2021; Wu, Peng, Liu, Weng, & Lin, 2022). A greenery shape index was proposed to measure the CBG-level and city-level green space heterogeneity. This index was adopted from the landscape shape index which indicates diverse landscape shapes from the ideal circle landscapes (McGarigal, 1995). Similarly, the proposed greenery shape index focuses on the landscape shapes of green space, with more diverse patterns representing higher heterogeneity and exhibiting greater impacts on green space accessibility. Specifically, the greenery shape index is calculated as:

$$GSI_j = \frac{E_{sum,j}}{2*\sqrt{\pi * A_j}} \tag{4}$$

where GSI_j is the greenery shape index of the jth CBG or city. $E_{sum,j}$ refers to the total greenery boundaries and A_j indicates the area of the jth CBG or city. Greater greenery shape index values reveal high-degree green space heterogeneity.

3.3.3. Land use

The usage of urban space with socioeconomic activities is strongly associated with the spatial allocation of different land uses (Xia, Yeh, & Zhang, 2020). In this study, we used the SafeGraph place dataset to assess the spatial patterns of urban land uses (Table 1). This dataset provides locations of points of interests and the urban land use information, showing the advantages of mapping fine-spatial-scale land use as well as their diversity (Xing & Meng, 2018). In this study, a total number of 1,789,713 places were included and were further classified into five land use classes (Liu et al., 2017; Zhang, Du, & Wang, 2017), including commercial places, public services, educational places, hospitals and health cares, and businesses and industries.

The measures of CBG-level land use focused on the distribution densities, which were calculated as the number of places divided by the total CBG area (km^2). To measure the heterogeneity of land use at the city level, we adopted the Average Nearest Neighbor Index (NNI) (Cressie, 2015). NNI is quantified by the mean distance of each place and its nearest neighbor's location divided by the expected mean distance, as follows:

$$NNI_k = \frac{DO_k}{DE_k} \tag{5}$$

where DO_k refers to the mean nearest neighbor distance of the kth city, which is measured as the average distance between each place and its nearest place. DE_k represents the expected average distance which is calculated as:

$$DE_k = \frac{0.5}{\sqrt{n/A}} \tag{6}$$

in which n corresponds to the total number of places and A refers to the minimum rectangle containing all places. Specifically, the expected distance is considered as the average distance in a hypothetical random distribution. Cities with smaller NNI values indicate shorter average distance among places than the expected distance revealing that the distribution of places exhibits clustering, while greater NNI shows the land use distribution towards dispersion compared with the random distribution. As the expected average distance is based on a random distribution with the same number of places and the same total area for each city, NNI provides an effective way to quantify the degree of spatial heterogeneity and compare the relative changes among cities.

3.4. Control variables

We considered socioeconomic variables including total populations and total housing units, as well as total area as control variables. Variables were quantified using datasets from the United States Census Bureau (data sources are available in Table 1). For CBG-level analysis, CBG-level total populations, CBG-level total housing units, and individual CBG area were directly used as control variables. For city-level analysis, total populations, housing units and total area were summed by CBGs in individual cities for association analysis. One should be noted that as CBG boundaries changed between 2019 and 2020, we only considered the total population and total housing units in 2020 to reduce estimation biases.

3.5. Temporal changes of social restriction

COVID-19 Stringency Index, provided by the Oxford Coronavirus Government Response Tracker (OxCGRT) project (Hale et al., 2021), quantifies the degree of restriction of policy responses in terms of different places and urban land uses (Nivette et al., 2021). Quantified based on the project from the University of Oxford, this index could be more suitable to be fitted in the selected study area in the United States compared with other countries. This study utilized the COVID-19 Stringency Index to assess the lockdown policies during COVID-19 and divided different lockdown stages. Higher values indicate stricter responses to COVID-19 pandemic.

To identify the temporal changes of social restriction, we adopted a Detecting Breakpoints and Estimating Segments in Trend (DBEST) (Jamali, Jönsson, Eklundh, Ardö, & Seaquist, 2015) model that detected abrupt changing points of temporal Stringency Index. This algorithm could divide non-linear temporal trends into linear time periods to detect the significant temporal changes in time series analysis. Specifically, parameter breakpoints were set as 3 time periods to capture significant changes only and reduce estimation biases. Results showed that the periods from 13 Mar. 2020 to 19 Mar. 2020 as the abrupt changes of COVID-19 social restriction. According to the U.S. COVID-19 timeline, the Centers for Disease Control and Prevention recommended no gatherings of 50 or more people in the U.S. on 15 Mar. 2020. Thus, the date 14 Mar. 2020 was selected for COVID-19 stages division. Moreover, same periods in 2019 were also considered for modelling comparison. As a result, four time periods were considered as follows:

- Before COVID-19: 22 Jan. 2019–14 Mar. 2019 (2019 T1)
- Before COVID-19: 15 Mar. 2019–31 Dec. 2019 (2019 T2)
- Pre-social restriction during COVID-19: 22 Jan. 2020–14 Mar. 2020 (2020 T1)
- Social restriction during COVID-19: 15 Mar. 2020–31 Dec. 2020 (2020 T2)

3.6. Statistical analysis

The association between CBG-level and city-level built environment and usage of urban space was investigated using the GWR model. GWR model focuses on estimating the local relationships considering the spatial distribution patterns of the variables (Brunsdon, Fotheringham, & Charlton, 1998), and this model is thus suitable to assess various spatial patters of built environment and to what extent their relationships with usage of urban space changed due to the COVID-19 pandemic.

GWR model was performed in CBGs within each city separately (CBG-level analysis) and 459 cities (city-level) during 4 time periods. The features of built environment were used as independent variables and the measurement of urban space usage was the dependent variable; socioeconomic features were involved as the control variables (see Table 2). Specifically, a Box-Cox transformation, which transforms the non-normal variable into normal ones to meet the normal distribution model assumption, was used to preprocess data. To evaluation the effect

Table 2
Variables used in the GWR model.

	Variables	Measure
Independent variables	Length-node ratio	The ratio of road length and road nodes (at the CBG level) (m/per road node)
	Road intersection index	The road node density is multiplied by the number of edge nodes of roads crossing CBG boundaries (at the CBG level)
	Length density range	The data range of road density (at the city level) (m/square m)
	Greenery shape index	An index adopted from landscape shape index measuring the heterogeneity of green space (at the CBG and city level)
	Density of commercial places	For each land use class, the number of places is divided by the total CBG area (at the CBG level) (number of places/ square km)
	Density of public services	
	Density of educational places	
	Density of hospitals and health cares	
	Density of businesses and industries	
	NNI of commercial places	For each land use class, this index measures the heterogeneity of place distribution (at the city level)
	NNI of public services	
	NNI of educational places	
	NNI of hospitals and health cares	
	NNI of businesses and industries	
Control variables	Total populations	Total populations of each CBG/city (at the CBG and city level)
	Total housing units	Total housing units of each CBG/city (at the CBG and city level)
	Total area	Total area of each CBG/city (at the CBG and city level) (square m)
Dependent variable	Usage of urban space	The mean daily visits to places (at the CBG and city level) (visit times/per day)

of multicollinearity of the proposed variables and reduce estimation biases, the variance inflation factors (VIF) were quantified. A variable with VIF greater than 10 may have potential multicollinearity and would be excluded from the model. The model was implemented with Gaussian distribution and an optimal adaptive bandwidth with a bi-square kernel which assigns a weight of zero beyond the bandwidth. A leave-one-out cross validation was utilized for parameter optimization. In addition, GWR was compared with ordinary least squares (OLS) to assess the effects of spatial heterogeneity on the built environment features. Model with goodness of fit of higher values of adjusted R^2 gains better performance.

The output of GWR model exhibited independent coefficients for CBGs or cities. For the coefficients of each variable, the positive or negative coefficients indicate that one-unit increase of a built environment feature is associated with a coefficient-value-unit increase or a decline in the usage of urban space controlled by other variables.

4. Results

4.1. Descriptive statistics

The descriptive statistics of variables is listed in Table 3. The drastically decreasing activities in 2020 T2 compared with other periods (from 144.031 in 2019 T1 to 82.734 in 2020 T2 based on CBG level, and from 17,944.297 in 2019 T1 to 10,307.565 in 2020 T2 based on city level) revealed the changing responses of urban space usage under the governments' intervention.

Fig. 2 represents the changing activities across the 459 cities (details were provided in eTable 1 in the supplementary material). Based on the average values of CBG-level aggregated daily place visits calculated for each city during 4 periods, a significant reduction of urban space usage during the 2020 T2 period was revealed in most cities. The decreases of urban space usage during 2020 T2 varied from 0.25 % to 76.35 % among cities. Meanwhile, similar-degree daily activities in 2019 T1, 2019 T2 and 2020 T1 were shown, indicating that less impacts were revealed before country-scale social restriction policies even after the outbreak of COVID-19.

Table 3
Descriptive statistics of CBG-level and city-level built environment characteristics. Minimum, maximum, mean values, and standard deviation of built environment characteristics were summarized.

	Variables	CBG-level statistics				City-level statistics			
		Min.	Max.	Mean	St. Dev.	Min.	Max.	Mean	St. Dev.
Independent variables	Length-node ratio	15.449	944.505	58.619	19.705	–	–	–	–
	Road intersection index	0.000	2.971	0.465	0.242	–	–	–	–
	Length density range	–	–	–	–	8.251	28.505	15.480	3.750
	Greenery shape index	0.000	33.077	0.353	0.971	0.126	72.460	3.632	4.911
	Density of commercial places	0.000	10,096.242	47.390	150.916	–	–	–	–
	Density of public services	0.000	2691.169	13.782	37.267	–	–	–	–
	Density of educational places	0.000	336.651	3.480	11.136	–	–	–	–
	Density of hospitals and health cares	0.000	10,175.598	19.154	102.113	–	–	–	–
	Density of businesses and industries	0.000	3903.972	52.693	121.331	–	–	–	–
	NNI of commercial places	–	–	–	–	0.192	0.644	0.370	0.076
	NNI of public services	–	–	–	–	0.407	1.153	0.731	0.118
	NNI of educational places	–	–	–	–	0.405	1.738	0.958	0.212
	NNI of hospitals and health cares	–	–	–	–	0.149	0.777	0.342	0.099
	NNI of businesses and industries	–	–	–	–	0.290	0.796	0.526	0.087
Control variables	Total populations	0	13,527	1329	587	8226	3,292,243	70,146	187,358
	Total housing units	0	6170	563	260	22,274	8,022,848	165,551	450,808
	Total area	4.569E+03	2.154E+07	6.162E+05	7.223E+05	5.566E+06	9.468E+08	7.677E+07	1.124E+08
Dependent variables	Space usage (2019 T1)	0.000	61,040.769	144.031	395.178	1183.000	705,700.439	17,944.297	42,692.887
	Space usage (2019 T2)	0.027	65,713.065	147.689	416.733	1178.027	697,673.564	18,399.938	42,230.092
	Space usage (2020 T1)	0.019	65,875.679	156.631	428.855	1403.717	679,144.502	19,514.056	41,883.561
	Space usage (2020 T2)	0.024	20,804.024	82.734	188.616	514.099	289,971.260	10,307.565	19,416.652

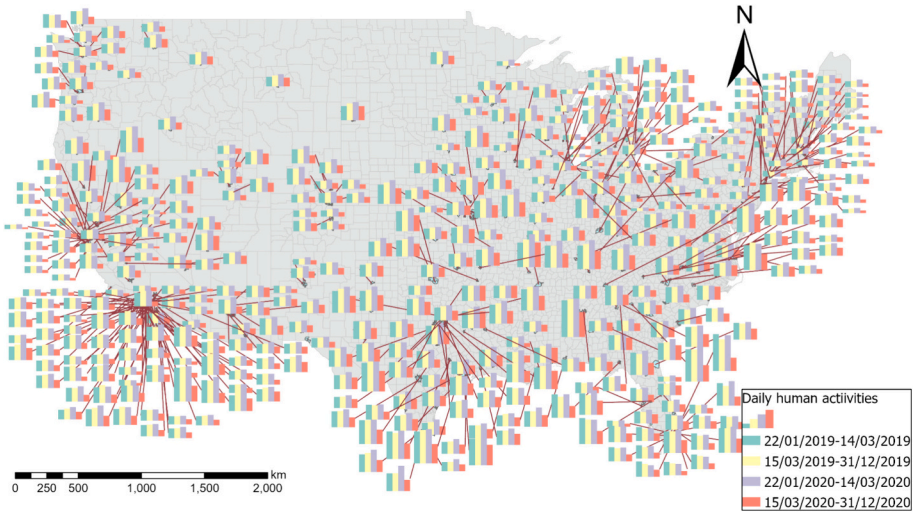


Fig. 2. Average daily CBG-level urban space usage of 4 periods among 459 U.S. cities. Bars with green, yellow, purple, and pink colors represent the urban space usage measured by daily place visits during 2019 T1, 2019 T2, 2020 T1, and 2020 T2, respectively. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

4.2. Built environment and usage of urban space at the CBG level

The changing associations of CBG-level built environment and usage of urban space during four periods was calculated as the mean coefficients of all GWR models (see Fig. 3). Compared with the results before social restriction, the coefficients exhibited significant changes during social restriction in 2020 T2. Specifically, road network features were less associated with usage of urban space since COVID-19 (coefficients of length-node ratio decreasing from −0.366 in 2019 T1 to −0.098 2020 T2; coefficients of road intersection decreasing from −0.094 in 2019 T1 to −0.058 2020 T2). That means social restriction exhibited significant impacts on reducing neighborhood social contact at the early COVID-19. The heterogeneity of green space was less associated with usage of urban space (coefficients decreasing from 0.016 to 0.013) after social restriction, showing that people were more responsive to neighborhood green space regardless of the proximity within CBGs. Moreover, decreasing correlations between CBG-level land use densities and usage of urban space were revealed, indicating less

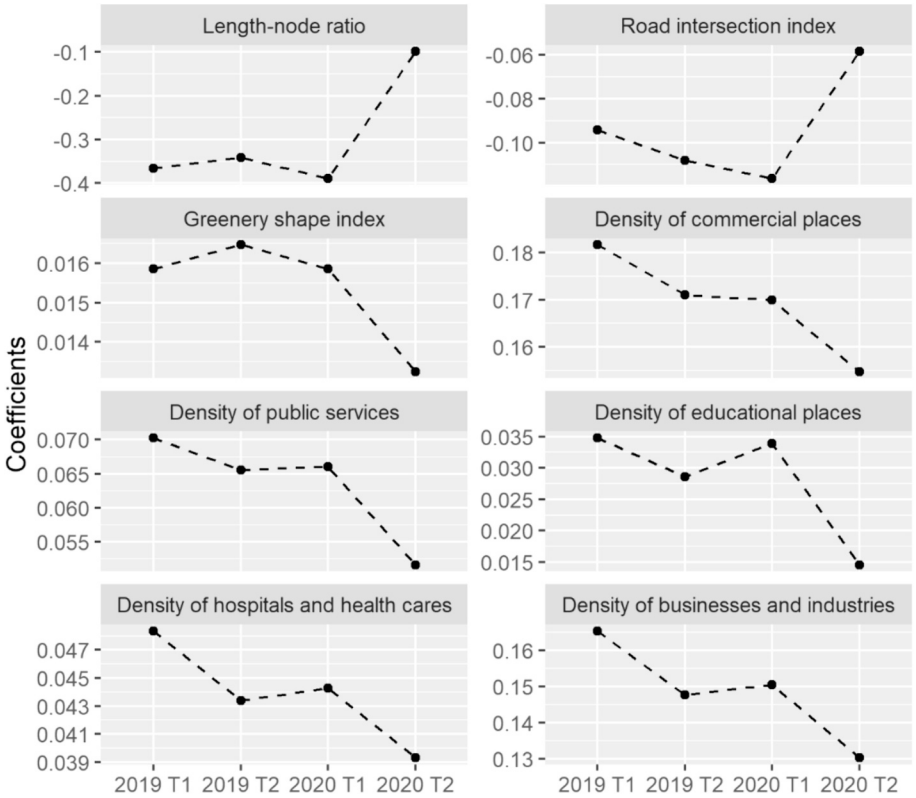


Fig. 3. Average GWR coefficients of CBG-level built environment features during 4 periods. The x-axis represents four periods including 2019 T1 and 2019 T2 and 2020 T1 and 2020 T2 during COVID-19. The y-axis represents GWR coefficients of CBG-level built environment features which were associated with the changes of usage of urban space.

attractiveness of high-density distributed urban facilities during social restriction. Such decrease trend implies the effect of stringency policies that lead to the decrease of visit frequencies during social restriction in the U.S.

We further distinguished their varying associations among individual CBGs from the coefficients of each GWR model. The significantly changing coefficients during social restriction (2020 T2) could be distinguished (see Fig. 4). High coefficients variability of road network features including length-node ratio and road intersection index in 2020 T2 were exhibited among CBGs. It could be explained by the reasons that the traffic volume could vary among the road types and classes such as primary, secondary roads, and highways (Lingras, Sharma, Osborne, & Kalyar, 2000). Moreover, the road intersection may cause both import and export of transportation among CBGs. As road types and classes could be highly varied due to urban functions among different neighborhoods, the connections of road networks between CBGs may lead to increasing mobilities in many areas while decreasing mobilities in other neighborhoods. Regarding green space, diverse associations were found with both increasing and decreasing trends between green space heterogeneity and usage of urban space. Like overall trends, the associations of land use densities and usage of urban space decreased in most CBGs. However, the densities of commercial places and public services in several CBGs exhibited increased association with usage of urban space. The potential factors including people's socioeconomic status and the spatial allocation of urban facilities may lead to such discrepancies.

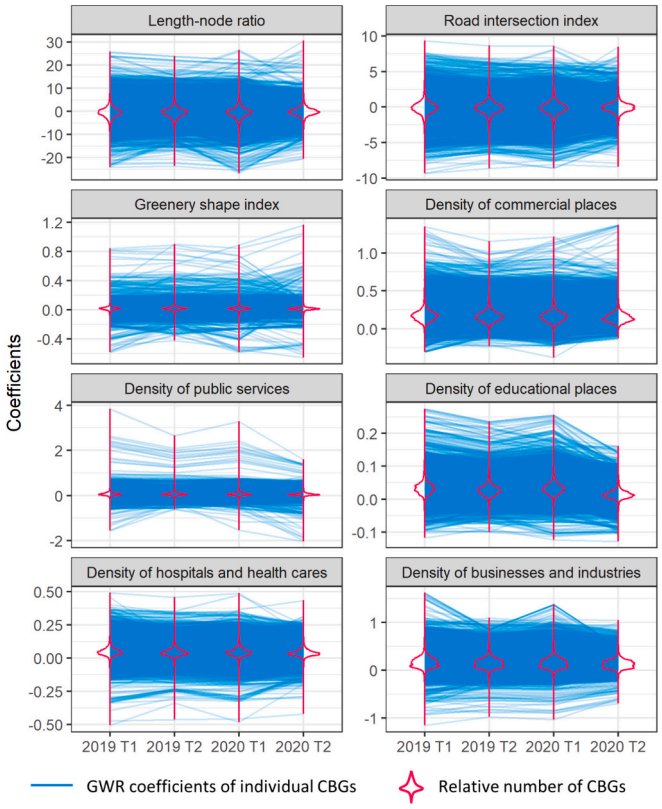


Fig. 4. GWR coefficients of CBG-level built environment features across individual CBGs. The x-axis represents 4 periods and y-axis represents GWR coefficients of CBG-level built environment features associated with usage of urban space. Each blue line represents the temporal coefficient changes from 2019 T1 to 2020 T2 of one CBG. Violin plots in red show the distribution of CBG numbers with different coefficients; larger violin width indicates more CBGs with similar coefficients. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

4.3. Built environment and usage of urban space at the city level

The mean coefficients of built environment features were calculated from all city-level GWR models (see Fig. 5). Road network heterogeneity exhibited positively increasing association with usage of urban space (coefficients increasing from 0.015 in 2019 T1 to 0.061 in 2020 T2). That means that the concerns about the accessibility to different places were increasingly influenced by social restriction during COVID-19. It provides evidence that the space use related to varying human activities could benefit more from high-density road networks with higher proximity while social contacts declined. For the city-level greenery heterogeneity, slightly decreasing associations with usage of urban space were shown during 2020 T2. It may indicate that the overall visit frequencies to green space might decline due to the policies or the reduced willingness of social contact. Regarding the heterogeneity of land use, higher NNI values of commercial places as well as hospitals and health cares were associated with less usage of urban space and such trend was increased during social restriction (coefficients of NNI of commercial places: from −0.017 to −0.026; coefficients of NNI of hospitals and health cares: from −0.014 to −0.028). That means people's daily visits were reduced with the dispersion of commercial, hospital, and health cares. In contrast, more usage of urban space was associated with the clustered distribution of those places in cities which indicates the increasing effectiveness of advanced accessibilities to attracts people during COVID-19. For the heterogeneity of public service, the increasing association of the heterogeneity with reducing usage of urban space could be explained by the people's willingness of maintaining social distance. Regarding the educational places, positive associations with usage of urban space were reported before social restriction but the association became negative during the social restrictions in 2020 T2. That means the clusters of educational facilities, which are usually connected with higher education compared with the dispersal places related to primary and secondary schools, were associated with more usage of urban space during social restriction. Additionally, the decreasing usage of urban space was found to be associated with the clustered business and industrial places during social restriction, which was consistent with the work-from-home policy in many companies to reduce social contact.

Coefficients of each built environment feature from city-level GWR models were shown in Fig. 6. While no significant changes of GWR coefficients were found before social restriction, high variability was revealed in 2020 T2 in most cities. Particularly, road network heterogeneity exhibited both positively and negatively increasing associations with usage of urban space during 2020 T2 (coefficients ranging from −0.059–0.085 in 2019 T1 to −0.086–0.208 in 2020 T2), revealing the variety of human activity responses to social restriction regarding the diversity of urban functions and road network types among cities. Similar evidence for the green space heterogeneity was also found (coefficients in 2019 T1 and 2020 T2: from −0.011 to 0.014, from −0.027 to 0.029). Specifically, cities exhibiting positively increasing associations, in which higher green space heterogeneity were linked with increasing space use, may be explained by the demands of visits in many green places to maintain physical and mental health regardless of the spatial accessibilities. Moreover, The NNI of commercial places, businesses and industries, public services, educational places, as well as hospitals and public cares exhibited increasingly positive or negative associations with usage of urban space during social restriction. It supports our hypothesis that the responses of usage of urban space to the built environment could change due to the COVID-19, and such changes may vary regarding different built environment features.

4.4. Sensitivity analysis

The GWR models assessed the spatial distribution of CBGs and cities and calculate local coefficients (as shown in Fig. 4 and Fig. 6), and thus revealed the local discrepancies in investigating built environment

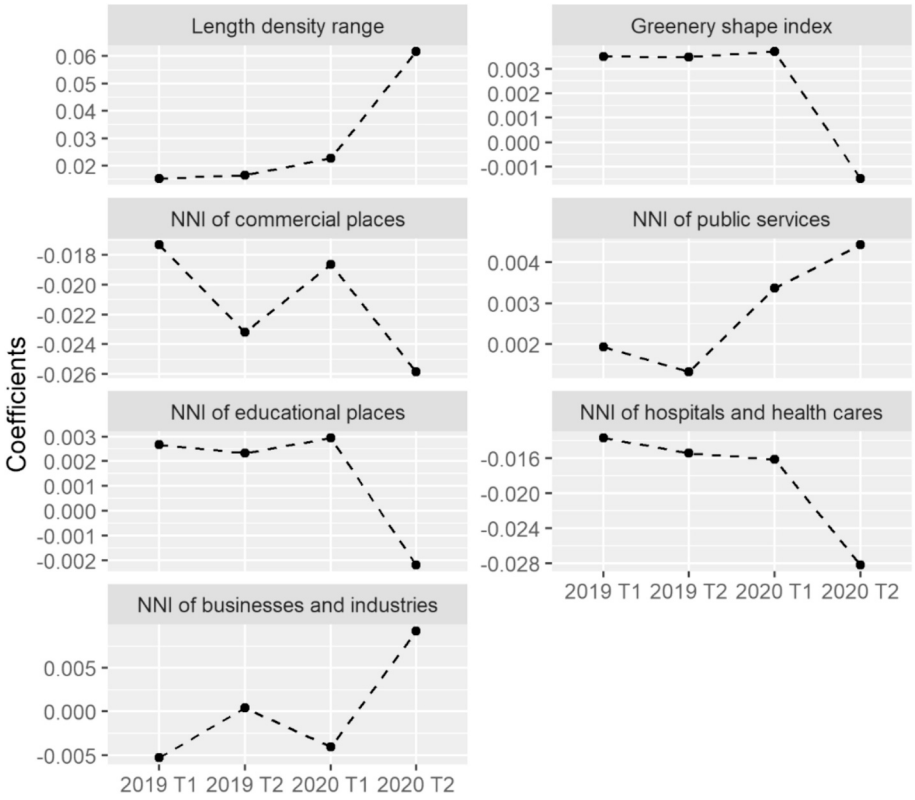


Fig. 5. Average GWR coefficients of city-level built environment features during 4 periods. The x-axis represents four periods including 2019 T1 and 2019 T2 and 2020 T1 and 2020 T2 during COVID-19. The y-axis represents GWR coefficients of city-level built environment features which were associated with the changes of usage of urban space.

features associated with usage of urban space at both CBG and city level. The OLS models were applied to compare and evaluate the performance of GWR with spatial effects. The adjusted R^2 of GWR was much higher than the adjusted R^2 of OLS during the same period (see Table 4). It revealed the better performance of GWR and highlighted the importance to analyze the local coefficients variation at the CBG and city level.

5. Discussion

This study used mobile-phone based data to assess the associations between built environment and usage of urban space in 459 cities across the U.S. Advancing from other studies, we evaluated changing benefits of both CBG-level and city-level built environment on usage of urban space due to COVID-19 social restriction. We found the overall decreasing association between CBG-level built environment features and usage of urban space during social restriction. Meanwhile, the heterogeneity of most city-level features including city-level road network, commercial, public places, as well as hospitals and health cares exhibited an overall increasing association while green space and city-level educational places showed decreasing association with usage of urban space.

Our results suggest that compared with the road network density and intersection at the CBG level, city-level road heterogeneity exhibited greater associations with the changing space use due to COVID-19 social restriction. It revealed the willingness of changing visit frequencies to places beyond neighborhood environment by changing work behaviors and routines and the travelling frequencies (Huang, Li, Jiang, Li, & Porter, 2020; Xiong et al., 2020). Moreover, as the spatial distribution of road length nodes were associated with the transportation capacities and traffic activities (Chen, Yang, Lo, & Tang, 2002), our results may reflect the fact regarding how the reduction of human activities could lead to a decline of traffic volumes below the capacity.

The heterogeneity of green space was found to be less associated with usage of urban space during social restriction at both CBG and city level. Previous studies have discussed the effectiveness of visiting green space beyond the concerns of proximity to reduce mental distress caused by COVID-19 pandemic (Larson et al., 2022; Wortzel et al., 2021), which provide suggestions for the green space design to help enhancing the effects of maintaining physical activities and mental wellbeing. On the other hand, our results revealed discrepancies of green space associated with usage of urban space within different CBGs and cities. It could be explained by the socioeconomic factors including the visit frequencies between males and females and people with varying income, and the diversity of the accessed green space types, which were discussed in previous studies (Ugolini et al., 2020).

Our results found that the land use features associated with usage of urban space varied significantly not only between CBG and city level but also within CBGs and cities. Their various effects could be explained by the socioeconomic discrepancies. For instance, the changing activities to the green space could be explained by the social and material deprivations that lead to inequal accessibilities (Burnett, Olsen, Nicholls, & Mitchell, 2021). In addition, the socioeconomic inequality has been assessed to closely linked to the varying physical distances to different urban facilities (Carvalho et al., 2020; Jay et al., 2020). The number of residents and the income variation could change the visit frequencies of public services, industries, and hospitals, as people with high-level income have more affordable ways to different places (Macedo, Lotero, Cardillo, Menezes, & Barbosa, 2022). Such discrepancies suggested the necessity to assess the urban planning and spatial allocation of current urban facilities to reasonably serve people's demands of people with varying income.

Several limitations are required to be addressed. First, the selected 459 cities only covered approximately 30 % of the nationwide urban area. Previous studies have reported that cities with more affluent area

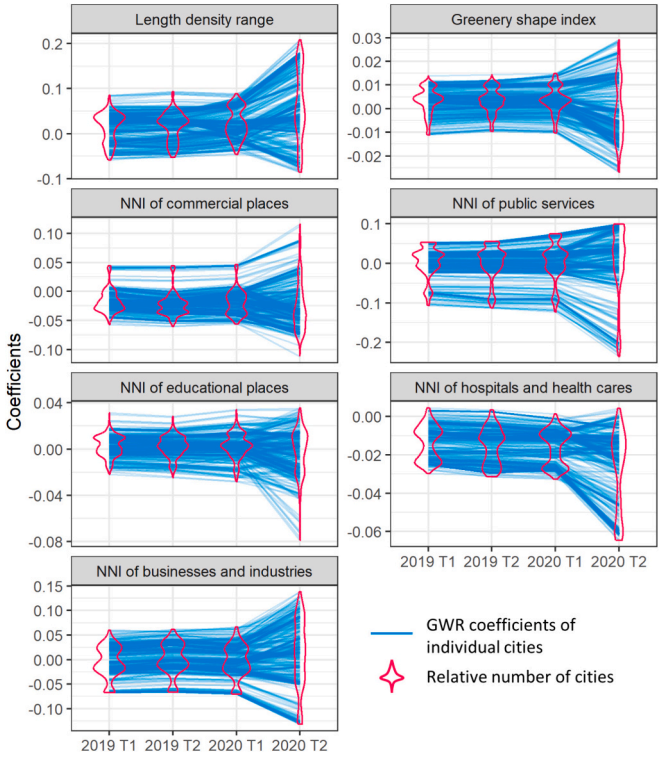


Fig. 6. GWR coefficients of city-level built environment features across individual cities. The x-axis represents 4 periods and y-axis represents GWR coefficients of city-level built environment features associated with usage of urban space. Each blue line represents the temporal coefficient changes from 2019 T1 to 2020 T2 of one city. Violin plots in red show the distribution of city numbers with different coefficients; larger violin width indicates more cities with similar coefficients. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

Table 4
Model assessment. CBG-level and city-level built environment – usage of urban space associations in four periods modeled by OLS and GWR were evaluated with adj. R^2.

	Time periods	OLS adj. R^2	GWR adj. R^2
CBG-level analysis	22 Jan. 2019–14 Mar. 2019	0.603	0.810
	15 Mar. 2019–31 Dec. 2019	0.595	0.815
	22 Jan. 2020–14 Mar. 2020	0.614	0.804
	15 Mar. 2020–31 Dec. 2020	0.586	0.809
City-level analysis	22 Jan. 2019–14 Mar. 2019	0.824	0.910
	15 Mar. 2019–31 Dec. 2019	0.833	0.907
	22 Jan. 2020–14 Mar. 2020	0.844	0.914
	15 Mar. 2020–31 Dec. 2020	0.852	0.925

and multi-functional urban facilities are closely associated with more human activities and usage of urban space (Lang et al., 2022; Tu et al., 2022). Thus, as the largest population cities in the U.S., the built environment features within those large cities could be measured and assessed with less biases. To keep such assessment accuracy, we also removed cities with less than 20 CBGs during the city selection. Second, COVID-19 Stringency Index, which only measured country-level lockdown conditions, may ignore the temporal inconsistency and the degree of stringency of the proposed social restriction policies in different cities. For instance, all non-essential construction sites were required to be shut down from 28 Mar. 2020 in New York City, while Houston government responded non-essential business work from home and limited the number of staff (50 %) in building from 20 Mar. 2020. Future studies should consider different periods of lockdown and social restrictions based on local policies of individual cities. Moreover, although this study has adopted total population, total housing units, and total area of cities and CBGs as control variables, the spatial coherence between the neighborhood deprivation (e.g., income) and local coefficients of built environment features, as we have discussed above, were not taken into consideration. City types, sizes and socioeconomics should be taken into consideration to deeply understand the varying associations between built environment and usage of urban space. We also suggest addressing CBG-level income condition and city-level GDP per capita in explaining the varying usage of urban space in futures studies.

6. Conclusion

This study evaluated the changing associations between built environment and usage of urban space due to the COVID-19 pandemic. We found different findings based on varying spatial-level analysis. While built environment at the CBG level including road length-node ratio, road intersection index and land use densities exhibited decreasing associations, the heterogeneity of road network, commercial, public places, as well as hospitals and health cares at the city level exhibited stronger relationship with the usage of urban space during COVID-19 social restriction. Meanwhile, both CBG-level and city-level green space heterogeneity showed less associations with usage of urban space during COVID-19. This indicated the changing connection between multi-spatial built environment configurations and usage of urban space and revealed the potential impact of social restriction during COVID-19. Findings could provide suggestions on evaluating how human activities responding to urban functions and amenities were reshaped during the post pandemic stage.

CRediT authorship contribution statement

Yuan Meng: Writing – review & editing, Writing – original draft, Software, Methodology, Conceptualization. **Hung Chak Ho:** Writing – review & editing, Supervision. **Man Sing Wong:** Writing – review & editing, Supervision, Resources, 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.

Data availability

Other datasets generated during and/or analyzed during the current study are available from the corresponding author on reasonable request.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.cities.2024.105205.

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