Since January 2020 Elsevier has created a COVID-19 resource centre with free information in English and Mandarin on the novel coronavirus COVID-19. The COVID-19 resource centre is hosted on Elsevier Connect, the company's public news and information website.

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The impacts of the built environment on the incidence rate of COVID-19: A case study of King County, Washington

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ABSTRACT

With COVID-19 prevalent worldwide, current studies have focused on the factors influencing the epidemic. In particular, the built environment deserves immediate attention to produce place-specific strategies to prevent the further spread of coronavirus. This research assessed the impact of the built environment on the incidence rate in King County, US and explored methods of researching infectious diseases in urban areas. Using principal component analysis and the Pearson correlation coefficient to process the data, we built multiple linear regression and geographically weighted regression models at the ZIP code scale. Results indicated that although socioeconomic indicators were the primary factors influencing COVID-19, the built environment affected COVID-19 cases from different aspects. Built environment density was positively associated with incidence rates. Specifically, increased open space was conducive to reducing incidence rates. Within each community, overcrowded households led to an increase in incidence rates. This study confirmed previous research into the importance of socioeconomic variables and extended the discussion on spatial and temporal variation in the impacts of urban density on the spread of COVID, effectively guiding sustainable urban development.

1. Introduction

COVID-19 (coronavirus disease 2019) is caused by SARS-CoV-2 and has rapidly spread across the world following its initial outbreak in December 2019, in Wuhan, China (Cascella, Rajnik, Cuomo, Dulebohn & Di Napoli, 2020). One year later, 62,662,181 confirmed cases of COVID-19 and 1460,223 deaths, had been reported globally (WHO, 2020). Predominantly spread from person-to-person (Cascella et al., 2020), COVID-19 has intensified problems in the urban environment, which might have previously been ignored by city planners (Hamidi, Sabouri & Ewing, 2020b). Reviewing the development of urban planning, there is a clear link between new planning theories and public health issues, particularly when major epidemics occur (Corburn, 2004). However, the impact of the built environment on emerging contagious diseases has rarely been studied (Alirol, Getaz, Stoll, Chappuis & Loutan, 2011; Carozzi & Felipe, 2020; Hamidi et al., 2020b). As COVID-19 continues to attract worldwide attention, determining the impact of the built environment on COVID-19 cases has become a research priority (Megahed & Ghoneim, 2020).

Researchers have examined the spatial-temporal variations of COVID-19 in different contexts (Gao, Rao, Kang, Liang & Kruse, 2020; Huang, Liu & Ding, 2020; Peng, Wang, Liu & Wu, 2020). The main focus of these studies has been on socioeconomic and meteorological indicators. However, there is a lack of detailed research into the influence of the built environment, which is vital for informing prevention and control efforts in urban areas (Peng et al., 2020). Several studies have identified socioeconomic indicators as key factors shaping patterns of COVID-19 cases and deaths (Almagro & Orane-Hutchinson, 2020; Coccia, 2020; Sannigrahi, Pilla, Basu, Basu & Molter, 2020; You, Wu & Guo, 2020). In Europe, income was found to strongly regulate COVID-19 cases (Sannigrahi et al., 2020). Occupation was also crucial in explaining infection risk. Research in Italy and the United States, showed that workers with a high degree of human interaction were more likely to be exposed to the virus (Almagro & Orane-Hutchinson, 2020; Barbieri, Basso & Scicchitano, 2020). Moreover, migration factors have been strongly correlated with COVID-19 deaths, and countries with high volumes of airline passenger traffic were associated with increased numbers of COVID-19 cases (Oztig & Askin, 2020). Additionally, the

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racial difference is obvious in the earlier stage of transmission, and household overcrowding may accelerate the rate of spread within neighborhoods (Almagro & Orane-Hutchinson, 2020; Chen & Krieger, 2021). Additional studies have foregrounded meteorological factors (Ahmadi, Sharifi, Dorosti, Jafarzadeh Ghoushchi & Ghanbari, 2020; Bashir et al., 2020a; Shahzad et al., 2020; Xie & Zhu, 2020). Temperature was significantly correlated with COVID-19 in areas with higher incidence rates in China (Shahzad et al., 2020; Xie & Zhu, 2020). In addition, air quality was strongly associated with infection cases (Bashir et al., 2020b; Coccia, 2020). Moreover, low wind speeds may exacerbate the impact of air quality on disease transmission (Coccia, 2020), since cases in areas with low wind speeds were noteworthy (Ahmadi et al., 2020). Although researchers have observed the importance of urban density in spreading virus (Almagro & Orane-Hutchinson, 2020; Carozzi & Felipe, 2020; Hamidi et al., 2020b), few studies have examined the association between the built environment and COVID-19 cases.

Observing a lack of COVID-19 studies related to the built environment, it is vital to examine the driving factors in urban settings through effective methods. Recent studies referring to the built environment are summarized in Table 1, to better position the present study. These articles include regions in North America, East Asia, and Europe, and reflect geographical diversity and a commonality of attributes. In North America, researchers have largely chosen the US as a study area, considering the significant number of infections and the accessibility of data (Carozzi & Felipe, 2020). At present, the research scale is largely nationwide, exploring issues from macro perspectives. Several studies focus on areas such as metropolitan counties and major cities (Hamidi, Ewing & Sabouri, 2020a). However, research at the meso and micro scales remains scarce, requiring greater focus on urban areas at the county level. In the built environment, population density, activity density (population and employment per square mile), ICU beds, room occupancy, and urgent care facilities are selected as influential factors in the research. The findings show that density-related factors have a critical role in producing higher incidence rates (Andersen, Harden, Sugg, Runkle & Lundquist, 2021). However, there is a lack attention to factors related to spatial density, such as building concentration, road networks, point of interest (POI) distribution, and land use intensity, which are essential for guiding sustainable development in cities. In East Asia, the study area largely comprises China and its surrounding regions, and researchers typically use cities as examples (Li, Peng, He, Wang & Feng, 2021; Yip, Huang & Liang, 2021). In addition to population density, built-environment attributes include POIs, housing size, building density, and distance. The main findings indicate that POIs such as public transportation, clinics and commercial services, are more likely to influence COVID-19 infections (Li, Ma & Zhang, 2021). In Europe, few studies are committed to analyzing attributes in the built environment. Most research discusses socioeconomic determinants and connections between cities (Ghosh, Nundy, Ghosh & Mallick, 2020). In general, these studies provide evidence that the built environment affects COVID-19 infections in different regions. However, analysis of built-environment

Table 1
Recent articles referring to the impacts of the built environment on COVID-19.

Source	Built environment attributes	Analysis method	Study area	Major findings
Carozzi & Felipe, 2020	Population density, earthquake risk, aquifer presence, soil drainage quality	Empirical analysis, ordinary least squares (OLS), Instrumental Variable (IV)	The contiguous United States	Density influenced the timing of the outbreak in each county. Denser areas were more likely to have an early outbreak.
Hamidi et al., 2020a	Metropolitan population, activity density (population plus employment per square mile), ICU beds per 10,000 population	Multi-level linear model	1165 metropolitan counties in the USA	Large metropolitan size led to significantly higher COVID-19 incidence rates and higher mortality rates.
Ghosh et al., 2020	Population density, distance from London	Pearson, Kendall, and Spearman rank correlation tests	London, UK	The distance from the UK epicenter (London) increased, the number of COVID-19 cases decreased. Necessary measures to control transmission in cities were discussed.
Andersen et al., 2021	Occupants per room, population density, Urgent Care Facilities	Cluster analysis, three-stage regression	The US	Several of the highly-likely case clusters were associated with outbreaks in high-density locales, such as correctional facilities and meat-packing plants.
Li, Ma & Zhang, 2021	Between centrality, POI density around railway stations, population density	Mixed geographically weighted regression model (MGWR)	At city level in China	POI density around railway stations, travel time by public transport to activity centers, and the number of flights from Hubei Province were associated with the spread.
Hu, Roberts, Azevedo & Milner, 2021	Housing (average household size, residence length, car-less households)	Multi-variable regression models	Washington, DC	Housing quality, living conditions, race and occupation were strongly correlated with the COVID-19 death count. Combined built and social environment variables were the most significant predictors of COVID-19 death counts. Among these variables, crowding ratio had the most significant influence, followed by work commute time and Black American ratio.
Kim, 2021	Ratio of semi-basement households, impervious area ratio, number of disaster risk facilities with a grade of D or lower, population density	Exploratory spatial data analysis and spatial regression	225 spatial units in South Korea	New infectious diseases differed from other infectious diseases related to the ecological environment.
Li, Peng, He, Wang & Feng, 2021	Commercial prosperity, medical services, transportation infrastructure, POIs, building density, housing price	Density-based clustering algorithm, structural equation modeling (SEM)	Urban district of Huangzhou in the city of Huanggang, China	Commercial vitality and transportation infrastructure directly and indirectly influenced the number of confirmed cases in an infectious cluster, indicating that10should implement sufficient measures and adopt effective interventions in areas with a high probability of crowded residents.
Yip et al., 2021	Household size, public housing area, number of clinics (restaurants, public markets and massive transit rail entrances), median value of the shortest distance between clinics (restaurants, public markets and MTR entrances) and residential buildings	Survival analysis, ordinary least squares analysis, and count data analysis	Hong Kong, China	Before social distancing measures: clinics and restaurants were more likely to influence the prevalence of COVID-19. During social distancing measures: public transportation (i.e., MTR), public markets, and clinics influenced COVID-19 prevalence.

attributes is limited, and research into spatial density from meso and micro perspectives is lacking. To address the research gap, we further explored the influence of the built environment on COVID-19 by focusing on density-related factors, including population density, POI distribution, building concentration, housing and land use intensity.

Similar research has employed several methods to assess the factors influencing infectious diseases. These approaches fall into two categories. The firsts comprises traditional statistical approaches, including principal component analysis or factor analysis (Santosi, Fisbergi, Marchionii, Baltarii & Castroi, 2019) and single or multiple regression (Almagro & Orane-Hutchinson, 2020; Hamidi et al., 2020a; Shahzad et al., 2020; Xie & Zhu, 2020). The second category consists of spatial statistical methods, including spatial regression models (SRMs), such as the spatial lag model (SLM) (Sannigrahi et al., 2020), spatial

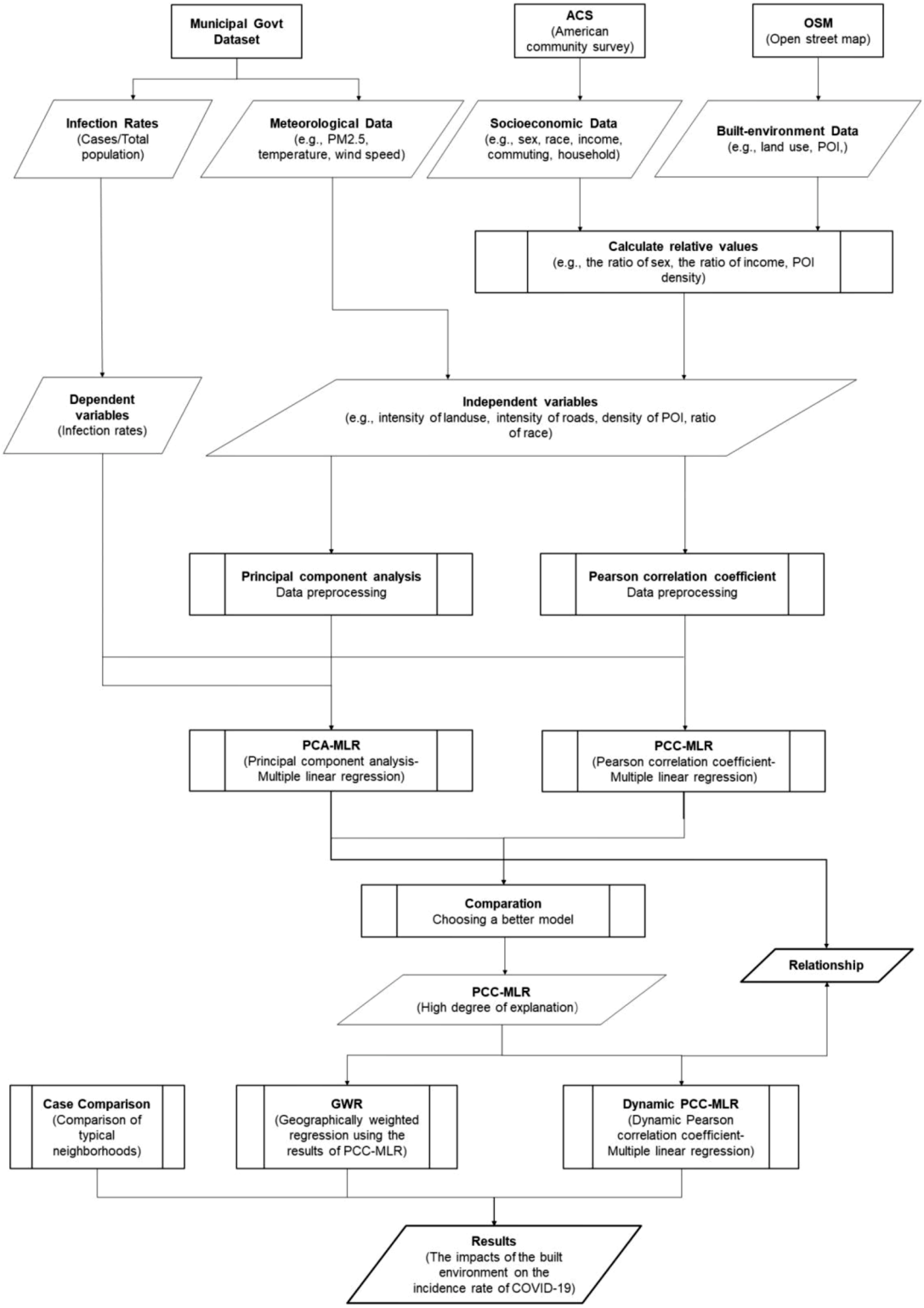

Fig. 1. Research flowchart.

error model (SEM) (Sannigrahi et al., 2020), and geographically weighted regression (GWR) (Liu et al., 2020; Sannigrahi et al., 2020). In urban and environmental research, multivariate statistical methods effectively classify samples and identify key sources by drawing meaningful information from large datasets (Gu et al., 2012; Meng et al., 2018). A typical application of multivariate statistical methods in environmental issues is land use regression (LUR). The LUR model, which was first created to map variations in intra-urban air pollution in the SAVIAH project (Briggs et al., 1997), has been widely used in epidemiological studies for the past decade (Briggs, 2005). In different settings, including Europe (Eeftens et al., 2012; Rivera et al., 2012), North America (Ross, Jerrett, Ito, Tempalski & Thurston, 2007; Su et al., 2008), Japan and China (Liu, Henderson, Wang, Yang & Peng, 2016; Wu et al., 2015), LUR has proved to be a robust technique for predicting concentrations of air pollutants (Jerrett et al., 2005) and could be extended to the study of airborne epidemics. Since traditional statistical methods neglect spatial autocorrelation among variables (Liu et al., 2020; Wu, Chen, Han, Ke & Liu, 2020), spatial statistical methods were introduced in this study to visualize the results of the multiple linear regression (MLR) models.

To address the gap in urban infectious disease research, the main purpose of this study is to identify the determinants of COVID-19 cases in King County, Washington. Since there is little research investigating the impact of built-environment factors on COVID-19, this paper provides preliminary conclusions regarding the association between the built environment and the transmission of infection. It also explores methods of researching infectious diseases in urban areas, and the methods employed in King County could be applied to other areas around the world. This is conducive to formulating effective response policies and the coherent distribution of urban resources (Coccia, 2020; Gössling, Scott & Hall, 2020; Honey-Rosés et al., 2020; Mehta, 2020).

This paper is organized as follows. Section 2 introduces the methodology used to build the models, including study area, data preparation, model setting and statistical analysis. Section 3 describes the results of each model. Sections 4 and 5 present the discussions and conclusions.

2. Methodology

Fig. 1 shows the study flow: choosing King County, Washington as the study area, we collected data at the ZIP code level from municipal government datasets. The dependent variable was the incidence rate per 1000 at the ZIP code scale. Socioeconomic, built environment, and meteorological data were selected as independent variables. Using principal component analysis (PCA) and the Pearson correlation coefficient (PCC) to process the independent variables, we built two models: a principal component analysis multiple linear regression (PCA-MLR) model and a Pearson correlation coefficient multiple linear regression (PCC-MLR). By comparing the results of the PCA-MLR and the PCC-MLR, we observed that the PCC-MLR obtained a high degree of explanation. Based on the results of the PCC-MLR, we built dynamic PCC-MLR and geographically weighted regression (GWR) models to visually describe temporal and spatial distributions in the results. Moreover, typical neighborhoods were selected for case comparison. Finally, we got the conclusion of the impacts of the built environment on the incidence rate of COVID-19 by combining all the results. Data cleaning and modeling were completed using statistical packages (SPSS, Tableau). We employed geographic information system (GIS) to analyze and visualize the results.

2.1. Study area

King County was selected as the study area for two reasons: firstly, King County is the most populous county in the state of Washington and a major metropolitan area representative of the US in general. Secondly, the coherence and uniformity of King County`s COVID-19 policy has stabilized the prevention and control of the epidemic, which is advantageous for analyzing spatial variation in a specific period. As shown in Fig. 2, King County is located in the US state of Washington. It is the largest county in Washington by population and the 12th most populous in the United States. In the 2018 census, the total population was 1,931,249. King County is also included in the Seattle-Tacoma-Bellevue metropolitan statistical area (including Snohomish County to the north and Pierce County to the south). The total land area of the study is 5480 km^2. Average population density is 352 per km^2. Median household and family incomes are $68,065 and $87,010 respectively. The study area includes 85 zip codes, covering 35 cities and four towns, including the largest city in the state of Washington—Seattle.

2.2. Model setting

2.2.1. Dependent variable

The dependent variable is the incidence rate per 1000. Incidence rate (or infection rate) is used to describe the probability or risk of an infection occurring in a defined population within a specific period (Haley, Culver, White, Morgan & Emori, 1985). We collected a cumulative number of infections at the ZIP code level from February 28, 2020 to October 5, 2020, from King County department of public health. To calculate the rate of infection, we divided the number of infection cases by the population at risk. Using 2018 population data from the American Community Survey (ACS, 2018), we calculated the incidence rate for each ZIP code per 1000. The normal distribution test was conducted by QQ plot in SPSS. Extreme cases were removed to filter outliers. Finally, 74 samples were selected to construct the model.

2.2.2. Independent variables

The independent variables used to build the PCA-MLR and PCC-MLR models may be categorized into three groups: socioeconomic indices, built environment indices, and meteorological indices. Socioeconomic indices included sex, age, race, commuting, income, room occupancy, and house structure. These were collected from the American Community Survey (ACS, 2018) and represent categories 1–7 in Table 2. By dividing the indices by the total population and the household number, we obtained the percentage for each index. Built-environment indices included land use (residential, industrial, open space, park, recreation ground, retail, and forest), population density, road networks, building concentration, and common POI data (catering, entertainment, hotel, medical, office, and culture). Built environment indices were obtained at the ZIP code level and represent categories 8–9 in Table 2. Meteorological indices included particulate matter (PM2.5), ambient temperature, room temperature, and wind speed, all of which were obtained from station reports in the Department of Ecology, State of Washington and represent category 10 in Table 2. The indices were subsequently georeferenced using GIS software to perform inverse distance weighted (IDW) analyses for the average values in each ZIP code. The variables are shown in Table 2.

2.2.3. Data processing

This study used PCA and the PCC to separate key variables and solve multicollinearity. PCA reduces sample dimensions of by converting the original variables into a comprehensive group of independent variables. This procedure is useful for extracting key information from multiple variables (Meng et al., 2018). Furthermore, the PCC is an effective method of measuring the degree of linear correlation between variables (Ahmadi et al., 2020).

For the PCA-MLR model, we applied PCA to three separate groups. For socioeconomic indices in categories 1–7, we obtained eight new components using PCA, abbreviated as factors 1–8 for analysis 1. For built environment indices from categories 8–9, we derived four new components, abbreviated as factors 1–4 for analysis 2. For meteorological indices in category 10, we acquired two new components, abbreviated as factors 1–2 for analysis 3. For clarity, each factor was renamed

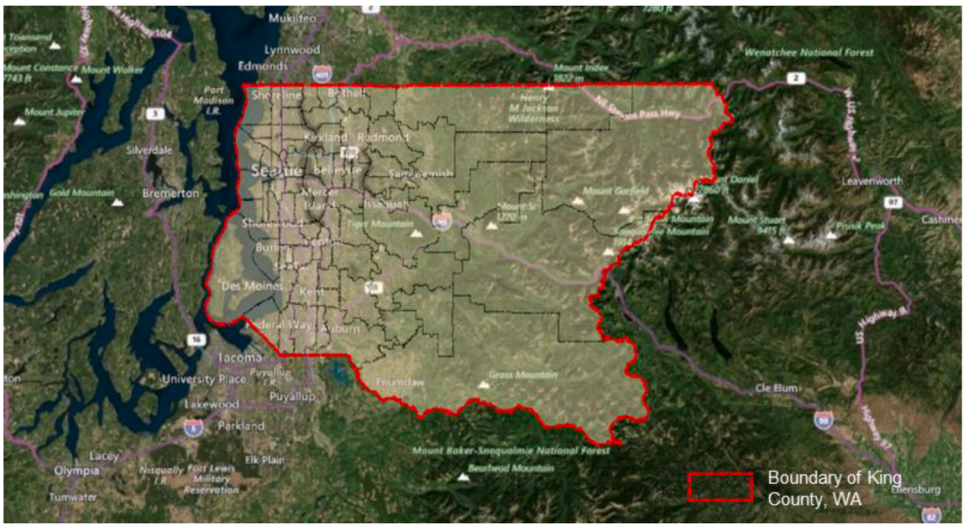

Fig. 2. Study area of King County, WA.

Table 2
A list of the variables used in the study.

Category	Name	Source	Description	Variables
1	**Sex**	ACS 2018 (American community survey in 2018)	Records of sex divided by population at ZIP code level	male_rate, female_rate, married_rate, male_household_rate, female_household_rate, nonfamily_alone_rate, nonfamily_notalone_rate
2	**Age**		Records of age divided by population at ZIP code level	0–17_rate, 18–65_rate, over65_rate, male_0–17_rate, female_0–17_rate, male_18–65_rate, female_18–65_rate, male_over65_rate, female_over65_rate
3	**Race**		Records of race divided by population at ZIP code level	white_rate, Black_Afican_rate, American_indian_Alaska_rate, Asian_rate, Hawaiian_Pacific_rate, other_rate, two_more_rate
4	**Commuting**		Records of commuting divided by the number of commuters at ZIP code level	drive_alone_rate, carpooled_rate, public_transportation_rate, walked_bicycle_motorcycle_home_rate
5	**Income**		Records of income divided by households at ZIP code level	less_than_15,000_rate, 15,000–35,000_rate, 35,000–100,000_rate, 100,000–200,000_rate, more_than_200,000_rate
6	**Bedroom**		Records of bedrooms divided by house units at ZIP code level	no_bedroom_rate, 1_bedroom_rate, 2_bedrooms_rate, 3_bedrooms_rate, 4_bedrooms_rate, 5_or_more_bedrooms_rate, 1_room_rate, 2_rooms_rate, 3_more_rooms_rate, less_than_1_occupant_rate, 1–2_occupants_rate, 2_more_occupants_rate, complete_plumbing_rate, not_complete_plumbing_rate
7	**House Structure**		Records of structure divided by house units at ZIP code level	attached_rate, detached_rate, 2_units_rate, 3_or_4_units_rate, 5_to_9_units_rate, 10_to_19_units_rate, 20_to_49_units_rate, 50_more_units_rate, mobile_rate, 2000later_rate, 1980–1999_rate, 1960–1979_rate, 1959_earlier_rate
8	**Land Use**	OSM (Open Street Map)	Ratio of land use area at ZIP code level	farm_rate, forest_rate, grass_rate, heath_rate, industrial_rate, meadow_rate, military_rate, nature_reserve_rate, orchard_rate, park_rate, quarry_rate, recreation_ground_rate, residential_rate, retail_rate, scrub_rate, building_density, road_density, population_density
9	**POI**		Ratio of POIs at ZIP code level	catering_rate, entertainment_rate, hotel_rate, medical_rate, education_rate, office_rate, culture_rate, open_space_rate, selling_rate, transportation_rate
10	**Meteorology**	Department of Ecology, State of Washington	Annual averages at ZIP code level	PM2.5, wind speed, ambient temperature, room temperature

in parentheses according to its components. Finally, the initial 92 variables were reduced to 14 components, as shown in Table 3. Detailed information about the components is shown in Tables S1~S3.

For the PCC-MLR model, we analyzed variable correlation to prevent multicollinearity. If the PCC value was greater than 0.7, the variables were considered to be strongly correlated and only one of the compared variables was retained. Scatter plots were created for each variable, and the most representative variables in each category were selected to build the model. After filtering, 46 variables were chosen for the final model. The selected variables are shown in Table 3.

2.3. Statistical analysis

To determine the independent variables that significantly impact the dependent variables, we employed forward stepwise multiple regression. To obtain the optimal model, in which all variables are significant for the dependent variables, the variables were added individually. Each time a new variable was introduced, an F-test was conducted, and t-tests were carried out for each of the previously added variables. Variables that were no longer significant after introducing a subsequent variable were eliminated. This process was repeated until no significant variables remained for model selection and all the insignificant independent variables had been removed from the regression equation (Crowley, Khoury, Urbina, Ippisch & Kimball, 2011; Yi, Zhang, Xu & Xi, 2003). The adjusted R-squared and residuals were analyzed to evaluate the suitability of fit, and the function of incidence rate and land use factors was determined. In addition, a simple spatial regression model was used to initially visualize the spatial distribution of the variables. In this study, the GWR model was selected to construct the spatial model. All data and spatial analyses were completed using ArcGIS, GWR4.0 and SPSS packages.

Table 3
Selected variables.

Category	Name	PCA-MLR components	PCC-MLR selected variables
1	**Sex**	factor 1 of analysis 1 (Integration), factor 2 of analysis 1 (Income), factor 3 of analysis 1 (House structure attached), factor 4 of analysis 1 (Building age), factor 5 of analysis 1 (Minority), factor 6 of analysis 1 (House structure), factor 7 of analysis 1 (Age over 65), factor 8 of analysis 1 (Mobile house)	nonfamily_alone_rate, married_rate
2	**Age**		over65_rate
3	**Race**		Black_Afican_rate, American_indian_Alaska_rate, Asian_rate, Hawaiian_Pacific_rate, two_more_rate
4	**Commuting**		carpooled_rate
5	**Income**		less_than_15,000_rate, 100,000—200,000_rate, more_than_200,000_rate
6	**Bedroom**		2_bedrooms_rate, 3_bedrooms_rate, 5_or_more_bedrooms_rate, 2_more_occupants_rate,
7	**House Structure**		attached_rate, 2_units_rate, 3_or_4_units_rate, 5_to_9_units_rate, 10_to_19_units_rate, mobile_rate, 2000later_rate, 1980–1999_rate
8	**Land Use**	factor 1 of analysis 2 (POI density), factor 2 of analysis 2 (Built-up density), factor 3 of analysis 2 (Residential land use), factor 4 of analysis 2 (Industrial land use)	industrial_rate, meadow_rate, park_rate, recreation_ground_rate, residential_rate, retail_rate, building_density, road_density, population_density
9	**POI**		catering_rate, entertainment_rate, hotel_rate, medical_rate, education_rate, office_rate, culture_rate, open_space_rate, selling_rate, transportation_rate
10	**Meteorology**	factor 1 of analysis 3 (Integration), factor 2 of analysis 3 (Room temperature)	PM2.5, Wind speed, Ambient temperature, Room temperature

3. Results

3.1. COVID-19 temporal-spatial distribution

According to King County`s COVID-19 data dashboard, 23,149 positive cases had been recorded by October 5, 2020, and the average incidence rate was 1.04%. Fig. 3 shows the daily number of positive counts of COVID-19 in King County. The maximum number of daily infections exceeded 200 per day during April and June. The average number of daily positive counts was 126 per day. Between February 28, 2020 and October 5, 2020, the number of infections increased steadily. A heat map of incidence rates (Fig. 4) indicates that the highest incidence rates occurred in the western area of King County, notably the southwest region where the city of Seattle is located. Incidence rates were generally lower in suburban areas, indicating that high density urban environments may have an impact on incidence rates.

3.2. PCA-MLR model results

As shown in Table 4, five factors were included in the final model, and the adjusted R-squared was 0.816. Of all the indicators selected, factor 2 of analysis 1 was the primary influencing marker. Comparing the PCA factors with the original indicators, we found that factor 2 of analysis 1 largely explained income composition, as shown in Tables S1 and S2 (see appendix). The second indicator in the model was factor 5 of analysis 1, which typically represented race. Factor 1 of analysis 2 was the third marker and largely included POI information density. Factor 6 of analysis 1 was the fourth indicator and was significantly associated with building age. Finally, factor 1 of analysis 1 largely represented socioeconomic indices.

3.3. PCC-MLR model results

Seven influencing factors were finally entered into the LUR in the PCC-MLR model. These included income, race, room occupancy, POIs, meteorology and land use (Table 5). The adjusted R-squared was 0.779. The two most influential factors explained 76% of the variation and were related to race, notably Black and African American and American Indian and Alaska Native. These two variables showed relatively strong correlations with incidence rates. The third indicator in the model was two or more occupants per room, which explained 9% of the variation and was positively correlated with incidence rates. Recreational land use (open green space for general recreation, which may include pitches, nets and so on, usually municipal but possibly also private to colleges or companies) was the fourth influential factor and demonstrated a significant negative correlation with incidence rates. As the ratio of recreation ground increased, the incidence rate declined. This suggests that open green spaces help slow the spread of the virus. The fifth indicator was office POI, followed by incomes between $100,000 and $200,000 and PM2.5. The incidence rate declined among groups with incomes between $100,000 and $200,000. This implies that high-income households are better able to avoid contact with disease sources. And the indicators of office POI and PM2.5 showed positive correlations with incidence rates.

3.4. Dynamic PCC-MLR model

Based on the PCC-MLR model, we added time as a factor (abbreviated to t). Using one month as the basic unit, we defined t as a time series of COVID-19 ($t = 1$, when the first case of COVID-19 occurred, $t = t + 1$, after the first case of infection occurred). The remaining independent variables were unchanged, and an incidence rate of 1000 people per month was used as the dependent variable to build a dynamic model. Following data screening, a total of 596 samples were selected for the model construction.

Ten influencing factors were entered into the dynamic PCC-MLR model, including income, time, family characteristics, race, room occupancy, land use and building structure (Table 6). The adjusted R-squared was 0.434. The first and third influencing factors were income-related, representing groups with incomes above $100,000, and explained 63% of the variation. Both variables showed negative correlations with incidence rates. Time was the second indicator, which

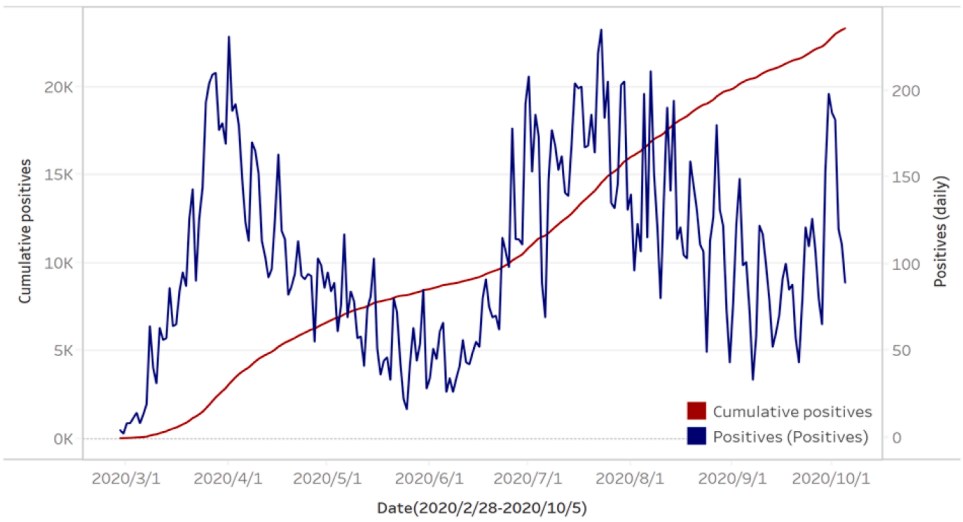

Fig. 3. COVID-19 daily counts from 2020/2/28 to 2020/10/5.

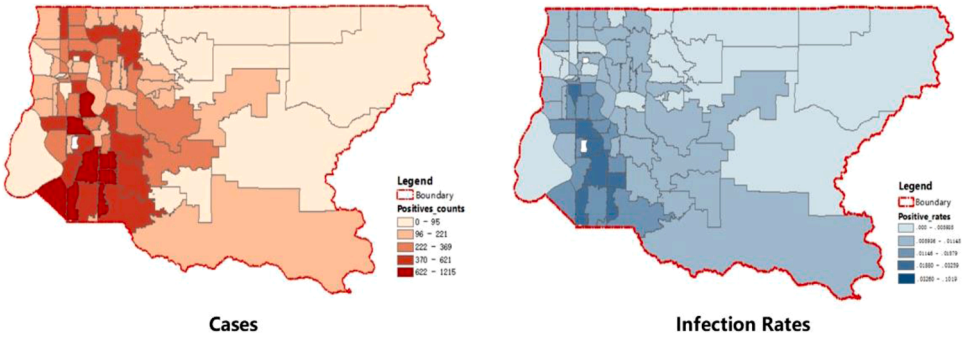

Fig. 4. COVID-19 cases and incidence rates.

Table 4
The PCA-MLR model results.

MODEL	Unstandardized coefficients	Standardized coefficients	t	Sig.
(constant)	9.962		38.199	<0.001
factor 2 of analysis 1 (Income)	4.559	0.871	17.318	<0.001
factor 5 of analysis 1 (Minority)	0.617	0.118	2.348	0.022
factor 1 of analysis 2 (POI density)	1.256	0.240	3.144	0.002
factor 6 of analysis 1 (House structure)	0.753	0.144	2.710	0.009
factor 1 of analysis 1 (Integration)	−0.711	−0.136	−1.830	0.072
Adjusted R^2	0.816			

explained 15% of the variation and was positively correlated with incidence rates. Family characteristics, notably non-family living alone, was the fourth influential factor and showed a negative correlation with incidence rates. The fifth and sixth factors were race-related, including American Indian and Alaska Native and Black and African American, which were positively correlated with incidence rates. Recreational land use was the seventh influencing indicator and demonstrated a significant negative correlation with incidence rates. The indicators eight to nine were an occupancy of two more per room, followed by two bedrooms and five to nine units.

The results of the PCC-MLR models with the time factor (Table 6) and without time factor (Table 5) were unanimous regarding the impacts of the built environment. As the proportion of recreational land use increased, incidence rates declined. Crowded households also showed a positive correlation with incidence rates. Moreover, higher income groups demonstrated lower incidence rates, whereas ethnic groups were more likely to contract the virus. We found that considering time would not improve the results, since policy and individuals' activities invariably change over time. This presents challenges when analyzing the remaining factors, supporting our previous analysis of the built environment.

The PCA-MLR and PCC-MLR models shared several indicators. Firstly, different ethnic groups, notably American Indian and Alaska Native and Black and African American demonstrated a strong positive correlation with incidence rates. Secondly, income was a significant influence in the two models. Thirdly, POI density and crowded housing increased incidence rates to different degrees.

3.5. GWR results

To determine the spatial distribution of the variables, we built GWR model (the first-order QUEEN was chosen to build a spatial weight matrix) based on the results of the PCC-MLR. The results of the GWR are given in Fig. 5. For the seven factors included in the PCC-MLR model, the R-squared of the GWR is 0.83, and the adjusted R-squared is 0.80. According to the standardized residuals (Std.Resid), two units extended the

Table 5
The PCC-MLR model results.

MODEL	Unstandardized coefficients	Standardized coefficients	t	Sig.
(constant)	−1.574		−0.327	0.745
Black_Afican_rate	25.950	0.301	3.882	<0.001
American_indian_Alaska_rate	259.089	0.283	4.479	<0.001
2_more_occupants_rate	410.663	0.200	3.032	0.003
recreation_ground	−2451.470	−0.201	−3.489	0.001
POI_office	12.013	0.096	1.622	0.110
I_100,000–200,000_rate	−17.439	−0.220	−2.807	0.007
PM2.5	1.604	0.188	2.806	0.007
Adjusted R^2	0.779			

Table 6
The dynamic PCC-MLR model results.

MODEL	Unstandardized coefficients	Standardized coefficients	t	Sig.
(Constant)	2.814		6.326	<0.001
Income_more_than_200,000_rate	−2.793	−0.240	−5.056	<0.001
t	0.134	0.261	8.456	<0.001
Income_100,000–200,000_rate	−3.971	−0.218	−4.565	<0.001
nonfamily_alone_rate	−3.019	−0.128	−3.193	0.001
American_indian_Alaska_rate	26.772	0.127	3.380	0.001
Black_Afican_rate	3.474	0.175	3.991	0.000
recreation_ground	−284.152	−0.101	−2.979	0.003
2_more_occupants_rate	55.140	0.117	3.034	0.003
Bedroom_2_rate	−2.107	−0.149	−3.052	0.002
Units_5to9	2.939	0.084	2.017	0.044
Adjusted R^2	0.849			

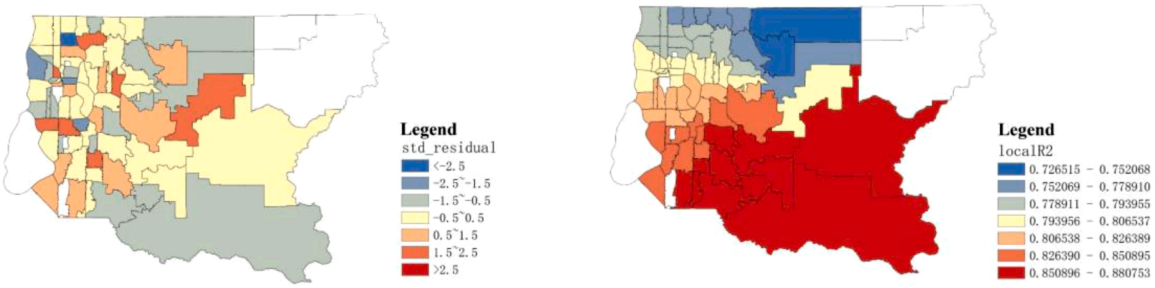

Fig. 5. Results of the GWR using variables in the PCC-MLR model.

range of a 2.5 standard deviation, both of which were located in the densely populated area of Seattle. The built environment and socio-economic conditions were different from those in the remaining study areas. Therefore, additional variables must be considered. The local R-squared showed a decreasing trend from south to north, as shown in Fig. 5.

Fig. 6 presents the spatial distribution of the coefficients for the seven factors included in the PCC-MLR. Income between $100,000 and $200,000 and recreational land use were negatively correlated with incidence rates. Furthermore, the recreation ground indicator demonstrated greater spatial variation. The coefficient values for dense urban areas were larger than those in the suburbs, as was also evident for income between $100,000 and $200,000. This was contrary to the situations for American Indian and Alaska Native and the hotel POI.

3.6. Comparison of typical neighborhoods

From micro scale, this study chose typical neighborhood cases of ZIP code 98,005 and 98,109 (shown in Fig. 7) to further explore the influence of built environment on the spread of epidemics. Socioeconomic conditions of the two areas had similarities, but built environment differed significantly, especially in the aspects of population density and open space, leading to the variation of incidence rates.

Table 7 showed the comparison of these two neighborhoods. Located in the east of Seattle, 98,005 is one of the best residential areas, where the ratio of open space is 3.01%. As for races, the people living in 98,005 are primarily white, accounting for 50.6% of total population, then followed by Asian (38.2%) and black (3.4%). Its population density is slightly lower than the average of King County. The household income is high compared to the rest areas of King County. Similarly, the median household income of 98,109 is slightly higher than the average of King County, and the population is mainly white (68.9%), followed by Asian (19.5%) and black (3.6%). However, 98,109 has an extremely high population density, with an open space ratio of 0.9%.

Having similarities in race and income, the difference in built environment of ZIP code 98,005 and 98,109 resulted in different incidence rates. With larger house size, more open space and lower population density, 98,005 had relatively low incidence rate of 8.1 per thousand people. By contrast, with smaller house size, less open space and higher population density, the incidence rate of 98,109 was 9.7 per thousand people, higher than the median of the whole county. The comparing results indicated that high population density might increase the infection risk of diseases. With regard to housing, the crowd within house would accelerate the transmission of virus. Also, more open space was conducive to decreasing incidence rates.

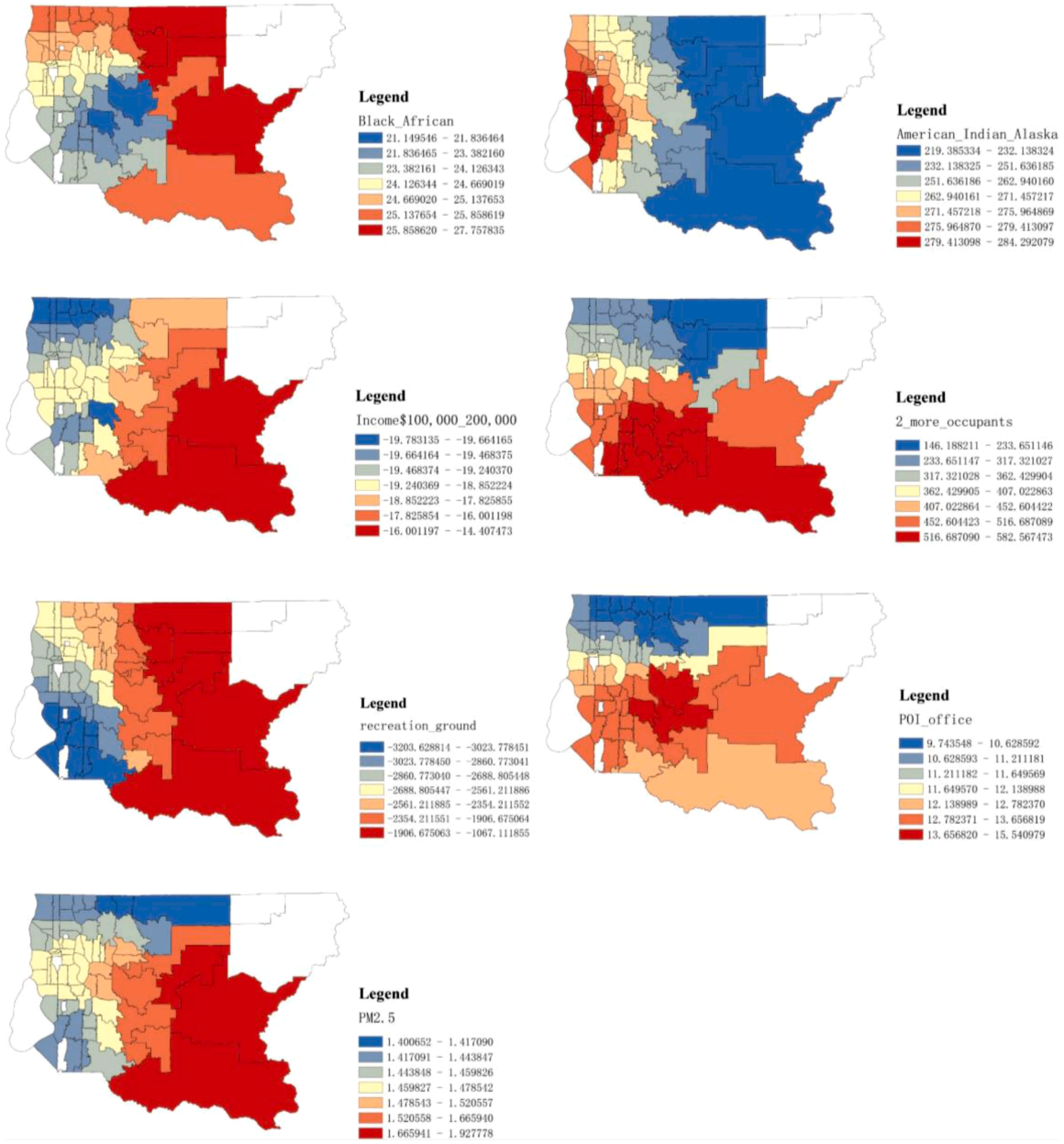

Fig. 6. GWR coefficients of the variables in the PCC-MLR model.

4. Discussion

At the time of writing, it is nearly a year since the local outbreak of COVID-19 spread to a global pandemic. This infectious disease has brought severe consequences and challenges to the world. Although considerable research was undertaken in the latter half of 2020, there remains little knowledge about the spatial variation, transmission mechanisms and explanatory factors of COVID-19. The factors influencing the outbreak are largely complicated and unpredictable. On the one hand, it is influenced by socioeconomic structure and the built environment, including economic development, medical facilities, decision-making systems and living habits. On the other hand, unpredictable elements such as leaders' political ideas and a specific time or location may also be influential. Moreover, these factors may be inextricably linked and exacerbated by each other, resulting in an accumulation of negative effects (Megahed & Ghoneim, 2020; Zhang, 2020).

In this study, both non-spatial (MLR) and spatial (GWR) statistical models were used to analyze socioeconomic, meteorological, and built-environment factors affecting the spread of the epidemic. It was observed that race and income remain the two primary factors influencing numbers of confirmed COVID-19 cases. A greater proportion of ethnic groups such as Black or African Americans, American Indians and Alaska natives accounted for a higher rate of infection. When income exceeded the median of $100,000 per year, the incidence rate was relatively reduced. This shows that socioeconomic dimension remains one of the most significant factors affecting COVID-19. Furthermore, individuals' behavior and activities largely determined the likelihood of becoming infected. Due to a lack of savings and alternative income sources, individuals in minority ethnic groups continued to commute to work during the epidemic, increasing the likelihood of infection. Groups with higher income levels typically had more alternatives: they could work from home and easily access necessary living resources without leaving their residences, greatly reducing the risk of infection. Previous research into COVID-19 and occupation supports this argument (Almagro & Orane-Hutchinson, 2020; Barbieri et al., 2020).

The underlying factors are related to the built environment, in which

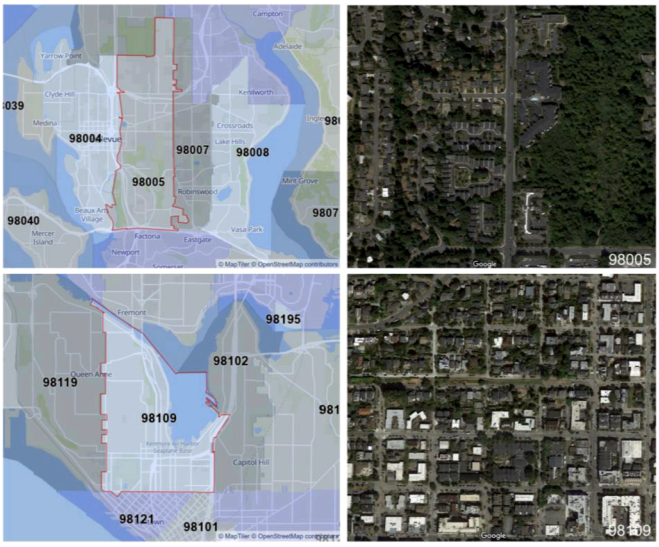

Fig. 7. Typical neighborhoods in Seattle, USA.

Table 7
Comparison of typical neighborhoods in Seattle, USA.

Neighborhood	98,005	98,109
Incidence rate (per 1000 people)	8.1	9.7
Land area (sq km)	19.4	5.2
Population	18,765	29,154
Population density (people per sq km)	967	5607
Household units	22,673	45,802
Occupancy of room (people per room)	<1	<1
Average room number (room per household)	2.6	1.6
Ratio of open space (area of open space/ area of land)	3.10%	0.90%
Median household income (dollar)	84,774	77,034
Races	White (50.6%,) Black (3.4%), Asian (38.2%), American Indian (0.1%)	White (68.7%), Black (3.6%), Asian (19.5%), American Indian (0.3%)

density is a significant factor affecting the spread of the disease. Recreation ground and office POI influenced COVID-19 cases to different degrees. Recreation ground refers to open green spaces used for public leisure and entertainment. The model results indicate that a higher ratio of recreation ground corresponds with a lower incidence rate. This suggests that additional open spaces may help prevent the spread of disease and informs planners to effectively organize public areas to build a healthier city. Conversely, office POI density was positively correlated with incidence rates. This also agreed with the conclusions drawn from socioeconomic factors and strongly supported the effect of working from home on preventing viral transmission.

Household structure also significantly influenced COVID-19 cases. At the neighborhood level, crowded households and family gatherings may exacerbate the spread of the epidemic (Almagro & Orane-Hutchinson, 2020; Chen & Krieger, 2021). Based on modeling results, when room occupancy was greater than or equal to two, the incidence rate increased. The density of housing units was also positively correlated with the incidence rate, highlighting the impact of per capita housing area on maintaining social distance.

Meteorological indicators showed little effect on incidence rates. Nevertheless, we observed that PM2.5 may accelerate transmission of the virus, as concluded in studies in the USA and Italy (Bashir et al., 2020b; Coccia, 2020). Since meteorological conditions were considered to be stable throughout the study area, the models showed no apparent conclusion that could be developed in subsequent research. Furthermore, we introduced time lag as a factor of the epidemic at monthly intervals. However, since policies and individuals' activities may change over time, the time series indicator did not improve the results. Therefore, future studies could include dynamic factors such as mobility and policy-making.

At the local scale, GWR models allow spatial comparison between different communities and neighborhoods. Residents in the suburbs, predominantly middle-income groups with low living density, large green areas, and good environmental conditions, reported fewer cases than residents in dense urban areas. As the GWR coefficient chart shows, the race coefficient influencing COVID-19 was the inverse of race distribution. A higher proportion of ethnic groups showed a relatively lower coefficient of influence, indicating that race had a marginal effect on COVID-19. This phenomenon also occurred in the income coefficient. In low-income urban areas, income level had a greater influence on incidence rates than in the suburbs containing wealthier households. The influencing coefficient for POI density also varied by location. In the suburbs, POI density showed a positive correlation with incidence rates. In urban areas, however, the effect of density was relatively minor. This indicates that high-density built environments caused an increase in infection, although the impact was reduced as density increased. For household structure, the density of units and occupants per room were both positively correlated with incidence rates. However, this relationship was not obvious in dense areas.

The above analyses may provide new perspectives on urban planning and design. Evidently, a dense built environment is associated with COVID-19, although the relationship is not as strong as previously assumed. This suggests that the effects of density are more apparent during the early stages of COVID-19, explaining why urban cores and mega cities get a head start on the spread of the disease (Carozzi & Felipe, 2020). As the epidemic expands, socioeconomic factors play an increasingly important role, and the impact of density on viral transmission becomes less apparent. Individuals' lifestyles and behavior in built environments determine the likelihood of contact with the infection. Nevertheless, the model results in this research suggest that there are several dimensions planners and designers could explore to promote resistance in cities. Creating more recreation ground and reducing POI density may effectively lower incidence rates. Moreover, it is feasible to avoid close contact between individuals by alleviating housing congestion, helping to block transmission within communities. Furthermore, by understanding the significance of everyday routines, planners and policy-makers must consider new ways of living, such as working from home, shopping online and exploring the virtual world, potentially reshaping future urban spaces.

5. Conclusion

This study drew initial conclusions regarding the association between the built environment and the transmission of infection in the typically metropolitan area of King County, Washington. Integrating socioeconomic and meteorological factors, we focused on attributes related to the built environment, notably land use, POI distribution, population density, building concentration, road networks and households. Conducting PCA-MLR, PCC-MLR and GWR models, we explored methods that could be used to study infectious diseases in urban areas.

The main novel contributions of this paper are as follow: firstly, this study is among the first to consider spatial factors (notably building density, road networks, POI distribution, and land use intensity) in urban areas at the county level, filling a research gap in the built environment. Secondly, we built different models to describe the temporal and spatial distributions of the results. Finally, the analysis results may effectively guide sustainable development in cities, making the built environment more suited to human settlement.

In conclusion, the built environment and the individuals who interact with it both impact COVID-19 cases. The results from King County, Washington, demonstrate that factors such as income and race are more influential than the physical environment. The initial peak of the outbreak led to much reflection on large cities such as New York City, which accounted for one-fifth of COVID-19 cases and deaths in the United States. Large cities such as London and Madrid were also center in which COVID-19 cases were highly concentrated. The inability to react to the pandemic in high-density built environments has been questioned by many and it has been suggested that the era of megacities is over (Alirol et al., 2011; Carozzi & Felipe, 2020; McCunn, 2020; Zhang, 2020). However, analysis of King County, Washington demonstrated that the facts were more complicated than previously asserted. Although high density was associated with elevated incidence rates to a degree, human behavior and socioeconomic factors played a detrimental role in the spread of COVID-19. Globally, residents behaved differently in face of the epidemic (including within similar built environments) resulting in different situations. Moreover, when analyzing the impact of human behavior on infection cases, working from home and maintaining social distance were found to be conducive to epidemic control. This also demonstrated that behavioral control measures were effective in preventing the spread of COVID-19. When confronting infectious diseases, management may prove to be more effective than urban planning, questioning conventional metropolitan planning to some degree. This was also reflected in the epidemic of areas with different density. Although a high-density built environment, Hong Kong employed timely and strict control measures to effectively contain the epidemic in a relatively short time. However, as an influencing factor, control policies were difficult to quantify and therefore not included in this study. Nevertheless, this topic should be promoted in future research.

Our study suggests that builders and administrators of city should rethink the impact of built environment on public health. It is not rational to immediately support low density and suburban living or totally oppose to high density and big cities. Evidence from King County implies that human behavior might be the key factor influencing epidemic diseases. People with different socioeconomic backgrounds show different behavior tendency. Built-environment-related indicators greatly affect activity density and preference. Meteorological factors such as temperature, wind, humidity and air quality are directly related to health and comfort. By controlling built environment factors like open space, POI density and room occupancy, city constructors could effectively guide human behavior, providing more chance for outdoor activities, avoiding crowd gathering around high-risk areas and reducing human contact. Also, policy-making could bring great gains for public health. All of the evidence shows the great potential of planning and control in urban areas. Though we have witnessed the vulnerability of metropolitan area during the pandemic, it is hasty to conclude that high density leads to high incidence rates. Considering the impacts of built environment are double-edged and indirect, this study calls for more research focusing various cases and factors to explore the complex influential mechanism of built environment on public health.

Declaration of Competing Interest

We declare that we have no financial and personal relationships with other people or organizations that can inappropriately influence our work, there is no professional or other personal interest of any nature or kind in any product, service or company that could be construed as influencing the position presented in, or the review of, the manuscript entitled, “The impacts of the built environment on the incidence rate of COVID-19: A case study of King County, Washington”

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Supplementary materials

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