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Original article

The uncertain geographic context problem (UGCoP) in measuring people's exposure to green space using the integrated 3S approach

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ABSTRACT

The "mobility turn" in environmental health studies promoted the integrated 3S (GIS, GPS, and remote sensing) approach in the study of urban residents' exposure to green space and corresponding health outcomes. However, few studies have examined the uncertainty induced by contextual settings when measuring people's exposure to green space using the conventional and integrated 3S approaches. In this paper, we compared the differences in green space exposure obtained from different geographic contexts using residence-based and mobility-based methods, multiple spatial resolutions, and buffer zones. We collected 7-day GPS trajectories from 208 participants at the 1-minute temporal resolution in Hong Kong. Entire Hong Kong's green space was delineated using multiple remote sensing data sources at 3 m, 10 m, and 30 m spatial resolutions. Lastly, the residence-based and mobility-based measurements of exposure to green space were calculated for each participant using 100 m, 300 m, and 500 m buffer zones at three spatial resolutions. Descriptive analyses, t-tests, and logistic regression were employed to examine the influence of different contextual settings on different measurements of green space exposure and their health effects. The results indicate multiple significant disparities. The most striking difference is that mobility-based measurements of exposure to green space are significantly higher than those of residence-based measurements, manifesting the uncertain geographic context problem (UGCoP). For future studies, we suggest using mobility-based measurements of exposure to green space, smaller buffer zones, and finer spatial resolutions, which enable more accurate measurements of green space exposure for the study of green space's health effects.

1. Introduction

Urban green space and green infrastructure provide essential ecosystem services that influence human health through diverse and complex pathways (Wolch et al., 2014; Dadvand and Nieuwenhuijsen, 2019). Numerous studies have indicated that access to green space is significantly associated with multiple health benefits. For instance, green space may promote the physical health of urban residents by encouraging more physical exercise (Richardson et al., 2013; Hillsdon et al., 2006). The improved landscape beautification by green space may promote the mental health of urban residents by reducing stress levels and decreasing the risks of mental disorders (Groenewegen et al., 2006; Nutsford et al., 2013). Other studies also indicate that some adverse health effects may be strongly associated with green space, like vector-borne diseases (Heylen et al., 2019; Barrios et al., 2012), aero-allergy and asthma caused by pollen (Cariñanos and Casares-Porcel, 2011), and the accumulation of pollutants in the soil (Lin et al., 2018; Rubel et al., 2019). Meanwhile, the uneven distribution of and unequal access to green space have also triggered an intensive discussion on green space as a social determinant of health, especially on the issues of environmental injustice (Liu et al., 2021) and the gentrification of living environments (Cole et al., 2017). In the recent two

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decades, research on the health effects of green space keeps growing rapidly and has never shown a declining trend.

The proper measurement of the interaction between urban residents and green space, namely the measurement of people's exposure to green space, is the most essential component in the quantitative analysis of the health effects of green space. Current prevailing approaches measure people's green space exposure around their residential locations (i.e., residence-based measurements, RBM). The research paradigm of RBM is easy to implement and be coupled with epidemiological health data, but it also easily incurs contextual errors and manifests the uncertain geographic context problem (UGCoP) (Kwan, 2012). The integration of GIS, global positioning systems (GPS), and remote sensing methods (the integrated 3S approach (Blaschke et al., 2011)) nowadays provides a new research paradigm for the measurement of people's exposure to green space. In this new paradigm, people's exposure to green space is measured along their daily activity-travel trajectories (i.e., mobility-based measurements, MBM). MBM can mitigate the contextual errors of RBM but still may be affected by improper contextual settings (e.g., the spatial resolution of the green space representation, the size of the contextual unit, and other geographic contexts), while current studies lack systematic investigation on this issue.

To fill this research gap, this study conducts a series of statistical tests to investigate the effects of contextual settings on measuring people's green space exposure, specifically with respect to the differences between RBM and MBM of green space exposure using a range of remote sensing imagery with different spatial resolutions, a range of buffer zones for representing proximity, and in different geographic contexts. The study's objectives are to examine 1) whether there are significant differences between RBM and MBM of green space exposure; 2) whether significant differences exist in the measurements of green space exposure while taking into account other contextual settings and different geographic contexts; and 3) whether these differences would lead to unreliable interpretations of green space's effects on human health.

2. Literature review

The magnitude of people's exposure to green space is essential for evaluating the health effects of green space on urban residents. But its measurement is not as straightforward as measuring the level of sound, the concentration of air/water/soil pollutants, and the luminosity of light. The complexity arises from several sources. First, green space is an aggregation of diverse health-impact factors. Green space not only serves as a feature that promotes urban residents' physical exercise (McCormack et al., 2010), but its components and characteristics (such as its flora, fauna, microbiota, inner air quality, inner soil, hydrology, local climate, and facilities) may also influence human health through diverse pathways. Second, green space may affect human health across a range of spatial scales. For example, *in-situ* close contact with green space may be associated with the risk of tick-borne Lyme diseases (VanAcker et al., 2019), while its effects on modifying local climate and mitigating urban heat waves may require a community-level investigation (Tan et al., 2007; Madrigano et al., 2015). Third, green space is a highly socialized and culturalized place in urban areas, and the different ways in which urban residents use green space may not yield equivalent health outcomes. Due to the complexity of green space exposure measurements, multiple approaches are currently available but most of them tend to have inherent biases.

The most straightforward approach to assessing people's green space exposure is to investigate people's subjective perception of urban green space through questionnaires and interviews (e.g., Balram and Dragićević, 2005). However, participants' self-reported perceptions of green space may contain recall errors, may be inconsistent in different socio-demographic groups, and thus may undermine the validity and generalizability of relevant studies.

Instead, objectively measured exposure to green space using GIS and real-time tracking and sensing is more consistent and can capture people's exposure as they move around. This approach first establishes a numerical model to represent green space and then derives the green space variable based on a specific human-relevant context (e.g., residential neighborhood) as people's exposure to green space. It generally used green space representations and derivations including green space indices (e.g., the normalized difference vegetation index, NDVI) and green space area ratio (Barboza et al., 2021), green space time-series (Cao et al., 2023), green space attributes and component statistics, and green space landscape and fragmentation (Tsai et al., 2016). The most generally used human-relevant contexts in current studies are residence-based spaces such as the residential neighborhood, administrative area, and buffer zone around a home location. The values of the green space variable in residential spaces are considered people's exposure to green space (i.e., RBM), while the spatial variation in green space settings across different residential spaces is considered the variation in people's exposure to green space.

Ignoring people's mobility is one essential shortage of RBM and it may lead to contextual errors. People may travel outside the residential area and the nominal residential contexts may include irrelevant green space that a person has never been exposed to while excluding essential green space that a person frequently visits. An alternative approach from time geography is to use activity space to replace residential space in the objective measurements of green space exposure (i.e., MBM) (Kwan, 2004). Practical implements include the 1-standard deviational ellipse, the minimum concave polygon, and the shortest path (and adjacent buffer zone) between people's visited locations (Wei et al., 2023), while people's visited locations can be obtained from activity-travel diaries (Kwan, 2000). MBM by definition is conceptually more reasonable than RBM, but conventional MBM faces the same validity issues since the self-reported visited locations in activity-travel diaries may be spatio-temporally sparse and may also contain recall errors.

The prevalence of portable GPS and sensing devices overcomes the limitations of conventional MBM since GPS data with high temporal resolution and adequate spatial accuracy enable the retrospective delineation of a person's every visited location and correspondingly the precise activity space. The new approach requires the integration of 3S techniques: GPS trajectories delineate people's precise activity space, remote sensing data numerically represent the spatial distribution of green space, and GIS techniques derive people's exposure to green space along their activity-travel trajectories.

Using either MBM or RBM, the ultimate goal is to maximally include the causally relevant green space in green space exposure measurements while minimally including the irrelevant green space. MBM can mitigate the contextual errors in RBM by replacing the nominal residential space with activity space, but the measurements may still be affected by other contextual settings. Previous studies have discussed these contextual settings only in RBM (e.g., Su et al., 2019; Nouri et al., 2020; Jimenez et al., 2022), but the knowledge and proper contextual settings obtained using RBM may not be directly transferable to MBM since they are two different research paradigms. This research gap motivates our study and we decide to articulate this issue through a systematic experiment. We conceptualize four potentially influential contextual settings and control these contextual settings to derive multiple groups of green space exposure measurements (Fig. 1 as an illustration of our conceptual framework). We then discuss the disparities between these measurements when using different contextual settings and their effects on modeling people's overall health outcomes. Our experiment is detailed in the following sections.

3. Study area

The study area for this research is Hong Kong, which is one of the most densely populated cities in the world. In this study, two representative communities, namely the Sham Shui Po (SSP) community and the Tin Shui Wai (TSW) community, were chosen for the field surveys (Fig. 2). TSW is a densely populated community in Hong Kong. The

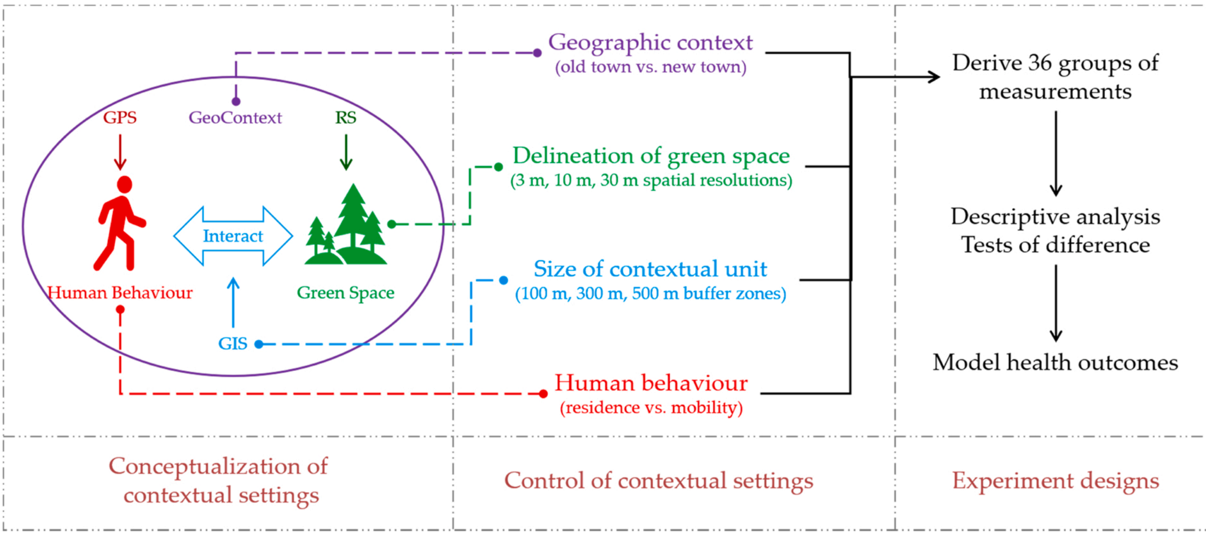

Fig. 1. The conceptual framework of this study.

blocks of TSW included in this study have a total area of 4.32 km^2 and the residential population is about 300,000 by 2018. TSW is a new town that is developed in the 1980 s (Liu et al., 2023) and it is enclosed by more rural areas like villages, fish farms, and wetlands (Fig. 2b). The facilities and infrastructures in TSW are well-designed with better open space and the roads are distant from residential buildings with green spaces between them as barriers. SSP shares a very similar population density as TSW but it is in an apparently different geographic context (Fig. 2c). The blocks of SSP included in this study have a total area of 5.35 km^2 and its residential population is also about 300,000 by 2018. SSP is an old town with a very long history and it is deeply urbanized. This community is near the downtown area of Hong Kong where green space is comparatively sparse.

4. Datasets

4.1. Remote sensing data

Three multispectral imagery data sources are employed in this study for examining the impacts of spatial resolutions on measuring people's green space exposure. The first is conventionally used Landsat imagery at the 30 m spatial resolution, the second is newly emerged Sentinel-2 imagery at the 10 m spatial resolution, and the last is a commercial remote sensing data source called PlanetScope, which has a spatial resolution of 3 m. More details about the data's attributes are shown in Table 1.

Landsat 8 images were collected from the United States Geological Survey (USGS) EarthExplorer (https://earthexplorer.usgs.gov/), Sentinel-2 images were collected from the European Space Agency (ESA) Copernicus Open Access Hub (https://scihub.copernicus.eu/dhus/#/home), and PlanetScope images were collected from Planet Labs, Inc. (https://www.planet.com/explorer/) at no cost using an Education and Research (ER) license. All three image sources provide a red band and a near-infrared (NIR) band (Roy et al., 2014; Drusch et al., 2012; Team, 2017), which enable the derivation of NDVI. All images have been radiometrically calibrated and atmospherically corrected into land surface reflectance: Landsat 8 images used Land Surface Reflectance Code (LaSRC) (Sayler and Zanter, 2020), Sentinel-2 images used the Scene Classification (SCL) and the Sen2Cor processor that ESA provides (Main-Knorn et al., 2017), and PlanetScope images used the 6S Model (Frazier and Hemingway, 2021). All three sets of images are orthorectified and georeferenced to UTM Zone 49N coordinate system with reference to the WGS84 ellipsoid, and they all can fully cover the entire Hong Kong. All images have cloud coverage of less than 1% and are collected within a narrow temporal window to avoid the seasonal changes in Hong Kong's green space. The cross-validation using pure pixels indicates that the reflectance differences among the three sets of images are not significantly different from 0, which confines the contextual settings to only spatial resolutions and has excluded other possible impact factors like seasonal changes in geographic contexts and remote sensors' configurations.

4.2. GPS-derived activity-travel trajectories and questionnaires

In total, 222 participants were recruited from SSP and TSW using a stratified sampling method (as a part of a larger project). The socio-demographic characteristics of the participants were designed to be representative of the characteristics of each community. Multiple axes of the socio-demography were used for stratification, including age, gender, employment status, and monthly household income. The survey was carried out from March 21st, 2021, to September 12th, 2021. Participants were asked to record and submit data through an integrated individual environmental exposure assessment system (Wang et al., 2021). For each participant, the visited locations of the 7 survey days were then assembled from participants' GPS-equipped mobile phones and integrated using the Kalman filter (Lee and Kwan, 2018). A time series of sequentially visited locations (in longitude and latitude) of each participant was derived at the 1-minute temporal resolution to retrospectively delineate the activity-travel trajectory during the 7-day survey period. More details on the survey can be found in our previous papers (Liu et al., 2023; Wang et al., 2021).

The overall health status, home addresses, and socio-demographic information of the recruited participants were collected using a questionnaire. In the questionnaire, each participant was asked to rate his or her overall health status. The response is provided on a 6-point scale ranging from excellent to terrible. Due to the comparatively small sample size, the health status responses were dichotomized as a binary variable based on either an overall good health status (excellent, very good, and good, recoded as 1) or an overall bad health status (bad, very bad, and terrible, recoded as 0).

By excluding void responses and incomplete activity trajectories, the survey finally yielded valid data from 208 participants: 104 participants in SSP and the other 104 participants in TSW. The participants cover a range of socio-demographic statuses through multiple axes (Table 2), including gender, age, education level, marital status, and monthly household income level.

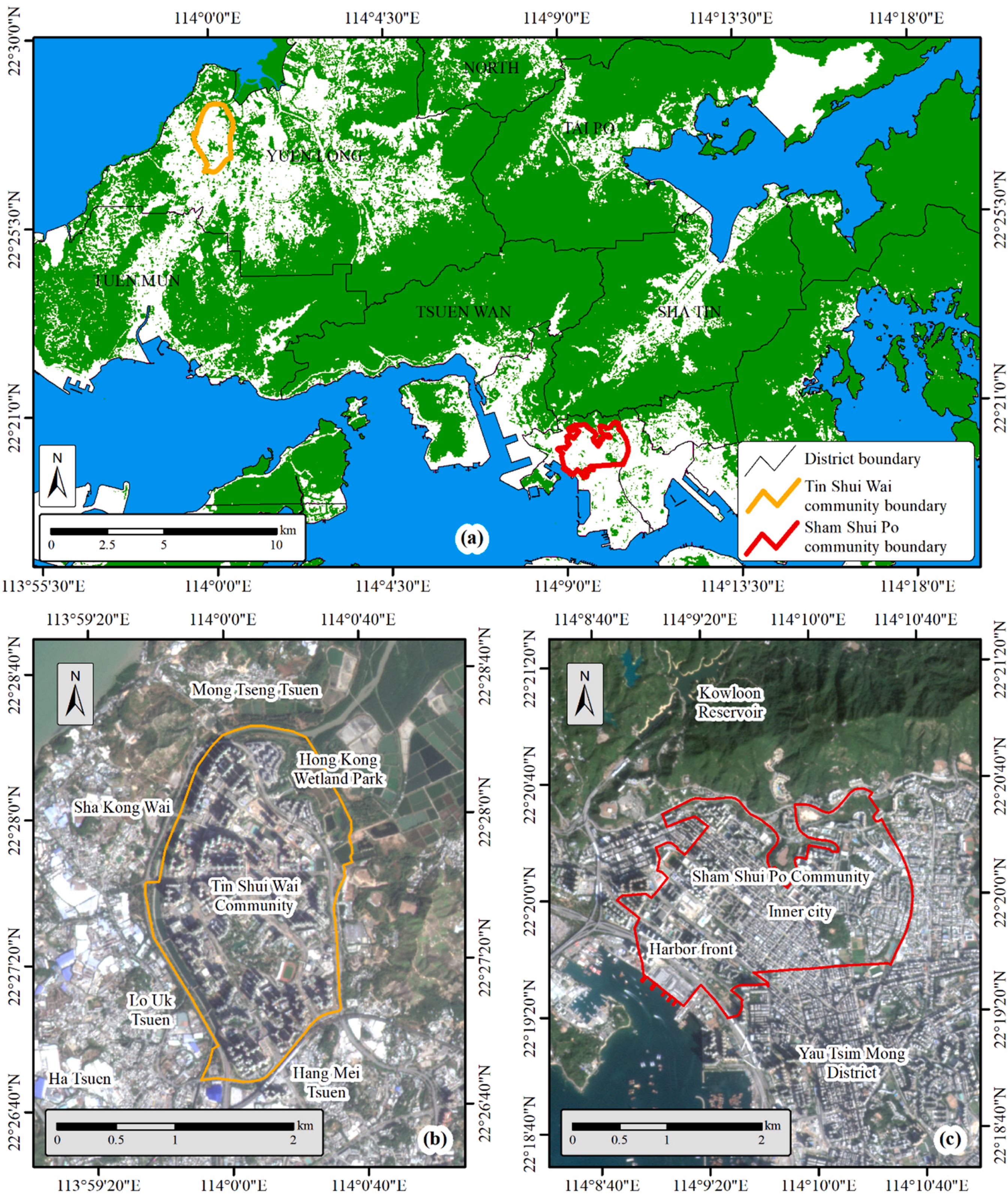

Fig. 2. The geographic settings of SSP and TSW. (a). The locations of SSP and TSW in Hong Kong, (b). the geographic settings of TSW, and (c). the geographic settings of SSP.

Table 1
The sensor configurations of the remote sensing data employed in this study.

Data source	Acquisition date	Spatial resolution	Red band	Near-infrared band
PlanetScope	1/29/2021	3 m	650 – 680 nm	845 – 885 nm
Sentinel-2	1/29/2021	10 m	650 – 680 nm	785 – 900 nm
Landsat 8	1/28/2021, 2/4/2021	30 m	640 – 670 nm	850 – 880 nm

5. Methods

5.1. The derivation of the NDVI and the delineation of green space

The NDVI (Purevdorj et al., 1998) is calculated using

$$NDVI = \frac{\rho_{NIR} - \rho_{Red}}{\rho_{NIR} + \rho_{Red}}, \tag{1}$$

where ρ_{NIR} and ρ_{Red} are the surface reflectance acquired from NIR and red bands, respectively. The NDVI theoretically ranges from -1 to 1. Health vegetations generally have high values of NDVI while other land covers do not.

We developed a thresholding method to delineate the green space in Hong Kong (Rafiee et al., 2009), where the threshold is determined by a logistic regression model. One experienced researcher in our team randomly interpreted 300 sites as a training sample set, where 220 of these sites are green spaces. We used the training sample set to fit a logistic regression model using the maximum likelihood estimation. The fitted model is as follows,

$$\log \frac{P(green \quad space)}{1 - P(green \quad space)} = \beta_0 + \beta_1 * NDVI, \tag{2}$$

where $P(green\ space)$ is the probability that a site is a green space, β_0 and β_1 are the intercept and coefficient of the logistic regression, respectively. Take $P(green\ space) = 0.5$, we have the threshold of NDVI as

$$NDVI_0 = -\frac{\beta_1}{\beta_0}. \tag{3}$$

Using $NDVI_0$ as a threshold, the region with NDVI higher than $NDVI_0$ is determined as green space, while the region with NDVI lower than $NDVI_0$ is determined as other spaces. Another experienced researcher of our team randomly interpreted one more independent test sample set from Google Maps to validate the delineated green space. The test set has 1000 sites, where 613 of them are green space and no site in the test set overlaps with that in the training set. The binary classification results are converted into a raster format for the following analysis.

5.2. Measuring exposure to green space

Similar to other studies, we used an area-based index to measure people's green space exposure (Huang and Kwan, 2022; Cherrie et al., 2019; Zhang and Wu, 2022). For residence-based measurements (RBM) of exposure to green space, the formula is constructed as

$$E_{GS-RSD} = \frac{A(GS_p \cap Buf_r)}{A(Buf_r)}, \tag{4}$$

where E_{GS-RSD} is the RBM of exposure to green space. Buf_r is the circular buffer zone around the home location of the participant with a radius r, and $r =$ 100 m, 300 m, and 500 m in different contextual settings, respectively. GS_p is the green space delineated at the spatial resolution of p, and $p =$ 3 m, 10 m, and 30 m in different contextual settings, respectively. Function $A()$ calculates the targeted area, namely the intersection area between the delineated green space and the buffer zone, and the buffer zone itself, respectively. E_{GS-RSD} ranges from 0 to 1. The higher the value, the more a participant is exposed to green space around his or her home location.

For mobility-based measurements (MBM) of exposure to green space given an activity-travel trajectory in the form of a series of visited locations $P(x_i, y_i, t_i)$, $i = 1, 2, 3\ldots$, the exposure is defined as an accumulation of a series of momentary exposure to green space at each location and weighted by the duration of exposure at that location:

$$E_{GS-MBL} = \sum WS_i WT_i, \tag{5}$$

where the momentary exposure to green space WS_i at the i-th location (x_i, y_i) is

$$WS_i = \frac{A(GS_p \cap Buf_{ri})}{A(Buf_{ri})}, \tag{6}$$

and the temporal weight WT_i at the i-th moment t_i within the duration

Table 2
The socio-demographic profiles and self-reported overall health status in SSP/TSW.

Variable		Sham Shui Po	Tin Shui Wai
Gender	Male	44 (42.3%)	48 (46.2%)
	Female	60 (57.7%)	56 (53.8%)
Age	18–24	16 (15.4%)	21 (20.2%)
	25–44	52 (50.0%)	51 (49.0%)
	45–64	36 (34.6%)	32 (30.8%)
Monthly household income[a]	Low	47 (45.2%)	27 (26.0%)
	Middle	32 (30.8%)	48 (46.2%)
	High	25 (24.0%)	29 (27.8%)
Education level[b]	Low	37 (35.6%)	36 (34.6%)
	Middle	55 (52.9%)	56 (53.8%)
	High	12 (11.5%)	12 (11.5%)
Marriage status[c]	Single	53 (51.0%)	58 (55.8%)
	Married	40 (38.5%)	35 (33.7%)
	Others	11 (10.6%)	11 (10.6%)
Overall health status	Excellent/very good/good	91 (87.5%)	93 (89.4%)
	Bad/very bad/terrible	13 (12.5%)	11 (10.6%)
Total		104 (100.0%)	104 (100.0%)

[a] Monthly household income: the low-income group has an income of less than 20,000 Hong Kong dollars (HKD), the middle-income group has an income of 20,000 ~ 39,999 HKD, and the high-income group has an income of 40,000 HKD or above.

[b] Education level: the low group graduated from middle school or lower, the middle group is with a bachelor's degree or certification, and the high group is with a master's degree or higher.

[c] Other marital statuses include those divorced and widowed.

Table 3
The determined threshold values [a] to delineate green space for each remote sensing data source and corresponding classification accuracy of green space [b].

	β_0	β_1	$NDVI_0$	Producer accuracy	User accuracy	Overall accuracy	KIA[c]
PlanetScope (3 m)	-68.952	165.627	0.416	93.3%	95.5%	93.2%	0.858
Sentinel-2 (10 m)	-50.619	142.517	0.355	94.3%	94.4%	93.1%	0.855
Landsat 8 (30 m)	-80.397	215.533	0.373	93.8%	93.5%	92.2%	0.835

[a] Sample size for training = 300.
[b] Sample size for validation = 1000.
[c] KIA: Kappa index of agreement.

(D) of the time series is

$$WT_i = \frac{t_{i+1} - t_i}{D}. \quad (7)$$

E_{GS-MBL} also ranges from 0 to 1. The larger the value, the more a participant gets exposed to green space along his or her activity-travel trajectory.

Here we argue that the health effects of green space on mobile people are not only from the closest *in-situ* green space but also from distant green space (e.g., seeing green space located outside one's normal walking distance). Thus, a buffer zone that includes all possible influential green space is necessary to calculate the momentary exposure to green space, especially for the fine-grain green space delineated from high spatial resolution remote sensing imagery. To be consistent with E_{GS-RSD}, Buf_{ri} is the buffer zone around the i-th visited location of the participant with a radius r, and r = 100 m, 300 m, and 500 m, respectively. On the other hand, a few time steps in the time series of visited locations may include scattered missing values. Technically, excluding a time step with a missing value results in a longer gap between its previous valid time step and its later valid time step, and a heavier weight (WT_i) of the previous adjacent visited location. This is used to mitigate the effects of invalid time steps with missing values. Both the RBM and MBM of the exposure to green space are calculated for each participant in both SSP and TSW, using a range of spatial resolutions and buffer zones, respectively. To promote computational efficiency, we developed a Python script using ArcGIS Pro to implement the proposed approaches. We implemented controls for 2 geographic contexts in Hong Kong (TSW/new town and SSP/old town), 2 measurement approaches (RBM and MBM), 3 buffer zone sizes (100 m, 300 m, and 500 m), and 3 spatial resolutions (3 m, 10 m, and 30 m). In total, 36 groups (combinations of different contextual settings) were established to systematically examine the effects of contextual settings on measuring people's exposure to green space.

5.3. Statistical analysis

Paired sample t-tests and Welch two-sample t-tests were employed to test the differences between the measured exposure to green space using different contextual settings. Meanwhile, the measured exposure to green space that contains contextual errors may lead to misleading results when analyzing the effects of green space on human health. To examine this problem, 36 binary logistic regression models were estimated to evaluate the overall health outcome using each measured exposure to green space as a predictor, respectively. Several socio-demographic variables are also incorporated into these models to control for the effects of possible confounders (Su et al., 2019; Dempsey et al., 2018), including age, gender, educational level, marital status, and socio-economic status. The effect size of each measured exposure to green space and the corresponding p-value are used to discuss the robustness of the measured exposure to green space across the gradients of contextual settings.

6. Results

6.1. The measured exposure to green space

Each of the contextual settings considered in this study has a different mechanism that leads to a possible bias in the measurements of people's exposure to green space. The first one is the delineation of green space using different data sources and spatial resolutions. Since the remote sensing process has been studied well and has been rigorously controlled, different multispectral sensors onboard various earth observation satellites may yield equivalent land surface reflectance and the NDVI after rigorous radiometric calibration and atmospheric correction (Moravec et al., 2021). However, the spatial resolution of the remote sensing imagery is one of the pre-determined sensor configurations that are not feasible for interconversion between different remote sensing platforms. Thus, the spatial resolution of remote sensing imagery may be a factor that affects the delineation of green space. Our approach has successfully delineated green space at different spatial resolutions with very high accuracy (Table 3), and Fig. 3 gives an example of the disparities in the delineation of green space. Coarser spatial resolution may lead to more mixed pixels, in which the spectral signature of the land surface is blurred (Jiang et al., 2006) and it has a higher risk of misclassification. The NDVI at the 30 m spatial resolution has many more mixed pixels and it loses multiple small essential green spaces that people may frequently use (Fig. 3). The NDVI at the 10 m spatial resolution enables the detection of green space with adequate location information but inaccurate boundary information. In contrast, the NDVI at the 3 m spatial resolution enables the reliable delineation of green space boundary. These disparities may induce influential errors when measuring people's exposure to green space.

The other influential factor is people's mobility when measuring their exposure to green space. Our approach has successfully derived participants' exposure to green space around both their home locations and the visited locations along their activity-travel trajectories at the 1-minute temporal resolution for 7 days. Our results indicate that people may have different levels of exposure to green space in different visited locations along their activity-travel trajectories (Fig. 4). In some cases, a person may live in a place with sparse green space but work in a place with rich green space. In other cases, a person may have sparse green space in both his home and workplace but may get exposed to dense green space through daily commuting. Moreover, participants' activity spaces are far beyond the often-used 500-m buffer zone around the home location, and RBM of people's exposure to green space or measurements using only home and the workplace unavoidably induce contextual errors in the quantitative analysis of the interaction between people's exposure to urban green space and associated health outcomes.

Buffer zone size is also an influential factor when measuring people's exposure to green space. Hong Kong is highly urbanized with fragmented green space and the exposure to green space may not be proportional to the area size of buffer zones. An example in Fig. 4 indicates that a larger buffer zone may enlarge the measured exposure to green space by containing more green space, especially in areas with sparse

Fig. 3. The delineation of green space at 3 m, 10 m, and 30 m spatial resolutions and *in-situ* references.

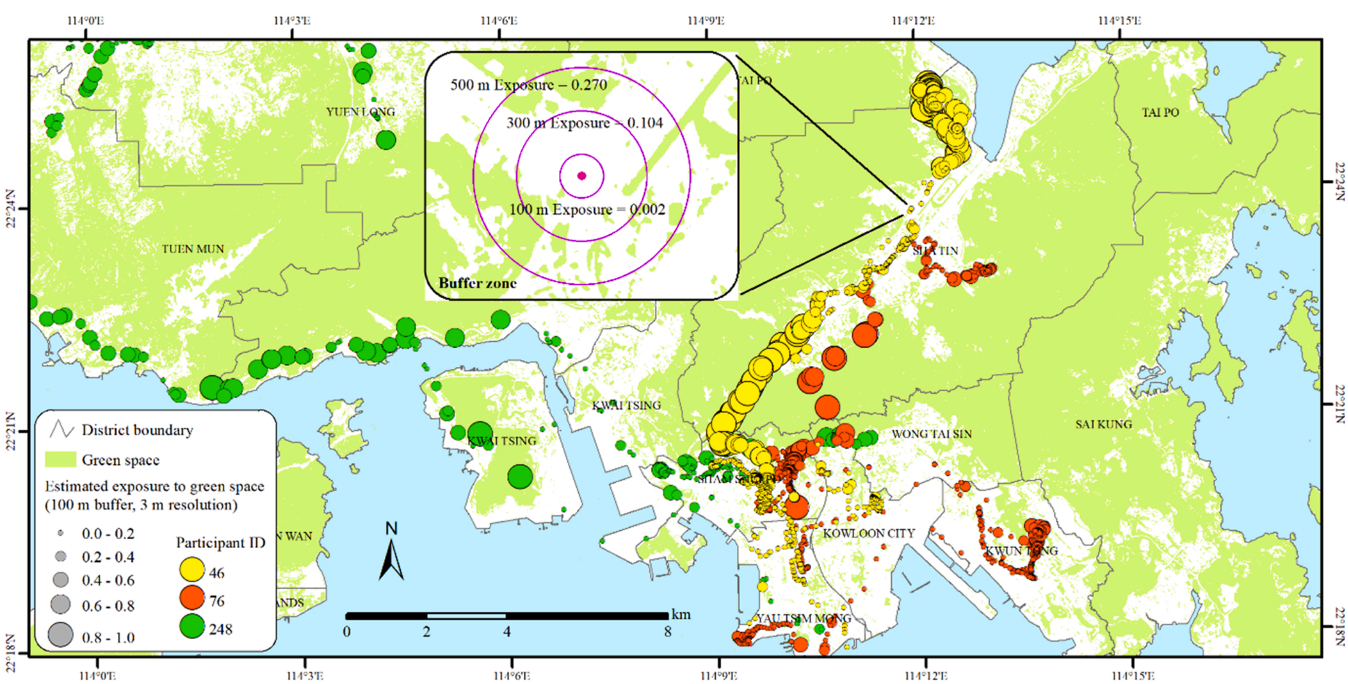

Fig. 4. The spatial variation of exposure to green space. Apparent spatial variation can be observed along a participant's activity-travel trajectory.

green space. Improper buffer zone may also induce contextual errors (e.g., buffer zones that are too large may include green space that a person is not exposed to).

6.2. The differences induced by contextual settings

Our observations of the participants' exposure to green space confirm the differences induced by contextual settings in different geographic contexts (Fig. 5 and Table 4). Participants in TSW are exposed to more green space than SSP, which agrees well with the geographic contexts of these two representative communities (Fig. 2). However, the differences are not significantly different from 0 at the 0.05 level when using a small buffer zone and using the 3 m and 30 m spatial resolutions.

The differences between MBM and RBM of exposure to green space all are significantly different from 0 at the 0.05 level, especially for smaller buffer zones. Our results show that MBM of exposure have higher values than RBM in all cases considered in this study. These results indicate that the measurements of people's exposure to green space may face significant underestimation while only considering people's residential neighborhoods and ignoring their exposure to green space through traveling (Fig. 5). The significant differences are observed for both an old town (SSP) and a new town (TSW) in Hong Kong.

The spatial resolution has inconsistent effects on measuring exposure

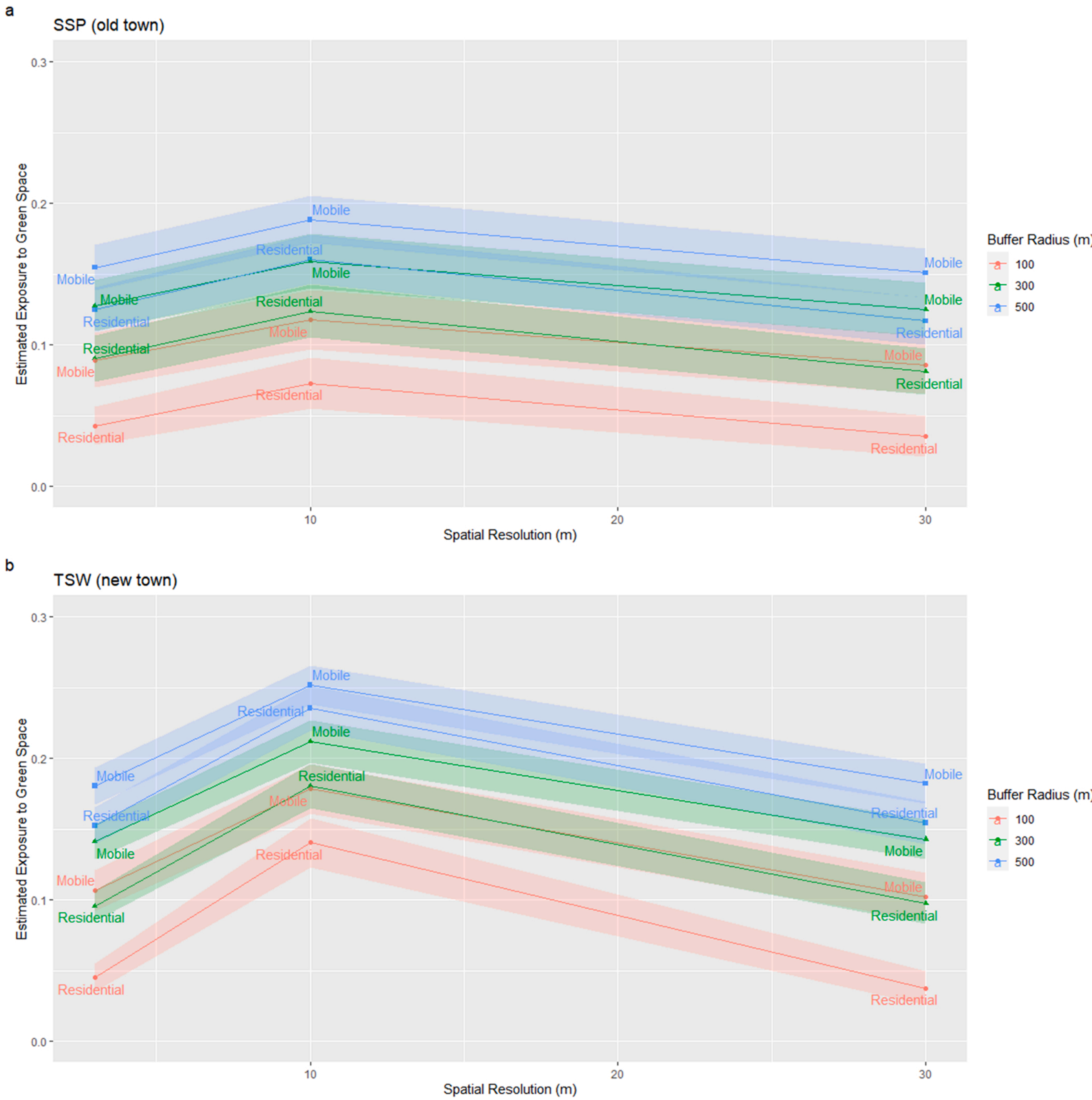

Fig. 5. The mean values of measured exposure to green space bounded with 95% confidence belts using the designated 36 groups of contextual settings: (a) in SSP, n = 104, and (b) in TSW, n = 104.

to green space. Compared to the finest spatial resolution (3 m), the moderate spatial resolution (10 m) tends to enlarge the measured exposure to green space because the misclassification on the edge of the green space may overestimate the extent of green space (Fig. 3). Compared to the moderate spatial resolution, the coarsest spatial resolution (30 m) tends to shrink the measured exposure to green space due to the misclassification and the loss of essential small green spaces that people may frequently visit (Fig. 3). Compared with the finest spatial resolution, the coarsest spatial resolution has an overestimating effect on the edge of the green space and an underestimating effect by losing small green spaces. The dual effects may yield similar values but the values from the coarsest spatial resolution cannot be called accurate since it contains multiple sources of biases.

A larger buffer zone tends to enlarge the measured exposure to green space. Hong Kong is a well-developed city with highly fragmented landscapes, which means the landscape changes rapidly across space. The closest exposure to green space can be captured using a small buffer zone like 100 m. In contrast, a large buffer zone, like 500 m, may include too much green space that a person does not get exposed to. Although all the differences are significantly different from 0 at the 0.05 level, our results also indicate that a larger buffer zone may mitigate the differences between RBM and MBM but enlarge the differences induced by spatial resolutions.

We also calculated the Pearson’s correlation coefficients between each pair of the exposure measurements and plotted the correlogram (Fig. 6). It is not surprising that the correlation coefficients quickly

Table 4
Paired sample t-tests and two-sample t-tests of measured exposure to green space with systematic controls of green space spatial resolutions, buffer zone sizes of proximity, measure approaches (RBM and MBM), and geographic contexts.

Section I: comparing green space spatial resolutions using paired sample t-tests

Geographic context	Measure approach	Buffer zone radius	Green space spatial resolution			
			10–3 m		30–10 m	
			t	*p*-value	t	*p*-value
SSP (old town)	RBM	100 m	8.865	< 0.001	-8.424	< 0.001
		300 m	17.725	< 0.001	-18.269	< 0.001
		500 m	28.259	< 0.001	-28.499	< 0.001
	MBM	100 m	13.538	< 0.001	-11.042	< 0.001
		300 m	22.126	< 0.001	-20.001	< 0.001
		500 m	31.977	< 0.001	-29.630	< 0.001
TSW (new town)	RBM	100 m	15.463	< 0.001	-17.151	< 0.001
		300 m	25.984	< 0.001	-29.583	< 0.001
		500 m	37.402	< 0.001	-45.031	< 0.001
	MBM	100 m	19.522	< 0.001	-20.887	< 0.001
		300 m	29.858	< 0.001	-31.844	< 0.001
		500 m	41.113	< 0.001	-45.148	< 0.001

Section II: comparing buffer zone sizes of proximity using paired sample t-tests

Geographic context	Measure approach	Spatial resolution	Buffer zone radius of proximity			
			300–100 m		500–300 m	
			t	*p*-value	t	*p*-value
SSP (old town)	RBM	3 m	7.981	< 0.001	7.318	< 0.001
		10 m	7.940	< 0.001	7.087	< 0.001
		30 m	6.664	< 0.001	7.921	< 0.001
	MBM	3 m	6.843	< 0.001	7.931	< 0.001
		10 m	6.904	< 0.001	8.011	< 0.001
		30 m	6.418	< 0.001	7.648	< 0.001
TSW (new town)	RBM	3 m	8.753	< 0.001	13.343	< 0.001
		10 m	5.745	< 0.001	11.728	< 0.001
		30 m	8.892	< 0.001	11.003	< 0.001
	MBM	3 m	6.720	< 0.001	11.526	< 0.001
		10 m	5.723	< 0.001	11.077	< 0.001
		30 m	6.327	< 0.001	10.583	< 0.001

Section III: comparing measurement approaches using paired sample t-tests and comparing geographic contexts using Welch two-sample t-tests

Spatial resolution	Buffer zone radius	MBM - RBM				TSW (new town) – SSP (old town)			
		SSP (old town)		TSW (new town)		RBM		MBM	
		t	*p*-value	t	*p*-value	t	*p*-value	t	*p*-value
3 m	100 m	5.537	< 0.001	8.450	< 0.001	0.299	0.765	1.414	0.159
	300 m	5.048	< 0.001	7.988	< 0.001	0.552	0.582	1.182	0.239
	500 m	4.419	< 0.001	4.634	< 0.001	2.626	0.009	2.466	0.015
10 m	100 m	5.224	< 0.001	4.663	< 0.001	5.350	< 0.001	4.340	< 0.001
	300 m	4.781	< 0.001	4.821	< 0.001	4.551	< 0.001	4.235	< 0.001
	500 m	4.244	< 0.001	2.462	0.015	6.344	< 0.001	5.774	< 0.001
30 m	100 m	5.576	< 0.001	9.091	< 0.001	0.220	0.827	1.183	0.238
	300 m	5.481	< 0.001	6.791	< 0.001	1.497	0.136	1.494	0.137
	500 m	4.642	< 0.001	4.197	< 0.001	3.279	0.001	2.773	0.006

decrease as the difference in the contextual settings increases. The changes range from 1.00 to 0.36 in SSP and from 0.99 to 0.20 in TSW. The correlograms confirm again that different contextual settings can lead to different measured exposure to green space and the measurements are less similar when there is more difference in the contextual settings.

6.3. The modeled health outcomes using measured exposure to green space

We employed a group of binary logistic regression models to assess the potential impacts of contextual settings on people's exposure to green space and self-reported overall health outcomes (Fig. 7). The results indicate the different effects of green space on human health in different geographic contexts. Similar to other studies, we found a possible promoting effect of exposure to green space on participants' self-reported overall health in TSW. However, none of these estimated effect sizes is significantly different from 0 at the 0.05 level. In contrast, we observed a possible adverse effect of exposure to green space in SSP, and most of the effect sizes are significantly different from 0. Note that our data are collected during the COVID-19 pandemic. Higher MBM of exposure to green space of the participants who live in the downtown area of Hong Kong may indicate more recreational visits to suburban green space, more contact with other visitors, and thus higher COVID-19 risks (Huang et al., 2020), which may explain the adverse effect of green space in SSP.

The most striking disparity is between MBM and RBM of exposure to green space. Multiple significant effect sizes are observed using MBM in SSP, while only these RBM using the smallest buffer zone can detect a significant effect size in SSP. The RBM of exposure and the measured exposure using a larger buffer zone may include too many contextual errors, and the erroneous measurements lead to a higher risk of Type II error that fails to reject the null hypothesis. The spatial resolution has less power to increase the risk of Type II error. Only coarse spatial

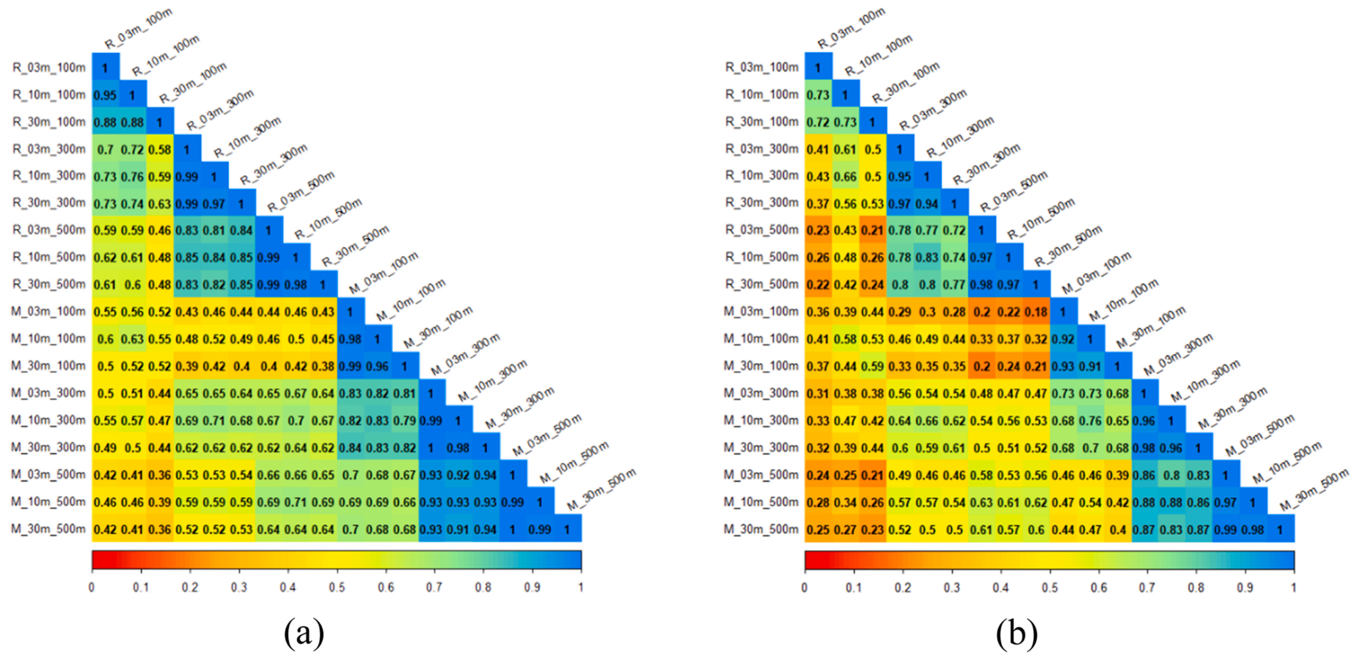

Fig. 6. The correlation coefficients between measured exposure to green space at 3 m, 10 m, and 30 m spatial resolutions and using 100 m, 300 m, and 500 m buffer zones in (a) SSP and (b) TSW. Each variable is named in the form of residence-based (R) / mobility-based (M) – spatial resolution – buffer zone radius. All correlation coefficients are significantly different from 0 at the 0.05 level.

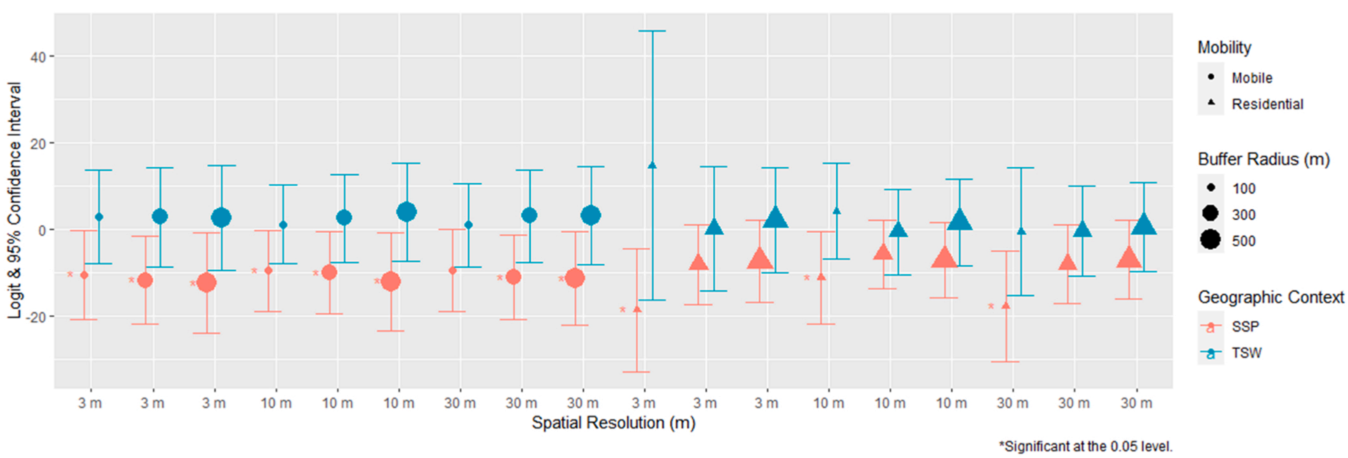

Fig. 7. The logit values bounded with 95% confidence intervals using the designated 36 groups of contextual settings and binary logistic regression. The estimated logit values were adjusted by age, gender, educational level, marriage status, and socio-economic status.

resolution, like 30 m, may lead to failure in the rejection of the null hypothesis while using the MBM in SSP.

7. Discussions

7.1. Methodological issues when measuring people's exposure to green space

The most striking disparity observed in this study is between MBM and RBM of exposure to green space. RBM only consider people's exposure to green space around their home locations (e.g., space within about 10 minutes of walking (Villeneuve et al., 2012)), and it may ignore a large amount of exposure to green space when people are moving around for daily activities. The contextual errors resulting from this mismatch can be influential especially when people's activity spaces are different from the determined buffer zone around their home locations, which manifests the UGCoP (Kwan, 2012). Using GPS-derived activity-travel trajectories and MBM of exposure to green space can effectively mitigate the UGCoP. Our results show that significant differences are observed between RBM and MBM. These differences can be considered the contextual errors mitigated by MBM and our results also indicate that these contextual errors may lead to erroneous results when using the RBM of exposure to green space to model people's health outcomes.

The other methodological issue revealed in our study is the different health effects of green space on urban residents in different communities, which manifests spatial non-stationarity (the effect of an environmental factor on human health varies over space) (Kwan, 2021). We have observed a significant adverse effect of green space in SSP and an insignificant promoting effect of green space in TSW, which indicates that green space may play different roles in different geographic contexts. Correspondingly, the measured exposure to green space may also be sensitive to geographic contexts: various contextual settings in TSW make no difference to the results, but the differences between MBM and RBM of exposure to green space may lead to erroneous results in SSP.

7.2. The implications of this study

In our systematic analysis, we have confirmed the uncertainty induced by the contextual settings when measuring people's exposure to green space, like between RBM and MBM, among different spatial resolutions, and among different buffer zones. The uncertainty induced by contextual settings does have an impact on the modeling of health outcomes and may increase the risk of Type II errors. As a result of this study, we suggest measuring people's exposure to green space using a mobility-based approach, a smaller buffer zone, and a finer spatial resolution. Due to spatial non-stationarity, systematic evaluations and tests may be necessary for other places.

Our empirical study can provide critical suggestions in the green space exposure measurements for a broad scope of studies that may consider green space as an essential environmental factor of human health. Our results also indicate that previously observed health effects of green space (especially those based on RBM) may risk improper contextual settings and context errors and they may need to be re-examined.

7.3. The limitations of this study

Our study also faces some limitations. First, this study is cross-sectional and thus cannot examine the temporality of the contextual uncertainty and temporal non-stationarity. Second, due to the difficulties in the data collection, we only have a relatively small sample size. Although we detected multiple significant differences using this small sample, a large sample from future longitudinal data collection may further strengthen and extend our understanding of the uncertainty induced by contextual settings when measuring people's exposure to green space.

8. Conclusions

In this study, we have discussed the uncertainty induced by contextual settings when measuring people's exposure to green space using the integrated 3S approach. The measurements of green space exposure are compared between residence-based and mobility-based approaches, using a range of spatial resolutions and buffer zones in different geographic contexts. The uncertainty induced by contextual settings is discussed for all participants and in the modeling of their overall health outcomes. We have observed multiple significant differences between different contextual settings. Mobility-based measurements of exposure to green space are significantly higher than residence-based measurements. A larger buffer zone tends to overestimate green space exposure and the spatial resolution has inconsistent effects on the measured exposure to green space. Improper contextual settings may lead to erroneous results in modeling people's health outcomes. These disparities are typical manifestations of the UGCoP and spatial non-stationarity. Consequentially, we suggest measuring people's exposure to green space using mobility-based approaches, a finer spatial resolution, and a smaller buffer zone. We also suggest a systematic analysis of the uncertainty induced by contextual settings when measuring people's exposure to green space in other places before discussing the health effects of green space.

Ethics approval

The study was approved by the Survey and Behavioral Research Ethics (SBRE) Committee of the Chinese University of Hong Kong (Protocol 14605920 approved on 8 January 2020).

Consent to participate

Informed consent was obtained from all subjects involved in the study.

Consent to publish

Not applicable to this study.

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CRediT authorship contribution statement

Yang Liu: Conceptualization, Methodology, Formal analysis, Validation, Writing – original draft, Writing – review & editing. **Mei-Po Kwan**: Supervision, Funding acquisition, Conceptualization, Methodology, Resources, Writing – original draft, Writing – review & editing. **Changda Yu**: Validation, Writing – review & editing. All authors have read and agreed to the final version of the paper.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data Availability

The datasets used in this study are available from the corresponding author on reasonable request.

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