Applied Geography 153 (2023) 102904

Contents lists available at ScienceDirect

Applied Geography

journal homepage: www.elsevier.com/locate/apgeog

Associations between COVID-19 risk, multiple environmental exposures, and housing conditions: A study using individual-level GPS-based real-time sensing data

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ARTICLE INFO

Handling Editor: Y.D. Wei

Keywords:
COVID-19 risk
Individual-level data
Neighborhood effect averaging problem
Multiple environmental exposures
Housing conditions

ABSTRACT

Few studies have used individual-level data to explore the association between COVID-19 risk with multiple environmental exposures and housing conditions. Using individual-level data collected with GPS-tracking smartphones, mobile air-pollutant and noise sensors, an activity-travel diary, and a questionnaire from two typical neighborhoods in a dense and well-developed city (i.e., Hong Kong), this study seeks to examine 1) the associations between multiple environmental exposures (i.e., different types of greenspace, $PM_{2.5}$, and noise) and housing conditions (i.e., housing types, ownership, and overcrowding) with individuals' COVID-19 risk both in residential neighborhoods and along daily mobility trajectories; 2) which social groups are disadvantaged in COVID-19 risk through the perspective of the neighborhood effect averaging problem (NEAP). Using separate multiple linear regression and logistical regression models, we found a significant negative association between COVID-19 risk with greenspace (i.e., NDVI) both in residential areas and along people's daily mobility trajectories. Meanwhile, we also found that high open space and recreational land exposure and poor housing conditions were positively associated with COVID-19 risk in high-risk neighborhoods, and noise exposure was positively associated with COVID-19 risk in low-risk neighborhoods. Further, people with work places in high-risk areas and poor housing conditions were disadvantaged in COVID-19 risk.

1. Introduction

The COVID-19 pandemic has caused a huge burden of disease around the world. A growing body of studies suggested that the disease is unequally transmitted over space in cities (Van Dorn, Cooney, & Sabin, 2020; Chang et al., 2021; Albani et al., 2022). For instance, using contact tracing data from Hong Kong, Huang, Kwan, and Kan (2021) found that vulnerable communities located in the central area had both susceptible and superspreading characteristics due to their intense spatial interactions with other areas. The U.K. also reported a higher mortality rate for low-skilled people with limited ability to change their mobility during the pandemic (e.g., cannot work from home) (Windsor-Shellard & Kaur, 2020). These phenomena stimulated many researchers to investigate the roles of environmental factors and human mobility in the transmission risk of COVID-19 (Kan et al., 2021; Kim & Kwan, 2021a; Huang & Kwan, 2022a; Meng et al., 2022; Pan & Bardhan, 2022).

One of the major assumptions underlying these studies is that people's daily behaviors and immune systems are partially shaped by their environmental exposures, which can further influence the transmission of COVID-19 (Kwan et al., 2019; Huang et al., 2020). For instance, greenspace can significantly promote people's outdoor physical activities, and therefore reduce their face-to-face contact rates in indoor spaces and improve immune functioning, which could further reduce the transmission of COVID-19 (Jiang et al., 2022). In contrast to greenspace, air pollutants (e.g., particulate matter [PM]) have a destructive impact on people's respiratory system and causes lung and cardiovascular diseases, which could further lead to severe COVID-19 outcomes (Mehmood et al., 2021). Particulate matter (PM) could also be one of the possible means that carry the virus into the human body and result in an increased transmission risk of COVID-19 (Shao et al., 2022). High levels of noise can weaken people's immune systems since it could significantly worsen individuals' mental health and disturb sleep cycles (Recio et al., 2016; 2017; Díaz et al., 2021). Besides, noise is also an indicator of human activity, which can be used to represent the

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https://doi.org/10.1016/j.apgeog.2023.102904
Received 28 September 2022; Received in revised form 11 February 2023; Accepted 13 February 2023
Available online 15 February 2023

presence of people's activities in venues or locations (Asensio et al., 2020). Therefore, people would be susceptible to COVID-19 if they were exposed to a high level of noise. Apart from greenspace, air pollution, and noise exposure, poor housing conditions with limited maintenance would also lead to a high transmission risk of COVID-19 since the virus can spread vertically in these buildings through faulty drainage or sewage pipes (Wang et al., 2022).

Along this line, previous studies have found significant associations between greenspace, air pollution, noise, and poor housing conditions with the transmission risk of COVID-19 by linking the incidence or mortality of the disease to specific environmental contexts using public spatially aggregated data (e.g., city, state, and county levels). For instance, using data aggregated at the authority level in England, Johnson et al. (2021) revealed that park use was associated with a low risk of COVID-19 transmission. Peng et al. (2022) reported a significant negative association between greenspace and COVID-19 incidence in China by using a dataset aggregated at the city level. Meanwhile, Klompmaker et al. (2021) and Grigsby-Toussaint and Shin (2022) reported a potential benefit of greenspace in reducing the incidence and mortality of COVID-19 based on a dataset aggregated at the county level in the U.S. Besides, using a dataset aggregated into ZIP code areas in 17 states in the U.S., Spotswood et al. (2021) indicated that communities with high COVID-19 incidence also have little greenspace.

With regard to air pollution (e.g., particulate matter [PM]) and noise, Ogen (2020) found that people's long-term exposure to air pollution is one of the most important contributors to the mortality of COVID-19 based on a dataset aggregated at the regional and administrative levels in four European countries (i.e., Italy, Spain, France, and Germany). A strong association between people's exposure to air pollution and the incidence and mortality of COVID-19 was also observed in China (Zhu et al., 2020), the U.S. (Chakrabarty et al., 2021), Poland (Czwojdzińska et al., 2021), and South Korea (Lym & Kim, 2022). Besides, Díaz et al. (2021) reported a significant association between people's noise exposure with the incidence of COVID-19 in the Province of Madrid.

Recent studies have also found that people were exposed to a high COVID-19 transmission risk if they live in dense old buildings with limited maintenance (Gurney, 2021; Kim & Bostwick, 2020; Plümper & Neumayer, 2020). For instance, using a spatially aggregated dataset in Hong Kong, Huang, Kwan, and Kan (2021) found that neighborhoods with dense urban-renewal buildings and high housing costs were associated with a high transmission risk of COVID-19. Meanwhile, Wang et al. (2022) further reported that old buildings in Hong Kong have a high transmission risk. Ahmad et al. (2021) also found a higher incidence and mortality rate among people who have poor housing conditions (e.g., overcrowdedness and housing types) based on a dataset aggregated at the county level in the U.S.

Notably, previous studies tend to use spatially aggregated data to examine the roles of environmental factors in COVID-19 transmission, which may generate misleading conclusions since most people travel beyond their residential areas to perform various daily activities and thus are exposed to different neighborhood contexts (Kwan, 2012, 2018). For instance, Huang and Kwan (2022a) examined an important methodological issue in the assessment of COVID-19 risk: the neighborhood effect averaging problem (NEAP), which suggests that the assessment of individuals' mobility-based COVID-19 risk would tend toward the average of the population when compared to their residence-based COVID-19 risk. The NEAP further implies that the examination of socio-demographic disparities in individuals' COVID-19 risk might be erroneous if people's daily mobility is ignored. Specifically, people's daily mobility would reduce or amplify their COVID-19 risk in residential areas. For instance, for people who live in high COVID-19-risk neighborhoods and travel to low COVID-19-risk neighborhoods in their daily life, their COVID-19 risk would be overestimated if their daily mobility is ignored, and verse vice (Huang & Kwan, 2022a). In this light, the NEAP underscored one particular phenomenon that has been largely ignored in previous studies: people would be doubly disadvantaged in COVID-19 risk if they live in a neighborhood with high COVID-19 risk and their mobility-based COVID-19 risk is higher than their residence-based COVID-19 risk (Huang & Kwan, 2022a). It should be noted that a similar phenomenon has been observed in the assessment of individuals' exposure to air pollution and traffic congestion (Kim and Kwan, 2019, 2021b, 2021c).

In addition, previous studies did not examine the combined relationships between individuals' COVID-19 risk on one hand and multiple environmental exposures and housing conditions on the other through individual-level data. Further, they did not examine who would be disadvantaged in COVID-19 risk through the perspective of the NEAP. Thus, this study seeks to bridge the research gaps by addressing the following two research questions: First, what are the associations between individuals' COVID-19 risk and multiple environmental exposures (i.e., greenspace, air pollution, and noise) and housing conditions (i.e., housing types, ownership, and over crowdedness), both in residential areas and along people's daily mobility trajectories? Second, who are disadvantaged in COVID-19 risk through the perspective of the NEAP? In other words, which social groups have a high level of COVID-19 risk in their residential areas while the COVID-19 risk in their daily mobility trajectories is equal to or higher than the risk in their residential areas? Answering these questions will enrich our understanding of the complicated associations among individuals' mobility, environmental factors, housing conditions, and COVID-19 risk. Further, the generated new knowledge will provide important insights for public health authorities to identify vulnerable groups during the COVID-19 pandemic.

2. Dataset and methods

This study seeks to address the abovementioned research questions using individual-level survey data. Specifically, a survey was conducted in Sham Shui Po (i.e., a high COVID-19 risk neighborhood) and Tin Shui Wai (i.e., a low COVID-19 risk neighborhood) in Hong Kong during the pandemic. The survey used real-time GPS tracking, mobile air pollutant and noise sensors, an activity-travel diary, and a questionnaire to collect individual-level data, which include participants' daily GPS trajectories, real-time $PM_{2.5}$ and noise exposures, housing conditions (e.g., house type, homeownership), and socio-demographic attributes (e.g., gender, educational level, age, income). Besides, we also collected a COVID-19 dataset, a Normalized Difference Vegetation Index (NDVI) layer, and a land-use dataset with four different types of greenspace (i.e., woodland, shrubland, open space, and recreational land and grassland) to evaluate COVID-19 risk and different types of greenspace environments in the city. Then, residence-based and mobility-based approaches were applied to measure participants' COVID-19 risk and different types of greenspace exposures both in their residential areas and along their daily mobility trajectories. We used separate regression models to examine the combined associations between individuals' COVID-19 risk with multiple environmental exposures (i.e., $PM_{2.5}$, noise, and different types of greenspace exposures) and housing conditions. Lastly, we identified people's disadvantages in COVID-19 risk through the perspective of the NEAP and examined the associations between people's disadvantages in COVID-19 risk with their socio-demographic attributes and housing conditions based on logistic models. The below sections describe the analytical methods in detail.

2.1. Study area and data collection

The study area of this work is Hong Kong, which consists of three major areas (i.e., the New Territories, Kowloon, and Hong Kong Island). The city has experienced five waves of COVID-19 outbreaks from January 2020 to March 2022. Note that the areas in Kowloon and Hong Kong Island have more serious COVID-19 transmission than the areas in New Territories. Besides, the high-risk areas for each outbreak in local communities are spatially similar (Huang et al., 2020, 2021a). The Hong Kong Government persistently applied a “zero-COVID” strategy from January 2020 to March 2022. Specifically, the mitigation measures include border control, social distancing, and closure of clubs, bars, and public facilities (e.g., schools) (Huang, Kwan, & Kim, 2021). All these measures have succeeded in preventing large-scale COVID-19 outbreaks in local communities until the Omicron-variant outbreak in January 2022.

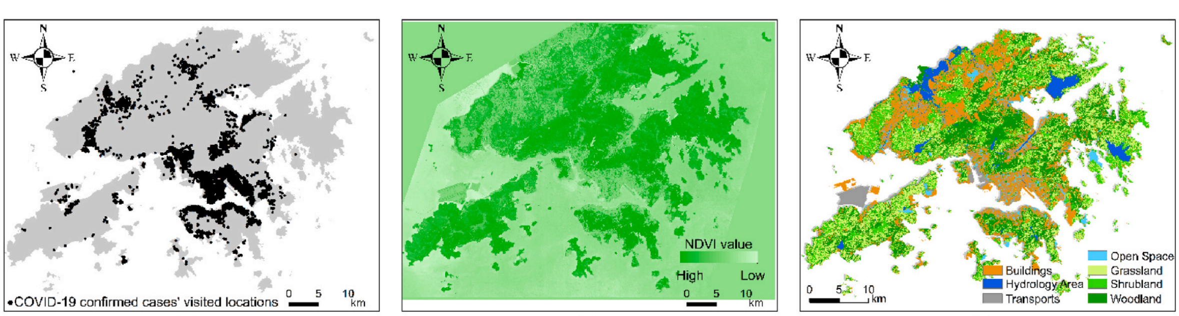
We conducted a survey in Sham Shui Po (SSP) and Tin Shui Wai (TSW) in the study area from April 2021 to September 2021. We selected these two neighborhoods to conduct the survey because they are two typical neighborhoods in Hong Kong in the early stage of the pandemic. Specifically, SSP is an old urban area (developed in the 1920s) located in the center of the city (i.e., Kowloon), while TSW is a new town (developed in the 1980s) and located in the suburban area of Hong Kong (i.e., the New Territories). Besides, SSP has a higher level of COVID-19 transmission risk than TSW due to its intense spatial interactions with other areas (Huang & Kwan, 2022b). A detailed introduction of the two neighborhoods can be found elsewhere (Kan et al., 2022; Huang & Kwan, 2022b).

We recruited 221 participants from the two neighborhoods through a stratified sampling approach. The survey includes the following stages: (1) the participants registered for the survey through online social media, posters, or mass mail (2) eligible participants (i.e., aged from 18 to 64 years old and can read and write Chinese) were invited to attend a face-to-face briefing section. In the briefing section, we first collected participants’ socio-demographic attributes (e.g., gender, age, educational level, income, and so on) and housing conditions (e.g., house type, homeownership, and the number of family members) through a questionnaire. Then, each participant was asked to carry a portable air pollutant sensor (logged at 1-s intervals) and a portable noise sensor (logged at 30-s intervals) and complete an activity-travel diary over two continuous survey days (i.e., one weekday and one weekend day). Participants were required to write down the time, locations, and travel modes of their daily activities in the activity-travel diaries. Meanwhile, each participant was also required to carry a GPS-tracking smartphone for one week (which includes the two survey days). Hence, the portable sensors, the smartphone, and the activity-travel diary were used together to collect participants’ real-time GPS trajectory data and the spatiotemporal data of their real-time exposures to $PM_{2.5}$ and noise. Note that there are many tall buildings in Hong Kong, which may lead to the smartphones’ poor reception of satellite signals used in GPS positioning (Huang & Kwan, 2022b). Therefore, GPS-tracking smartphones may provide inaccurate GPS data for the participants’ daily mobility trajectories. Thus, we used the activity-travel diary to evaluate the GPS-tracking data and made necessary corrections to ensure that the GPS data are accurate. Specifically, the participants’ GPS data were cleared based on two steps (see Table S1): (1) outliers were first removed; (2) the locations of points were then calibrated and validated according to the activity-travel diaries. The Survey and Behavioural Research Ethics Committee (SBRE) of the Chinese University of Hong Kong reviewed and approved the study protocol and survey instruments. In addition, we also obtained informed consent from all participants before the survey.

2.2. COVID-19 and greenspace dataset

We obtained a COVID-19 dataset from the Hong Kong Government’s open-data website (http://data.gov.hk) and used it to present the spatial distribution of COVID-19 risk in the city. The dataset includes historical activity locations and venues (i.e., the past 14 days) of all the local confirmed cases (Fig. 1a) from July 1, 2020 to May 31, 2021 in Hong Kong (i.e., the third and fourth waves). Using the COVID-19 dataset, the spatial distribution of COVID-19 risk was represented by density surfaces derived based on a kernel density estimation (KDE) function, which estimates a density surface from the locations of a set of points using the kernel function and a predetermined search radius (i.e., spatial bandwidth). The spatial resolution is 100 m $\times$ 100 m and the search radius is 1 km in the KDE. We selected 1 km as the search radius because it represents a distance that can be reached easily by the participants by walking during the pandemic (Huang & Kwan, 2022a). We used the method to present the spatial distribution of COVID-19 risk based on the main mode of COVID-19 transmission: a high density of visits by confirmed cases means a high level of COVID-19 risk due to a higher risk of face-to-face contact with infected persons. In other words, this study uses a proxy that represents individual-level COVID-19 risk as the likelihood of a person catching COVID-19 through face-to-face contact with dense infected individuals (Huang & Kwan, 2022a).

In addition, we also collected two different types of data to represent different types of greenspace distribution in Hong Kong. We first obtained a Normalized Difference Vegetation Index (NDVI, Fig. 1b) layer with a spatial resolution of 6 m $\times$ 6 m, which has pixel values ranging from -1 to 1 and higher values indicating a greater density of greenspace. The NDVI layer was derived using SPOT-7 satellite images (2017). It should be noted that pixel values below 0 have been recoded as 0 since these values represent non-greenspace (e.g., roads and water bodies). Besides, a land-use dataset (Fig. 1c) was obtained from the Hong Kong Planning Department. The dataset includes the spatial distributions of different types of green land (i.e., woodland, shrubland, and grassland) and open space and recreational land (i.e., parks, stadiums, playgrounds, and recreational facilities) in the city in 2020. Compared to the NDVI, greenspace in the land-use dataset is more associated with publicly accessible space (e.g., country parks and recreational space) for the residents. Dissimilar from the land-use dataset, the NDVI layer also contains private greenery (e.g., private gardens in buildings) and street greenery (e.g., trees along roads).



(a) (b) (c)

Fig. 1. The spatial distribution of (a) Locations visited by confirmed COVID-19 cases, (b) the Normalized Difference Vegetation Index (NDVI), and (c) Land use data a land-use dataset obtained from the Hong Kong Planning Department.

2.3. Methods

2.3.1. Measuring residence- and mobility-based COVID-19 risk and multiple environmental exposures

Using the collected dataset, we first assessed participants' COVID-19 risk and different types of greenspace exposures (i.e., NDVI, open space and recreational land, grassland, shrubland, and woodland) using two different approaches (see Table S2): residence-based approach and mobility-based approach. The residence-based and mobility-based COVID-19 risk and NDVI exposures were assessed according to the mean value derived from a 100 m buffer around the participants' home addresses and each GPS point. Specifically, we first used the average value of COVID-19 risk and the NDVI within a 100 m buffer around each GPS point to represent participants' exposure to COVID-19 risk and the NDVI at each GPS location. After that, the mean values of participants' COVID-19 risk and NDVI exposures in all GPS locations were calculated to assess the mobility-based COVID-19 risk and NDVI exposures. Meanwhile, the residence-based and mobility-based open space and recreational land, grassland, shrubland, and woodland exposures were measured based on the ratio of the area of each type of greenspace inside the participants' home address and each GPS point. We selected 100 m as the buffer size for this purpose because it represents an area that the participant can easily reach in their daily life (see Mueller et al., 2020; Roberts & Helbich, 2021).

Besides, we also assessed participants' $PM_{2.5}$ and noise exposures using data obtained through the portable air pollutant and noise sensors they carried during the survey. The portable sensors can simultaneously measure and record participants' $PM_{2.5}$ and noise exposures along their daily mobility trajectories at high spatiotemporal resolution (i.e., every second for $PM_{2.5}$ and every 30th second for noise level). Note that the $PM_{2.5}$ concentrations reported by the air pollutant sensors were adjusted to increase their accuracy based on a machine-learning calibration model developed earlier. A more elaborate description of the calibration model is provided in Huang et al. (2022).

We also used a professional-grade CEM SC-05 Sound Level Calibrator to calibrate the portable noise sensors before the survey. The calibrated noise sensors meet IEC61672 Type 2 Sound Level Meter standards. Specifically, the calibrated noise sensors can measure the range of participants' real-time ambient noise from 30 to 130 dBA with an accuracy of <1.5 dBA error. Then, the equivalent A-weighted sound pressure levels were further used to evaluate participants' real-time ambient sound levels during the daytime (08:00 a.m.–08:00 p.m.). The A-weighted equivalent sound pressure level was widely used in previous studies to measure individuals' noise exposures (Ma, Rao, et al., 2020; Tao et al., 2021).

We applied the paired sample *t*-test to examine whether there is a significant difference between residence- and mobility-based COVID-19 risk and different types of greenspace exposures in SSP and TSW. Meanwhile, we used the Spearman correlation analysis to examine the bivariate associations between participants' residence- and mobility-based COVID-19 risk and multiple environmental exposures.

2.3.2. Examining the associations between participants' COVID-19 risk with their multiple environmental exposures and housing conditions

We applied separate multiple linear regression models to examine the associations between participants' COVID-19 risk and their multiple environmental exposures (i.e., different types of greenspace, $PM_{2.5}$, and noise exposures) and housing conditions (i.e., house type, homeownership, number of family members), both in their residential areas and along their daily mobility trajectories. Specifically, we first focused on SSP participants in Models 1–6, where residence-based COVID-19 risk was examined by Models 1–3 and mobility-based COVID-19 risk was assessed by Models 4–6. Then, we focused on TSW participants in Models 7–12, which include residence-based models (Models 7–9) and mobility-based models (Models 10–12). In Models 1, 4, 7, and 10, we examined the associations between individuals' residence- and mobility-based COVID-19 risk and multiple environmental exposures. In Models 2, 5, 8, and 11, we examined the associations between individuals' residence- and mobility-based COVID-19 risk and their housing conditions. Finally, we included all variables in the full models (3, 6, 9, and 12). All models were controlled for participants' socio-demographic features (e.g., gender, age, income, and so on). Note that the results of the variance inflation factor (VIF) indicated no significant collinearity among the independent variables (i.e., all VIFs <8).

2.3.3. Examining the associations between people's disadvantage in COVID-19 risk with socio-demographic features and housing conditions

We defined people's disadvantages in COVID-19 risk through the perspective of the neighborhood effect averaging problem (NEAP) with the following conditions (i.e., D_{COVID} in Equation (1)), which have been applied in previous studies (Kim and Kwan, 2021b, 2021c; Ma, Li, et al., 2020): (1) an individual's residence-based COVID-19 risk level is relatively high; (2) the person's mobility-based COVID-19 risk is higher than his/her residence-based COVID-19 risk.

$$D^{i}_{COVID} = \begin{cases} 1, if\ Z\left(RE^{i}_{COVID}\right) \geq 0.5\ and\ ME^{i}_{COVID} > RE^{i}_{COVID} \\ 0, \text{otherwise} \end{cases} \tag{1}$$

where D^{i}_{COVID} denotes if individual i is disadvantaged (=1; otherwise = 0) in COVID-19 risk. Next, we used two logistic regression models to examine the associations between people's disadvantage in COVID-19 risk and their socio-demographic features and housing conditions in SSP (i.e., Model 13) and TSW (i.e., Model 14). The dependent variables for Models 13 and 14 are individuals' disadvantages in COVID-19 risk (i.e., D_{COVID}) in SSP and TSW. The independent variables include participants' socio-demographic features and housing conditions. In Models 13 and 14, all VIFs were less than 5, indicating no significant collinearity among the independent variables.

3. Results

3.1. Results of measuring residence-based and mobility-based COVID-19 risk and multiple environmental exposures

After data cleaning, we excluded 5 participants with missing data in their activity-travel diaries (i.e., less than 6 activity records) and portable real-time sensor records (i.e., missing records of GPS points as well as air pollutant and noise levels). We finally have valid data from 216 participants (108 in SSP, and 108 in TSW). Table 1 presents the participants' socio-demographic and housing conditions in the two neighborhoods. Among the participants, the distribution of gender, age groups, household income, education status, employment status and marital status are comparable between the two neighborhoods. There are more female participants (56% in SSP and 53% in TSW) than male participants (44% in SSP and 47% in TSW). Most participants are 25–44 years old (47% in SSP and 46% in TSW), have high education degrees (i.e., higher diploma or above, 64% in SSP and 65% in TSW), have full-time employment (67% in SSP and 60% in TSW), and are married (40% in SSP and 36% in TSW). Most SSP participants (45%) reported that their monthly household income is less than HK$20,000, while 29% of TSW participants reported that their monthly household income is less than HK$ 20,000. In terms of housing conditions, more than half of the participants live in rented housing (63% in SSP and 56% in TSW). Meanwhile, most of the participants live in public housing (45% in SSP and 85% in TSW). It should be noted that 28% of SSP participants live in *tong lau* and subdivided units, and no TSW participants live in *tong lau* and subdivided units. The detailed profiles of the two neighborhoods and samples are available elsewhere (please see Kan et al., 2022; Huang & Kwan, 2022b).

We first measured participants' residence- and mobility-based COVID-19 risk and multiple environmental exposures (i.e., different types of greenspace, $PM_{2.5}$, and noise). Table 2 presents the descriptive

Table 1
Sociodemographic characteristics of Sham Shui Po (SSP) and Tin Shui Wai (TSW) participants.

		SSP (n = 108)	TSW (n = 108)
		N (%)	N (%)
Gender	Male	47 (44%)	51(47%)
	Female	61 (56%)	57 (53%)
Age group	18–24 years	18 (17%)	24 (22%)
	25–44 years	51 (47%)	50 (46%)
	45–65 years	39 (36%)	34 (32%)
Education status	With a high education degree	69 (64%)	70 (65%)
	without a high education degree	39 (36%)	38 (35%)
Monthly household income level (HKD)	Less than 20,000	49 (45%)	31 (29%)
	20,000–39,999	34 (32%)	47 (43%)
	40,000 or over	25 (23%)	30 (28%)
Employment status	Housewife	10 (9%)	13 (12%)
	Employed (full-time	72 (67%)	65 (60%)
	Employed (part-time)	16 (15%)	16 (15%)
	Student	10 (9%)	14 (13%)
Marital status	Married	43 (40%)	39 (36%)
	Single, widowed, or divorced	65 (60%)	69 (64%)
Homeownership	Rented	68 (63%)	60 (56%)
	Owned	40 (37%)	48 (44%)
House type	Public housing	49 (45%)	92 (85%)
	Private housing	29 (27%)	16 (15%)
	Tang lau and subdivided units	30 (28%)	0 (0%)
Number of family members	Mean (SD)	2.6 (1.35)	3.5 (1.08)

statistics. As expected, the results indicate that participants in SSP were exposed to a higher level of COVID-19 risk than participants in TSW both in residence- and mobility-based measurements. Meanwhile, we also found that using the NDVI and the land-use dataset to assess participants' greenspace exposures can generate different results: participants in SSP have lower levels of NDVI exposure than participants in TSW both in residence- and mobility-based measurements, while participants in SSP and TSW have similar levels of different types of greenspace exposures (i.e., open space and recreational land, grassland, shrubland, and woodland). The difference seems reasonable because TSW is a new town built in the 1980s with more private and street greenery than SSP, which would be simplified as other types of land use (e.g., transport or building land) in the land-use dataset. Therefore, using the land-use dataset to assess people's greenspace in TSW would underestimate their greenspace exposure.

In addition, we also found that the pairwise differences between residence- and mobility-based exposure to COVID-19 risk and different types of greenspace are significant, except that the pairwise differences between residence- and mobility-based exposure to NDVI in TSW are insignificant (i.e., p-value >0.05). These results are consistent with previous studies, which indicated that using residence- and mobility-based approaches to assess individuals' exposure to environmental exposures (e.g., $PM_{2.5}$, COVID-19 risk, ozone, and traffic congestion) would generate different results (Ma, Li, et al., 2020; Kim & Kwan, 2019; Kim & Kwan, 2021b,c; Huang and Kwan, 2022).

3.2. Bivariate analysis

Fig. 2 shows the Spearman correlations among the residence- and mobility-based COVID-19 risk and multiple environmental exposures in SSP (Fig. 2a and b) and TSW (Fig. 2c and d). We found that COVID-19 risk is significantly and negatively correlated with NDVI ($r = -0.50$ to -0.81, $p < 0.05$) in SPP and TSW for both residence- and mobility-based measurements. Meanwhile, in SSP, residence-based COVID-19 risk is significantly and negatively correlated with residence-based shrubland ($r = -0.19$, $p < 0.05$), and mobility-based COVID-19 risk is significantly and negatively correlated with mobility-based open space and recreational land ($r = -0.21$, $p < 0.05$), grassland ($r = -0.45$, $p < 0.05$), shrubland ($r = -0.20$, $p < 0.05$), and woodland ($r = -0.22$, $p < 0.05$). In TSW, residence-based COVID-19 risk has a significant negative correlation with open space and recreational land ($r = -0.27$, $p < 0.05$), grassland ($r = -0.48$, $p < 0.05$), and woodland ($r = -0.34$, $p < 0.05$), and mobility-based COVID-19 risk has a significant negative correlation with shrubland ($r = -0.28$, $p < 0.05$).

Besides, correlations between $PM_{2.5}$ and noise with COVID-19 risk and different types of greenspace are insignificant (i.e., p-value >0.05) in SSP, while $PM_{2.5}$ has a significant negative correlation ($r = -0.22$, $p < 0.05$) with COVID-19 risk in TSW. Meanwhile, the exposure of TSW participants to $PM_{2.5}$ has a significant negative correlation with grassland ($r = -0.20$, $p < 0.05$), shrubland ($r = -0.34$, $p < 0.05$), and woodland ($r = -0.20$, $p < 0.05$) exposures. Noise ($r = 0.21$, $p < 0.05$) is significantly positively correlated with open space and recreational land exposure in TSW.

3.3. The associations between participants' exposure to COVID-19 risk with multiple environmental exposures and housing conditions

We examined the associations between individual COVID-19 risk and multiple environmental exposures (i.e., different types of greenspace, $PM_{2.5}$, and noise exposures) and housing conditions (i.e., housing type, number of family members, and home ownership) using separate multiple linear regression models. Table 3 presents the results of Models 1–6, which focus on SSP participants. The results indicated that NDVI had significant negative associations (Coef. = -0.52, SE. = 0.14, Model 6) with COVID-19 risk for both residence- and mobility-based models (i.

Table 2
COVID-19 risk and multiple environmental exposure measurements among surveyed participants in Sham Shui Po (SSP) and Tin Shui Wai (TSW).

	SSP			TSW		
	Residential-based	Mobility-based	p-value	Residential-based	Mobility-based	p-value
	M (SD)	M (SD)		M (SD)	M (SD)	
COVID-19 Risk	4713.41 (1736.49)	4166.45 (1460.09)	<0.001***	969.31 (332.11)	1155.07 (483.45)	<0.001***
NDVI	0.19 (0.07)	0.21 (0.07)	0.004**	0.24 (0.04)	0.25 (0.04)	0.201
Open space and recreational land	0.05 (0.08)	0.07 (0.08)	0.003**	0.04 (0.09)	0.07 (0.07)	<0.001***
Grassland	0.01 (0.02)	0.01 (0.03)	<0.001***	0.01 (0.01)	0.01 (0.02)	<0.001***
Shrubland	0.00 (0.00)	0.01 (0.02)	0.006**	0.00 (0.00)	0.00 (0.01)	<0.001***
Woodland	0.00 (0.00)	0.02 (0.04)	<0.001***	0.00 (0.00)	0.01 (0.02)	<0.001***
$PM_{2.5}$ (ug/m^3)	–	12.39 (5.53)	–	–	12.74 (5.72)	–
Noise (dBA)	–	64.86 (6.53)	–	–	62.80 (6.53)	–

** Represents statistically significant at the $p < 0.01$ level.
*** Represents statistically significant at the $p < 0.001$ level.

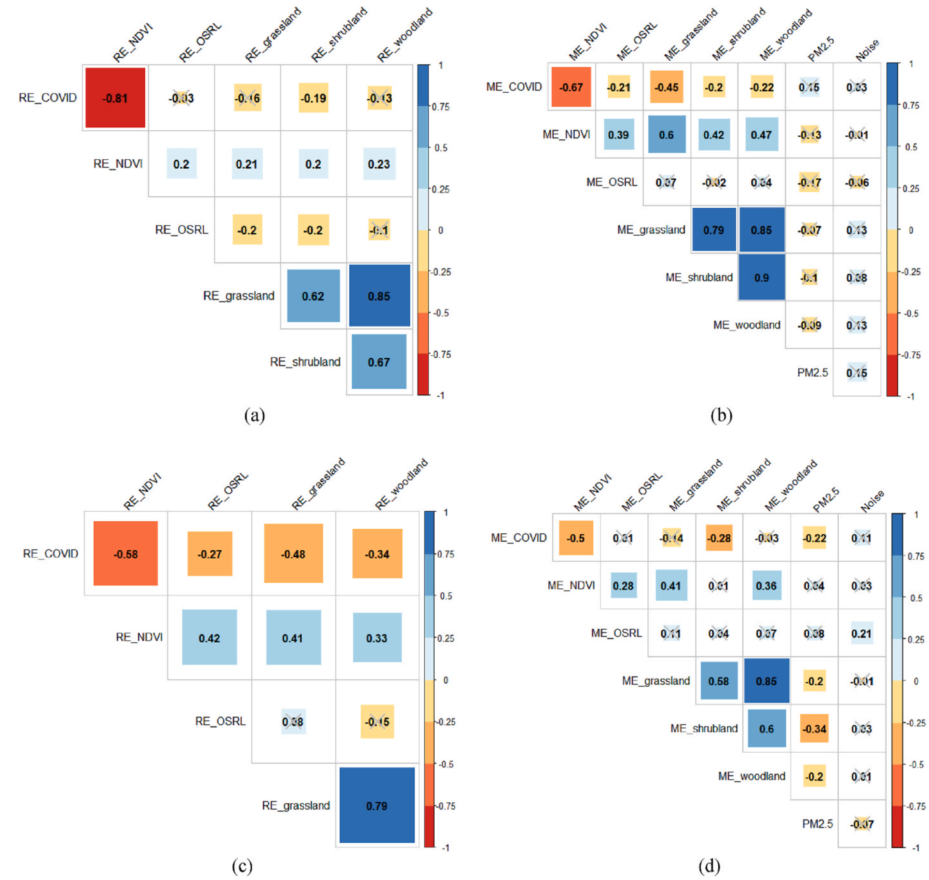


Fig. 2. Correlation matrices of residence- and mobility-based COVID-19 risk and multiple environmental exposures based on Spearman correlation coefficients: (a)–(b) residence- and mobility-based measurements in Sham Shui Po (SSP); (c)–(d) residence- and mobility-based measurements in Tin Shui Wai (TSW). *OSRL* refers to open space and recreational land.

Table 3
Results of the regression models on the association between SSP participants' COVID-19 risk with their multiple environmental exposures and housing conditions.

	Residence-based			Mobility-based		
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
	Coef. (SE.)	Coef. (SE.)	Coef. (SE.)	Coef. (SE.)	Coef. (SE.)	Coef. (SE.)
Environmental exposures						
NDVI	−0.81*** (0.08)		−0.59*** (0.11)	−0.73*** (0.12)		−0.52 *** (0.14)
Open space and recreational land	0.20* (0.08)		0.19* (0.08)	0.12 (0.09)		0.08 (0.09)
Grassland	0.02 (0.11)		0.07 (0.10)	−0.21 (0.16)		−0.15 (0.15)
Shrubland	−0.01 (0.11)		0.03 (0.11)	0.06 (0.17)		−0.05 (0.16)
Woodland	0.06 (0.15)		0.04 (0.15)	0.21 (0.21)		0.17 (0.20)
$PM_{2.5}$	–		–	0.05 (0.08)		−0.01 (0.08)
Noise	–		–	−0.03 (0.08)		−0.07 (0.07)
Housing conditions						
Public house		0.75*** (0.21)	0.39 (0.26)		0.53* (0.23)	0.14 (0.27)
Tong lau or subdivided units		0.91*** (0.22)	0.57 ** (0.20)		0.81*** (0.23)	0.69 ** (0.20)
Number of family members		−0.05 (0.08)	0.01 (0.08)		−0.09 (0.08)	−0.04 (0.07)
Rented		−0.09 (0.21)	−0.09 (0.20)		−0.11 (0.22)	−0.13 (0.20)
Intercept	−0.23 (0.36)	0.26 (0.41)	0.13 (0.38)	−0.29 (0.37)	−0.30 (0.44)	−0.16 (0.38)
Adjusted R^2	0.523	0.464	0.578	0.484	0.399	0.559
AIC	244.83	256.62	235.99	254.97	268.94	233.2

Notes: *** denotes $p < 0.001$. ** denotes $p < 0.01$. * denotes $p < 0.05$. Models were controlled for age, gender, educational level, marital status, working place, monthly household income level, employment status, and monthly household rent/mortgage payment.

e., Models 1, 3, 4, and 6). Residence-based exposure to open space and recreational land was significantly and positively associated (Coef. = 0.19, SE. = 0.08, Model 3) with COVID-19 risk. $PM_{2.5}$ and noise were not significantly associated with COVID-19 risk in any of the models. In Models 2 and 5, living in public housing had a significant positive association (Coef. = 0.53, SE. = 0.23, Model 5) with COVID-19 risk. In the full Models 3 and 6, the significant association between living in public housing with COVID-19 risk was rendered nonsignificant. Meanwhile, living in *tong lau* or subdivided units had a significant positive association (Coef. = 0.69, SE. = 0.20, Model 6) with COVID-19 risk for both residence- and mobility-based models (i.e., Models 2, 3, 5, and 6).

Table 4 presents the results of Models 7–12, which focus on TSW participants. The results also indicated that NDVI had significant negative associations (Coef. = -0.52, SE. = 0.14, Model 12) with COVID-19 risk for both residence- and mobility-based models (i.e., Models 7, 9, 10, and 12). Besides, we found that noise had a significant positive association (Coef. = 0.16, SE. = 0.10) with COVID-19 risk in Model 10. After simultaneously considering individuals' multiple environmental exposures and housing conditions in Model 12, noise was still significantly and positively associated (Coef. = 0.17, SE. = 0.10) with COVID-19 risk. $PM_{2.5}$ and housing conditions were not significantly associated with COVID-19 risk in any of the models.

3.4. The associations between people's disadvantage in COVID-19 risk with socio-demographic features and housing conditions

We examined how people's disadvantage in COVID-19 risk is related to their socio-demographic attributes and housing conditions using logistic models. According to the criteria mentioned in Section 2.3.3, we found that 77 participants (41 SSP and 36 in TSW) have a relatively high residence-based COVID-19 risk. Among these participants, 34 participants (18 in SSP and 16 in TSW) were disadvantaged in COVID-19 risk.

Table 5 presents the results of Models 13 and 14. The results indicated that working in Kowloon was significantly and positively associated with the disadvantage in COVID-19 risk of SSP participants (OR = 7.54, 95% CI= (1.70–23.53)) and TSW participants (OR = 8.42, 95% CI= (1.77–27.89)). In TSW, working in Hong Kong Island was also significantly and positively associated with people's disadvantage in COVID-19 risk (OR = 9.41, 95%= (1.93–39.05)). Besides, in SSP, living in public housing was significantly and positively associated with people's disadvantage in COVID-19 risk (OR = 6.72, 95% CI = (1.56–12.91)).

Table 5
Results of the logistic regression models on the associations between the individuals' odds of being disadvantaged during the COVID-19 pandemic with their disadvantaged in multiple environmental exposures and housing conditions.

	SSP		TSW	
	Model 13		Model 14	
	OR	95% CI	OR	95% CI
Housing conditions				
Public house	6.72 *	1.56–12.91	1.23	0.27–5.68
Tong lau or subdivided units	1.40	0.15–7.89	–	–
Number of family members	0.80	0.40–1.60	0.84	0.50–1.42
Rented	1.10	0.18–6.55	0.29	0.08–1.11
Socio-demographic features				
Female	0.81	0.21–3.13	0.58	0.17–2.04
Age group 1 (18–24)	0.35	0.04–3.37	0.27	0.07–0.62
Age group 2 (25–44)	1.04	0.23–4.80	0.34	0.07–1.63
High education	0.86	0.14–5.19	1.65	0.36–7.52
Married	1.04	0.23–4.80	0.31	0.08–1.29
Income 1 (<20,000 HKD)	0.90	0.09–8.69	1.82	0.55–4.50
Income (20,000–40,000 HKD)	0.60	0.19–3.84	0.98	0.28–3.42
Rent/Loan (1–4000 HKD)	2.19	0.54–8.85	2.52	0.67–9.39
Rent/Loan (4000–10,000 HKD)	1.14	0.10–4.72	0.80	0.16–4.05
Employment (full-time)	0.61	0.13–2.91	1.22	0.29–5.09
Student	1.01	0.36–6.29	2.06	0.24–7.64
Household wife	3.77	0.68–5.72	0.59	0.06–3.32
Working place 1 (Kowloon)	7.54**	1.70–23.53	8.42*	1.77–27.89
Working place 2 (Hong Kong Island)	1.07	0.12–9.85	9.41*	1.93–39.05
Nagelkerke R^2	0.354		0.301	
AIC	121.13		125.92	

Notes: *** denotes $p < 0.001$. ** denotes $p < 0.01$. * denotes $p < 0.05$.

4. Discussion

4.1. Main findings and comparisons with previous studies

This study seeks to examine the combined associations between individuals' COVID-19 risk with multiple environmental exposures and housing conditions using individual-level survey data. Besides, the study also examines which social groups are disadvantaged in COVID-19 risk through the perspective of the neighborhood effect averaging problem (NEAP). Using individual-level survey data collected from Sham Shui Po (SSP) and Tin Shui Wai (TSW) in Hong Kong, our regression models revealed significant associations between individuals' COVID-19 risk with multiple environmental exposures and housing conditions.

First, our findings suggest that a high level of exposure to NDVI has a significant negative association with people's COVID-19 risk in their residential areas and along their daily mobility trajectories. In line with our results, recent studies also reported a significant negative

Table 4
Results of the regression models on the association between TSW participants' COVID-19 risk with their multiple environmental exposures and housing conditions.

	Residence-based			Mobility-based		
	Model 7	Model 8	Model 9	Model 10	Model 11	Model 12
	Coef. (SE.)	Coef. (SE.)	Coef. (SE.)	Coef. (SE.)	Coef. (SE.)	Coef. (SE.)
Environmental exposures						
NDVI	−0.40** (0.12)		−0.42** (0.13)	−0.49*** (0.14)		−0.52*** (0.14)
Open space and recreational land	0.04 (0.11)		0.07 (0.12)	0.05 (0.11)		0.03 (0.11)
Grassland	−0.09 (0.11)		−0.08 (0.11)	−0.09 (0.12)		−0.08 (0.12)
Shrubland	–		–	0.09 (0.12)		0.14 (0.13)
Woodland	−0.11 (0.11)		−0.11 (0.11)	0.01 (0.15)		0.02 (0.15)
$PM_{2.5}$	–		–	−0.09 (0.10)		−0.10 (0.10)
Noise	–		–	0.16* (0.10)		0.17* (0.10)
Housing conditions						
Public house		0.38 (0.31)	0.01 (0.29)		0.09 (0.31)	−0.12 (0.29)
Number of family members		0.14 (0.11)	0.08 (0.10)		−0.03 (0.11)	−0.13 (0.11)
Rented		0.12 (0.26)	0.31 (0.25)		0.01 (0.26)	0.03 (0.24)
Intercept	−0.62 (0.48)	−1.27* (0.60)	−0.70 (0.58)	−0.24 (0.48)	−0.83 (0.61)	−0.22 (0.57)
Adjusted R^2	0.180	0.090	0.173	0.225	0.074	0.212
AIC	242.39	328.3	307.44	300.3	332	304.27

Notes: *** denotes $p < 0.001$. ** denotes $p < 0.01$. * denotes $p < 0.05$. Models were controlled for age, gender, educational level, marital status, working place, monthly household income level, employment status, and monthly household rent/mortgage payment.

association between greenspace with COVID-19 incidence and mortality in the U.S. (Klompmaker et al., 2021; Russette et al., 2021), China (Peng et al., 2022), South Korea (Lee et al., 2022), and England (Johnson et al., 2021). Existing evidence was mainly obtained based on spatially aggregated datasets that captured the effects of people's residential neighborhood environment on health outcomes. In this study, we go beyond previous studies that typically rely on a residence-based approach and adopt a mobility-based approach to exposure assessment. Moreover, to the best of our knowledge, this is the first study to examine the association between individuals' greenspace exposure with COVID-19 risk through an individual-level GPS-based real-time sensing dataset. Therefore, our findings provide strong evidence of the benefits of greenspace in the reduction of individual COVID-19 risk in people's residential areas and along their daily trajectories.

In contrast to NDVI, our results also suggested that a high level of exposure to open space and recreational land in a high-risk neighborhood (i.e., SSP) would significantly increase people's COVID-19 risk in their residential neighborhoods. Note that previous studies have found mixed effects of open space and recreational land on COVID-19 risk: Pan et al. (2021) reported that highly connected open spaces and parks were associated with a high risk of COVID-19 transmission in London, while Liu (2021) suggested that increased open space was associated with reduced COVID-19 transmission risk in King County, Washington. One possible explanation for the difference include that Hong Kong and London are well-known high-density cities and have built environments with diversity, compactivity, and connectivity (Zhong et al., 2016; Sulis et al., 2018; Kwok et al., 2021), whereas King County has a built environment characterized by dispersion and lower densities (Liu et al., 2021). Therefore, the open space and recreational land in Hong Kong would affect people's face-to-face contact rates and thus increase COVID-19 transmission risk in high-risk and dense neighborhoods. Our findings highlight the need for future studies to control different types of greenspace in both residence-based and mobility-based approaches and to avoid incorrectly estimating the effect of a single type of greenspace exposure using the residence-based approach with a single data source.

In addition to different types of greenspace, we also examined the associations between COVID-19 risk with $PM_{2.5}$ and noise exposures. We did not observe any significant associations between COVID-19 risk and $PM_{2.5}$ both in SSP and TSW. However, this result is inconsistent with findings from previous studies, which suggested a high level of $PM_{2.5}$ exposure was associated with high COVID-19 transmission risk (Curtis, 2021; Meo et al., 2021; Marquès & Domingo, 2022). The differences may be attributed to how COVID-19 transmission risk was measured: our study uses a proxy that represents individual-level COVID-19 risk as the likelihood of a person catching COVID-19 through face-to-face contact with dense infected individuals, while previous studies used spatially aggregated COVID-19 incidence or mortality rate as the risk at the population level. Besides, we did observe a significant association between COVID-19 risk and noise exposure for TSW participants along their daily mobility trajectories. Our findings supplement previous research that has observed a significant association between COVID-19 incidence and noise exposure in the Province of Madrid, Spain (Díaz et al., 2021). In this study, we made a novel contribution to the discussion about the effects of noise exposure on COVID-19 risk as the first to consider individuals' exposure to noise along their daily mobility trajectories.

Our results also reported significant positive associations between public housing with COVID-19 risk in SSP. Meanwhile, our results further revealed that living in *tong lau* or subdivided units in SSP has a significant positive association with people's COVID-19 risk both in the residential neighborhood and along their daily mobility trajectories. These findings are consistent with previous research that has reported a high COVID-19 transmission risk in old buildings or public housing in Hong Kong (Wang et al., 2022), the U.S. (Ahmad et al., 2020), India (Das et al., 2021), and Canada (Pirrie & Agarwal, 2021). We further observed that these people were exposed to high COVID-19 transmission risk along their daily mobility trajectories. It should be noted that we did not observe significant associations between public housing with COVID-19 risk in TSW. The differences in SSP and TSW imply the spatial nonstationarity in the associations between housing conditions with COVID-19 risk: the effects of housing conditions on COVID-19 risk vary over space (Huang, Kwan, & Kan, 2021; Kwan, 2021).

In terms of people's disadvantaged in COVID-19 risk through the perspective of the neighborhood effect averaging problem (NEAP), we found that people working in high-risk areas (e.g., Kowloon and Hong Kong Island) have the highest odds of being disadvantaged in COVID-19 risk. This result provides empirical evidence to strongly support the conclusions from previous studies (Huang and Kwan, 2022a, 2022b), which revealed an important mechanism of the NEAP in individual COVID-19 risk: people are disadvantaged if they live in low-risk neighborhoods but have to work in high-risk areas (e.g., living in TSW and working in Kowloon or Hong Kong Island) or live in high-risk neighborhoods but cannot reduce their COVID-19 risk through daily mobility (e.g., living in SSP and working in Kowloon). Further, we also found that living in public housing has higher odds of being disadvantaged in COVID-19 risk than living in private housing in SSP. Our findings imply that people with workplaces in high-risk areas and poor housing conditions may be systematically disadvantaged in COVID-19 risk due to their limited options to decide which trips to make or to forego.

4.2. Significance and implications

Our study has three main strengths. First, to our knowledge, the study is significant because it is the first study to quantitatively examine the combined associations between individuals' COVID-19 risk with multiple environmental exposures and housing conditions both with a residence-based approach and a mobility-based approach using individual-level survey data. Second, the study used portable sensors (noise and air pollutant sensors and GPS-tracking smartphones) and activity-travel diary to simultaneously collect individuals' real-time locations and multiple environmental exposures data at a very fine scale, which enables us to expand the traditional residence-based approach to also include a mobility-based approach in geography and health research. Lastly, the use of residence- and mobility-based approaches allows us to identify the disadvantaged groups in COVID-19 risk through the perspective of the NEAP. In this way, the study is also one of the first studies that empirically investigates the NEAP in the evaluation of people's disadvantages in COVID-19 risk.

Further, the study is significant because it has several significant implications for public health based on our findings during the COVID-19 pandemic. First, our results provide empirical evidence to suggest the positive effects of greenspace exposure (e.g., NDVI) on the reduction of COVID-19 risk based on individual-level GPS data. Therefore, the study recommends policymakers to keep the country parks open and encourage people to visit them during the pandemic. In addition, we also found that people's COVID-19 transmission risk might be increased via face-to-face contact with others if they frequently visit open spaces and recreational land (e.g., community parks) in dense and high-risk neighborhoods (e.g., Sham Shui Po) in Hong Kong. Hence, policymakers can apply control measures (e.g., vaccination or testing passports) to reduce the transmission risk of COVID-19 by restricting people's access to open space and recreational land in dense and high-risk neighborhoods.

Second, our findings reveal that people living in a high-risk neighborhood (e.g., Sham Shui Po) and having poor housing conditions were exposed to a higher level of COVID-19 transmission risk in their daily life compared to those living in a low-risk neighborhood (e.g., Tin Shui Wai). Therefore, our findings imply that policymakers should also consider spatial nonstationary (e.g., the varying association between COVID-19 risk and housing conditions over space) and spatially targeted measures when designing mitigation measures for the pandemic. For instance, they could put more resources (e.g., vaccinations and testing centers) for people with poor housing conditions in high-risk neighborhoods to reduce their COVID-19 risk.

Lastly, we also found that people with workplaces in high-risk areas and poor housing conditions may be systematically disadvantaged in the COVID-19 pandemic due to their limited ability to change their daily mobility (e.g., cannot work from home) through the perspective of neighborhood effect averaging problem (NEAP). In this light, our findings strongly suggest that policymakers should take the NEAP into account to identify vulnerable groups when designing supporting measures for the pandemic.

4.3. Limitations

Our study also has a few limitations. First, one of the assumptions under the proxy of individuals' COVID-19 risk in this study is that the disparities in people's COVID-19 risk mainly arise from the differences in people's behavior, which could influence individuals' contact rates with COVID-19-infected persons. People's physiological differences (e.g., immune system) were not considered in the COVID-19 risk measurement. Besides, our methods cannot precisely capture what people or objects the participants contact with in their daily life.

Second, the COVID-19 dataset we used might not capture the whole picture of high-risk areas in the entire city across different periods (e.g., the fifth wave from December 2021 to April 2022). However, the results of individuals' COVID-19 risk assessment are unlikely to be significantly affected because the results are influenced more by how different people's daily mobility is captured than by the small errors in estimating the COVID-19 risk environment.

Lastly, the small sample used in the study might limit the generalizability of our findings, although a strict strategy has been applied to select representative neighborhoods and recruit participants according to the census profiles of the general populations in the two neighborhoods during the pandemic. Meanwhile, the study did not consider neighborhood-level confounders such as neighborhood social-economic status since the variation in individuals' COVID-19 risk between the two neighborhoods is insignificant (i.e., the intraclass correlation coefficient [ICC] < 0.05). Besides, the survey was conducted in a short-term period (i.e., from April to September 2021), which may not be able to capture the seasonal variations in human activities and their dynamic interactions with multiple environments. Future studies should try to obtain larger samples.

5. Conclusion

We found that high exposure to greenspace (i.e., NDVI) was associated with low COVID-19 risk in Hong Kong. Meanwhile, high exposure to open space and recreational land and living in public housing, *tong lau* or subdivided units would increase individuals' COVID-19 risk in high-risk neighborhoods, while high noise exposure would also increase individuals' COVID-19 risk in low-risk neighborhoods. Then, from the perspective of the neighborhood effect averaging problem (NEAP), we also found that people with workplaces in high-risk areas and poor housing conditions were disadvantaged in COVID-19 risk. Our findings have important implications for the health authorities to design effective mitigation measures during the COVID-19 pandemic.

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.

Acknowledgments

This research was supported by grants from the Hong Kong Research Grants Council (General Research Fund Grant no. 14605920, 14611621; Collaborative Research Fund Grant no. C4023-20 GF; Research Matching Grants RMG 8601219, 8601242), and Grant no. 3110156 and a grant from the Research Committee on Research Sustainability of Major Research Grants Council Funding Schemes (3133235) of the Chinese University of Hong Kong.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.apgeog.2023.102904.

References

Ahmad, K., Erqou, S., Shah, N., Nazir, U., Morrison, A. R., Choudhary, G., & Wu, W. C. (2020). Association of poor housing conditions with COVID-19 incidence and mortality across US counties. *PLoS One, 15*(11), Article e0241327. https://doi.org/10.1371/journal.pone.0241327

Albani, V., Welsh, C. E., Brown, H., Matthews, F. E., & Bambra, C. (2022). Explaining the deprivation gap in COVID-19 mortality rates: A decomposition analysis of geographical inequalities in England. *Social Science & Medicine, 311*, Article 115319. https://doi.org/10.1016/j.socscimed.2022.115319

Asensio, C., Pavón, I., & De Arcas, G. (2020). Changes in noise levels in the city of Madrid during COVID-19 lockdown in 2020. *Journal of the Acoustical Society of America, 148*(3), 1748–1755. https://doi.org/10.1121/10.0002008

Chakrabarty, R. K., Beeler, P., Liu, P., Goswami, S., Harvey, R. D., Pervez, S., van Donkelaar, A., & Martin, R. V. (2021). Ambient $PM_{2.5}$ exposure and rapid spread of COVID-19 in the United States. *Science of the Total Environment, 760*, Article 143391. https://doi.org/10.1016/j.scitotenv.2020.143391

Chang, S., Pierson, E., Koh, P. W., Gerardin, J., Redbird, B., Grusky, D., & Leskovec, J. (2021). Mobility network models of COVID-19 explain inequities and inform reopening. *Nature, 589*(7840), 82–87. https://doi.org/10.1038/s41586-020-2923-3

Curtis, L. (2021). $PM_{2.5}$, NO_2, wildfires, and other environmental exposures are linked to higher Covid 19 incidence, severity, and death rates. *Environmental Science and Pollution Research, 28*(39), 54429–54447. https://doi.org/10.1007/s11356-021-15556-0

Czwojdzińska, M., Terpińska, M., Kuźniarski, A., Płaczkowska, S., & Piwowar, A. (2021). Exposure to $PM_{2.5}$ and PM_{10} and COVID-19 infection rates and mortality: A one-year observational study in Poland. *Biomedical Journal, 44*(6), S25–S36. https://doi.org/10.1016/j.bj.2021.11.006

Das, A., Ghosh, S., Das, K., Basu, T., Dutta, I., & Das, M. (2021). Living environment matters: Unravelling the spatial clustering of COVID-19 hotspots in Kolkata megacity, India. *Sustainable Cities and Society, 65*, Article 102577. https://doi.org/10.1016/j.scs.2020.102577

Díaz, J., Antonio-López-Bueno, J., Culqui, D., Asensio, C., Sánchez-Martínez, G., & Linares, C. (2021). Does exposure to noise pollution influence the incidence and severity of COVID-19? *Environmental Research, 195*, Article 110766. https://doi.org/10.1016/j.envres.2021.110766

Grigsby-Toussaint, D. S., & Shin, J. C. (2022). COVID-19, green space exposure, and mask mandates. *Science of the Total Environment, 836*, Article 155302. https://doi.org/10.1016/j.scitotenv.2022.155302

Gurney, C. M. (2021). Dangerous liaisons? Applying the social harm perspective to the social inequality, housing and health trifecta during the covid-19 pandemic. *International Journal of Housing Policy*, 1–28. https://doi.org/10.1080/19491247.2021.1971033

Huang, J., & Kwan, M. P. (2022a). Uncertainties in the assessment of COVID-19 risk: A study of people's exposure to high-risk environments using individual-level activity data. *Annals of the Association of American Geographers, 112*(4), 968–987. https://doi.org/10.1080/24694452.2021.1943301

Huang, J., & Kwan, M. P. (2022b). Examining the influence of housing conditions and daily greenspace exposure on people's perceived COVID-19 risk and distress. *International Journal of Environmental Research and Public Health, 19*, 8876. https://doi.org/10.3390/ijerph19148876

Huang, J., Kwan, M. P., Cai, J., Song, W., Yu, C., Kan, Z., & Yim, S. H. L. (2022). Field evaluation and calibration of low-cost air pollution sensors for environmental exposure research. *Sensors, 22*(6), 2381. https://doi.org/10.3390/s22062381

Huang, J., Kwan, M. P., & Kan, Z. (2021a). The superspreading places of COVID-19 and the associated built-environment and socio-demographic features: A study using a spatial network framework and individual-level activity data. *Health & Place, 72*, Article 102694. https://doi.org/10.1016/j.healthplace.2021.102694

Huang, J., Kwan, M. P., Kan, Z., Wong, M. S., Kwok, C. Y. T., & Yu, X. (2020). Investigating the relationship between the built environment and relative risk of COVID-19 in Hong Kong. *ISPRS International Journal of Geo-Information, 9*(11), 624. https://doi.org/10.3390/ijgi9110624

Huang, J., Kwan, M. P., & Kim, J. (2021b). How culture and sociopolitical tensions might influence people's acceptance of COVID-19 control measures that use individual-level georeferenced data. *ISPRS International Journal of Geo-Information, 10*(7), 490. https://doi.org/10.3390/ijgi10070490

Jiang, B., Yang, Y., Chen, L., Liu, X., Wu, X., Chen, B., Webster, C., Sullivan, W. C., Larsen, L., Wang, J., & Lu, Y. (2022). Green spaces, especially nearby forest, may reduce the SARS-CoV-2 infection rate: A nationwide study in the United States.

Landscape and Urban Planning, 228, Article 104583. https://doi.org/10.1016/j.landurbplan.2022.104583
Johnson, T. F., Hordley, L. A., Greenwell, M. P., & Evans, L. C. (2021). Associations between COVID-19 transmission rates, park use, and landscape structure. *Science of the Total Environment, 789*, Article 148123. https://doi.org/10.1016/j.scitotenv.2021.148123
Kan, Z., Kwan, M. P., Huang, J., Wong, M. S., & Liu, D. (2021). Comparing the space-time patterns of high-risk areas in different waves of COVID-19 in Hong Kong. *Transactions in GIS, 25*(6), 2982–3001. https://doi.org/10.1111/tgis.12800
Kan, Z., Kwan, M. P., Ng, M. K., & Tieben, H. (2022). The impacts of housing characteristics and built-environment features on mental health. *International Journal of Environmental Research and Public Health, 19*(9), 5143. https://doi.org/10.3390/ijerph19095143
Kim, S. J., & Bostwick, W. (2020). Social vulnerability and racial inequality in COVID-19 deaths in Chicago. *Health Education & Behavior, 47*(4), 509–513. https://doi.org/10.1177/1090198120929677
Kim, J., & Kwan, M. P. (2019). Beyond commuting: Ignoring individuals' activity-travel patterns may lead to inaccurate assessments of their exposure to traffic congestion. *International Journal of Environmental Research and Public Health, 16*(1), 89. https://doi.org/10.3390/ijerph16010089
Kim, J., & Kwan, M. P. (2021a). The impact of the COVID-19 pandemic on people's mobility: A longitudinal study of the U.S. From March to september of 2020. *Journal of Transport Geography, 93*, Article 103039. https://doi.org/10.1016/j.jtrangeo.2021.103039
Kim, J., & Kwan, M. P. (2021b). Assessment of sociodemographic disparities in environmental exposure might be erroneous due to neighborhood effect averaging: Implications for environmental inequality research. *Environmental Research, 195*, Article 110519. https://doi.org/10.1016/j.envres.2020.110519
Kim, J., & Kwan, M. P. (2021c). How neighborhood effect averaging might affect assessment of individual exposures to air pollution: A study of ozone exposures in los angeles. *Annals of the Association of American Geographers, 111*(1), 121–140. https://doi.org/10.1080/24694452.2020.1756208
Klompmaker, J. O., Hart, J. E., Holland, I., Sabath, M. B., Wu, X., Laden, F., Dominici, F., & James, P. (2021). County-level exposures to greenness and associations with COVID-19 incidence and mortality in the United States. *Environmental Research, 199*, Article 111331. https://doi.org/10.1016/j.envres.2021.111331
Kwan, M. P. (2012). The uncertain geographic context problem. *Annals of the Association of American Geographers, 102*(5), 958–968. https://doi.org/10.1080/00045608.2012.687349
Kwan, M. P. (2018). The neighborhood effect averaging problem (NEAP): An elusive confounder of the neighborhood effect. *International Journal of Environmental Research and Public Health, 15*(9), 1841. https://doi.org/10.3390/ijerph15091841
Kwan, M. P., Wang, J., Tyburski, M., Epstein, D. H., Kowalczyk, W. J., & Preston, K. L. (2019). Uncertainties in the geographic context of health behaviors: A study of substance users' exposure to psychosocial stress using GPS data. *International Journal of Geographical Information Science, 33*(6), 1176–1195. https://doi.org/10.1080/13658816.2018.1503276
Kwok, C. Y. T., Wong, M. S., Chan, K. L., Kwan, M. P., Nichol, J. E., Liu, C. H., Wong, J. Y. H., Wai, A. K. C., Chan, L. W. C., Xu, Y., & Li, H. (2021). Spatial analysis of the impact of urban geometry and socio-demographic characteristics on COVID-19, a study in Hong Kong. *Science of the Total Environment, 764*, Article 144455. https://doi.org/10.1016/j.scitotenv.2020.144455
Lee, K. S., Min, H. S., Jeon, J. H., Choi, Y. J., Bang, J. H., & Sung, H. K. (2022). The association between greenness exposure and COVID-19 incidence in South Korea: An ecological study. *Science of the Total Environment, 832*, Article 154981. https://doi.org/10.1016/j.scitotenv.2022.154981
Liu, C., Liu, Z., & Guan, C. (2021). The impacts of the built environment on the incidence rate of COVID-19: A case study of king county, Washington. *Sustainable Cities and Society, 74*, Article 103144. https://doi.org/10.1016/j.scs.2021.103144
Lym, Y., & Kim, K. J. (2022). Exploring the effects of $PM_{2.5}$ and temperature on COVID-19 transmission in Seoul, South Korea. *Environmental Research, 203*, Article 111810. https://doi.org/10.1016/j.envres.2021.111810
Ma, X., Li, X., Kwan, M. P., & Chai, Y. (2020b). Who could not avoid exposure to high levels of residence-based pollution by daily mobility? Evidence of air pollution exposure from the perspective of the neighborhood effect averaging problem (NEAP). *International Journal of Environmental Research and Public Health, 17*(4), 1223. https://doi.org/10.3390/ijerph17041223
Ma, J., Rao, J., Kwan, M. P., & Chai, Y. (2020a). Examining the effects of mobility-based air and noise pollution on activity satisfaction. *Transportation Research Part D: Transport and Environment, 89*, Article 102633. https://doi.org/10.1016/j.trd.2020.102633
Marquès, M., & Domingo, J. L. (2022). Positive association between outdoor air pollution and the incidence and severity of COVID-19. A review of the recent scientific evidences. *Environmental Research, 203*, Article 111930. https://doi.org/10.1016/j.envres.2021.111930
Mehmood, K., Bao, Y., Abrar, M. M., Petropoulos, G. P., Soban, A., Saud, S., Khan, Z. A., Khan, S. M., & Fahad, S. (2021). Spatiotemporal variability of COVID-19 pandemic in relation to air pollution, climate and socioeconomic factors in Pakistan. *Chemosphere, 271*, Article 129584. https://doi.org/10.1016/j.chemosphere.2021.129584
Meng, Y., Wong, M. S., Kwan, M. P., & Zhu, R. (2022). Association between global air pollution and COVID-19 mortality: A study of forty-six cities in the world. *Annals of the Association of American Geographers, 6*, 1777–1793. https://doi.org/10.1080/24694452.2022.2029342
Meo, S. A., Abukhalaf, A. A., Alomar, A. A., Alessa, O. M., Sami, W., & Klonoff, D. C. (2021). Effect of environmental pollutants PM-2.5, carbon monoxide, and ozone on the incidence and mortality of SARS-COV-2 infection in ten wildfire affected counties in California. *Science of the Total Environment, 757*, Article 143948. https://doi.org/10.1016/j.scitotenv.2020.143948
Mueller, W., Steinle, S., Pärkkä, J., Parmes, E., Liedes, H., Kuijpers, E., Pronk, A., Sarigiannis, D., Karakitsios, S., Chapizanis, D., & Maggos, T. (2020). Urban greenspace and the indoor environment: Pathways to health via indoor particulate matter, noise, and road noise annoyance. *Environmental Research, 180*, Article 108850. https://doi.org/10.1016/j.envres.2019.108850
Ogen, Y. (2020). Assessing nitrogen dioxide (NO_2) levels as a contributing factor to coronavirus (COVID-19) fatality. *Science of the Total Environment, 726*, Article 138605. https://doi.org/10.1016/j.scitotenv.2020.138605
Pan, J., & Bardhan, R. (2022). Evaluating the risk of accessing green spaces in COVID-19 pandemic: A model for public urban green spaces (pugs) in London. *Urban Forestry and Urban Greening, 74*, Article 127648. https://doi.org/10.1016/j.ufug.2022.127648
Pan, J., Bardhan, R., & Jin, Y. (2021). Spatial distributive effects of public green space and COVID-19 infection in London. *Urban Forestry and Urban Greening, 62*, Article 127182. https://doi.org/10.1016/j.ufug.2021.127182
Peng, W., Dong, Y., Tian, M., Yuan, J., Kan, H., Jia, X., & Wang, W. (2022). City-level greenness exposure is associated with COVID-19 incidence in China. *Environmental Research, 209*, Article 112871. https://doi.org/10.1016/j.envres.2022.112871
Pirrie, M., & Agarwal, G. (2021). Older adults living in social housing in Canada: The next COVID-19 hotspot? *Canadian Journal of Public Health, 112*(1), 4–7. https://doi.org/10.17269/s41997-020-00462-8
Plümper, T., & Neumayer, E. (2020). The pandemic predominantly hits poor neighbourhoods? SARS-CoV-2 infections and COVID-19 fatalities in German districts. *The European Journal of Public Health, 30*(6), 1176–1180. https://doi.org/10.1093/eurpub/ckaa168
Recio, A., Linares, C., Banegas, J. R., & Díaz, J. (2016). Road traffic noise effects on cardiovascular, respiratory, and metabolic health: An integrative model of biological mechanisms. *Environmental Research, 146*, 359–370. https://doi.org/10.1016/j.envres.2015.12.036
Recio, A., Linares, C., Banegas, J. R., & Díaz, J. (2017). Impact of road traffic noise on cause-specific mortality in Madrid (Spain). *Science of the Total Environment, 590*, 171–173. https://doi.org/10.1016/j.scitotenv.2017.02.193
Roberts, H., & Helbich, M. (2021). Multiple environmental exposures along daily mobility paths and depressive symptoms: A smartphone-based tracking study. *Environment International, 156*, Article 106635. https://doi.org/10.1016/j.envint.2021.106635
Russette, H., Graham, J., Holden, Z., Semmens, E. O., Williams, E., & Landguth, E. L. (2021). Greenspace exposure and COVID-19 mortality in the United States: January–july 2020. *Environmental Research, 198*, Article 111195. https://doi.org/10.1016/j.envres.2021.111195
Shao, L., Cao, Y., Jones, T., Santosh, M., Silva, L. F., Ge, S., da Boit, K., Feng, X., Zhang, M., & BéruBé, K. (2022). COVID-19 mortality and exposure to airborne PM2.5: A lag time correlation. *Science of the Total Environment, 806*, Article 151286. https://doi.org/10.1016/j.scitotenv.2021.151286
Spotswood, E. N., Benjamin, M., Stoneburner, L., Wheeler, M. M., Beller, E. E., Balk, D., McPhearson, T., Kuo, M., & McDonald, R. I. (2021). Nature inequity and higher COVID-19 case rates in less-green neighbourhoods in the United States. *Nature Sustainability, 4*(12), 1092–1098. https://doi.org/10.1038/s41893-021-00781-9
Sulis, P., Manley, E., Zhong, C., & Batty, M. (2018). Using mobility data as proxy for measuring urban vitality. *Journal of Spatial Information Science, 16*, 137–162. https://doi.org/10.5311/JOSIS.2018.16.384
Tao, Y., Kou, L., Chai, Y., & Kwan, M. P. (2021). Associations of co-exposures to air pollution and noise with psychological stress in space and time: A case study in beijing, China. *Environmental Research, 196*, Article 110399. https://doi.org/10.1016/j.envres.2020.110399
Van Dorn, A., Cooney, R. E., & Sabin, M. L. (2020). COVID-19 exacerbating inequalities in the US. *The Lancet, 395*(10232), 1243–1244. https://doi.org/10.1016/S0140-6736(20)30893-X
Wang, Q., Lung, D. C., Chan, P. T., Jia, W., Dung, C. H., Miao, T., Huang, J., Chen, W., Wang, Z., Leung, K. M., & Xu, P. (2022). High attack rate in a Tong Lau house outbreak of COVID-19 with subdivided units in Hong Kong. *Interface Focus, 12*(2), Article 20210063. https://doi.org/10.1098/rsfs.2021.0063
Windsor-Shellard, B., & Kaur, J. (2020). *Coronavirus (COVID-19) related deaths by occupation, England and wales: Deaths registered up to and including 20 April 2020. Statistical bulletin*. London: Office for National Statistics.
Zhong, C., Batty, M., Manley, E., Wang, J., Wang, Z., Chen, F., & Schmitt, G. (2016). Variability in regularity: Mining temporal mobility patterns in London, Singapore and Beijing using smart-card data. *PLoS One, 11*(2), Article e0149222. https://doi.org/10.1371/journal.pone.0149222
Zhu, Y., Xie, J., Huang, F., & Cao, L. (2020). Association between short-term exposure to air pollution and COVID-19 infection: Evidence from China. *Science of the Total Environment, 727*, Article 138704. https://doi.org/10.1016/j.scitotenv.2020.138704