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Spatial distributive effects of public green space and COVID-19 infection in London

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ARTICLE INFO

Handling Editor: Wendy Chen

Keywords:

COVID-19
Urban green space
Pandemic
Spatial analysis
Risk assessment

ABSTRACT

While public green spaces (PGS) are opined to be central in the pandemic recovery, higher accessibility to PGS also mean a higher risk of infection spread from the raised possibility of people encountering each other. This study explores the distributive effects of accessibility of PGS on the COVID-19 cases distribution using a geo-spatially varying network-based risk model at the borough level in London. The coupled effect of social deprivation with accessibility of the PGS was used as an adjustment factor to identify vulnerability. Results indicate that highly connected green spaces with high choice measure were associated with high risk of infection transmission. Socially deprived areas demonstrated higher possibility of infection spread even with moderate connectivity of the PGS. The study demonstrated that only applying a uniform social distancing measure without characterising the infrastructure and social conditions may lead to higher infection transmission.

1. Introduction

The unexpected emergence of the novel coronavirus disease 2019 (COVID-19) has developed to a worldwide public health challenge in the past one year. Characterised as the ‘once-in-a-century pandemic’, COVID-19 is not simply an immediate health crisis, the social and economic consequences caused by this pandemic can pose long-term global challenges. The spreading of the novel coronavirus and the corresponding control strategies have reshaped the individual’s life and behaviour significantly, and this alteration of the living and behavioural patterns is also expected to have a relatively long-term effect. The World Health Organization (World Health Organisation (WHO), 2018) urges a whole society approach to tackle 21st-century epidemics.

Social distancing measure refers to the public health measure of keeping space and reducing social interactions between people (Public Health England, 2020). It is adopted as a non-pharmaceutical intervention to reduce the contact rate and prevent the spread of the contagious disease. In the coronavirus outbreak, it is widely applied in different countries with different levels of social distancing restrictions. Scientific models have demonstrated the effectiveness of this measure on controlling the transmission. As a result, a set of restrictions to limit the travels and activities by residents are imposed.

During the pandemic, the need for more accessible green spaces around the neighbourhoods has been highlighted (The Royal Society for

the Protection of Birds (RSPB), 2020). At the background of the social distancing measure, the use of public open spaces is changed significantly as the parks have become the only ‘out-of-home’ option (Shoari et al., 2020). While people are suffering from the symptoms like fatigue, depression, insomnia and anxiety, parks and green spaces have an irreplaceable function in improving their well-being (Geng et al., 2021). Although there is a reduction on green space visitation due to the containment measures, the observed behavioural changes suggest an increase in ‘necessary activities’ like the walking the dog and exercise. Urban residents reinforce the importance of green space as the place of solace and respite (Ugolini et al., 2020). Despite an initial reduction in park visitor numbers, evidence of an eventual increase to the level higher than the baseline before the outbreak is found. There is a higher demand to access the green space during the pandemic. When the government has less stringent restriction policies, the park visits can lead to an increase in the number of new cases (Geng et al., 2021). Also, the gathering of six people from two different households in the outdoor green space is the first step of the lockdown easing plan in UK in order to fulfil the need of meeting other people. Therefore, the public green spaces (PGS) could have a negative impact on containing the spread of the pandemic by providing chances for people to cluster and spread the disease. The idea of ‘urban green spaces’ mainly refers to the area covered by greeneries in cities, including parks, gardens, natural and semi-natural green spaces, green corridors, amenity greens, community

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<https://doi.org/10.1016/j.ufug.2021.127182>

Received 3 February 2021; Received in revised form 2 April 2021; Accepted 10 May 2021

Available online 13 May 2021

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gardens and city farms. The accessibility evaluation of green spaces is one of the key attributes that urban planners and designers would consider when making masterplans. The connection of streets and roads around the green space needs to be analysed and planned with careful considerations, especially at the pedestrian level, in order to promote the use of spaces and the development of local identity. In planning consensus, the more accessible, the better the green spaces. However, the high accessibility promotes the interaction between people, which could lead to a high risk of virus infection.

According to Tobler (1970), everything has a relation to everything else, while near things are more related than distant things. While the connection between the built environment and infectious disease transmission was demonstrated in several previous research, the studied or reviewed built environment elements include public transport (Mohr et al., 2012), indoor environment (Dietz et al., 2020; Pardeshi et al., 2020) and household infrastructure features (Spencer et al., 2020). At the same time, how the spatial distribution of the built environment factors relating to the epidemic transmission remains a gap in research, while the spatial pattern could be significant in the control of spreading. The spatial regression model incorporates the spatial correlation structure into the linear regression model (Anselin, 2009; Mehrotra et al., 2019). In this study, the exploratory statistical tools of ordinary least squares (OLS) regression and spatial lag model were applied to establish a correlation between the COVID-19 case and the PGS accessibility. The accessibility factors with a positive contribution to the concentration of COVID-19 cases were identified. The spatial statistical model was also applied in the examination of the association between socio-demographic factors and COVID-19 cases (Sannigrahi et al., 2020). To understand the local spatial autocorrelation pattern, the Local Moran's I and bivariate Local Moran's I were presented with the cluster maps. The bivariate Local Moran's I has been adopted to identify the risk susceptibility of the urban green space in exposure to the urbanisation in the work by Bardhan et al. (2016), thus a risk matrix was developed here with bivariate Local Moran's I between the case number and each accessibility factor to demonstrate the risk of infection when accessing to the green space. As an addition, the deprivation index at the borough level was added to assist the risk modelling.

This study intends to explore the correlation between the COVID-19 cases distribution and the PGS accessibility using the spatial statistical approaches at the level of boroughs in London. The high accessibility to PGS promotes the interaction between people over there, which could lead to a high risk of virus infection. Considering the potential risks in infectious disease transmission, planners need to think about how to arrange the planning of green spaces in the post-coronavirus pandemic period. The objectives are (1) demonstrating the spatial distribution pattern and the regression relationships between the number of COVID-19 cases and the seven accessibility factors measured by space syntax analysis and UNA; and (2) generating a Risk Matrix to evaluate the risk of infection in each borough and using the matrix as a guidance to the restriction policies on specific locations. The study will contribute to the demonstration of the linkage between COVID-19 and urban green spaces, and it will make further discussions on the relationship between infectious diseases and the urban environment. The immediate influences of this 'Grey Rhino' event and its subsequent impacts worth exploring and would lead to a reflection of the current urban planning.

2. Literature review

The review of literature includes three parts: a discussion about how social distancing is applied as a key transmission control measure during the pandemic especially in the UK, a review of the association between infectious diseases and built environment and an overview of the concept of urban green space and the measurement of green space accessibility.

2.1. Social distancing as a virus containment measure

The disease caused by the severe acute respiratory syndrome coronavirus 2 (SARS-CoV-2), known as COVID-19 and the novel coronavirus, is a respiratory illness designated as the ongoing pandemic by the World Health Organisation (WHO) (2020). The virus is mainly transmitted via person-to-person close contact and through the respiratory droplets produced by the infected person when coughs, sneezes or talks (Centers for Disease Control and Prevention, 2020). Social distancing, also known as physical distancing, refers to the non-pharmaceutical containment measure requiring people to stay away from and reduce interactions with each other. The control of coronavirus outbreak relies significantly on the aggressive social distancing measure, and the measure has disconnected the social networks in human societies, especially in urban areas. Social distancing seems to be the only option to slow down the transmission and bring the reproductive rate down in the absence of an effective vaccine (Stier et al., 2020; Debnath and Bardhan, 2020). Sun and Zhai (2020) validate the effectiveness of social distancing on reducing the infection probability by quantifying the impacts of social distancing and ventilation in the Wells-Riley model.

In the UK, a social distancing of two meters (6 feet) is the standard distancing requirement by the authority. The government announced the implementation of whole lockdown measure on 23 March 2020. During the lockdown, strict travel advice is stated which asks people only go out for food and health reasons and in the case when working at home is not possible. One form of exercise per day, like running, walking or cycling, is allowed, while the communal places within parks, such as playgrounds, sports courts and outdoor gyms, are closed to the public (Cabinet Office, 2020). The later easing plan on 10 May allows unlimited outdoor exercise and sports and a gathering of six people outdoor with social distancing. Therefore, it can be concluded that people are still able to access the PGS for daily exercise use, with the expectation of keeping social distancing between each other. The PGS remain the major place for people to encounter and meet, hence have a high risk of possible virus transmission.

2.2. Association between the built environment and infectious disease

The association between the built environment and public health is mainly illustrated by the influences of the built environment on infectious disease and chronic disease (Perdue et al., 2003). The spreading of the epidemic has been closely related to the built environment since the 19th century. People didn't realise the importance of designing a modern sewage system until the cholera outbreak across the world. The similar cases also include the Athens plague which transformed the city's law and identity and the Black Death which led to the change in the class power balance in European cities (Shenker, 2020). The design of buildings, including design for daylight, ventilation and sewer and drainpipes, contributes significantly to the control of infectious disease transmission in the indoor environment. The concerns over public health have promoted the shape of design in the built environment responding to health needs (Perdue et al., 2003).

Pandemic is always a key shaping factor of the urban environment. Cities, especially the modern metropolises, are the major centres of trade and travel, also the hub of contagious disease transmission. The urbanisation process has shaped the way people living, working and interacting and it has transformed the understanding of public health. The need for strengthening the urban system to prevent the large-scale epidemic transmission is highlighted by Lee et al. (2020), including the high population density and high public transportation volume, the interface between humans and animal communities, governance by local authorities, the diversified subpopulation, centres of economic activities and unconventional communications and interactions. At the same time, the big data collection, surveillance and analysis in smart city help to trace the infections, understand the distribution pattern and predict the potential transmission cluster (Shenker, 2020). The

application of data technology contributes to the track of human activities and ensures information availability to the public.

The discussion of the association between the novel coronavirus and the built environment remains a gap in the current research. Megahed and Ghoneim (2020) argue that the built environment is transformed by this epidemic due to the fear of infection, which requires a new paradigm for adaptation. At the building level, Dietz et al. (2020) review the influences of the indoor environment on the control and mitigation of coronavirus transmission suggested in literature, covering the factors such as humidity, ventilation, daylight and electric light, the spatial configuration of the buildings and temperature. Corburn et al. (2020) outline the potential risk and challenges brought by COVID-19 to the highly vulnerable urban informal settlements. The recommendations to protect the residents and arrest the pandemic transmission in urban slums are suggested in their work, such as creating emergency planning committee for slums, suspending the eviction and displacement of the residents, providing immediate financial support and healthcare services to the poor and improving the condition of water supply and sanitation. Stier et al. (2020) study the association between the virus growth rates and the population size in cities. They find evidence of cases growing faster in larger cities. Social distancing measure affects city differently based on city sizes, and larger cities need more aggressive measure considering the higher reproductive rate.

Also, the influences of the pandemic on residents in poverty have been widely demonstrated in the reported data and literature. The deprived population are generally more vulnerable in the pandemic, thus experiencing higher risk in the transmission. At the global scale, UN report shows the population in poverty is heavily influenced by the pandemic in terms of food insecurity, unemployment and violence (United Nations Development Programme (UNDP), 2020). In the UK, the data from Office for National Statistics (ONS), 2020a, 2020b reports a proportionally higher impact of COVID-19 on the most deprived area in England, where the deaths per 100,000 population is significantly higher in the most deprived area comparing to the least deprived ones. For people of low socio-economic status, there are a set of factors that increase their risk of exposure to the virus, including overcrowded housing, limited access to private open spaces, lack of opportunities to work from home and poorer access to health services (Patel et al., 2020).

As the coronavirus may become a long-term public health crisis, it could be expected that urban life will not go back to normal before the mass production and application of the effective vaccine and treatment. The interaction between citizens and the urban environment has been altered significantly by the epidemic containment measures, and how to understand and manage this change has become a key question for urban professionals to think about. In the short term, a better understanding of the correlation between the built environment factors, such as green spaces, traffic links, and public buildings and the development of the coronavirus cases could contribute to the design of containment measures. In the long term, how to plan for the flexible and resilient cities will become the focus of planning work.

2.3. Urban Green Space and accessibility

The terms ‘green space’ and ‘open space’ have been used loosely and interchangeably in planning practice without consistent definitions (Swanwick et al., 2003a, 2003b). Urban green space is defined as the piece of land in urban area covered by vegetation, varying in size, plant type, facilities and services (Tzoulas et al., 2007; Wolch et al., 2014). Open space usually refers to the undeveloped land outside the building. Town and Country Planning Act 1990 Section 336 (UK Parliament, 1990) defines the open space as ‘any land laid out as a public garden, or used for public recreation, or land which is a disused burial ground’. Fig. 1 is developed based on the classification by Swanwick et al. (2003a, 2003b) to illustrate the definition of green space and open space. The presence of urban green spaces has a significant positive influence on climate mitigation, public health, biodiversity conservation and general well-being, which has been widely recognised in the existing literature (Bardhan et al., 2015; Mehrotra et al., 2019; Sathyakumar et al., 2020). Richardson et al. (2010) identify three key mechanisms explaining the influence of urban green spaces on health, which are increasing physical activity level, facilitating social contacts, and promoting attention fatigue and stress recovery. The investigation by Kim and Miller (2019) indicates the positive health influences of closer distance and higher visiting frequency to green spaces. The importance of natural environment and green spaces is reinforced in the pandemic. The access to natural green spaces has been identified as a significant advantage during the COVID-19 outbreak that can improve the public health, and the time spent with nature environment has become more important to people since the pandemic (The Royal Society for the Protection of Birds (RSPB), 2020).

The accessibility to green spaces is an important assessment factor when evaluating the distributive spatial effects green spaces on quality of life. A set of accessibility measurement approaches are defined to assess the accessibility, such as ‘container’ measurement, ‘coverage’ measurement, ‘minimum distance’ approach, ‘travel (summarised by Zhang et al., 2019), and ‘residential proximity’ metrics and ‘cumulative opportunity’ metrics (reviewed by Dinand Ekkel and de Vries, 2017). Dinand Ekkel and de Vries (2017) address the association between the green space accessibility metrics and the health aspects, and they conclude that the green spaces within a walkable distance have a positive effect on human health. Also, the distance to green spaces matters, though no specific cut-off value for distance is found in the empirical studies reviewed. Dong et al. (2020) investigate the connectivity of green spaces and the PGS use with the case of 42 sub-districts in the inner area of Wuhan. The impact factors involved in the research include a set of other green space characteristics such as normalised difference vegetation index, PGS area per capita and the ratio of arbour to shrub and a group of facility function characteristics indicated by the point of interest datasets. The connectivity is measured by the integral index of connectivity. However, a relatively weak correlation is found in their study. In this study, the measure of accessibility is based on the street

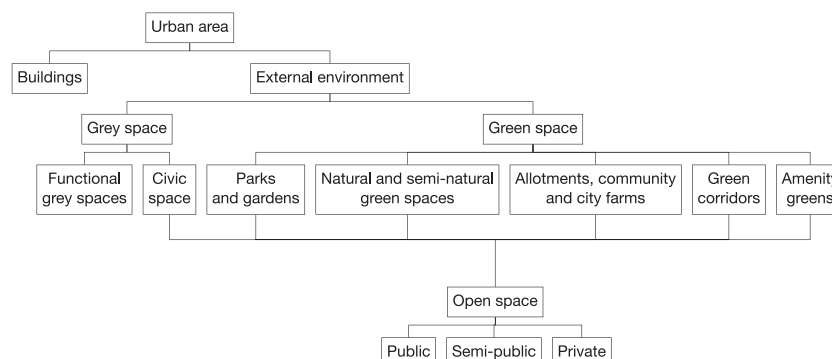


Fig. 1. Definition of the urban green space and the open public space.

network structure without the consideration of attractions and other land uses, by applying space syntax analysis and Urban Network Analysis (UNA).

3. Data and methods

This section gives an overview of the case study area, data collection process and statistical methods applied in the analysis. A framework of methods is established in this section, and how the statistical tools are used for the analysis and the generation of a borough-level risk assessment model are presented.

3.1. Study area

London (51°30'26"N, 0°7'39"W) is the capital and the largest city of the UK. It is also the city suffering most in the COVID-19 outbreak, with exponential growth in the number of cases observed. From 26 March to 17 May 2020, London has witnessed a growth in the number of cases from 3919 to 26,440. Borough, as the basic spatial unit, is the local authority district in London. There are a total of 32 London boroughs, plus the City of London as the central business district managed by the City of London Corporation. Twelve boroughs are designated as the Inner London boroughs, while the other twenty boroughs are the Outer London boroughs.

The importance of open public space is outlined in the policy papers at different levels in London, from city to borough. London Plan 2016 Chapter 7 London's Living Spaces and Places has reinforced the importance of protecting, promoting and enhancing London's open spaces (Greater London Authority, 2016). According to Greenspace Information for Greater London CIC (GiGL) (2019), there are a total of 67,541 ha open spaces occupying 42.36 % land in Greater London. The designated public open spaces occupy an area of 28,683 ha with a percentage of 17.99 % in Greater London. The access to the PGS is important in the lockdown given that 21 % of the households in London have no access to a private or shared garden and the private gardens are the smallest in the nation. At the same time, there are 44 % of Londoners

living within a five minutes walks distance to a park and 58 % when including the playfields (Office for National Statistics (ONS), 2020b). Fig. 2 shows the number of PGS per 100,000 population in London. Higher PGS density is found in Outer London comparing to Inner London.

3.2. Data collection and statistical methods

A systematic methodological framework is adopted in this study to measure the accessibility to explore the correlation. The dependent variable is the number of COVID-19 cases, and the independent variables are the seven accessibility measures Integration, Choice, Reach, Gravity, Betweenness, Closeness, Straightness. The correlations are tested in analytical software IBM SPSS Statistics 26 and GeoDa 1.14.0.4.1. Fig. 3 presents the step-by-step illustration of this research, and this part will give a detailed introduction of how this analysis is conducted, from data collection and the accessibility measurement to spatial statistics analysis.

3.2.1. COVID-19 cases

COVID-19 related statistics such as the number of lab-confirmed cases, virus-associated deaths, daily increase, and the number of cases at national, regional and local level are published by Public Health England (Public Health England, 2020) every day. Only the number of cases by London borough is adopted for the analysis. The dataset applied in this research is extracted on 17 May 2020. Fig. 4 shows the map of cases by borough.

3.2.2. Accessibility measurements

The collection of PGS data involves three information sources, the accessible park information from the borough websites and local green strategy, OS Open Green Space from Edina Digimap and the full open space sites list from GiGL. The information from three sources is combined to draw a full picture of the PGS in London. While the OS Open Green Space and GiGL data provide the location and size of the open and green spaces around London, the local borough councils usually outline

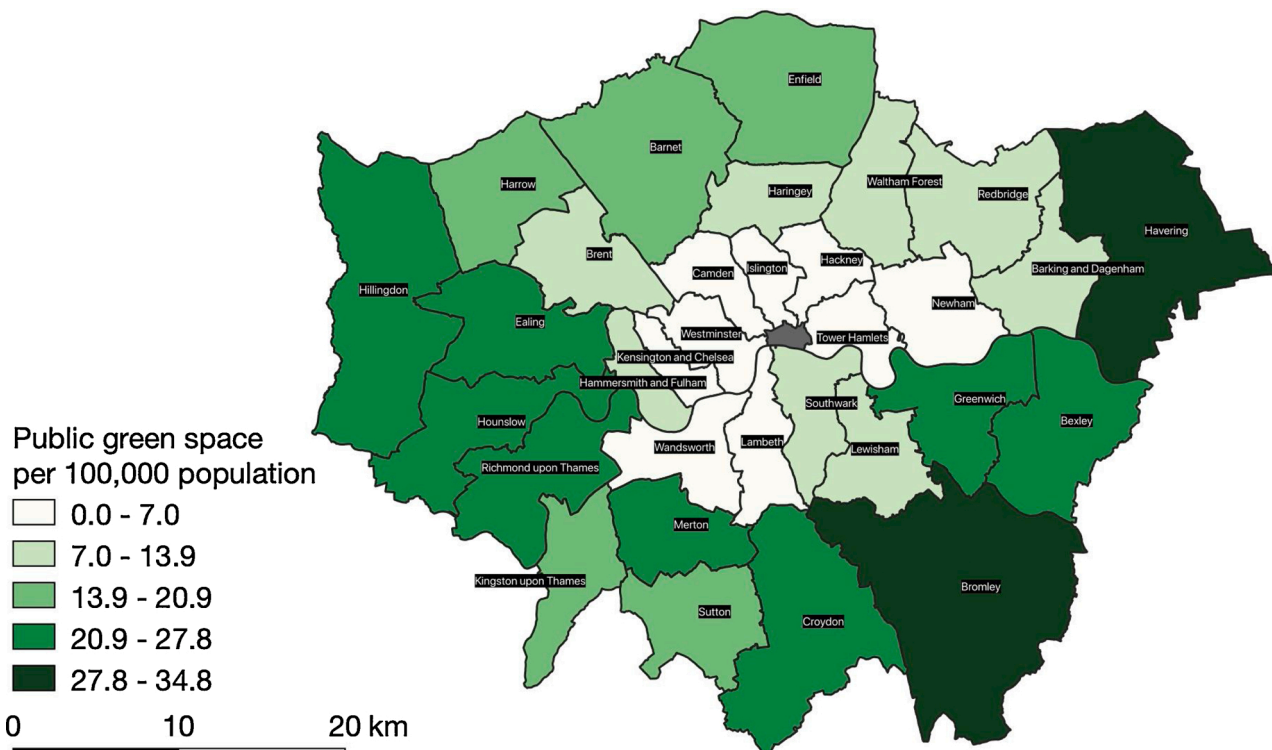


Fig. 2. Number of public green space per 100,000 population in London.

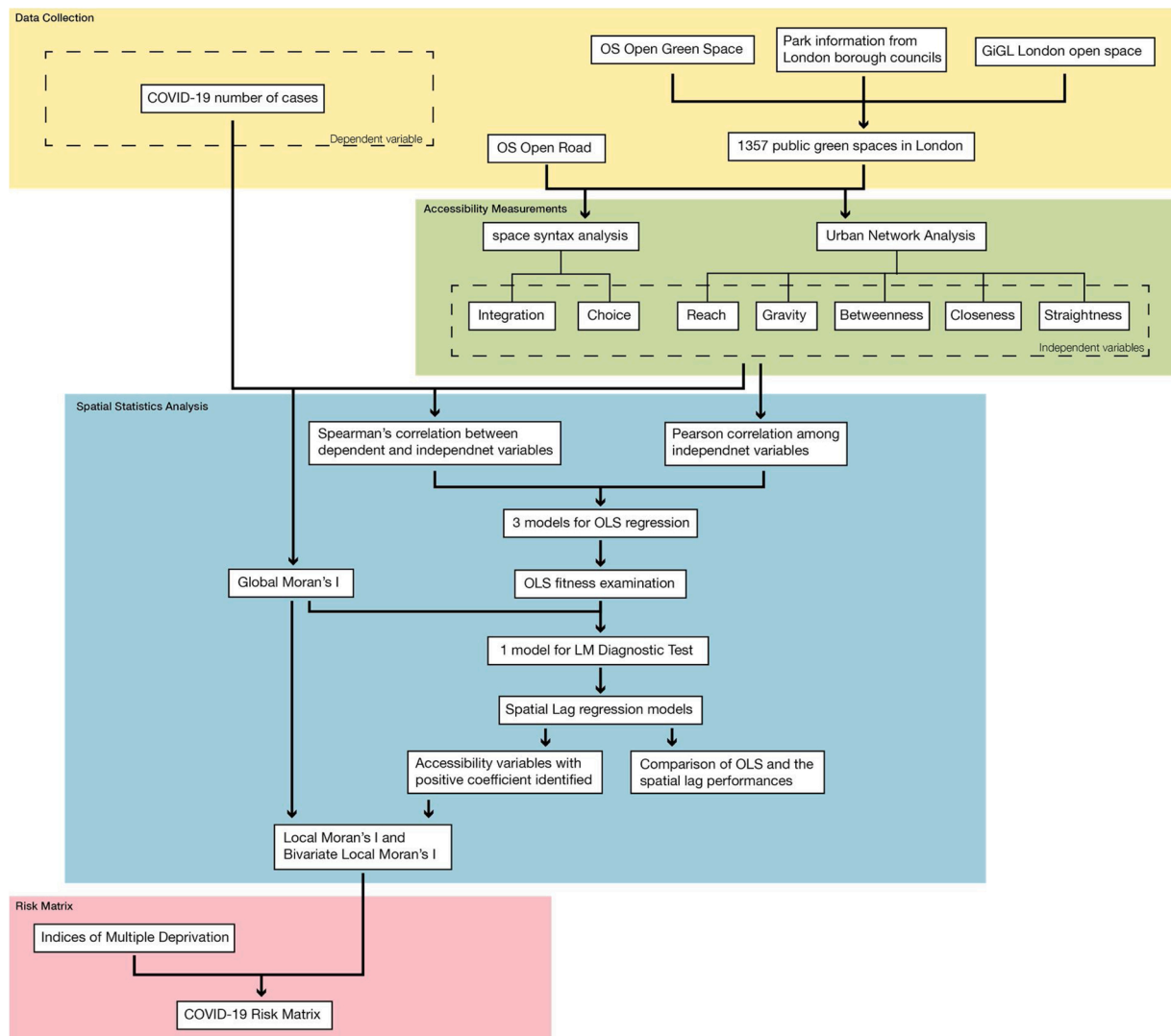


Fig. 3. Steps of the research.

the information about accessibility and classification in their recreation study, park open space strategy or the leisure sector on the official website.

A set of conditions are set to filter the raw green space data. Firstly, the green spaces at the district, metropolitan and regional level with the size over 2 ha are retained, while under 2 ha are removed. The threshold of 2 ha is determined based on the public green space categorisation outlined by the London Plan 2016 (Mayor of London., 2016), as the green spaces under 2 ha are classified as the local level green spaces and pocket parks. Those green spaces are excluded because they are relatively small with less people visit and stay. Secondly, only the publicly accessible green spaces are involved in this study, while the privately owned places and those with access restrictions, such as playfields owned by the sports club, the open spaces for educational purpose, cemeteries and churchyards, reservoirs and community allotments, are excluded from the list. As a result, the PGS included are mainly from the types of parks and gardens and natural and semi-natural urban green spaces. There are a total number of 1357 green spaces involving in the analysis.

The accessibility measurements are conducted in two different tools. The space syntax results are calculated from DepthMapX with the version of depthMapXnet 35 MacOSv2, while the UNA is computed by ArcGIS 10.5 Urban Network Analysis toolbox. Considering the pedestrian accessibility, a radius of 800 m is defined for the calculation.

3.2.2.1. Space syntax analysis: integration and choice. Space syntax analysis, developed by the Space Syntax Laboratory in The Bartlett, UCL, is a number of theories and research areas representing and evaluating the spatial configuration. At the urban level, space syntax analysis is an emerging tool for pedestrian accessibility measurement and a well-functioned predictor of vehicular and pedestrian movement (Hillier et al., 2012). This measure is found to be the most important measure of the configurational correlation of urban pedestrian movements (Hillier et al., 1993). It provides a generalised description of the spatial structure and the connectivity hierarchy of streets without taking the land use into account (Ozbil et al., 2011).

Several basic values are generated directly from the segment analysis, including angular connectivity, total depths (TD) and node counts (NC). Total depth refers to the cumulative total of the shortest angular paths to all segments. Node counts indicate the number of segments encountered on the path from the current ones to all other segments (Al-Sayed, 2014). Two key measures generated based on those values are adopted as the accessibility variables in this research - integration and choice:

- Integration (availability): a to-movement potential measurement examines how integrated the street is to the whole network and indicating how many people are likely to be in the space, and it functions as a predictor to the potential of each segment in the radius

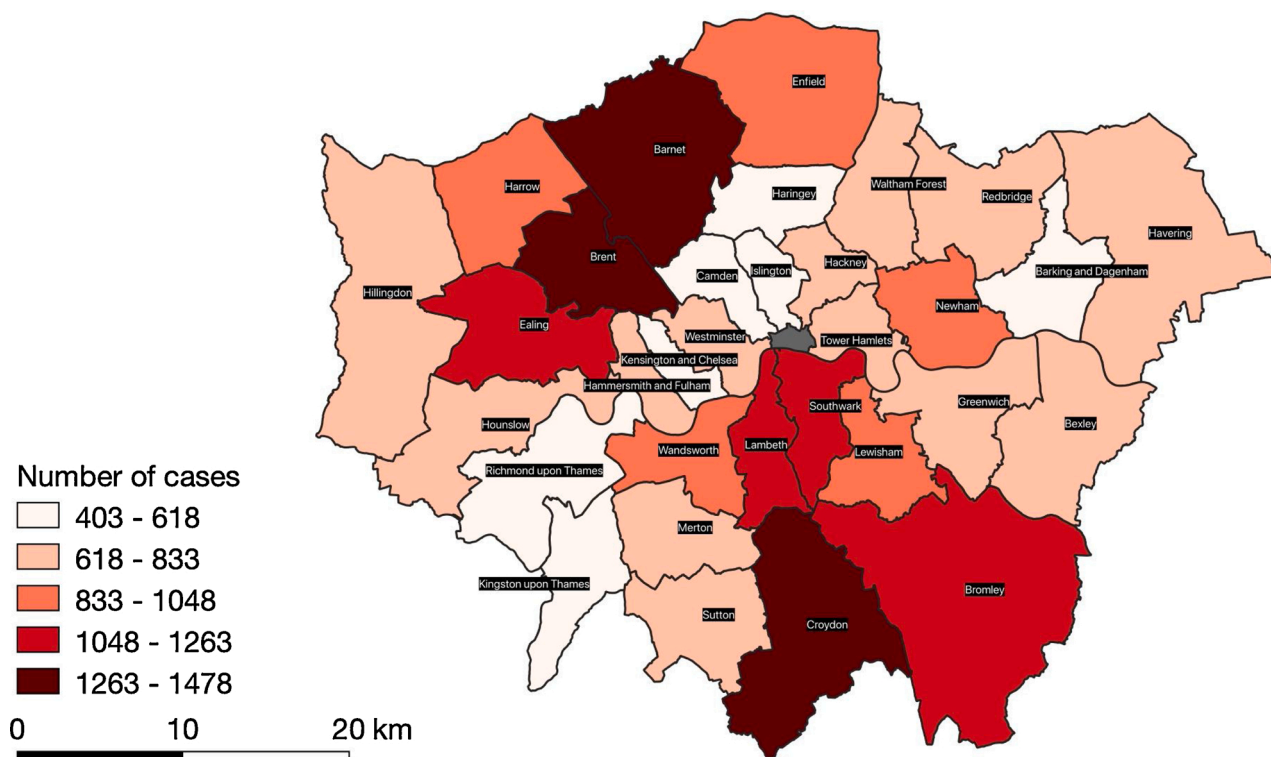


Fig. 4. Distribution of the number of COVID-19 cases by London borough.

distance to be the desired destination. The equation for integration calculation is $NC \times NC \div TD$ (Al-Sayed, 2014).

- Choice (betweenness): a through-movement potential measurement calculates the possibility for each segment to be chosen by the pedestrians as the shortest or simplest route (Hillier et al., 2012). A value of '1' is assigned to every segment from any origin to any destination when computing the shortest angular path in the system, while the value '2' is recorded when the shortest path goes through the segment twice. The values add up until all the shortest angular paths are identified and taken into account in the system. All the equivalent shortest angular routes are identified randomly and one in each pair is eliminated (Al-Sayed, 2014).

The segment analysis counts the accessibility values of each segment in the network and how one single street segment relates to the other segments in the defined metric radius. Metric radius is used to select the street network segments for analysis, which usually refers to a group of spaces within a certain metric distance away from the root space (Turner, 2008). As the Integration and Choice results are presented in terms of values by segments, a further step is taken to extract the values for each green space. The Integration and Choice values of the segments within 25 m distance around a green space are added up as the result for that green space.

3.2.2.2. Urban Network Analysis (UNA): centrality measures. UNA is a toolbox developed by the City Form Lab at MIT for the spatial network analysis. It accounts for both geometry and topology in the input networks and takes either metric distance or topological distance as the impedance factors. UNA operates based on three network elements, which are nodes, edges and buildings, and weights can be assigned to buildings according to their specific features. While the buildings are the basic units of analysis, each building is assumed to connect to a street lying closest to it along the shortest perpendicular distance from the centroid of the building's footprint (Sevtsuk and Mekonnen, 2012). UNA is an addition to the space syntax measures to understand the accessibility, while the tendency of green space users to reach other green space

through one green space or in the circumstances of seeking for substitutions is put into focus. The green spaces are treated as the network element 'building' in this analysis, while no particular weights are assigned. The key measures adopted in this research are the graphic analysis measures from Centrality tool. The definitions by Sevtsuk et al. (2013) are given below, and the formula of each measure and the

Table 1

Expressions of UNA Centrality measures and their normalised values (extracted from Sevtsuk et al., 2013).

Measure	Definition	Normalization
Reach	$Rea[i]^r = \sum_{j \in G - \{i\}, d[i,j] \leq r} W[j]$	$Rea[i]_{norm}^r = \frac{Rea[i]^r}{\sum_{j \in G - \{i\}} W[j]}$
Gravity	$Gra[i]^r = \sum_{j \in G - \{i\}, d[i,j] \leq r} \frac{W[j]}{e^{\beta \times d[i,j]}}$	$Gra[i]_{norm}^r = \frac{Gra[i]^r}{Rea[i]^r}$
Betweenness	$Bet[i]^r = \sum_{j,k \in G - \{i\}, d[i,j] \leq r, d[i,k] \leq r} \frac{n_{jk}[i]}{n_{jk}} \times W[j]$	$Bet[i]_{norm}^r = \frac{Bet[i]^r}{(\sum_{j \in G - \{i\}} \{jG - \{i\} : d[i,j] \leq r\} - 1) \cdot Rea[i]^r}$
Closeness	$Clo[i]^r = \frac{1}{\sum_{j \in G - \{i\}, d[i,j] \leq r} (d[i,j] \times W[j])}$	$Clo[i]_{norm}^r = Clo[i]^r \times Rea[i]_{norm}^r$
Straightness	$Str[i]^r = \frac{\sum_{j \in G - \{i\}, d[i,j] \leq r} \frac{\delta[i,j]}{d[i,j]} W[j]}{\sum_{j \in G - \{i\}, d[i,j] \leq r} W[j]}$	$Str[i]_{norm}^r = \frac{Str[i]^r}{Rea[i]^r}$

$[i]^r$ is building i within research radius r .

$d[i, j]$ is the shortest distance between i and j .

$\delta[i, j]$ is the shortest Euclidian distance between i and j .

n_{jk} is the total number of shortest paths from j to k .

$n_{jk}[i]$ is n_{jk} pass by i .

β is exponent of the distance decay effect.

G is the graph.

W is the weight.

normalised expression are presented in Table 1:

- **Reach:** Reach calculates the number of surrounding buildings or destinations that every single building reaches within a given radius on the network.
- **Gravity:** as an addition to Reach, Gravity takes the spatial impedance required to travel to each of the destinations into account.
- **Betweenness:** Betweenness measures the fraction of the shortest paths between pairs of other buildings in the given network that pass by one particular building, which captures the potential of passerby of the buildings on the network.
- **Closeness:** Closeness refers to the inverse of cumulative distance required to reach from one building to all other buildings within the set radius along the shortest routes.
- **Straightness:** Straightness illustrates the level of resemblance between the shortest paths from a building to all other buildings and the straight-line Euclidian distance.

The borough level accessibility values are generated by adding up the results from each green space within the borough. Table 2 shows the descriptive data of the accessibility measures, including the maximum, minimum, mean and standard deviation of each accessibility measure at the borough level.

3.2.3. Regression analysis

3.2.3.1. Data standardisation and bivariate correlation. Considering the large differences among the raw datasets as Table 2 shown, the two sets of data are standardised to a similar scale before proceeding to the statistical analysis. Z-score normalisation shows the number of standard deviations away from the mean value. The result values are generalised with a mean of 0 and standard deviation 1.

Two bivariate correlations are adopted as a basic exploration of the dependent variable and independent variables. A Pearson correlation is run to illustrate the correlations among the accessibility variables, while a Spearman's correlation is applied to understand the relations between the dependent variable and independent variables. The result matrices are generated with a two-tailed test significance.

The Pearson correlation shows that the variables of Reach, Closeness and Straightness are highly correlated at a significant level of 0.01. Therefore, only one from each set of highly correlated variables is kept for the OLS in order to get a possible improvement in model performance. In this case, Straightness and Integration are kept. According to the results from Spearman's, two variables, Gravity and Betweenness, show a very weak correlation to COVID-19 cases by rank. Therefore, they could also be removed in the model. As a result, three models are generated based on the bivariate correlation results and tested in OLS.

3.2.3.2. Ordinary least square (OLS) regression. OLS regression refers to the linear regression model applying linear least square methods to estimate the unknown parameters, which provides a regression equation to predict the variables. The sum of square differences between the observed and predicted values are minimised in this model. The results

Table 2

Descriptive data of the seven accessibility measures.

Measure	Maximum	Minimum	Mean	Standard Deviation
Integration	2.03×10^7	8.76×10^5	1.11×10^7	4.99×10^6
Choice	3.49×10^5	1.36×10^4	1.89×10^5	7.93×10^4
Reach	0.0479	0	0.0162	0.0137
Gravity	$9.53 \times 10 - 8$	0	$3.07 \times 10 - 9$	$1.68 \times 10 - 8$
Betweenness	3.167	0	0.557	0.914
Closeness	0.1719	0	0.0418	0.0394
Straightness	34.63	0	12.21	9.91

generated from OLS are assumed to be constant in the whole measured area, while for the variables with spatial pattern OLS fails to identify the spatial characteristics.

3.2.3.3. Spatial dependence models. When OLS could not fully illustrate the correlation, the spatial autocorrelation may exist, therefore, the spatial regression models are involved to demonstrate the correlation. The spatial dependence models mainly include two types, the spatial lag model and the spatial error model. Spatial lag model, also known as the spatial autoregressive model, is an extension from the pure spatial autoregressive model which captures the substantive spatial dependencies like external effects or spatial interactions. Spatial error model is applied when the spatial pattern is in error due to the omitted random factors (Darmofal, 2015). The spatial dependence diagnostic test, Lagrange multiplier (LM) statistics, LM-lag and LM-error, are used to identify which model could be applied. LM-lag diagnostic refers to the spatial lag model as the alternative, while LM-error relates to the spatial error model as the alternative. The diagnostic value with a higher statistical significance indicates the selection of the corresponding model.

3.2.4. Moran's I's

3.2.4.1. Global Moran's I. The spatial autocorrelation is the correlation of a variable and its surrounding neighbours across the space. Moran's I is one of the most commonly used measures in evaluating global spatial autocorrelation. Moran's I is also used as the unfocused diagnostic for spatial dependence, but it only tests the presence of spatial dependence instead of telling the presence of spatial lag or error dependence (Darmofal, 2015). Moran's I shows the relation between a variable and its spatial lag, defined by equation 1 (Anselin, 2018a):

$$I = \frac{\sum_i (\sum_j w_{ij} z_i \times z_j) / S_0}{\sum_i z_i^2 / n}$$

w weight

z variable derivation from the mean

S_0 sum of all weights

n number of observations

i, j locations

3.2.4.2. Local Moran's I. Defined by Anselin (1995), the LISA statistics refer to the statistics that indicate the significance of the clustering of similar values around one observation and the sum of LISAs for all observation is proportional to a global indicator, which functions as a decomposition of the global indicators. They work as the interpretation of the local pockets of non-stationarity, the assessment of the impact of individual locations on the global statistics magnitude and the identification of hotspots and outliers. Local Moran's I is one of the LISAs used to identify the spatial hotspots and outliers (Anselin, 2018c), which is defined as equation 2.

$$I_i = c z_i \sum_j w_{ij} z_j$$

c scalar, same for all locations

z variable derivation from the mean

w weight

3.2.4.3. Bivariate Moran's I. The bivariate spatial correlation does not take the in-situ correlation between two variables, instead, it explores the correlation between one variable and the spatial lag of another variable. The bivariate Global Moran's I measures the degree of how the value for a given variable at a location is correlated to its neighbours with a different variable, presenting by equation 3 (Anselin, 2018b).

$$I_B = \frac{\sum_i (\sum_j w_{ij} y_j \times x_i)}{\sum_i x_i^2}$$

x , y variables derivation from the mean

The bivariate Local Moran's I follows its global counterpart and explores the association between the value of one variable at the location and the average of the neighbouring values for another variable, showing in equation 4 (Anselin, 2018d).

$$I_{B,i} = cx_i \sum_j w_{ij} y_j$$

Therefore, the patterns of how the value of one variable at a certain location is influenced by the values of the other variable from its surrounding locations could be analysed using the bivariate Local Moran's I.

3.3. Risk matrix

When the lockdown is gradually released and people are allowed to travel more for a longer distance and have more activities in the open green spaces, it is important to provide corresponding information to evaluate the risk of using the green space. While going to the areas with a high concentration of cases should be avoided, residents should also avoid accessing the places with a high possibility of encountering other people. For policymakers, the understanding of the risk level of each borough is significant when easing the green space access restrictions. When policymakers attempt to control the transmission by putting restrictions on the specific area instead of taking a whole lockdown, the number of cases should not be the only factor to consider.

The risk of accessing green spaces at the borough level is evaluated with a designed matrix based on the correlation found between the accessibility of PGS and number of cases. As the results of clustering pattern found Local Moran's I is limited and not apparent enough to explain the full situation, bivariate Local Moran's I results are also taken into consideration. The impacts of the accessibility factors of the neighbouring boroughs on the core borough are presented by the results of bivariate analysis. For example, if a borough with a high case or rate is surrounded by the boroughs with a high possibility of transmission, restriction measures should be put on the area with a higher possibility for transmission as well because people may travel to the places in the neighbouring borough and get infected. If a borough with a low concentration of cases has the neighbours with a high possibility of transmission, the residents in that borough should be advised to avoid accessing the surrounding boroughs. The results from bivariate Local Moran's I have demonstrated the level risk of transmission from the neighbouring boroughs that the borough is exposed to, thus the areas requiring more focuses or measures for the control of spread are

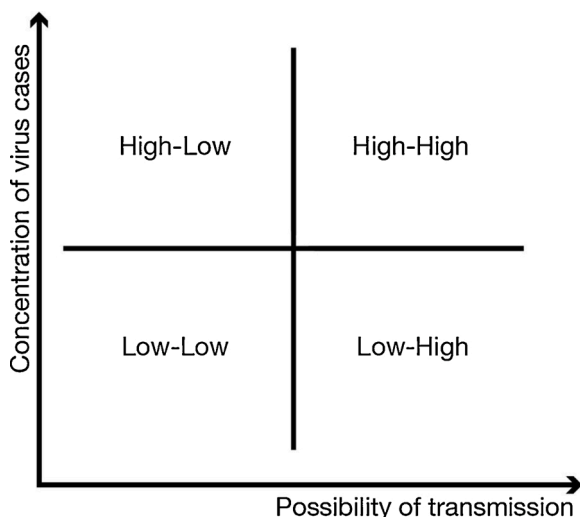


Fig. 5. Matrix from bivariate Local Moran's I.

identified. Fig. 5 shows the four possible results generated in bivariate Local Moran's I, high-high, high-low, low-high and low-low.

A conceptual risk evaluation matrix is therefore developed based on the bivariate Local Moran's I results and expected to contribute to people's decision-making on the access to PGS use and the policy maker's decision-making on setting restrictions on specific areas. The accessibility to the green spaces indicates the possibility of transmission, while the number of cases indicates the concentration of infections. The risk based on these two factors is identified by the results of bivariate Local Moran's I. In addition to the PGS accessibility and COVID-19 number of cases, the deprivation level is added to the Risk Matrix as a factor to measure the vulnerability of local residents in virus transmission. The Indices of Multiple Deprivation (IMD) score is used to represent the vulnerability in the matrix. The IMD data in 2019 is collected from London Datastore directly (Ministry of Housing Communities and Local Government (MHCLG), 2019a). This index combines the measurements of seven domains, including income, employment, education, health, crime, barriers to housing and services and living environment. The higher score indicates a more deprived area (Ministry of Housing Communities and Local Government (MHCLG), 2019b). The total of 33 boroughs are sorted based on the score, ranking from the highest score to the lowest score, and they are classified into three levels, high, medium and low, with eleven boroughs at each level.

The Risk Matrix is shown in Fig. 6. By integrating the three parameters of the possibility of transmission, the concentration of infections and the vulnerability of local residents, twelve scenarios are classified in five risk levels in the matrix, from very high, high, to medium, low and very low. For the borough with a higher risk level, more restrictions of green space access should be imposed within and between boroughs.

4. Results

The results generated from the statistical models of the OLS model, spatial dependence diagnostic test, spatial lag model, Global and Local Moran's I are presented in this part. A brief view of the result from the proposed risk assessment model is also included.

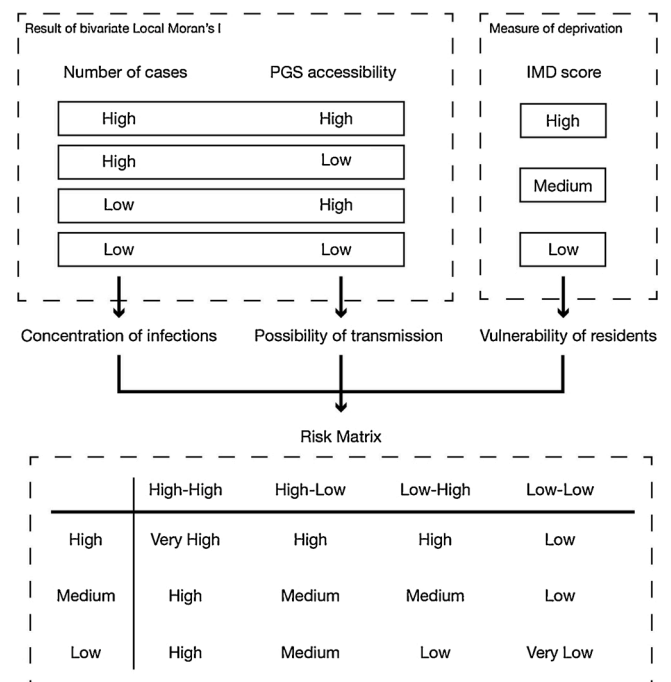


Fig. 6. Risk Matrix.

4.1. Exploratory regression results

4.1.1. OLS model fitness

Three models generated from are tested in OLS regression. Table 3 shows the composition and the fitness parameters of the OLS models. The coefficient value represents the strength and the type of relationship between each explanatory variable and the dependent variable. R2 and Akaike information criterion (AIC) reflects the level of fitness and performance of the OLS model. Adjusted R2 is used more in the evaluation because R2 value is sensitive to the number of independent variables put in the model. The resulted R2 values are small and close to zero, which indicates a relatively weak fitness of all tested models. One possible inference is a lack of attention to the spatial distribution pattern.

4.1.2. Spatial clustering of the variables by Global Moran's I

Global Moran's I is run to understand the spatial autocorrelation of every single variable. Table 4 presents the results of univariate Global Moran's I, and the pseudo p-value and z-value are generated after 999 permutations. The interpretation of the spatial correlation of each variable shows that the spatial autocorrelations exist in the variable distribution. Relatively strong positive spatial correlation is found in the COVID-19 number of cases and the accessibility variables of Reach, Straightness and Closeness, with the values of 0.217, 0.198, 0.115 and 0.199 respectively.

4.1.3. Spatial dependence diagnostic test

As the OLS results shown, Model 3, with all the seven accessibility variables, has a better performance with adjusted R2 values of 0.147. Therefore, the spatial regression analysis proceeds with Model 3. To figure out the best fit spatial regression model to apply after OLS, five LM diagnostics are run. Table 5 shows the results of the diagnostic test for the selected models. The diagnostic results show that the spatial lag model would fit better than the spatial error model, since the probability values for LM-lag results are lower. Therefore, the analysis proceeds with the computation of the spatial lag model.

4.1.4. Model performance comparison

An improvement of performance when the spatial weights are considered in the regression. Table 6 gives the comparison of the fitness parameters of the OLS and spatial lag model. According to Anselin (2005), the higher the Log-Likelihood, the better the model fits, while the decrease in AIC and Schwarz criterion (SC) suggests an improvement in fitness. For Model 3, an increase in Log-Likelihood from -38.3 (for OLS) to -35.8 (for spatial lag model) is noticed, and the values for AIC and SC decrease from 92.5–89.5 and from 104.2–102.7 separately.

4.1.5. Spatial lag model results

The results from the spatial lag regression show the influences of each accessibility factors on the COVID-19 cases distributions (presented in Table 7). As the models shown, the variables Choice, Gravity, Closeness and Straightness have a positive contribution to the number of cases, with the coefficient value of 1.268, 0.172, 0.227 and 0.608 respectively.

4.2. Spatial autocorrelation results

The accessibility variables with a positive correlation to the dependent variable are identified from the spatial lag model and put in the

local spatial autocorrelation analysis by borough. With the default setting of 999 permutations and a p-value of 0.05, cluster maps are generated, and four types of spatial correlation location pattern are presented.

4.2.1. Local Moran's I

While the univariate Global Moran's I shows the existence of the spatial pattern, the univariate Local Moran's I of variables is applied to understand the local pattern. Fig. 7 presents the set of cluster maps generated with Local Moran's I, including the number of COVID-19 cases, and the accessibility variables of Choice, Gravity, Closeness and Straightness which correspond to the factors identified from spatial lag models.

The spatial hotspots with a high number of cases are Harrow, Lambeth and Bromley, while Wandsworth is identified as a spatial outlier with a high value surrounded by low values. For the Choice value, Lambeth is the high-high spatial hotspot, and Hackney and Redbridge are the high-low spatial outlier. Similar spatial clustering patterns are found in Closeness and Straightness. In the cluster map of Closeness, Bexley is the high-high hotspot and Hackney, while Westminster and Kensington and Chelsea are the low-low hotspots. In the cluster map of Straightness, Hillingdon and Hounslow show the high-high pattern while Hackney, Westminster and Kensington and Chelsea are the cores of low-low spatial clusters. Only spatial outliers are found in the cluster map of Gravity - Ealing is noted with high Gravity value surrounded by low values, while Hillingdon, Hounslow and Harrow present a low-high pattern.

4.2.2. Bivariate local Moran's I

The bivariate Global Moran's I of the number of cases and factors of Choice, Gravity, Closeness and Straightness computed are 0.066, 0.034, 0.040 and 0.107 respectively. This indicates that a positive correlation of high case number surrounded by high accessibility values exists, but the pattern is not apparent, which needs a further specify in bivariate Local Moran's I. Bivariate Local Moran's I gives the spatial correlation between the COVID-19 cases of the core borough and the accessibility variables of its neighbours in terms of the cluster map. Fig. 8 illustrates the bivariate spatial correlations between the number of cases and accessibility variables Choice, Gravity, Closeness and Straightness.

There are three spatial clusters shown in the Case-Choice map, including two low-low clusters of Redbridge and Hackney and one high-high cluster of Lambeth. Only spatial outliers are identified in the cluster map of Case-Gravity, showing that 10 core boroughs with a high number of cases surrounded by low Gravity values and two boroughs of Hillingdon and Hounslow with a low number of cases surrounded by high Gravity values. The Case-Straightness map and Case-Closeness map illustrate three low-low clusters of Hackney, Westminster and Kensington and Chelsea. Bexley is the core borough of the low case number surrounded by high Closeness value, while Hillingdon and Hounslow are the cores of the low case number surrounded by high Straightness value.

4.3. Risk evaluation results

As described in Section 4.2, the results of univariate Local Moran's I show that Bromley, Lambeth and Harrow are the three boroughs identified as the high-high cluster core for the number of cases. Lambeth is also the core of the high-high cluster in terms of Choice value, while Harrow has a low Gravity value surrounded by high ones. It could be

Table 3
OLS fitness parameters for three tested models.

Model	R2	Adjusted R2	AIC	Jarque-bera	Koenker	Spatial Autocorrelation	Measure
1	0.218	0.102	91.9	4.047	2.30	0	Reach, Betweenness, Gravity, Integration
2	0.250	0.106	99.2	1.801	2.57	0	Reach, Closeness, Straightness, Integration, Choice
3	0.340	0.147	102.7	4.079	2.69	0	Reach, Gravity, Betweenness, Closeness, Straightness, Integration, Choice

Table 4
Results of univariate Global Moran's I.

	Space Syntax Measure		UNA Measure				COVID-19 data	
	Integration	Choice	Reach	Gravity	Betweenness	Closeness	Straightness	Number of Cases
Moran's I	-0.091	-0.102	0.198	-0.039	-0.096	0.115	0.199	0.217
Pseudo p-value	0.305	0.274	0.027	0.290	0.285	0.095	0.028	0.024
z-value	-0.549	-0.641	2.104	-0.647	-0.634	1.359	2.152	2.196
p-value and z-value generated from 999 permutations								

Table 5
Results of spatial dependence diagnostic test.

Model	Moran's I	LM-lag	Robust LM-lag	LM-error	LM-error
3					
Value	1.932	4.347	3.393	2.481	1.526
Probability	0.053	0.037	0.065	0.115	0.217

Table 6
Comparison of the performance of the OLS model and the spatial lag model.

Model		Log-Likelihood	AIC	SC
3	OLS	-38.3	92.5	104.2
	Spatial lag	-35.8	89.5	102.7

Table 7
Coefficients of Model 3 in the spatial lag model.

Variable	Coefficient	z-value	Probability
Spatial autoregressive coefficient	0.533	3.073	0.002
Constant	-0.033	-0.261	0.794
Integration	-0.883	-1.514	0.130
Choice	1.268	1.974	0.048
Reach	-0.777	-1.245	0.213
Gravity	0.172	1.156	0.248
Betweenness	-0.352	-1.855	0.064
Closeness	0.227	0.818	0.414
Straightness	0.608	0.982	0.326

seen that Lambeth is characterised with the core of a high-risk borough cluster with its neighbour boroughs Westminster, Wandsworth, Croydon and Southwark. The number of clusters identified from the univariate analysis is very limited and not enough to build the matrix.

In the bivariate analysis, a total of 17 out of 32 boroughs are assigned with a risk level. Table 8 shows the level of three parameters for each borough and their corresponding risk level identified. There are eight different patterns identified in this real case over a total of 12 combinations. The boroughs with high deprivation index and a high number of cases surrounded by high green space accessibility neighbours are mostly found. There are four boroughs marked with high concentration, low possibility and low vulnerability, and another four marked with low concentration, low possibility and medium vulnerability. However, there is no borough found at 'very low' risk level indicating by low concentration, low possibility and low vulnerability. Lambeth is still the borough at 'very high' risk level with high case concentration, high possibility of transmission and high resident vulnerability, which needs extra focus.

5. Discussion

A clear overview of the key statistical results is presented in the previous section. This part will look at the discussion of the findings on the spatial patterns and the risk assessment matrix.

5.1. Spatial pattern

From the analysis results, it could be seen that the spatial lag model provides a better fit model comparing to the OLS regression model, which indicates that the relationship between accessibility variables and COVID-19 cases varies geographically with a location-specific nature. The identification of accessibility variables with positive correlation to the number of cases can give an indication on how to plan for the green space.

In the long run, the accessibility factors of PGS should be taken into consideration when planning for the green spaces in the post-coronavirus period. In the planning consensus, the higher the accessibility, the better the green space. However, given the positive contribution of the accessibility factors to the COVID-19 cases found by spatial regression, the consensus is challenged and the planners need to figure out new accessibility standards for green space planning. The investigation results point out the accessibility factors which need more focuses, and the factors are interpreted to give a rough guidance on the future green space planning. Gravity measures the amount of the surrounding green space within the 800-meters-radius that could be selected as a substitution of one specific green space. Closeness and Straightness are captured based on the distance from one green space to the other green spaces within the radius. Those UNA features demonstrate that in order to lower the risk of transmission, a larger distance between the green spaces is required to lower the possibility of them to be chosen as the substitution for each other. The Integration and Choice values reveal the to-movement and through-movement potentials, showing the tendency for people to choose the green space as their destination or passing route in the network. To reduce the Choice value, planners can place the green space in the pedestrian walkable area instead of the area with key vehicle transport nodes and traffic linkages around.

In the new pandemic normal, planners aim to provide safe PGS that can facilitate the social distancing rule (Shoari et al., 2020). The need for green space to serve short-distance activities in the pandemic is demonstrated by Kleinschroth and Kowarik (2020) and Ugolini et al. (2020). Due to the correlation between PGS accessibility and the disease transmission illustrated above, planners may consider about shifting from providing the highly-accessible PGS to some private gardens, semi-public greens or community greens that are only accessible by a certain group of residents within the walking distance to reduce the mix of people from different places. The access to private gardens and shared green spaces is positively associated with the physical health and mental health improvement. The smaller green areas in the neighbourhood also encourage the recreational walks (Dinand Ekkel and de Vries, 2017), and they fulfil visitor's functional needs of relaxation and rest, physical exercise and meeting friends. Also, the residential green space use is negatively associated with the park use, which indicates a certain substitution effect (Wang et al., 2021). While the large public green spaces with high accessibility tend to have high visitor density, the private and semi-public green spaces present a similar function and have less stress of visitor concentration thus reduced disease transmission possibility.

5.2. Risk matrix

This section looks into the boroughs at each risk level. There is one

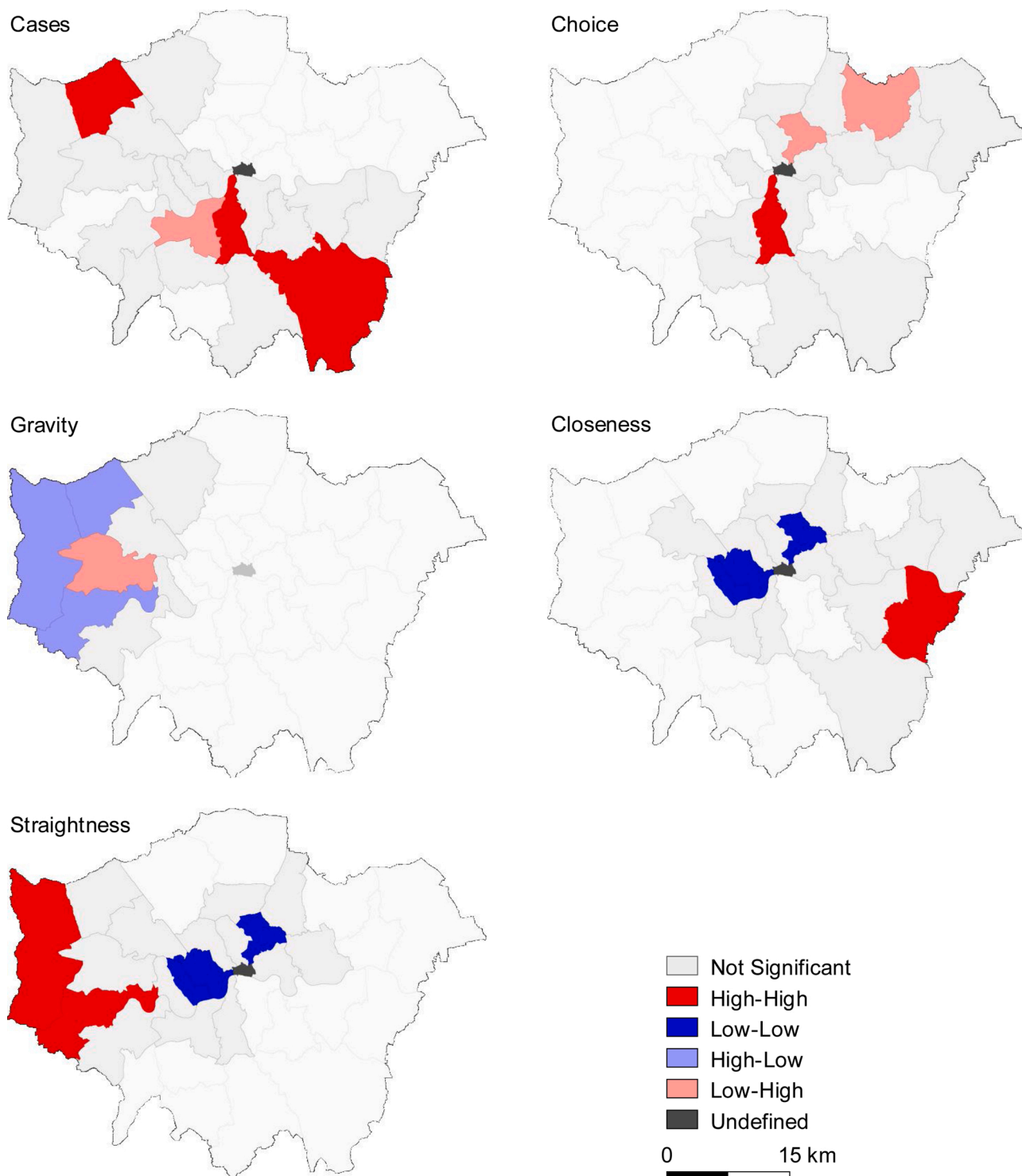


Fig. 7. Local Moran's I cluster maps (Number of cases (Cases), Choice, Gravity, Closeness and Straightness).

borough at very high risk level, five at high risk, six at medium risk, five at low risk and none at very low risk. For the borough at very high-risk level like Lambeth, the strict restrictions should be imposed that residents should be suggested to minimise their visit to the green spaces within the borough and the neighbouring boroughs. The boroughs at high risk, Brent, Enfield, Lewisham, Newham and Southwark, all share the common characteristics of high case concentration, low accessibility and high vulnerability, need to limit the access to green spaces within the borough and restrict the access to their surrounding boroughs. The medium risk boroughs can have less restrictions on travelling and using

green spaces comparing to the two higher levels. No specific restriction is needed for the low-risk boroughs except for the general COVID-19 social distancing rules. The risk matrix helps to determine the differentiated restriction policies for different areas. More flexible reopening policies are needed, while more attentions need to be paid on the areas suffering more in social disparities. The findings in [Chang et al. \(2021\)](#) also suggest that infection disparities are inevitable consequences of the reopening policies, which indicates a need for specific policies to mitigate the infection disparities in disadvantaged communities during the reopening process.

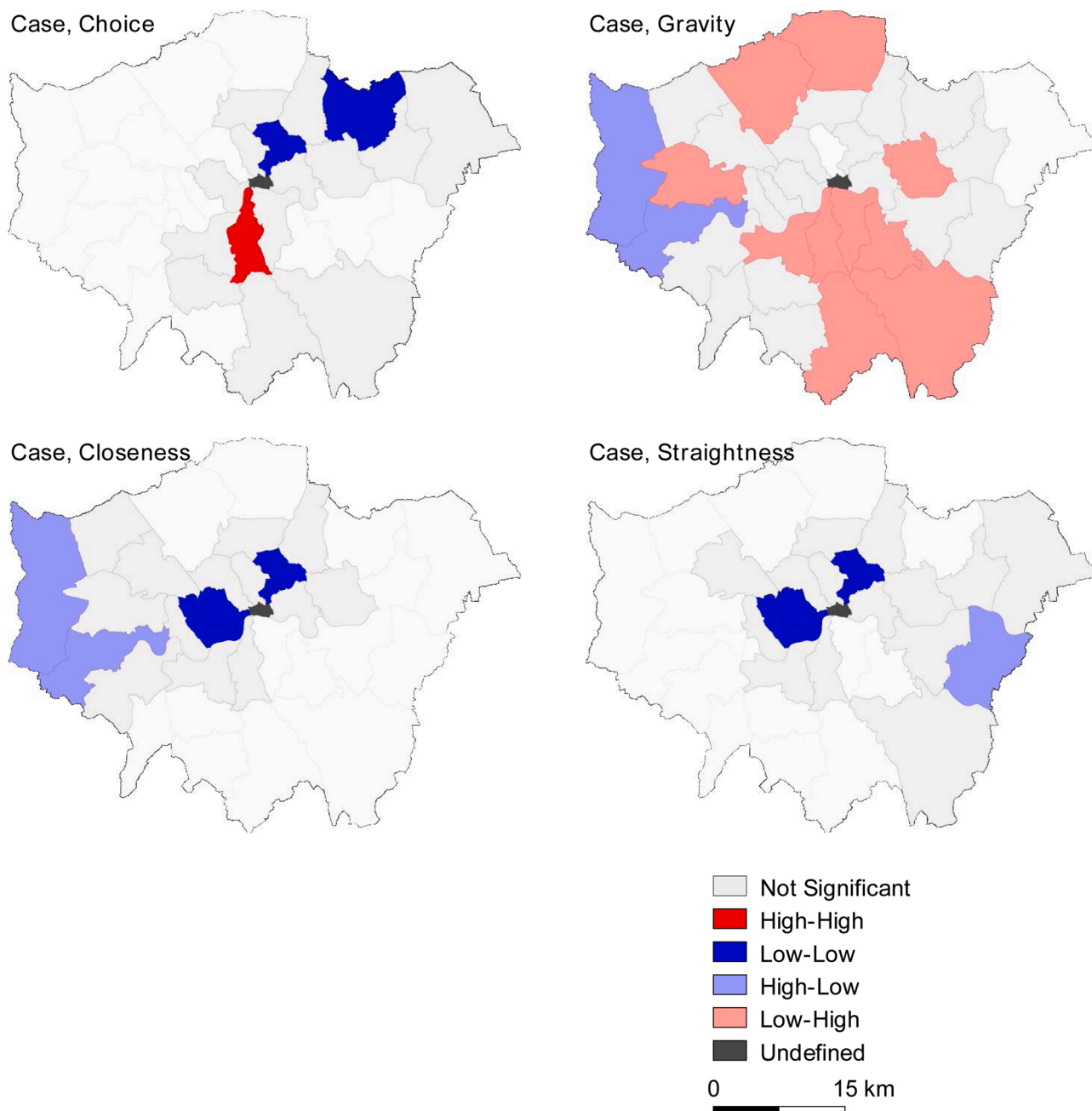


Fig. 8. Bivariate Local Moran's I cluster maps, number of cases (Cases) to accessibility factors (Choice, Gravity, Closeness, Straightness).

6. Conclusions and implications

As the global pandemic of COVID-19 has led to a significant and potentially long-term effect around the world, the built environment professionals need to respond to the change and consider the corresponding post-COVID adjustments. In the long run, planners need to work towards building the city with higher resilience and flexibility in special circumstances like an epidemic outbreak. At the same time, the implementation of lockdown and social distancing measure has led to a profound transformation in the daily life. In the foreseeable future, before an effective vaccine put into mass production and use, the set of restrictions on the activities will become a part of the normal life. During the lockdown, the daily exercise in public open spaces is one of the several limited activities allowed, while PGS have become the major place for people to encounter, and potentially spread the disease. Also, due to the restriction on travelling by public transport, walking and

cycling have become the key way of travelling. Therefore, the level of pedestrian access to PGS indicates a possibility of transmission, because higher the accessibility, the more people may access and encounter in the green space which becomes a potential cause of virus spreading.

This study has explored the correlation between the PGS accessibility and COVID-19 distribution with a set of spatial statistical approaches. London is adopted as the case study. The statistical analysis is conducted at the borough level. A total of seven accessibility measures for each green space are computed based on the space syntax analysis and Urban Network Analysis, and the generated values for each measure are added up as the borough value. The accessibility measures for each borough, as the independent variables, are correlated with the number of COVID-19 cases as the dependent variable, using the OLS and spatial lag model. Global Moran's I, Local Moran's I and bivariate Local Moran's I are applied to explore the spatial pattern of the datasets. This research builds a new understanding of the association between the public health

Table 8
Parameters and risk level for each borough.

	Concentration of Infections	Possibility of transmission	Vulnerability of residents	Risk level
Barnet	High	Low	Low	Medium
Bexley	Low	High	Low	Low
Brent	High	Low	High	High
Bromley	High	Low	Low	Medium
Croydon	High	Low	Medium	Medium
Enfield	High	Low	High	High
Hackney	Low	Low	High	Low
Hillingdon	Low	High	Medium	Medium
Hounslow	Low	High	Medium	Medium
Kensington and Chelsea	Low	Low	Medium	Low
Lambeth	High	High	High	Very High
Lewisham	High	Low	High	High
Newham	High	Low	High	High
Redbridge	Low	Low	Medium	Low
Southwark	High	Low	High	High
Wandsworth	High	Low	Low	Medium
Westminster	Low	Low	Medium	Low

and green space planning and fills the knowledge gap in the influences of the urban environment on epidemic transmission.

Generally, the results have demonstrated the spatial non-stationary relationship between the accessibility to PGS and the COVID-19 case number. The performance of the spatial lag regression model is better than the stationary OLS regression model, because of the improvement on the fitness parameters observed. The coefficients generated from the spatial lag model have given a PGS accessibility planning guide for the post-coronavirus planning, to explain what kind of accessibility factor to consider when planning for green space. The accessibility factors of Choice, Gravity, Closeness and Straightness of each borough are found to have a positive correlation to the concentration of COVID-19 cases in London. Also, considering about that the high accessibility to the PGS would lead to a high infection likelihood, planners could think about advocating for more semi-public green spaces with access restrictions to limit the amount of access.

When the policy tends to put restrictions on certain areas to control the transmission in the following stage, the results of this research contribute not only to identify the spatial hotspots and outliers but step further to evaluate the risk of exposure to the virus transmission. To evaluate the risk in virus spreading, the Risk Matrix, based on the results from the bivariate Local Moran's I, is designed to provide an insight on how to manage the access to PGS and give the information for green space users. The deprivation index is added to the Risk Matrix to help the evaluation of risk. Based on the matrix, the corresponding risk level is identified in 17 boroughs. Lambeth is found with a high risk, while Hackney, Redbridge and Westminster have very low risks.

There are several limitations of this research. Firstly, the COVID-19 case data is based on the lab-confirmed cases published by UK government, while the capacity for testing in the country was very limited at the beginning of the virus outbreak and not every single case with symptoms is tested. The test is not opened to any people who have symptoms of coronavirus until the beginning of June. Also, there are a group of asymptomatic patients who are excluded from the test and statistics. Therefore, the infected case data used in this study may not fully reflect the epidemiological pattern. Secondly, this study only counts the accessible PGS with the size over 2 ha, while the small-scale green spaces where people may also encounter and get infected, like pocket parks, local community gardens or semi-public green spaces in the estates are not taken into account. The measure of accessibility is mainly based on the OS Road Links, while some pedestrian paths might be omitted in the provided network dataset.

Furthermore, though there is a correlation proved between the virus cases and the PGS accessibility, the correlation found is not as high as

expected. Dong et al. (2020) also find a weak correlation between the PGS use and connectivity, and they suggest that the possible reason might be that the use of green space is affected by multifaceted competing impact factors. The accessibility to the green spaces based on the street network is just one of the factors driving people to choose the place for activities, while the other factors, such as the quality of landscapes, facilities, surrounding environment and available time, will also have impacts on the people's choice. Also, in this research, due to the complexity of the virus transmission process, there are many other factors influencing the transmission. For example, the household spread is also a key reason for transmission, especially in the early outbreak and when there is a lack of proper isolation condition. At the borough level, the number of cases identified may relate to the population composition and socio-economic-demographic characteristics of the borough, like the age group, socioeconomic status and BAME residents distribution. The general population factor could be adjusted by calculating the rates per 100,000 residents population, while the elder group, racial and ethnic minorities and people in poverty are more vulnerable in the virus outbreak with a higher risk of infection. The indices of deprivation are brought in the risk evaluation model regarding the consideration of population characteristics. However, there are more factors worth exploring for future research. As a result, the accessibility to PGS just represents one of high transmission risk factors that should be taken into consideration in the policymaking.

The analysis by Local Moran's I only identified the risk level for some of the boroughs instead of all. To improve the practical use of this risk assessment system, the second step of this research will be bringing the risk assessment down to the scale of green space as the number of cases data being available at a lower census output area. A more detailed risk modelling will be performed based on the parameters in Risk Matrix developed in this study by evaluating the risk level for each PGS in London. The measure of the possibility of transmission by accessibility, the number of infected cases found around the area in the recent time and the population vulnerability by local deprivation index mark the risk of exposure to the transmission. Therefore, residents could check the risk level to get rid of selecting the 'high risk' PGS and search for the alternatives with a lower risk when they want to use the green space.

Except for the PGS, this set of methods and models could be applied on exploring the correlation and evaluating the risk of other urban elements on virus spreading, such as the traffic nodes and public buildings, to provide a guidance for the users and policy-makers. Moreover, this study has only discussed the green spaces with public access, while the private and semi-public green spaces also have a significant function on providing spaces for daily exercise and activities, especially in the lockdown. A comprehensive framework for post-coronavirus green space planning could be drawn from a combination of the analysis on different types of green spaces, so that planners could have a better understanding on how to find a balance among various types of green infrastructures to improve the resilience of the city in the infectious disease outbreak.

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.

Acknowledgements

This work was in part undertaken as a contribution to the Rapid Assistance in Modelling the Pandemic (RAMP) initiative, coordinated by the Royal Society, United Kingdom as a contribution to the United Kingdom and global effort to tackle Coronavirus COVID-19. RB and YJ would like to thank Sandpit and Seed-Funding on Smart Imaging for Development, delivered by Cambridge Global Challenges SRI, University of Cambridge and CamBridgeSens SRN and supported by the Isaac

Newton Trust for their funding support. All opinion, findings and/or conclusion are that of the authors and do not necessarily reflect the view of the funding organisations.

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