



Spatial uncertainty and environment-health association: An empirical study of osteoporosis among “old residents” in public housing estates across a hilly environment

Hung Chak Ho^{a,b,c,*}, Wei Cheng^b, Yimeng Song^d, Yuqi Liu^e, Yingqi Guo^f, Shiyu Lu^g, Terry Yat Sang Lum^{h,i}, Rebecca Chiu^b, Chris Webster^{a,j,**}

^a Healthy High Density Cities Lab, The University of Hong Kong, Hong Kong

^b Department of Urban Planning and Design, The University of Hong Kong, Hong Kong

^c Department of Anaesthesiology, School of Clinical Medicine, LKS Faculty of Medicine, The University of Hong Kong, Hong Kong

^d School of the Environment, Yale University, New Haven, CT, 06511, United States

^e Department of Urban Planning, School of Architecture, South China University of Technology, Guangzhou, China

^f Department of Rehabilitation Sciences, Hong Kong Polytechnic University, Hong Kong

^g Department of Social and Behavioural Sciences, City University of Hong Kong, Hong Kong

^h Sau Po Centre on Ageing, The University of Hong Kong, Hong Kong

ⁱ Department of Social Work and Social Administration, The University of Hong Kong, Hong Kong

^j Faculty of Architecture, The University of Hong Kong, Hong Kong

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ABSTRACT

Background: Built environment can influence physical conditions of older adults (e.g. osteoporosis). However, traditional methods using 2-dimensional circular buffer as a spatial structure to measure neighbourhood effect may create bias in health estimation, especially for the hilly and compact environment across low-income neighbourhoods (e.g. public housing estates).

Methods: We evaluated the environmental influences on self-reported osteoporosis among “old residents” (age ≥ 65) in Hong Kong (n = 2077). Twelve public housing estates across hilly neighbourhoods in Hong Kong were selected as study sites. A cross-validated approach was developed to evaluate four spatial structures (2D circular, 2D service area, 3D circular, 3D service area). To determine problems of spatial uncertainty, we compared odds ratios (OR) and differences in effect sizes from models using different spatial structures. When all adjusted models achieve significant results based on 95% confidence intervals (CI) and with all positive/negative ORs, this study reported to have reached “a result with consistency”. Results from the 3D service area were then used to explain the environment-health relationship.

Results: Different spatial structures can yield different results. Particularly, circular buffers overestimated environmental effects on self-reported osteoporosis. Overestimated measures were related to walkability and accessibility but not greenery. Specifically, results from the 3D service area showed that more public space and health facilities within a walkable distance (500 m) from a location of subject’s residence were negatively associated with self-reported osteoporosis (adjusted ORs: 0.44 [0.29, 0.66]; 0.94 [0.90, 0.99]). However, more major transport facilities at the immediate distance from residence (200 m) was positively associated with self-reported osteoporosis (adjusted OR: 1.11 [1.01, 1.23]).

Conclusions: Physical conditions (e.g. osteoporosis) of older adults living in a hilly neighbourhood could be driven by walking behaviours. It is necessary to include local terrain and road network to define a walkable neighbourhood for environment-health estimations to minimize spatial bias.

* Corresponding author. Department of Anaesthesiology, School of Clinical Medicine, The University of Hong Kong, Hong Kong.

** Corresponding author. Healthy High Density Cities Lab, The University of Hong Kong, Hong Kong.

E-mail addresses: hcho21@hku.hk (H.C. Ho), cwebster@hku.hk (C. Webster).

Credit author statement

H.C. Ho conceived the study design. H.C. Ho and W. Cheng performed the data collection and pre-processing. H.C. Ho and Y. M Song conducted the data analysis. H.C. Ho prepared the draft of the manuscript. Y. Liu, Y. Guo, S. Lu and T. Lum provided comments on health implications. C. Webster and R. Chiu provided comments on built environment interventions. C. Webster provided comments on spatial uncertainty and geospatial analyses. All authors provided critical feedback on all versions of the manuscript.

1. Introduction

Populations are aging all over the world, and older adults (age \geq 65) are among the least mobile in society (Wiles et al., 2012). Thus, many studies have examined associations between built environment and community health risk, in order to explore the possible solutions of using urban design and community planning to reduce health burdens among these aging individuals (de Keijzer et al., 2016; Marquardt et al., 2014; Phillips et al., 2004, 2005; Sarkar et al., 2013; Takano et al., 2002; Woo et al., 2017). In particular, environmental health studies have covered built environment in various dimensions: urban greenery (Yang et al., 2020), building form (Ho et al., 2017), and local accessibility (Sarkar et al., 2013).

However, despite the extensive environmental health research, there is an unsolved problem regarding spatial estimation between built environment variables and health outcomes, namely, “spatial uncertainty” (Ho et al., 2015; Labib et al., 2020; Parenteau and Sawada, 2011; Reid et al., 2018; Schuurman et al., 2007; Su et al., 2019; Sun et al., 2018). The uncertainty pertains to levels of spatial aggregation of environmental data surrounding a residential location, leading to a Modifiable Areal Unit Problem (MAUP). MAUP refers to how different spatial scales used for data aggregation lead to different results (scaling effect), or how different zones/boundaries for grouping data may vary the results (zoning effect).

Scaling and zoning effects can pose a problem in environmental health estimation. Traditional methods to measure characteristics of the built environment mainly use the circular buffer as a spatial structure to aggregate data (Reid et al., 2018; Su et al., 2019). This creates a zoning effect as data aggregated using Euclidian geometry may not represent the real walkable environment, which is determined by road networks. Using various radii for data aggregation could also induce scaling effects. The scaling and zoning effects due to various spatial structures should be considered as they may engender significant differences in estimating the association between built environment and physical functions among the older adults. This is because physical functions (e.g. osteoporosis) could be directly influenced by self-management, physical activities and daily living (Abbott et al., 2004; Verghese et al., 2003; Vogt et al., 1994), and this disease burden is also a growing health issue among older adults (Mithal and Kaur, 2012; Lau et al., 2001; Wang et al., 2009).

In addition, most of the environmental health studies only considered a 2-dimensional method to measure built environment (Ho et al., 2022; Lin et al., 2021; Reid et al., 2018; Su et al., 2019), ignoring the fact that many cities are built on hilly terrain and comprise a complex three-dimensional urban form. More accurate measurement of the built environment based on 3-dimensional information and actual walkable network is therefore preferable, if not essential. This is particularly important for understanding the mobility of low-income older adults (e.g. seniors living in subsidized housing) in a compact and hilly city (e.g. Hong Kong), since these adults mostly walk to their daily activity destinations (Wiles et al., 2012), confining their “community” to be near their residential locations. An investigation of 3-dimensional built environment will enhance the prediction of risk and protective factors associated with these older adults. The prediction can be used for public health surveillance, community planning and urban design

interventions.

To fill the above research gaps, this study applies a data-driven cross-sectional analysis to rapidly assess the relationship between multiple characteristics of built environment and self-reported osteoporosis among older adults in Hong Kong. The objective is to estimate the relationship between walkable built environment and self-reported osteoporosis based on four types of datasets with various levels of spatial uncertainty. These datasets consider neighborhood-level built environment using different spatial structures (Parenteau and Sawada, 2011), so that adjustment of various walking behaviors and terrain types can be included. From observing the consistency of results from the datasets, we show how greater certainty can be obtained in the statistical associations between built environment and older adults’ physical functions. Results of the study will also be useful for: 1) improving urban design and housing management for better elderly living in public housing estates, 2) facilitating community planning regarding health care and social services provision, and 3) improving spatial navigation to enhance physical activities among older adults.

2. Data and methods

2.1. Health outcome data

A baseline cohort of health data from 12 selected public housing estates in Hong Kong was collected in 2014. Data collection was approved by the Human Research Ethics Committee at the University of Hong Kong (No: EA050814). After removing 4 subjects with missing information, a total of 2077 subjects (age \geq 65) with validated data were included in the cohort. The 12 estates were developed and are managed by the Hong Kong Housing Society, and include various urban types in Hong Kong (e.g. urban, suburban, new town). More than half of the 12 estates are located in hilly environments (Fig. 1). All subjects were stratified-randomly in the following age strata: 65–74, 75–84, 85 or above. They are Cantonese-speaking Chinese tenants without a known psychiatric disorder (e.g. dementia).

In this study, osteoporosis was determined by a question about medical history. To answer the question, each subject self-reported whether they had osteoporosis or they were diagnosed with osteoporosis. The cohort also included the following sociodemographic information: age, gender, BMI, sleep quality, smoking status, alcohol consumption, low education, unhealthy diet, quality of life, activities of daily living.

Particularly, age is a continuous variable which was derived from the age reported by participants. Gender is a binary variable indicating whether subjects were males or females. BMI is a measure of body fat based on height and weight. Sleep quality was determined by the following self-reported question: “Do you have any difficulties related to sleeping in the past 7 days?” Smoking status is a binary variable regarding whether a subject was a current smoker. Alcohol consumption is a binary variable indicating whether a subject has ever or rarely consumed any alcohol beverages. Subjects categorized as having low education are individuals who only finished or did not finish primary school, based on definitions from other local studies (Ho et al., 2017; Wong et al., 2017). Unhealthy diet is a binary variable regarding whether the subject self-reported to have imbalanced diet or not. Quality of life (QOL) is determined by the EUROHIS-QOL 8-item index, comprising eight items (overall QOL, general health, energy, daily life activities, esteem, relationships, finances, and home) taken from the WHOQOL-BREF. Activities of daily living were determined by the Chinese version of the Lawton Instrumental Activities of Daily Living scale (IADLs), and this instrument could assess the functional ability of an Asian individual (Tong and Man, 2002).

Additional measures relating to medical history were included in the analytic dataset: self-reported cardiovascular disease, stroke, chronic obstructive pulmonary disease (COPD), pain, cognitive function, depression, walking ability, and frailty. Cognitive function was



Fig. 1. Hilly environment of the selected public housing estates. Lai Tak Tsuen (Left) is a public housing estate in a suburb near a middle-class neighbourhood. Cho Yiu Chuen (Middle) is a public housing estate in a new town. Kwun Tong Garden Estate (Right) is a public housing estate in an urbanized area near a low-income neighbourhood and industrial area.

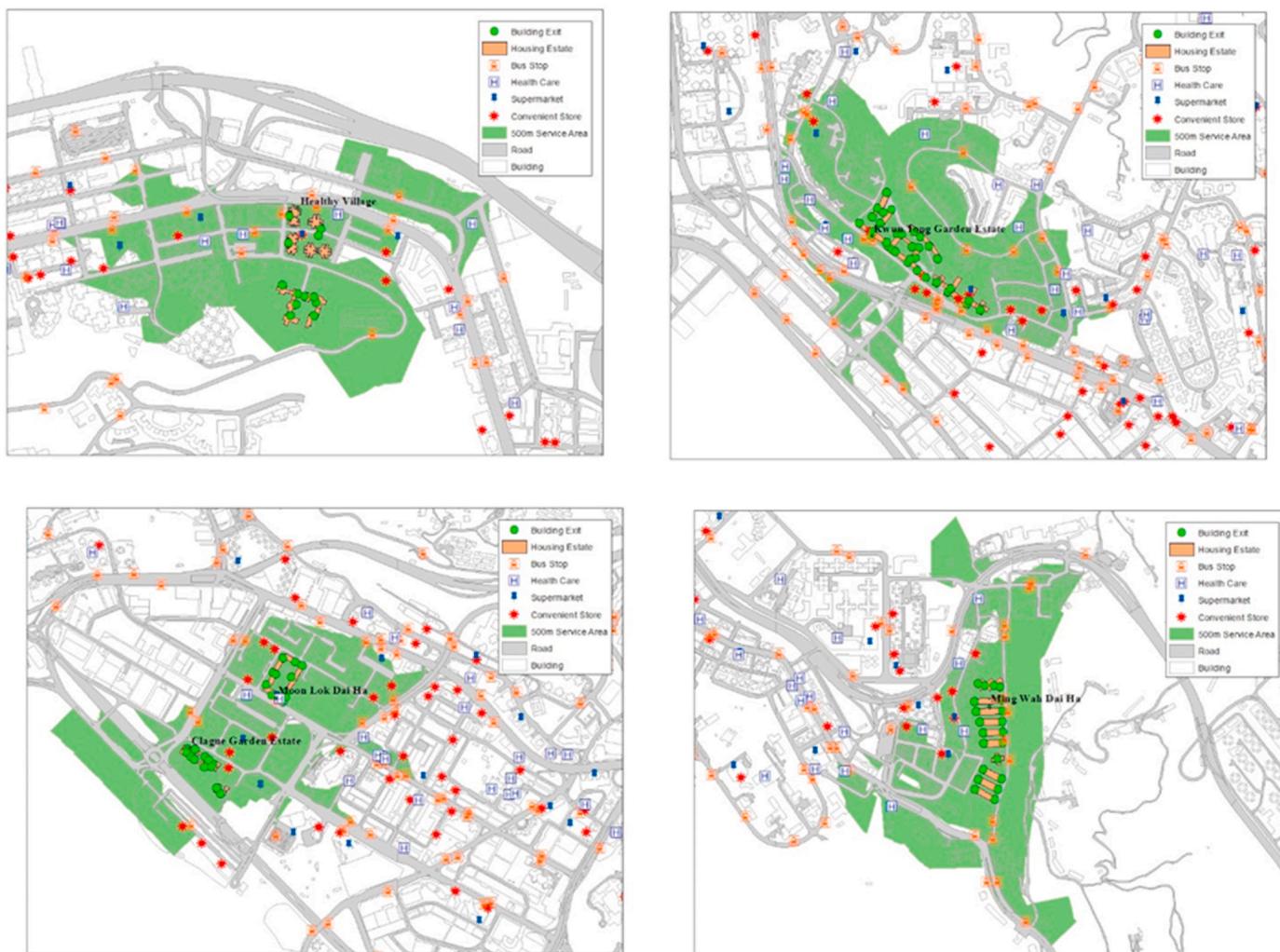


Fig. 2. Examples of greenery and facilities surrounding five of the twelve selected public housing estates. Healthy Village (Top left) and Ming Wah Dai Ha (Bottom Right) are public housing estates located in urbanized areas of Hong Kong Island. Kwun Tong Garden Estate (Top Right) is a public housing estate in an urbanized area near a low-income neighbourhood and industrial area of Kowloon. Clague Garden Estate and Moon Lok Dai Ha (Bottom Left) are public housing estates located in a new town of New Territories.

determined based on a Cantonese version of Montreal – Cognitive Assessment (MoCA) (Wong et al., 2009; Yeung et al., 2014; Chu et al., 2015). Depression was determined by a Chinese version of Geriatric Depression Scale-15 (Lee et al., 1993; Wong et al., 2002). Walking ability was a self-rated response regarding whether the subject had difficulties to walk independently. Frailty was pre-screened based on the five-item FRAIL Questionnaire (Morley et al., 2012). The FRAIL scale includes five components: fatigue, resistance, ambulation, illness, and weight loss, with the overall score ranging from 0 to 5 (0 = best to 5 = worst). Following previous studies (Perneger and Burnand, 2005), missing information of each measure was replaced by the average score.

2.2. Measures of built environment

Eleven measures of built environment were applied in this study, covering three dimensions: greenery, walkability and accessibility.

Dimension of greenery: 1) % greenery, 2) greenness, 3) green heterogeneity, which assessed the characteristics of vegetation from different perspectives. % greenery is the percentage of natural greenery within a walkable network distance from location of residence. We mapped greenery (Fig. 2) based on information from the Google Earth Engine (Tsai et al., 2018; Xie et al., 2019). A supervised method for spatial delineation was applied to classify landscape with and without vegetation. Greenness is a measure of intensity of natural greenery, which is determined by the average of Normalized Difference Vegetation Index (NDVI) within a walkable distance. NDVI is calculated from the red and near-infrared band of a multispectral remote sensing image with a range from -1 to 1, and is commonly used in local studies for environmental health estimations (Sarkar et al., 2018; Sun et al., 2020b; Yang et al., 2020). The index can determine the differential absorbance and reflectance wavelengths by chlorophyll in green vegetation, with a larger value of NDVI indicating higher intensity of natural greenery. We computed NDVI from a 2016 SPOT-6 image (spatial resolution: 6 m). Green heterogeneity is a measure of the mixture of natural greenery/non-greenery. The measure was determined by the standard deviation of NDVI within a walkable distance, with a higher value of green heterogeneity indicating a higher degree of mixture, which may function independently to Greenness in inducing or inhibiting walking.

Dimension of walkability: 1) % public space, 2) % building coverage, 3) land use mix. Jane Jacob's theory of urban design provides support for the use of these indicators for this dimension – a neighbourhood's vitality and diversity are indicated and categorized by four specific elements: 1) mixed land use to attract local people who have different social purposes, 2) small blocks to enhance physical and social contacts among people, 3) a diversity of building types to develop socially-mixed neighborhoods for both high-income and low-income occupants and to enhance social inclusion, and 4) sufficient concentration of buildings to build up adequate density to maintain social connections (Schmidt, 1977; Steil and Delgado, 2019). Accordingly, % public space was used as a measure of public open space as it was designed and managed by the local government to provide spaces for leisure, culture and sport activities within walkable distance of place of residence. A higher percentage of public space within a neighbourhood implies good walkability due to a better design for socialization and mobilization. % building coverage was measured by the percentage of building footprint within walkable distance, manifested as building density of the neighbourhood at the spatial scale. It further indicates the physical compactness of a community better illustrating sufficiency of building concentration. Land use mix was measured based on the following five types of land use combined using an entropy function commonly used in previous studies (Frank et al., 2005, 2006): residential lands, commercial/industrial lands, institutional lands, public space and others. Land use mix is ranging from 0 to 1, in which higher values indicate areas with higher potential walkability due to mixed land use and the resultant greater density of walking destinations. The above spatial information was retrieved from ib1000 datasets provided by Lands Department of Hong

Kong.

Dimension of accessibility: 1) major transportation facilities, 2) facilities for municipal services, 3) community facilities, 4) leisure facilities, and 5) health facilities. Generally, more facilities within a certain level of proximity indicates higher accessibility of a neighbourhood. Data for these facilities were retrieved from the GeoCommunity Database 3.0 provided by Lands Department of Hong Kong (Fig. 2).

Intervals of % greenery, % public space, and % building coverage were set as 10%, and intervals of Greenness, Green heterogeneity, and Land use mix were set as 0.1.

2.3. Spatial buffering for uncertainty assessment

Two scales of buffers were applied to determine an immediate distance (200 m) and a walkable distance (500 m) from a location of residence. Specifically, immediate distance is associated with an approximately 6-min walk for older adults in Hong Kong, and walkable distance is associated with an approximately 15-min walk (Lu et al., 2021). Walking buffers are commonly used in local studies as well as previous research for other cities (Ho et al., 2017; Sarkar et al., 2018; Su et al., 2019; Sun et al., 2020b; Yang et al., 2020).

For each spatial scale, we further applied four types of spatial structures to create the eleven measures of built environment stated above: 1) 2D circular, 2) 2D service area, 3) 3D circular, and 4) 3D service area. Particularly, the hypothesis of potential difference from circular buffers and service areas was based on a conceptual framework of a previous study in Hong Kong (Sun et al., 2018). For visual difference between circular buffers and service areas in Hong Kong, details have been noted in Sun et al. (2018). In this study, we further included 2-dimensions and 3-dimensions as components and applied this conceptual framework to an empirical study. Specifically, 2D circular applied a circular buffer as a spatial structure to measure environmental characteristics from the central point of a location of residence (building-level). This spatial structure does not account for terrain. 2D service area also does not consider terrain but improves on the circle by measuring walking paths from the central point of a location of residence along the walking paths. Walking paths were constructed for each housing estate on the basis of road network, open spaces and physical barriers, with paths extending inside and outside the estates into surrounding neighbourhoods. 3D circular used a circular buffer as spatial structure, but with terrain adjustment. 3D service area was measured on a network and adjusted for slope and elevation. To add accuracy to these measures, free standing walls, fences and construction areas were considered barriers to walking paths.

2.4. Statistical analyses

A cross-validated, data-driven approach was developed in this study. At first, binomial regression was applied to evaluate the relationship between built environment and self-reported osteoporosis. Crude model and adjusted model were both applied in this study. Odds ratios (OR) for all regressions with 95% confidence intervals (CI) were reported.

For the crude model, we repeatedly applied the following univariate binomial regression for all health outcomes and all measures of built environment derived from all spatial structures, separately:

$$\text{outcome} \sim \beta_0 + \beta_1 \times BE$$

where *outcome* is the self-reported osteoporosis for the specific model, and *BE* is a specific measure of built environment.

For the adjusted model, we repeatedly applied the following regression for all health outcomes and all measures of built environment derived from all spatial structures, separately:

$$\text{outcome} \sim \beta_0 + \beta_1 \times BE + \beta_2 \times \text{covariate}(1) + \dots + \beta_n \times \text{covariate}(n)$$

where *covariate*(*n*) are the controlling factors for medical history and sociodemographic characteristics, and *n* are the numbers of covariates selected based on Variance inflation factor (VIF) < 2.

After selecting for VIF < 2 to minimize multicollinearity, the following confounding variables remained in the model: age, cardiovascular disease, stroke, COPD, pain, depression, cognitive function, frailty, low education, gender, BMI, quality of life, sleep quality, smoking status, alcohol consumption, unhealthy diet, walking ability. All the above covariates were found to be associated with osteoporosis in previous studies (Chang et al., 2014; Chou et al., 2013; Graat-Verboom et al., 2009; Leidig-Bruckner et al., 1997; Rolland et al., 2008; Sampson, 2002; Van der Voort et al., 2001).

In order to determine problems of spatial uncertainty, we compared significant ORs from adjusted models using different spatial measurement strategies (spatial structure) to evaluate whether using different spatial structures as buffers could yield different results. Particularly, if the results have been yielded, we reported the difference in effect sizes for the comparison of magnitude. We also highlighted the consistency of each measure of built environment, based on whether OR and 95% CI from all adjusted models (using different spatial structures) with significant results were all positive/negative. We further compared the adjusted models with significant results based on Akaike Information Criterion (AIC). In theory, a lower score of AIC indicates better model fit.

We then used the results from 3D service area to explain the relationship between the specific environmental characteristics and health outcome, as 3D service area was hypothesized to be more related to walking behaviours of older adults and urban form across Hong Kong. Particularly, previous studies have tested the above hypothesis and found that 3D pedestrian/road network could be more related to walking behaviours of older adults and urban form in Hong Kong (Sun et al., 2021; Tang et al., 2021).

3. Results

3.1. Summary of analytic dataset

T-tests were applied to compare the statistical differences between subjects with/without self-reported osteoporosis in the analytic dataset. Among 2077 subjects, 245 of them (11.8%) self-reported suffering with symptoms of osteoporosis, and this group were generally overweight, with average BMI >23 across both subgroups (Table 1).

For the ten measures related to lifestyle and sociodemographic characteristics, t-tests showed that four of these measures had a

significant difference between subjects with/without self-reported osteoporosis, including gender, smoking status, quality of life and IADLS (Table 1). There were 85.7% female with osteoporosis but only 51.8% female without osteoporosis (p-value <0.05). There were only 1.6% subjects with osteoporosis who smoked while 7.7% of subjects without osteoporosis smoked, although both percentages were overall low (<10%). Specifically, quality of life and daily living (determined by IADLS) were significantly lower among subjects with osteoporosis than participants without osteoporosis (quality of life: 27.9 vs 29.1, IADLS: 14.1 vs 15.0), with p-values < 0.05.

For the eight measures of medical history, a large percentage of subjects with osteoporosis self-reported to have pain-related issues (18.0% vs 7.4%), determined to have depressive symptoms (17.6% vs 9.8%) and pre-screened to have frailty (20.8% vs 10.8%), compared to the subjects without osteoporosis. However, there was not a significant difference in cognitive function between subjects with/without self-reported osteoporosis.

3.2. Local characteristics of built environment

Generally, all subjects were living in a high-density environment with mixed land uses (Table 2). Disregarding the measurement based on different spatial structures, the older adults were generally living in a neighbourhood with more than 25% building coverage but also more than 25% greenery within 500-m of their homes. There was at least 5% public space within 500 m from subjects' homes, and the values of land use mix were greater than 0.6, indicating multi-functionality of these neighbourhoods. There was also at least one facility for municipal service within 500 m of all residences, as well as multiple spots of major transportation facilities, community facilities, leisure facilities, and health facilities within this distance. The results of greenness and green heterogeneity showed a mixture of urban trees and impervious surfaces across a neighbourhood. Furthermore, the great difference in measures of percentages of greenery and public spaces implies that open spaces in Hong Kong may not necessarily be "green", and urban greenery in Hong Kong may not be inaccessible. This evidence was matched with observations from local studies (Guo et al., 2021; Ho et al., 2022).

The motivation of our study comes from recognising that the above results could be affected by the spatial structure of measurements (the MAUP). Our descriptive results and *a priori* reasoning suggests that using circular buffers to measure built environment might overrate liveability, especially using 2D circular buffers. Based on the significant difference of minimum, maximum and average values of each built environment

Table 1

Summary of lifestyle and sociodemographic characteristics and medical history of all subjects (N = 2077) in the analytic dataset. Bold text indicated a significant difference between subjects with and without physical/cognitive functions based on t-test.

		with osteoporosis	without osteoporosis	t-test
		n = 245	n = 1832	p-value
Lifestyle and sociodemographic characteristics	Age	79.5	79.7	0.69
	Gender (Females versus males)	85.7%	51.8%	<0.05
	BMI	23.5	23.7	0.58
	Sleep Quality (Bad versus good)	20.8%	14.7%	0.27
	Smoking Status (Yes versus no)	1.6%	7.7%	<0.05
	Alcohol consumption (Yes versus no)	0.4%	1.3%	0.06
	Low education	79.6%	78.2%	0.61
	Unhealthy Diet	5.7%	4.0%	0.27
	Quality of Life	27.9	29.1	<0.05
	Instrumental activities of daily living (IADLS)	14.1	15.0	<0.05
Medical history	cardiovascular disease	19.2%	17.2%	0.46
	Stroke	8.6%	6.4%	0.26
	chronic obstructive pulmonary disease (COPD)	1.6%	0.9%	0.37
	Pain	18.0%	7.4%	<0.05
	Depression	17.6%	9.8%	<0.05
	walking ability (low versus high)	13.9%	10.4%	0.13
	Frailty	20.8%	10.8%	<0.05
	Cognitive function (low versus high)	40.4%	41.5%	0.75

Table 2 Summary: local characteristics of built environment among all subjects (N = 2077) in the analytics. Four types of spatial structure separately applied to measure the local characteristics.

Built Environment	2D circular				2D service area				3D circular				3D service area			
	min	max	mean	SD	Min	max	mean	SD	min	max	mean	SD	min	max	mean	SD
Greenery (200 m)	3.6%	66.5%	29.9%	16.6%	1.0%	37.2%	17.1%	10.4%	2.1%	68.4%	27.8%	15.6%	1.0%	36.8%	16.8%	10.3%
Greenery (500 m)	8.0%	68.9%	33.2%	20.5%	5.9%	56.8%	27.1%	14.9%	8.2%	70.0%	32.3%	19.8%	5.8%	56.7%	26.9%	15.0%
greenness (200 m)	0.14	0.57	0.32	0.11	0.15	0.40	0.25	0.07	0.14	0.58	0.31	0.10	0.15	0.40	0.25	0.07
greenness (500 m)	0.15	0.59	0.33	0.14	0.15	0.51	0.30	0.10	0.15	0.60	0.33	0.14	0.15	0.51	0.30	0.10
green heterogeneity (200 m)	0.09	0.30	0.22	0.06	0.07	0.25	0.17	0.05	0.08	0.30	0.21	0.06	0.07	0.25	0.16	0.05
green heterogeneity (500 m)	0.14	0.32	0.24	0.06	0.12	0.29	0.21	0.06	0.14	0.31	0.23	0.06	0.11	0.29	0.21	0.06
% Public Space (200 m)	0.0%	31.9%	6.9%	6.2%	0.0%	24.3%	4.9%	7.3%	0.0%	31.0%	6.4%	5.6%	0.0%	24.5%	4.9%	7.4%
% Public Space (500 m)	1.0%	27.0%	8.0%	6.9%	0.5%	25.2%	5.2%	4.8%	1.3%	30.1%	8.1%	7.2%	0.5%	25.7%	5.2%	4.9%
% Building coverage (200 m)	10.6%	47.7%	29.2%	9.0%	18.1%	45.5%	30.4%	7.0%	10.0%	49.6%	29.9%	10.0%	18.5%	45.5%	30.4%	6.9%
% Building coverage (500 m)	11.3%	43.7%	27.1%	10.5%	11.5%	46.1%	30.2%	8.2%	10.8%	44.1%	27.9%	10.0%	11.3%	46.3%	30.4%	8.3%
Land Use Mix (200 m)	0.47	0.89	0.70	0.09	0.25	0.98	0.72	0.17	0.51	0.91	0.71	0.10	0.24	0.98	0.72	0.17
Land Use Mix (500 m)	0.48	0.84	0.64	0.08	0.56	0.84	0.69	0.80	0.48	0.82	0.65	0.08	0.55	0.84	0.69	0.08
Major transportation (200 m)	0	9	2.5	2.8	0	7	0.7	1.3	0	9	2.1	2.3	0	7	0.7	1.3
Major transportation (500 m)	2	20	10.4	5.5	0	12	3.8	3.3	1	19	9.1	5.2	0	12	3.8	3.3
Municipal Services (200 m)	0	4	0.8	1.0	0	1	0.1	0.3	0	4	0.7	0.8	0	1	0.1	0.3
Municipal Services (500 m)	0	5	2.6	1.4	0	4	1.3	1.2	0	5	2.4	1.3	0	4	1.3	1.2
Community Facilities (200 m)	4	28	14.8	6.5	0	14	5.7	3.6	1	26	12.8	6.0	0	13	5.5	3.6
Community Facilities (500 m)	26	84	57.1	14.3	8	48	24.1	9.8	22	79	51.0	13.7	8	47	23.8	9.8
Leisure Facilities (200 m)	1	14	6.2	2.7	0	6	1.5	1.6	1	11	5.2	2.4	0	6	1.5	1.6
Leisure Facilities (500 m)	11	57	30.2	9.5	1	18	8.4	3.7	9	49	26.8	8.2	1	18	8.2	3.6
Health Facilities (200 m)	0	8	2.2	2.2	0	5	0.6	1.1	0	6	1.8	2.0	0	5	0.6	1.1
Health Facilities (500 m)	0	21	11.0	5.6	0	12	3.8	3.1	0	19	9.8	5.3	0	10	4.2	3.1

measure, we found that circular buffer overestimated the conditions of “urban green” surrounding the place of residence of older adults. 2D circular averages measure 2.1%, 12.8% and 13.1% more greenery within an immediate distance (200 m) and 0.9%, 5.1%, and 6.3% more greenery within a walkable distance (500 m) than using 3D circular, 2D service area and 3D service area, respectively. Results of green heterogeneity reported from circular buffers were also significantly higher than the results measured from service areas.

Furthermore, using 2D circular, on average, reported 0.5%, 2.0% and 2.0% more public space within an immediate distance than using 3D circular, 2D service area and 3D service area, and 2.8% more public spaces than results from service areas based on walkable distance. In contrast, the percentage of building coverage measured from circular buffers was usually lower than the percentage measured by service areas. Additionally, circular buffers overestimated the number of major transportation facilities, community facilities, leisure facilities, health facilities as well as facilities for municipal service surrounding the residences in both immediate distance and walkable distance. Some facilities were estimated to be 2–3 times more than when measured using service areas (network-buffers).

By comparison, greenness and land use mix were more stable across spatial structures of measurement. There was no significant difference between results from the compared buffer structures.

3.3. Built environment and osteoporosis

For measuring associations between built environment and osteoporosis, using different spatial structures as buffers yielded different results. Particularly, results from circular buffers are very different from results using service areas along walking paths (Table 3). In general, two measures of built environment showed significant results when using data from 2D circular or 3D circular in modelling, while the results became insignificant by using models from 2D service area or 3D service area. Two measures (% building coverage and leisure facilities) showed significant results when using 2D service area or 3D service area as spatial structures, however, the results became insignificant when using 2D circular or 3D circular. Notably, all of these measures were related to walkability and accessibility but not greenery, while % public space at an immediate distance (200 m) found the greatest difference based on effect sizes.

Furthermore, even though results from all spatial structures could be consistent (OR and 95% CI from all models (using different spatial structures) were all positive or all negative), there were still large differences between effect sizes from circular and network buffers. For example, % public space at a walkable distance (500 m) from a residence was found to be consistently associated with self-reported osteoporosis in all models, but the effect sizes of results from 2D circular and 3D circular could be 34–36% lower than the results from 2D service area and 3D service area. Furthermore, the 2D/3D differences (difference in 2D and 3D estimations) were more significant when using circular buffers as spatial structure, while the difference was weaker when using service areas.

Based on the consistency results, higher % public space and more health facilities within a walkable distance (500 m) from a residence were negatively associated with self-reported osteoporosis and the effect of % public space was found to be the most significant. Measured using 3D service area, a 10-percent increase in public space was associated with an adjusted OR of 0.44 [0.29, 0.66]. One more spot of health facilities could also be associated with adjusted OR of 0.94 [0.90, 0.99]. In contrast, one more spot of major transport facilities at the immediate distance from the residence of older adults (200 m) was positively associated with self-reported osteoporosis. Based on the results of 3D service area, adjusted OR was 1.11 [1.01, 1.23].

A test of AIC among all significant models was also conducted (Table 4). Although 3D service area is hypothesized to be more related to urban forms and walking behaviors of Hong Kong (Sun et al., 2021; Tang

Table 3

Association between built environment and osteoporosis. Bold text highlighted in green indicated a significant result from a model for a specific spatial structure. Bold text highlighted in yellow indicated the result with consistency for a measure of built environment, based on whether OR and 95% CI from all models using different spatial structures were all positive or all negative.

Built Environment	2D circular		2D service area		3D circular		3D service area	
	crude OR	adjusted OR	crude OR	adjusted OR	crude OR	adjusted OR	crude OR	adjusted OR
Greenery (200m)	0.96 [0.89, 1.04]	0.99 [0.91, 1.08]	1.03 [0.91, 1.17]	1.06 [0.93, 1.22]	0.96 [0.88, 1.04]	0.98 [0.90, 1.08]	1.03 [0.90, 1.17]	1.06 [0.93, 1.22]
Greenery (500m)	0.99 [0.92, 1.05]	1.01 [0.95, 1.09]	0.997 [0.92, 1.09]	1.03 [0.94, 1.14]	0.99 [0.92, 1.05]	1.01 [0.84, 1.09]	0.997 [0.91, 1.09]	1.03 [0.94, 1.13]
greenness (200m)	0.97 [0.86, 1.10]	1.02 [0.90, 1.16]	1.14 [0.93, 1.39]	1.21 [0.98, 1.49]	0.97 [0.85, 1.10]	1.02 [0.89, 1.17]	1.14 [0.93, 1.40]	1.22 [0.99, 1.51]
greenness (500m)	0.98 [0.89, 1.07]	1.02 [0.92, 1.12]	1.03 [0.90, 1.18]	1.10 [0.95, 1.26]	0.98 [0.89, 1.08]	1.02 [0.92, 1.13]	1.03 [0.91, 1.18]	1.10 [0.95, 1.26]
green heterogeneity (200m)	0.93 [0.75, 1.16]	1.00 [0.80, 1.26]	1.13 [0.87, 1.47]	1.24 [0.94, 1.63]	0.93 [0.74, 1.16]	0.996 [0.79, 1.26]	1.13 [0.87, 1.47]	1.24 [0.94, 1.64]
green heterogeneity (500m)	0.97 [0.78, 1.21]	1.03 [0.82, 1.31]	0.97 [0.77, 1.23]	1.06 [0.82, 1.36]	0.96 [0.77, 1.21]	1.03 [0.80, 1.31]	0.97 [0.76, 1.23]	1.06 [0.82, 1.37]
% Public Space (200m)	0.63 [0.49, 0.82]	0.60 [0.45, 0.78]	0.87 [0.72, 1.06]	0.85 [0.70, 1.04]	0.65 [0.50, 0.86]	0.61 [0.46, 0.81]	0.87 [0.72, 1.06]	0.86 [0.70, 1.04]
% Public Space (500m)	0.79 [0.63, 0.98]	0.78 [0.62, 0.98]	0.48 [0.32, 0.71]	0.43 [0.28, 0.65]	0.80 [0.65, 0.98]	0.79 [0.63, 0.98]	0.48 [0.32, 0.72]	0.44 [0.29, 0.66]
% Building coverage (200m)	1.01 [0.87, 1.17]	0.99 [0.84, 1.15]	0.92 [0.76, 1.11]	0.90 [0.74, 1.11]	1.00 [0.87, 1.16]	0.99 [0.85, 1.15]	0.91 [0.75, 1.10]	0.89 [0.73, 1.10]
% Building coverage (500m)	0.93 [0.82, 1.05]	0.89 [0.78, 1.02]	0.86 [0.73, 1.01]	0.82 [0.69, 0.98]	0.92 [0.80, 1.05]	0.89 [0.77,1.02]	0.86 [0.73, 1.01]	0.82 [0.70, 0.98]
Land Use Mix (200m)	0.92 [0.79, 1.07]	0.89 [0.76, 1.04]	0.98 [0.91, 1.06]	0.96 [0.88, 1.04]	0.93 [0.81, 1.06]	0.90 [0.78, 1.04]	0.98 [0.91, 1.06]	0.96 [0.88, 1.04]
Land Use Mix (500m)	0.93 [0.79, 1.10]	0.92 [0.77, 1.09]	0.88 [0.74, 1.04]	0.86 [0.72, 1.03]	0.91 [0.76, 1.09]	0.89 [0.74, 1.07]	0.88 [0.74, 1.05]	0.87 [0.72, 1.04]
Major transportation (200m)	1.07 [1.02, 1.12]	1.07 [1.02, 1.13]	1.12 [1.02, 1.23]	1.11 [1.01, 1.23]	1.08 [1.03, 1.14]	1.09 [1.03, 1.15]	1.12 [1.02, 1.23]	1.11 [1.01, 1.23]
Major transportation (500m)	1.02 [0.99, 1.04]	1.02 [0.99, 1.04]	1.01 [0.97, 1.05]	1.02 [0.97, 1.06]	1.02 [0.99, 1.05]	1.02 [0.99, 1.05]	1.01 [0.97, 1.06]	1.02 [0.98, 1.06]
Municipal Services (200m)	0.98 [0.86, 1.13]	0.94 [0.81, 1.09]	1.49 [1.03, 2.14]	1.44 [0.98, 2.12]	0.95 [0.80, 1.12]	0.90 [0.76, 1.08]	1.49 [1.03, 2.14]	1.44 [0.98, 2.12]
Municipal Services (500m)	0.93 [0.85, 1.03]	0.92 [0.84, 1.02]	0.89 [0.79, 1.00]	0.86 [0.76, 0.98]	0.89 [0.81, 0.99]	0.88 [0.79, 0.98]	0.89 [0.79, 1.00]	0.86 [0.76, 0.98]
Community Facilities (200m)	0.997 [0.98, 1.02]	0.99 [0.97, 1.01]	1.00 [0.97, 1.04]	0.99 [0.95, 1.03]	1.00 [0.98, 1.02]	0.996 [0.97, 1.02]	1.00 [0.97, 1.04]	0.99 [0.95, 1.03]
Community Facilities (500m)	0.995 [0.99, 1.00]	0.99 [0.98, 1.00]	0.99 [0.98, 1.00]	0.99 [0.97, 1.00]	0.996 [0.99, 1.01]	0.99 [0.98, 1.00]	0.99 [0.98, 1.00]	0.99 [0.97, 1.00]
Leisure Facilities (200m)	0.98 [0.93, 1.03]	0.97 [0.92, 1.02]	0.98 [0.90, 1.06]	0.96 [0.88, 1.05]	0.98 [0.93, 1.03]	0.97 [0.92, 1.03]	0.98 [0.90, 1.07]	0.97 [0.89, 1.06]
Leisure Facilities (500m)	1.00 [0.99, 1.01]	1.00 [0.99, 1.02]	0.96 [0.92, 0.995]	0.95 [0.92, 0.99]	0.9998 [0.98, 1.02]	1.00 [0.99, 1.02]	0.96 [0.92, 0.995]	0.95 [0.91, 0.99]
Health Facilities (200m)	0.96 [0.89, 1.01]	0.93 [0.87, 0.99]	0.99 [0.88, 1.12]	0.97 [0.85, 1.11]	0.96 [0.89, 1.02]	0.94 [0.87, 1.01]	0.99 [0.88, 1.12]	0.97 [0.85, 1.10]
Health Facilities (500m)	0.96 [0.94, 0.98]	0.96 [0.93, 0.98]	0.95 [0.91, 0.99]	0.94 [0.90, 0.99]	0.96 [0.93, 0.98]	0.95 [0.93, 0.98]	0.95 [0.91, 0.99]	0.94 [0.90, 0.99]

Table 4

A comparison of results with consistency based on Akaike information criterion (AIC) among adjusted models.

Built Environment	Akaike information criterion (AIC) among adjusted models			
	2D circular	2D service area	3D circular	3D service area
% Public Space (500m)	1381.4	1365	1381.2	1365.2
Major transportation (200m)	1378.4	1382	1378.1	1382
Health Facilities (500m)	1374	1379.9	1372.6	1379.8

et al., 2021), the use of this spatial structure may not always result in a better model fit. Based on the results of % public space, AICs from service areas were much lower than those from circular buffers. This is linked to our previous results, which the effect of % public space was found to be the most significant. However, difference of AICs were marginal when we compared the results from health facilities within a walkable distance (500 m) and transport facilities at the immediate

distance (200 m).

4. Discussion

In this study, we compared measures of built environment based on four types of spatial structures (2D circular, 2D service area, 3D circular, 3D service area). We evaluated how these measures yielded the relationships between built environment and self-reported osteoporosis across public housing estates in a hilly city. We found that using circular buffers as spatial structure, especially 2D circular, might induce more spatial uncertainty into the measure and the analytical results (e.g. more measurement error). We also found that 2D/3D difference among circular buffers could be greater than 2D/3D difference among service areas.

In general, natural greenery did not associate with osteoporosis. Controlling for medical and sociodemographic factors, our results also indicated that more public space and health facilities within a walkable distance (500 m) were consistently negatively associated with osteoporosis. More leisure and municipal facilities as well as high percentage of building coverage are somewhat negatively associated with osteoporosis. However, more major transport facilities at the immediate

distance from residence (200 m) was positively associated with self-reported osteoporosis. These results were somewhat consistent with other local studies. A recent study conducted four-time follow ups over 14 years and indicated that long-term living close to natural greenery in Hong Kong did not improve health conditions of osteoporosis but increased major osteoporotic fracture incidence risks among older adults (Lin et al., 2021). The hazard ratio from these follow-up results was high (HH: 1.53 [1.13, 2.07]). Another study found that a higher percentage of planned greenspace surrounding the residence was negatively associated with osteoporosis while coverage of natural greenspace was not associated with osteoporosis (Ho et al., 2022). Specifically, a 10% increase of planned greenspace within the 600-m radius area surrounding the residence was negatively associated with osteoporosis (−2.8% [−5.1%, −0.5%]).

Our results regarding spatial uncertainty were also somewhat consistent with previous studies (Ho et al., 2015; Labib et al., 2020; Parenteau and Sawada, 2011; Reid et al., 2018; Schuurman et al., 2007; Su et al., 2019; Sun et al., 2018). For example, Parenteau and Sawada (2011) conducted a study on air pollution and respiratory health at the neighbourhood-level in Ottawa, Canada, finding that regression results differed significantly using different units of analysis, leading to a lack of agreement across spatial analytical strategies. Su et al. (2019) conducted a cross-sectional study in Barcelona, Spain and found that measuring greenspace in different buffer sizes could affect the results of perceived health and physical activity. Reid et al. (2018) also conducted a study of greenspace and self-rated health for New York City by using six aggregation units (five radial buffer sizes and a self-described neighbourhood) and found that different aggregation units yielded different results. On the basis of our findings, we add a high-density Asian city study to this body of knowledge.

4.1. Strengths of this study

Advancing from the previous studies, one contribution of our study is its inclusion of 3D walkable environment and considerations of free-standing walls, fences and construction areas as barriers to walking paths. Most previous studies such as Parenteau and Sawada (2011) or Su et al. (2019), were conducted in cities with generally gentle slopes and open terrain. Also, the urban design of cities previously studied have tended toward a “grid plan”, and polycentricity, with clear separation of land uses (e.g. residential lands versus commercial area) as well as the levels of greenery associated with radial city suburbs (García-López and Muñiz, 2010; Muñiz et al., 2003; Sweet et al., 2017). However, there are dispersed cities worldwide (especially cities in East Asia) due to constraints of natural landscape and land policies (e.g. Taipei, Seoul, Hong Kong), resulting in a high-density and compact built environment. Some parts of these cities were even as hilly as the selected areas in Hong Kong (Tu and Lin, 2008). Taking these attributes into consideration, walking paths as well as land use patterns in these cities would be quite different from those of Barcelona or Ottawa or other European/North American cities examined in those previous studies.

Without consideration of terrain, slopes and road network as barriers of spatial buffers, the results of past studies could not demonstrate the sophisticated patterns of walking behaviours across dispersed cities with hilly environment. The neglect of these considerations was in fact acknowledged. For example, Su et al. (2019) suggested that buffer sizes could affect the results of greenspace metrics but not spatial resolution of a pixel. However, these results could actually be caused by the regular patterns of land use across the study area (e.g. Barcelona) at the sub-pixel level, thus they cannot be generalized to the other cities. This may also be the reason why the results of Su et al. (2019) on scaling effects were contradicted by a greenspace study of Singapore (Zhang and Tan, 2019), although both studies applied similar methods and data (e.g. Worldview image). More importantly, while some studies have demonstrated the differences in using various spatial structures to study environment-health association in high-density cities (Sun et al., 2018;

Zhang and Tan, 2019), they did not consider the effects of terrain and slope. In this regard, our study was more advanced because we have demonstrated buffering results better matching local walking behaviours.

Linking to the above strength, our results were also more conclusive than the other studies because we included information of built environment in multiple dimensions for testing. Most of the previous studies only tested for a single dimension of built environment such as greenery (Labib et al., 2020; Reid et al., 2018; Su et al., 2019; Zhang and Tan, 2019). Such tests disregarded the facts that there were more urban elements within a built environment, and each of these elements might separately and simultaneously influence a specific health outcome of an individual. Further, these environmental influences would be more significant on the physical functions among older adults, as older adults and related illnesses could be affected by walkable distance and behaviours. Within this context, Sun et al. (2018) attempted to estimate spatial uncertainty of various measures of built environment, which is compatible with the dimensions of walkability and accessibility. However, this study did not examine the relationship between built environment and any health outcomes, leaving a gap for researchers to further address the questions of spatial uncertainty. Therefore, our study could provide additional information for reference, as we applied eleven measures of built environment under three dimensions (greenery, walkability and accessibility) to test with a health outcome related to physical health.

Another strength of this study is its data-driven comparison, enhancing robustness and reflecting how different measures influence health outcomes systematically. We did not define distance from the residence as a part of spatial uncertainty caused by scaling effects or buffer sizes (Reid et al., 2018; Su et al., 2019; Zhang and Tan, 2019). Instead, we applied different distances to hypothesize walkable behaviours in multiple scales: immediate distance (200 m) and walkable distance (500 m). Our approach is more realistic because as older adults are walking-dependent, their usages of spaces could be varied by distance. This approach enables our study to be open in identifying which specific elements are more functional for which distances, instead of testing how an urban element in a presumed distance (e.g. 1000 m) might be the best for a health outcome.

4.2. Planning recommendations and policy implications from this study

Our results could also be easier for urban planners and health officials to develop community plans and to minimize health risk at the neighbourhood-level. Specifically, our results regarding the association of built environment and physical functions were not only aligned with findings from previous studies, but added new insights and information to the literature. For example, several studies have indicated that larger amount of public space surrounding a residence can increase walkability within urban areas as well as physical activity of a person, resulting in better physical health (Fisher et al., 2004; Kaczynski et al., 2008; Li et al., 2005).

More importantly, these results were also consistent with the hypothesis from recent local studies (Ho et al., 2022; Lin et al., 2021), while we could provide more details for planning purposes. A recent study (Lin et al., 2021) using clinical data and 2D circular buffer without considering walking paths to evaluate the neighbourhood effect on health risk among older adults in Hong Kong. This study found an adverse effect of natural greenery on osteoporosis related failure risk (Lin et al., 2021) and hypothesized that the adverse effect could be due to lower physical level among those older adults living near higher amounts of greenery with steep slopes. However, this study did not characterize various influences from different types of spaces and facilities. The discussion simply implied that the adverse effects should be from different natures of “green spaces” (e.g. natural greenery, public spaces) and could be due to the terrain factors which limited the accessibility to greenery and facilities. Our results are therefore able to

further prove the hypothesis of this study (Lin et al., 2021), while we can also pinpoint which types of spaces/facilities should more be relevant for the prevention of osteoporosis, as well as providing a more comprehensive picture regarding how walking paths, physical/daily activities and usage of space/facilities could play additional roles on osteoporosis. Another study found that “planned greenspace” was negatively associated with osteoporosis while “natural greenspace” was not associated with osteoporosis (Ho et al., 2022). This finding is somewhat similar to our study, however, the protective effect from public space showing in the previous research was much lower than our results. It is possibly due to the living conditions of participants. In the previous study (Ho et al., 2022), it was a territory-wide investigation including both high-income and low-income older adults living in areas with gentle slopes or steep terrains. Our subjects were low-income older adults living in public housing estates with hilly environment. Therefore, our findings may be more useful for the development of planning/housing protocols targeting low-income adults who live in hilly environment or public housing estates.

In a local context, previous studies have pointed out the positive association between Tai Chi and health among the older adults in Hong Kong (Woo et al., 2007; Qin et al., 2002), and these older adults who conducted Tai Chi could be those who jog in public space daily or those who gathered in public space for social activities. In our study, older adults without osteoporosis were individuals with more activities of daily living, better functional ability and better quality of life (Table 1). Without controlling for IADL, our results showed that greater provision of public space within a walkable distance (500 m) could have negative associations with self-reported osteoporosis. This implies the strong functionality of public space for the physical wellbeing of older adults in a very local context. Consistent with previous studies (Rolland et al., 2008), older adults with osteoporosis among older adults were associated with depression, pain and frailty (Table 1). Therefore, the negative association between health facilities and self-reported osteoporosis could be explained by the relationships among IADLs, co-morbidity and potential walking behaviours. This also implied the reason behind the positive association between major transport facilities and self-reported osteoporosis at the immediate distance from the residence.

Thus, paths and terrain/slope and their relationship with facilities should be considered for urban planning, especially for hilly environment and public housing estates. Particularly, an urban design to improve the access to public space and facilities for functional activities (e.g. health facilities, leisure facilities) is recommended.

4.3. Limitations

The study has several limitations. Following other studies, we used location of residence to map neighbourhood effect on older adults (Ho et al., 2017; Lin et al., 2021; Reid et al., 2018; Su et al., 2019; Wong et al., 2017). However, recent studies have suggested that urban citizens can be highly mobile within a day (Zhang et al., 2018). Future studies might consider daytime and night-time behaviours to estimate the full activity spaces of individuals (Song et al., 2020). This approach best involves GPS tracking or social media data to map the behaviours of individuals, which may not work with older adults less comfortable with smart information and communications technology (ICT). As the living environment of older adults was mostly related to their residential neighbourhood instead of workplace, we regard our use of residential locations to estimate neighbourhood effect as appropriate.

Similar to the other studies (Reid et al., 2018; Sarkar et al., 2018, Sun et al., 2018), we used NDVI to measure greenness. However, some studies have found that other vegetation indices such as the wide dynamic range vegetation index (WDRVI) and enhanced vegetation index (EVI) may be more sensitive to biophysical characteristics of vegetation, and these spatial indices might be more suitable to estimate urban greenness. Future studies could therefore compare the association of these vegetation indices with health outcomes to further determine the

abilities and limitations of each index. We chose NDVI because local studies have found an association between NDVI and vegetation in Hong Kong (Ho et al., 2017), and NDVI has been widely used in local health studies (Ho et al., 2022; Lin et al., 2021; Sun et al., 2020).

Our comparisons between different spatial units of analysis are likely not to be compromised by the cross-sectional design of the study. Further assessments and implications with path analyses to evaluate causal effects between variables may be necessary.

Finally, as we used self-reported medical records to determine whether a subject has osteoporosis, it may create bias regarding the distribution of disease prevalence. Therefore, we compared our analytical dataset with Hong Kong’s clinical studies (Kwok et al., 2013; Lo, 2021). Although the percentage of having osteoporosis among our subjects was slightly lower than the other local studies (11.8%), the dataset was still comparable with those data from clinical assessments. Particularly, Lo et al. (2021) assessed the older females based on clinical assessment and found that 23.7% of the females were osteoporotic, while the percentage of having osteoporosis among our female subjects was about 22%. Kwok et al. (2013) evaluated the prevalence and risk factors of radiographic vertebral fractures among 4000 older adults in Hong Kong and found that 15.7% of the older adults had at least one vertebral deformity and 8.6% of the adults were defined as having at least one vertebra fracture. Among the 4000 older adults, those with older ages and with frailty related issues (e.g. lower bone mineral density, lower physical activity, and low back pain) were significantly associated with higher vertebral fracture rates. These results were matched with demographic information and medical history among our subjects, which implied that using our analytical dataset for statistical modelling was appropriate.

5. Conclusion

We conducted a cross-sectional analysis with a data-driven, cross-validated approach to evaluate the influences of built environment on physical functions among older adults living in hilly neighbourhoods. We found that different spatial structures yielded different results. By using the results from 3D service areas, more public space and health facilities within a walkable distance (500 m) had a negative association with self-reported osteoporosis, but more major transport facilities at the immediate distance (200 m) were positively associated with self-reported osteoporosis. This indicated that a walkable neighbourhood with more spaces for physical activities as well as basic requirements of daily living (e.g. groceries, local healthcare) should be provided, while measuring neighbourhood effect should be linked with local terrain and road network so that community plans to maintain a self-manageable lifestyle could be developed effectively and appropriately.

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References

- Abbott, R.D., White, L.R., Ross, G.W., Masaki, K.H., Curb, J.D., Petrovitch, H., 2004. Walking and dementia in physically capable elderly men. *JAMA* 292 (12), 1447–1453.
- Chu, L.W., Ng, K.H., Law, A.C., Lee, A.M., Kwan, F., 2015. Validity of the Cantonese Chinese Montreal cognitive assessment in Southern Chinese. *Geriatr. Gerontol. Int.* 15 (1), 96–103.
- Chang, K.H., Chung, C.J., Lin, C.L., Sung, F.C., Wu, T.N., Kao, C.H., 2014. Increased risk of dementia in patients with osteoporosis: a population-based retrospective cohort analysis. *Age* 36 (2), 967–975.
- Chou, Y.C., Shih, C.C., Lin, J.G., Chen, T.L., Liao, C.C., 2013. Low back pain associated with sociodemographic factors, lifestyle and osteoporosis: a population-based study. *J. Rehabil. Med.* 45 (1), 76–80.
- de Keijzer, C., Gascon, M., Nieuwenhuijsen, M.J., Davdand, P., 2016. Long-term green space exposure and cognition across the life course: a systematic review. *Curr. Environ. Health Rep.* 3 (4), 468–477.

- Fisher, K.J., Li, F., Michael, Y., Cleveland, M., 2004. Neighborhood-level influences on physical activity among seniors: a multilevel analysis. *J. Aging Phys. Activ* 12 (1), 45–63.
- Frank, L.D., Schmid, T.L., Sallis, J.F., Chapman, J., Saelens, B.E., 2005. Linking objectively measured physical activity with objectively measured urban form: findings from SMARTRAQ. *Am. J. Prev. Med.* 28 (2), 117–125.
- Frank, L.D., Sallis, J.F., Conway, T.L., Chapman, J.E., Saelens, B.E., Bachman, W., 2006. Many pathways from land use to health: associations between neighborhood walkability and active transportation, body mass index, and air quality. *J. Am. Plann. Assoc.* 72 (1), 75–87.
- García-López, M.Á., Muñoz, I., 2010. Employment decentralisation: polycentricity or scatteration? The case of Barcelona. *Urban Stud.* 47 (14), 3035–3056.
- Guo, Y., Liu, Y., Lu, S., Chan, O.F., Chui, C.H.K., Lum, T.Y.S., 2021. Objective and perceived built environment, sense of community, and mental wellbeing in older adults in Hong Kong: a multilevel structural equation study. *Landscape Urban Plann.* 209, 104058.
- Graat-Verboom, L., Wouters, E.F.M., Smeenk, F.W.J.M., Van Den Borne, B.E.E.M., Lunde, R., Spruit, M.A., 2009. Current status of research on osteoporosis in COPD: a systematic review. *Eur. Respir. J.* 34 (1), 209–218.
- Ho, H.C., Knudby, A., Huang, W., 2015. A spatial framework to map heat health risks at multiple scales. *Int. J. Environ. Res. Publ. Health* 12 (12), 16110–16123.
- Ho, H.C., Lau, K.K.L., Yu, R., Wang, D., Woo, J., Kwok, T.C.Y., Ng, E., 2017. Spatial variability of geriatric depression risk in a high-density city: a data-driven socio-environmental vulnerability mapping approach. *Int. J. Environ. Res. Publ. Health* 14 (9), 994.
- Ho, H.C., Wang, D., Leung, J., Yu, B., Woo, J., Kwok, T.C.Y., Lau, K., 2022. “Planned greenspace” or “natural greenspace” in a high-density city with compact environment? An empirical study of osteoporosis among senior population. *Build. Environ.* 219, 109117.
- Kaczynski, A.T., Potwarka, L.R., Saelens, B.E., 2008. Association of park size, distance, and features with physical activity in neighborhood parks. *Am. J. Publ. Health* 98 (8), 1451–1456.
- Kwok, A.W.L., Gong, J.S., Wang, Y.J., Leung, J.C.S., Kwok, T., Griffith, J.F., Leung, P.C., 2013. Prevalence and risk factors of radiographic vertebral fractures in elderly Chinese men and women: results of Mr. OS (Hong Kong) and Ms. OS (Hong Kong) studies. *Osteoporos. Int.* 24 (3), 877–885.
- Labib, S.M., Lindley, S., Huck, J.J., 2020. Scale effects in remotely sensed greenspace metrics and how to mitigate them for environmental health exposure assessment. *Comput. Environ. Urban Syst.* 82, 101501.
- Lau, E.M.C., Lee, J.K., Suriwongpaisal, P., Saw, S.M., De, S.D., Khir, A., Sambrook, P., 2001. The incidence of hip fracture in four Asian countries: the Asian Osteoporosis Study (AOS). *Osteoporos. Int.* 12 (3), 239–243.
- Leidig-Bruckner, G., Minne, H.W., Schlaich, C., Wagner, G., Scheidt-Nave, C., Bruckner, T., et al., 1997. Clinical grading of spinal osteoporosis: quality of life components and spinal deformity in women with chronic low back pain and women with vertebral osteoporosis. *J. Bone Miner. Res.* 12 (4), 663–675.
- Lee, H.C.B., Chiu, H.F., Kowk, W.Y., Leung, C.M., 1993. Chinese elderly and the GDS short form: a preliminary study. *Clin. Gerontol.: J. Aging Ment. Health* 14 (2), 37–42.
- Li, F., Fisher, K.J., Brownson, R.C., Bosworth, M., 2005. Multilevel modelling of built environment characteristics related to neighbourhood walking activity in seniors. *J. Epidemiol. Community Health* 59 (7), 558–564.
- Lin, J., Leung, J., Yu, B., Woo, J., Kwok, T., Lau, K.K.L., 2021. Association of green space with bone mineral density change and incident fracture in elderly Hong Kong Chinese: Mr. OS and Ms. OS study. *Environ. Res.* 201, 111547.
- Lo, S.S.T., 2021. Prevalence of osteoporosis in elderly women in Hong Kong. *Osteoporos. Sarcopenia* 7 (3), 92–97.
- Lu, S., Liu, Y., Guo, Y., Ho, H.C., Song, Y., Cheng, W., Chui, C., Chan, O.F., Chiu, R.L.H., Webster, C., Lum, T.Y., 2021. Neighborhood Built Environment and Late-Life Depression: a Multilevel Path Analysis in a Chinese Society. *The Journals of Gerontology: Series B* gbab037.
- Marquardt, G., Bueter, K., Motzek, T., 2014. Impact of the design of the built environment on people with dementia: an evidence-based review. *HERD: Health Environ. Res. Des. J.* 8 (1), 127–157.
- Morley, J.E., Malmstrom, T.K., Miller, D.K., 2012. A simple frailty questionnaire (FRAIL) predicts outcomes in middle aged African Americans. *J. Nutr. Health Aging* 16 (7), 601–608.
- Mithal, A., Kaur, P., 2012. Osteoporosis in Asia: a call to action. *Curr. Osteoporos. Rep.* 10 (4), 245–247.
- Muñoz, I., Galindo, A., García, M.Á., 2003. Cubic spline population density functions and satellite city delimitation: the case of Barcelona. *Urban Stud.* 40 (7), 1303–1321.
- Parenteau, M.P., Sawada, M.C., 2011. The modifiable areal unit problem (MAUP) in the relationship between exposure to NO₂ and respiratory health. *Int. J. Health Geogr.* 10 (1), 58.
- Perneger, T.V., Burnand, B., 2005. A simple imputation algorithm reduced missing data in SF-12 health surveys. *J. Clin. Epidemiol.* 58 (2), 142–149.
- Phillips, D.R., Siu, O.L., Yeh, A.G., Cheng, K.H., 2004. Factors influencing older persons' residential satisfaction in big and densely populated cities in Asia: a case study in Hong Kong. *Ageing Int.* 29 (1), 46–70.
- Phillips, D.R., Siu, O.L., Yeh, A.G., Cheng, K.H., 2005. The impacts of dwelling conditions on older persons' psychological well-being in Hong Kong: the mediating role of residential satisfaction. *Soc. Sci. Med.* 60 (12), 2785–2797.
- Qin, L., Au, S., Choy, W., Leung, P., Neff, M., Lee, K., et al., 2002. Regular Tai Chi Chuan exercise may retard bone loss in postmenopausal women: a case-control study. *Arch. Phys. Med. Rehabil.* 83 (10), 1355–1359.
- Reid, C.E., Kubzansky, L.D., Li, J., Shmool, J.L., Clougherty, J.E., 2018. It's not easy assessing greenness: a comparison of NDVI datasets and neighborhood types and their associations with self-rated health in New York City. *Health Place* 54, 92–101.
- Rolland, Y., Van Kan, G.A., Benetos, A., Blain, H., Bonnefoy, M., Chassagne, P., et al., 2008. Frailty, osteoporosis and hip fracture: causes, consequences and therapeutic perspectives. *J. Nutr. Health Aging* 12 (5), a319–a330.
- Sampson, H.W., 2002. Alcohol and other factors affecting osteoporosis risk in women. *Alcohol Res. Health* 26 (4), 292.
- Sarkar, C., Gallacher, J., Webster, C., 2013. Built environment configuration and change in body mass index: the Caerphilly Prospective Study (CaPS). *Health Place* 19, 33–44.
- Sarkar, C., Webster, C., Gallacher, J., 2018. Residential greenness and prevalence of major depressive disorders: a cross-sectional, observational, associational study of 94 879 adult UK Biobank participants. *Lancet Planet. Health* 2 (4), e162–e173.
- Schmidt, C.G., 1977. Influence of land use diversity upon neighborhood success: an analysis of Jacobs' theory. *Ann. Reg. Sci.* 11 (1), 53–65.
- Schuurman, N., Bell, N., Dunn, J.R., Oliver, L., 2007. Deprivation indices, population health and geography: an evaluation of the spatial effectiveness of indices at multiple scales. *J. Urban Health* 84 (4), 591–603.
- Song, Y., Chen, B., Kwan, M.P., 2020. How does urban expansion impact people's exposure to green environments? A comparative study of 290 Chinese cities. *J. Clean. Prod.* 246, 119018.
- Steil, J.P., Delgado, L.H., 2019. Limits of diversity: Jane Jacobs, the Just city, and anti-urbanization. *Cities* 91, 39–48.
- Su, J.G., Davvand, P., Nieuwenhuijsen, M.J., Bartoll, X., Jerrett, M., 2019. Associations of green space metrics with health and behavior outcomes at different buffer sizes and remote sensing sensor resolutions. *Environ. Int.* 126, 162–170.
- Sun, G., Webster, C., Ni, M.Y., Zhang, X., 2018. Measuring high-density built environment for public health research: uncertainty with respect to data, indicator design and spatial scale. *Geospatial Health* 13 (1).
- Sun, S., Sarkar, C., Kumari, S., James, P., Cao, W., Lee, R.S.Y., et al., 2020. Air pollution associated respiratory mortality risk alleviated by residential greenness in the Chinese Elderly Health Service Cohort. *Environ. Res.* 183, 109139.
- Sun, G., Webster, C., Zhang, X., 2021. Connecting the city: a three-dimensional pedestrian network of Hong Kong. *Environ. Plann. B: Urban Anal. City Sci.* 48 (1), 60–75.
- Sweet, M.N., Bullivant, B., Kanaroglou, P.S., 2017. Are major Canadian city-regions monocentric, polycentric, or dispersed? *Urban Geogr.* 38 (3), 445–471.
- Takano, T., Nakamura, K., Watanabe, M., 2002. Urban residential environments and senior citizens' longevity in megacity areas: the importance of walkable green spaces. *J. Epidemiol. Community Health* 56 (12), 913–918.
- Tang, B.S., Wong, K.K., Tang, K.S., Wong, S.W., 2021. Walking accessibility to neighbourhood open space in a multi-level urban environment of Hong Kong. *Environ. Plann. B: Urban Anal. City Sci.* 48 (5), 1340–1356.
- Tong, A.Y., Man, D.W., 2002. The validation of the Hong Kong Chinese version of the Lawton instrumental activities of daily living scale for institutionalized elderly persons. *OTJR Occup. Participation Health* 22 (4), 132–142.
- Tsai, Y.H., Stow, D., Chen, H.L., Lewison, R., An, L., Shi, L., 2018. Mapping vegetation and land use types in Fanjingshan national nature reserve using Google Earth engine. *Rem. Sens.* 10 (6), 927.
- Tu, K.J., Lin, L.T., 2008. Evaluative structure of perceived residential environment quality in high-density and mixed-use urban settings: an exploratory study on Taipei City. *Landscape Urban Plann.* 87 (3), 157–171.
- Van der Voort, D.J.M., Geusens, P.P., Dinant, G.J., 2001. Risk factors for osteoporosis related to their outcome: fractures. *Osteoporos. Int.* 12 (8), 630–638.
- Vergheze, J., Lipton, R.B., Katz, M.J., Hall, C.B., Derby, C.A., Kuslansky, G., et al., 2003. Leisure activities and the risk of dementia in the elderly. *N. Engl. J. Med.* 348 (25), 2508–2516.
- Vogt, M.T., Cauley, J.A., Kuller, L.H., Nevitt, M.C., 1994. Functional status and mobility among elderly women with lower extremity arterial disease: the Study of Osteoporotic Fractures. *J. Am. Geriatr. Soc.* 42 (9), 923–929.
- Wang, Y., Tao, Y., Hyman, M.E., Li, J., Chen, Y., 2009. Osteoporosis in China. *Osteoporos. Int.* 20 (10), 1651–1662.
- Wiles, J.L., Leibing, A., Guberman, N., Reeve, J., Allen, R.E., 2012. The meaning of “aging in place” to older people. *Gerontol.* 52 (3), 357–366.
- Wong, M.T.P., Ho, T.P., Ho, M.Y., Yu, C.S., Wong, Y.H., Lee, S.Y., 2002. Development and inter-rater reliability of a standardized verbal instruction manual for the Chinese Geriatric Depression Scale—short form. *Int. J. Geriatr. Psychiatry.* 17 (5), 459–463.
- Wong, A., Xiong, Y.Y., Kwan, P.W., Chan, A.Y., Lam, W.W., Wang, K., et al., 2009. The validity, reliability and clinical utility of the Hong Kong Montreal Cognitive Assessment (HK-MoCA) in patients with cerebral small vessel disease. *Dement. Geriatr. Cognit. Disord.* 28 (1), 81–87.
- Wong, M.S., Ho, H.C., Yang, L., Shi, W., Yang, J., Chan, T.C., 2017. Spatial variability of excess mortality during prolonged dust events in a high-density city: a time-stratified spatial regression approach. *Int. J. Health Geogr.* 16 (1), 26.
- Woo, J., Hong, A., Lau, E., Lynn, H., 2007. A randomised controlled trial of Tai Chi and resistance exercise on bone health, muscle strength and balance in community-living elderly people. *Age Ageing* 36 (3), 262–268.
- Woo, J., Yu, R., Wong, M., Leung, J., Lau, K., Ho, H.C., Au, A., 2017. Urban characteristics influencing health of older people: what matters. *Int. J. Innov. Res. Med. Sci.* 2 (12), 1561.
- Xie, Z., Phinn, S.R., Game, E.T., Pannell, D.J., Hobbs, R.J., Briggs, P.R., McDonald-Madden, E., 2019. Using Landsat observations (1988–2017) and Google Earth Engine to detect vegetation cover changes in rangelands-A first step towards identifying degraded lands for conservation. *Rem. Sens. Environ.* 232, 111317.

- Yang, L., Ho, J.Y., Wong, F.K., Chang, K.K., Chan, K.L., Wong, M.S., et al., 2020. Neighbourhood green space, perceived stress and sleep quality in an urban population. *Urban For. Urban Green.* 54, 126763.
- Yeung, P.Y., Wong, L.L., Chan, C.C., Leung, J.L., Yung, C.Y., 2014. A validation study of the Hong Kong version of Montreal Cognitive Assessment (HK-MoCA) in Chinese older adults in Hong Kong. *Hong Kong Med. J.* 20 (6), 504–510.
- Zhang, L., Zhou, S., Kwan, M.P., Chen, F., Lin, R., 2018. Impacts of individual daily greenspace exposure on health based on individual activity space and structural equation modeling. *Int. J. Environ. Res. Publ. Health* 15 (10), 2323.
- Zhang, L., Tan, P.Y., 2019. Associations between urban green spaces and health are dependent on the analytical scale and how urban green spaces are measured. *Int. J. Environ. Res. Publ. Health* 16 (4), 578.