Landscape and Urban Planning 258 (2025) 105336

Contents lists available at ScienceDirect

Landscape and Urban Planning

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

Research Paper

Effects of green space exposure on acute respiratory illness in community-dwelling older people: A prospective cohort study

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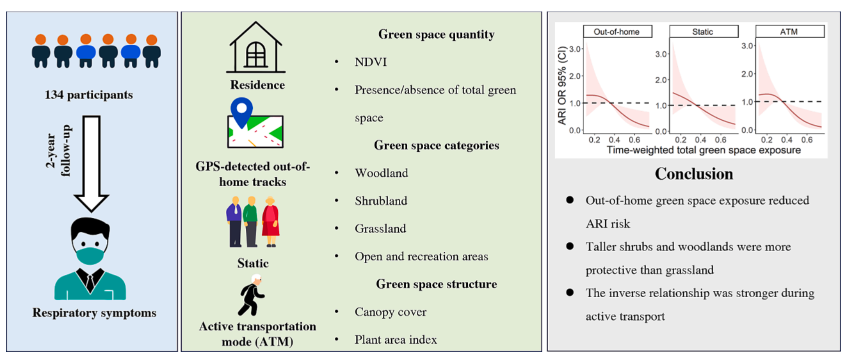
HIGHLIGHTS

- Increased out-of-home green space exposure was significantly associated with the reduced risk of acute respiratory illness (ARI) in a prospective cohort of community-dwelling older adults in Hong Kong.
- The association of green space with ARI was more evident for taller shrubs and woodlands than for grassland.
- The inverse relationship between green space exposure and ARI incidence was more pronounced in active transportation mode.

GRAPHICAL ABSTRACT



ARTICLE INFO

Keywords:
Green space
Respiratory Tract Diseases
Global Positioning System tracker
Longitudinal study

ABSTRACT

Background: Few studies have investigated the effects of green space exposure during individuals' daily activities on respiratory health. This study aims to evaluate how exposure to green space both within residential vicinities and during out-of-home activities influences the incidence of acute respiratory illness (ARI) among older adults.
Methods: Participants were recruited from a prospective cohort of community-dwelling older people in Hong Kong, who were followed for two years to monitor the occurrence of ARI. Using GPS watches, we tracked participants' movements for seven consecutive days to gather data on their daily paths. The time-weighted spatial averaging method (TWAM) was used to calculate daily exposure to green space, incorporating metrics such as the presence or absence of total green space and its subtypes, the normalized difference vegetation index (NDVI), canopy cover, and plant area index (PAI). Generalized linear mixed-effects models analyzed the association between these exposures and ARI incidence across warm and cool seasons, with restricted cubic spline models examining dose–response relationships.

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https://doi.org/10.1016/j.landurbplan.2025.105336
Received 6 August 2024; Received in revised form 9 January 2025; Accepted 23 February 2025
Available online 5 March 2025

Results: Among the 134 participants (average age 76.2 years, 82.8 % female), after adjusting confounders, significant protective effects against ARI were observed with increased exposure to canopy cover (odds ratio 0.36, 95 % confidence interval 0.14, 0.88) and PAI (odds ratio 0.38, 95 % confidence interval 0.17, 0.84) outside the home. In warm or cool seasons, total green space and its subcategories also had an inverse relationship with ARI, except for grassland. No significant relationships were observed with NDVI. The protective relationship between green space exposure and ARI incidence demonstrated a dose–response pattern, more pronounced in active mode. No residential green space exposures were significantly associated with ARI risk.

Conclusions: Increased green space exposure outside the home is associated with a reduced risk of ARI among older adults living in urban areas. These findings highlight the potential health benefits of engaging in outdoor activities within green environments for respiratory health.

1. Introduction

Previous research has established a positive association between exposure to green spaces near residences and improved respiratory health outcomes. A systematic review that included 108 studies on the relationship between green space and respiratory health found that a majority of studies reported a protective effect of green space, primarily focusing on allergic respiratory conditions such as asthma and rhinitis (Mueller et al., 2022). More recent studies have suggested that increased access to green spaces may also reduce the incidence and mortality rates associated with COVID-19-like illnesses (Chen et al., 2023; Russette et al., 2021). However, these studies typically assessed environmental exposures within varying distances from individuals' homes, ranging from 50 m to 5 km, which introduced uncertainties in geographic context and might have led to biased results (Kwan et al., 2019; Zhang and Tan, 2019). There is a need for studies that utilize more precise measurements of green space exposure to better understand its association with respiratory diseases. Moreover, few research has investigated the health impacts of out-of-home exposure to green spaces, as individuals navigate their daily activities.

Recent studies have shown that urban green spaces improve health by offering opportunities for stress reduction, physical activity, and social interactions (Jennings and Bamkole, 2019; Richardson et al., 2013; Ward Thompson et al., 2016). Active transportation modes, such as walking, jogging, and cycling, not only promote physical health and well-being but also affect how individuals engage with their environment. The locations that people frequently visit are closely linked to their social connections. Given that daily mobility determines when, where, and how individuals access and experience different environments, it is crucial to examine green space exposure across various transportation modes (both active and static) to capture its diverse health impacts. While several studies have explored the health benefits of dynamic interactions with green spaces (such as improvements in mental health and metabolic indicators) using GPS data, they have often overlooked the mode of transportation (Lan et al., 2022; Letellier et al., 2024). Recognizing that green spaces can significantly enhance public health by encouraging physical activity, it is important to consider how different mode of transportation—whether stationary, walking, running, or cycling—could have distinct health implications (Roberts and Helbich, 2021). The variation in green space exposure based on transportation mode and its health impact is an area that warrants further investigation.

Many early studies used simplistic indicators to quantify green spaces, such as NDVI, green space coverage, and accessibility, measuring different aspects like vigor, amount and distance. This approach may have led to inconsistent conclusions across research. Different types and qualities of green spaces can support various activities, provide different ecosystem services, and result in diverse health effects in multiple contexts (Wheeler et al., 2015). For example, Yu *et al.* found that the type of vegetation plays a significant role in the association between greenness exposure and asthma (Yu et al., 2021). Specifically, exposure to trees may reduce the likelihood of asthma, while exposure to grass may increase it. The quality of green space, especially its functionality within natural ecosystems, is also crucial when conducting researches related to health outcomes. Essential structural characteristics of urban vegetation, such as vegetation canopy cover and leaf area index (LAI), significantly impact on ecosystem services like air pollution removal, shade provision, and rainfall interception (Jennings et al., 2019). The vegetation canopy cover indicates the extent of the forest floor shaded or covered by tree crowns, while LAI, defined as the total one-sided leaf area per unit ground area, emphasizes photosynthetic tissue rather than just crown projection. Both metrics are vital for ecological processes like photosynthesis, transpiration, and carbon cycling. (Li et al., 2022). A similar indicator, plant area index (PAI), which considers all plant materials rather than just leaves, has rarely been utilized in previous epidemiological studies. Despite their importance, many studies overlook these structural features of green spaces. There is a need to use multiple indicators of green space and investigate how different types and qualities relate to health outcomes.

In a previous prospective cohort study, we focused on community-dwelling older adults aged 65 and above in Hong Kong to explore how indoor environmental conditions (such as temperature and humidity) influence the occurrence of acute respiratory infections (ARIs) (Han et al., 2020). Our findings indicated a negative correlation between indoor absolute humidity and the risk of developing ARIs. However, the effects of environmental factors outside the home, such as green space on ARI risk remained uncertain. To address this gap, we initiated a sub-cohort study, wherein participants were asked to wear Global Positioning System (GPS) trackers. These devices were used to continuously monitor each participant's outdoor movements over seven consecutive days during both warm and cool seasons. The primary goal of this study was to assess how exposure to green space, both residential and out-of-home, affects the incidence rates of ARIs.

2. Materials and methods

2.1. Participant recruitment and data collection

The participants were a sub-cohort from a prospective cohort of community-dwelling adults aged 65 and above in Hong Kong (Han et al., 2020), who were initially recruited between December 2016 and May 2017 for a study on indoor environments and the risk of ARI, with follow-up continuing until May 2019. All participant's baseline data, including sociodemographic, lifestyle, frailty, medical conditions, history of pneumococcal and influenza vaccinations, and household characteristics, were collected at recruitment. In June 2018, we invited all participants to join this sub-cohort study, and a supermarket gift voucher of HK$50 (~US$6.4) was given as a token of appreciation. After obtaining written consent, participants were asked to wear a Qstarz BT-Q1000X GPS logger on their dominant wrist to log their location data at a one-minute epoch. The GPS data collection lasted for seven consecutive days during the warm (May–October 2018) and cool (November 2018–April 2019) seasons, respectively. The GPS loggers, previously validated for accuracy and reliability, were calibrated by the manufacturer before distribution (Kerr et al., 2011). Research assistants gave detailed instructions and a leaflet on how to use the GPS loggers, with data logging starting at midnight of the following day. Participants documented their outdoor activities in a daily journal and were reminded by SMS to charge the loggers every day to ensure uninterrupted data collection.

2.2. Green space indicators

Hong Kong's sub-tropical climate predominantly supports evergreen vegetation. Research shows that most woody vegetation in Hong Kong is generally evergreen, with minimal seasonal variation (Morgan and Guénard, 2019). We considered green space exposures including the normalized difference vegetation index (NDVI), total green space presence/absence, and the subcategories, canopy cover, and PAI in this study. The NDVI ranges from −1 to 1, with higher values indicating a higher density and vigor of vegetation coverage. We extracted NDVI values from Satellite Pour l'Observation de la Terre (SPOT) 6 images taken on February 29, 2016, with a spatial resolution of 6*6 m. The image underwent atmospheric correction, and one with minimal cloud cover during the winter of 2016 was selected for analysis. The methodology for this product was detailed in our previous study (Yang et al., 2020). Similar to previous studies, we masked the area with negative NDVI values to avoid the influence of these values when aggregating mean indices in each area (Markevych et al., 2017). The study also included the presence/absence of total green space extracted from the land cover and land use database in Hong Kong. We used the 2018 Land Utilization product for Hong Kong and defined 'total green space' as areas with vegetation and open recreational spaces. Analyses were conducted independently for the presence and absence of specific types of green space, such as open recreational areas, grasslands, woodlands, and shrublands. Using the 1-km resolution Gridded GEDI Vegetation Structure Metrics database, we extracted mean PAI and canopy cover as indices of vegetation structure characteristics from 2019 to 04-17 to 2023–03-17 (Burns et al., 2024). Canopy cover is defined as the percentage of the ground covered by the vertical projection of canopy material, while PAI, which takes into account all above-ground plant components including branches and trunks, is defined as one side of the total plant area per unit of ground surface.

2.3. Outcome measurement

During the follow-up period of January 2017 to May 2019, participants were requested to report acute respiratory symptoms within two days of symptom onset via an online reporting platform. Research assistants also made monthly phone calls to each participant to increase the reporting rate. Similar to previous studies, ARI incidence was defined as the presence of at least two of the following symptoms: fever, cough, headache, sore throat, and myalgia (Han et al., 2020; Monto et al., 2002). If symptom onset occurred within one week of overseas travel or two weeks of the prior ARI episode in the same participant, these cases were not considered as new ARI incidences in this study.

2.4. Data analysis

2.4.1. GPS data cleaning

Similar to previous studies (Gong et al., 2014; Stopher et al., 2008; Stopher et al., 2005), we excluded the GPS data that: 1) were collected from three satellites or less, 2) had a horizontal dilution of the precision (HDOP) value of five or greater, or 3) had a moving speed > 250 km/h. Missing GPS data were imputed using the mean center of GPS points collected before and after the lapses. The cleaned GPS data, collected at least five hours each day (3 AM to 3 AM) for at least three days, were included for further analysis. The selected time window between 3 AM to 3 AM the following day helped to exclude GPS points recorded while participants were likely in bed. Similar to Carlson *et al.*, the criteria for valid days focused on obtaining a significant number of participants and observing their out-of-home activities, rather than estimating long-term routine activities with a steady estimate (Carlson et al., 2015a).

Residential green space exposure was estimated using a 50-meter buffer zone centered at each participant's home address. We chose 50 m to define home areas for this study due to the small residential spaces in Hong Kong, where the average area is approximately 16 m^2 per person, and most households typically do not exceed 100 m^2. Similar to a previous study (Schneider et al., 2013), the whole week's GPS data were subsequently divided into daily segments starting at 3 AM. The time of GPS data located outside individuals' residential areas was defined as an out-of-home period.

2.4.2. Out-of-home green space exposures

Out-of-home green space exposures were estimated based on individuals' mobility modes, which were classified into static, active transportation (ATM), and passive transportation modes (PTM), according to individuals' moving speed estimated from the GPS data (Fillekes et al., 2019). The GPS points were first divided into static and move segments using the algorithm developed by Montoliu et al (Montoliu et al., 2013). The move segment was then further split into ATM and PTM according to speed. Specifically, static mode referred to maintaining zero speed for at least five consecutive minutes, PTM was defined as a moving segment with a 90th percentile speed ≥ 25 km/h, while the remaining were classified as ATM (Carlson et al., 2015b; Fillekes et al., 2019; Vanwolleghem et al., 2016). Since PTM typically occurs in public transportation, such as buses or underground trains, which is not the primary mode of exposure to environmental factors being investigated in this study, we excluded PTM data from subsequent data analyses.

We used the time-weighted spatial averaging method (TWAM) (Jankowska et al., 2023) to calculate out-of-home green space exposure, with an example shown in **Supplementary** Fig. 1. Briefly, individuals' time-weighted green space exposure was constructed from their out-of-home GPS data using the density ranking (DR) method (Chen, 2017; Chen and Dobra, 2020). The green space data layers were transformed into a raster grid surface with a resolution of 10 m and multiplied by the DR raster, which adopted a 200-meter bandwidth and a quartic kernel function (**Supplementary** Fig. 1**D**). Fifty-meter buffers were generated centered at each out-of-home GPS point in static mode and ATM (**Supplementary** Fig. 1**C**). These buffers were utilized by zonal statistical analysis to calculate the mean green space exposures (**Supplementary** Fig. 1**E–L**) across the participants' entire activity spaces. The residential exposure within the 50-meter buffer was also calculated (**Supplementary** Fig. 1**B**).

2.5. Statistical analysis

Baseline characteristics of participants were summarized using median and interquartile range (IQR) for non-normally distributed continuous variables, and frequencies (percentages) for categorical variables. The Mann-Whitney test for continuous variables and the Chi-square test for categorical variables were used to test the differences between the participants with and without ARI incidence during the follow-up period. Fisher's exact test was used when the expected frequencies in any contingency table cell were less than five (Kim, 2017).

We employed the generalized linear mixed-effects models (GLMMs) with a logit link function to estimate the association between different green space exposures and the incidence of ARI. To account for repeated measurements, as some participants attended the study during both warm and cool seasons, an individual random effect term was included in the models. To facilitate comparison between the exposure distributions in residential and out-of-home environments, we normalized all green space exposure metrics using min–max scaling. Spearman's rank correlation coefficients and variance inflation factors (VIF) were calculated to assess the multicollinearity between green space exposures. A VIF lower than 4 was considered to indicate the absence of multicollinearity for the included variables. The following baseline sociodemographic and lifestyle variables were adjusted for in the models: age, sex, body mass index (BMI), education levels (primary school or none, high school, and tertiary education), monthly family income (less than HK$5000, 5000–14999, over than 15000), family members (1, 2, ≥3), diagnosed medical conditions (≥1), smoking history (yes and no), and influenza vaccination at baseline and during the follow-up period. We also considered each participant's frailty status, classified into robust (0 points), pre-frail (1–2 points), or frail (3–5 points) groups, based on their fried frailty index (FFI) collected at baseline (Fried et al., 2001) (Logan et al., 2013). Additionally, population density in 2018 was incorporated as a covariate, with data obtained at a resolution of 1 km from WorldPop (https://hub.worldpop.org/). Our previous study indicated that indoor absolute humidity has an impact on ARI, which we also included as a covariate. Detailed measurement of absolute humidity can be found in our earlier work (Han et al., 2020).

The association between ARI incidence and residential/out-of-home green space exposure was analyzed using different multivariate regression models. Model 1 included only the variable of green space exposure and season. Model 2 was additionally adjusted for covariates including family members, monthly family income, age, gender, and educational levels, the history of smoking, vaccination history, diagnosed medical conditions, population density, and frailty. Model 3 was further adjusted for indoor absolute humidity (Han et al., 2020). The marginal R-squared or McFadden's R-squared was computed for all models to select the final model for further analysis (Nakagawa and Schielzeth, 2013). Dose-response relationships were also investigated by adding the restricted cubic spline functions into the regression models, with three knots set at the 10th, 50th, and 90th percentiles.

Stratified analysis was conducted in warm and cool seasons to explore any seasonal variations in the effect estimates. Sensitivity analyses were conducted by 1) adopting 100-meter, 500-meter, and 1000-meter buffers for both residential and out-of-home green space exposure, 2) resampling the NDVI, green space presence/absent, and subcategories into 1 km resolution, and 3) excluding participants who experienced an ARI episode within 7 days before or after the GPS data collection period, as these participants might have changed their daily activity patterns due to illness. The acquisition and extraction of environmental exposures were conducted within the ArcGIS Pro Version 3.2 (Esri Inc., Redlands, CA), and Python 3.9. The DR calculation and subsequent data analyses were performed using RStudio Version 4.2.2.

2.6. Ethical consideration

Written consent forms were obtained from all participants at recruitment. Ethics approval was obtained from the Institutional Review Board of Hong Kong Polytechnic University.

3. Results

Invitations were sent to 397 participants in the initial cohort, with 197 agreeing to participate in this sub-cohort study, resulting in a response rate of 49.6 %. During the follow-up period, 175 participants provided mobility data via GPS loggers from May 2018 to October 2018 (warm season), while 187 participants did so from November 2018 to April 2019 (cool season). After data cleaning, the data analysis included GPS data from 134 participants, including 67 from the warm season and 107 from the cool season, with a total of 265,785 GPS points (Fig. 1). Among the participants, 40 (29.9 %) contributed data during both seasons. The characteristics of participants included in the study were generally similar to those who were excluded (Supplementary **Table 1**).

The median age of participants was 76.2 years, with 82.8 % being female (Table 1). A total of 74.6 % were classified as frail or pre-frail, 73.1 % had at least one medical condition, and 79.1 % reported having received influenza vaccine at baseline or during follow-up. Participants spent a median of 19.5 h at home daily (interquartile range 18–21 h) and 5.9 h outside (interquartile range 5.1–7.5 h), with 2.3 h classified as the ATM mode. There were 20 and 36 ARI incidents in warm and cool seasons, respectively. Baseline characteristics were similar between ARI and non-ARI cases. Participants with ARI were less likely to live alone and less likely to engage in the ATM mode outdoors during the cool season compared to those without ARI.

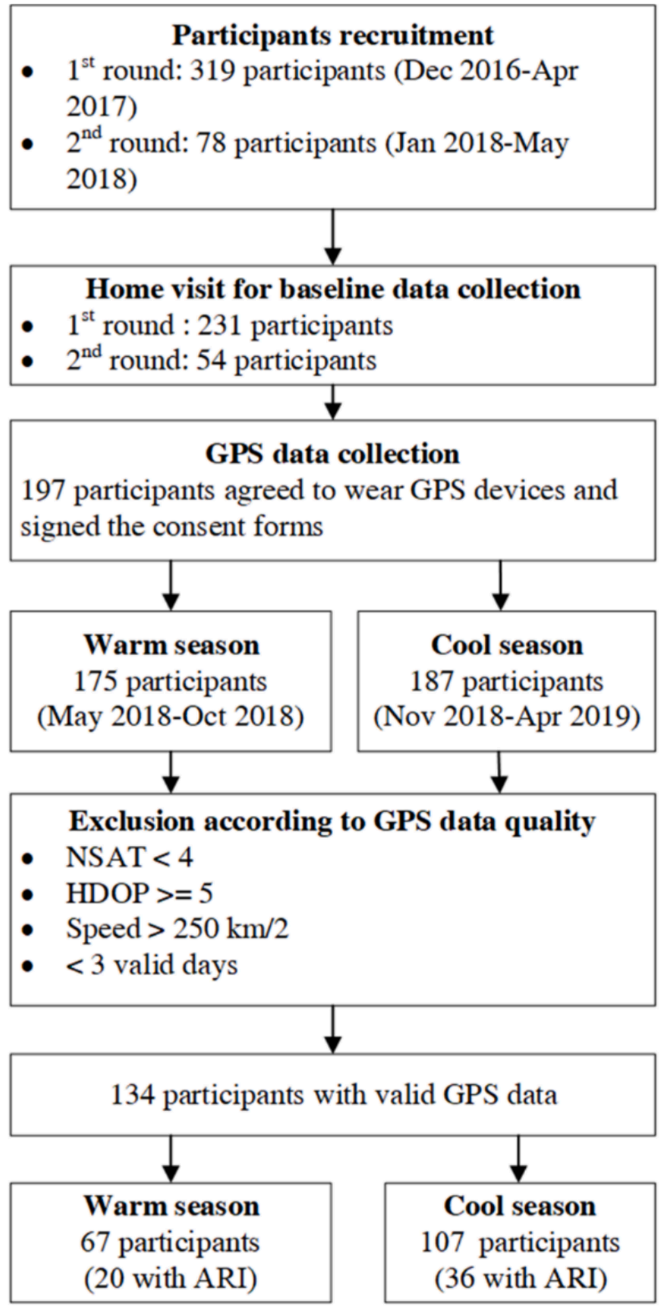

Fig. 1. Flowchart of participants inclusion according to GPS data collection. Abbreviations: GPS: Global positioning system; HDOP: Horizontal Dilution of Precision; NSAT: Number of Satellites Used/View.

The exposure to green space was similar across warm and cool seasons (Fig. 2). Residential green space exposure was significantly more varied than to out-of-home exposure. The distributions of green space exposures in static mode were significantly more dispersed than in ATM mode. High correlations were found among out-of-home green space variables (**Supplementary** Fig. 2). No significant multicollinearity was detected in any of the models, with VIFs ranging from 1.07 to 1.49. Model 3 obtained a higher R^2 value than the other models

Table 1
Descriptive characteristics of participants.

	All seasons (n = 134)	Warm season (n = 67)			Cool season (n = 107)		
Variables [a]		ARI (n = 20)	Non-ARI (n = 47)	P value [b]	ARI (n = 36)	Non-ARI (n = 71)	P value
Age, median (IQR)	76.2 (71.7, 82.1)	75.4 (71.8, 83.7)	78.5 (72.0, 83.4)	0.584	74.2 (70.6, 80.7)	78.2 (72.2, 83.0)	0.084
Gender (F), n (%)	111 (82.8 %)	15 (75.0 %)	36 (76.6 %)	0.998	29 (80.6 %)	60 (84.5 %)	0.596
BMI (kg/m^2)	23.5 (21.8, 26.0)	23.8 (22.1, 26.4)	23.6 (21.5, 26.1)	0.676	22.6 (21.8, 25.5)	23.6 (21.5, 26.0)	0.491
PASE score	78.0 (59.8, 109.6)	72.4 (50.0, 103.0)	90.0 (52.6, 121.3)	0.307	76.4 (59.8, 89.2)	85.7 (62.4, 127.9)	0.061
Absolute humidity, g/m^3	23.8 (23.1, 24.6)	23.5 (22.9, 24.3)	24.0 (23.3, 24.7)	0.138	23.6 (22.5, 24.5)	24.1 (23.2, 24.7)	0.200
Population density (people/km^2)	6375.6 (4695.9, 8096.5)	6605.9 (5397.4, 9370.1)	6847.8 (5693.7, 8932.6)	0.620	6029.3 (4684.6, 10424.6)	5801.4 (4290.0, 7367.1)	0.155
Education				0.450			0.092
Primary School	78 (58.2 %)	10 (50.0 %)	30 (63.8 %)		17 (47.2 %)	45 (63.4 %)	
High School	42 (31.3 %)	8 (40.0 %)	12 (25.5 %)		16 (44.4 %)	17 (23.9 %)	
Tertiary Education	14 (10.4 %)	2 (10.0 %)	5 (10.6 %)		3 (8.3 %)	9 (12.7 %)	
Family Income ($HKD per month)				0.796			0.682
Low (<5000)	79 (59.0 %)	11 (55.0 %)	29 (61.7 %)		20 (55.6 %)	44 (62.0 %)	
Medium (5000–14999)	38 (28.4 %)	6 (30.0 %)	13 (27.7 %)		11 (30.6 %)	21 (29.6 %)	
High (>15000)	17 (12.7 %)	3 (15.0 %)	5 (10.6 %)		5 (13.9 %)	6 (8.5 %)	
Family members				0.940			0.290
1	52 (38.8 %)	9 (45.0 %)	18 (38.3 %)		15 (41.7 %)	26 (36.6 %)	
2	56 (41.8 %)	7 (35.0 %)	19 (40.4 %)		12 (33.3 %)	34 (47.9 %)	
>= 3	26 (19.4 %)	4 (20.0 %)	10 (21.3 %)		9 (25.0 %)	11 (15.5 %)	
Pre-/frailty (Y)	100 (74.6 %)	17 (85 %)	33 (70.2 %)	0.238	28 (77.8 %)	51 (71.8 %)	0.643
Medical condition (at least one)	98 (73.1 %)	15 (75 %)	32 (68.1 %)	0.772	29 (80.6 %)	54 (76.1 %)	0.807
Smoking history (Y)	10 (7.5 %)	1 (5.0 %)	5 (10.6 %)	0.660	3 (8.3 %)	7 (9.9 %)	0.998
Influenza vaccination (Y) [c]	106 (79.1 %)	17 (85 %)	37 (78.7 %)	0.740	27 (75 %)	56 (78.9 %)	0.634
Daily average time spent (hours)							
Home	19.5 (18.0, 21.0)	20.5 (18.1, 21.2)	19.5 (18.5, 21.0)	0.466	19.8 (18.0, 22.0)	19.5 (18.0, 21.0)	0.237
Out-of-home	5.9 (5.1, 7.5)	5.7 (4.4, 7.1)	6.0 (4.9, 8.1)	0.317	5.7 (4.9, 7.2)	6.5 (5.4, 7.8)	0.090
Static	3.6 (2.7, 5.0)	3.4 (2.8, 4.7)	3.6 (2.6, 5.3)	0.760	3.4 (2.6, 4.8)	3.8 (2.8, 5.1)	0.375
ATM	2.3 (1.6, 2.9)	1.9 (1.1, 2.5)	2.4 (1.6, 2.9)	0.069	2.2 (1.4, 3.0)	**2.6 (2.1, 3.1)**	**0.048**
PTM	0.0 (0.0, 0.1)	0.0 (0.0, 0.0)	0.0 (0.0, 0.1)	0.291	0.0 (0.0, 0.1)	0.0 (0.0, 0.1)	0.753

Abbreviations: ARI, acute respiratory illness; ATM: active transportation mode; BMI, body mass index; IQR, interquartile range; PASE: Physical Activity Scale for the Elderly; PTM: passive transportation mode.

[a] Data were demonstrated as median (IQR) or n (%).

[b] Denotes statistically significant (P < 0.05) difference between ARI cases and non-cases in Mann–Whitney *U* test, Chi-square tests, or Fisher's exact test.

[c] The study participants received at least one influenza vaccine between 2014 and 2019.

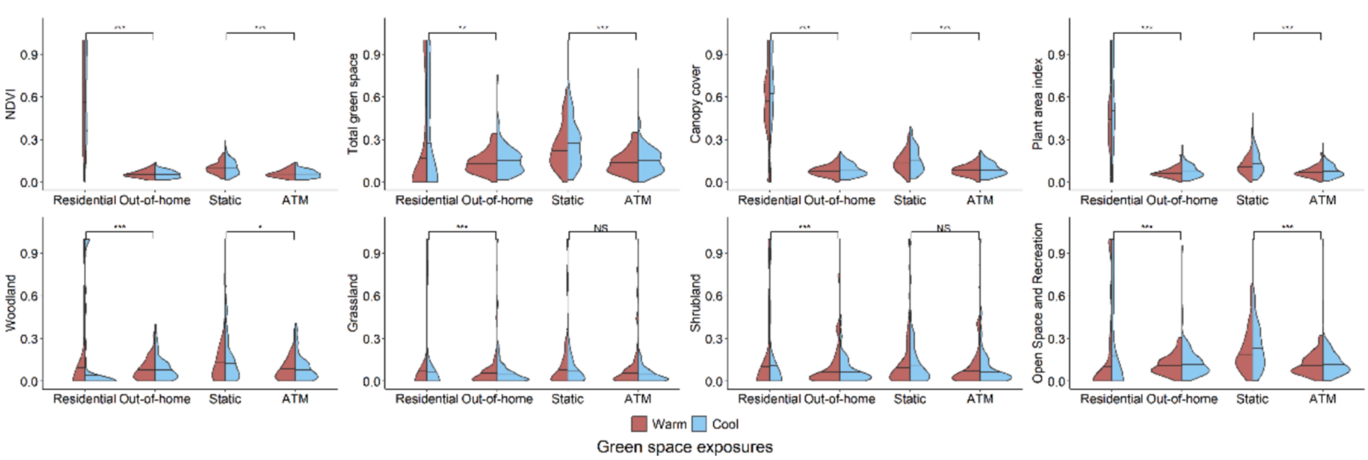

Fig. 2. Distribution of green space indicators by mobility modes in the warm season and cool season. Abbreviations: ATM: active transportation mode. NS: not significant. The green space exposures were normalized to 0–1. The Mann–Whitney *U* test was used to examine the difference in environmental exposures between residential areas and out-of-home areas, static mode, and ATM mode respectively. *: P < 0.05; **: P < 0.01; ***: P < 0.001.

(Supplementary **Table 2**), and the results from this model are presented hereafter (Fig. 3).

A lower risk of ARI was associated with per 0.1 unit increase in out-of-home canopy cover (odds ratio (OR) 0.36, 95 %CI: 0.14, 0.88) and PAI (OR 0.38, 95 %CI: 0.17, 0.84). In the warm season, significant inverse associations were also found for total green space (OR 0.53, 95 % CI: 0.31, 0.80), shrubland (OR 0.61, 95 %CI: 0.39, 0.89), and open space and recreation (OR 0.55, 95 %CI: 0.33, 0.85). No significant associations were found between residential green space indicators and ARI (Table 2). In the stratification analysis by transportation mode,

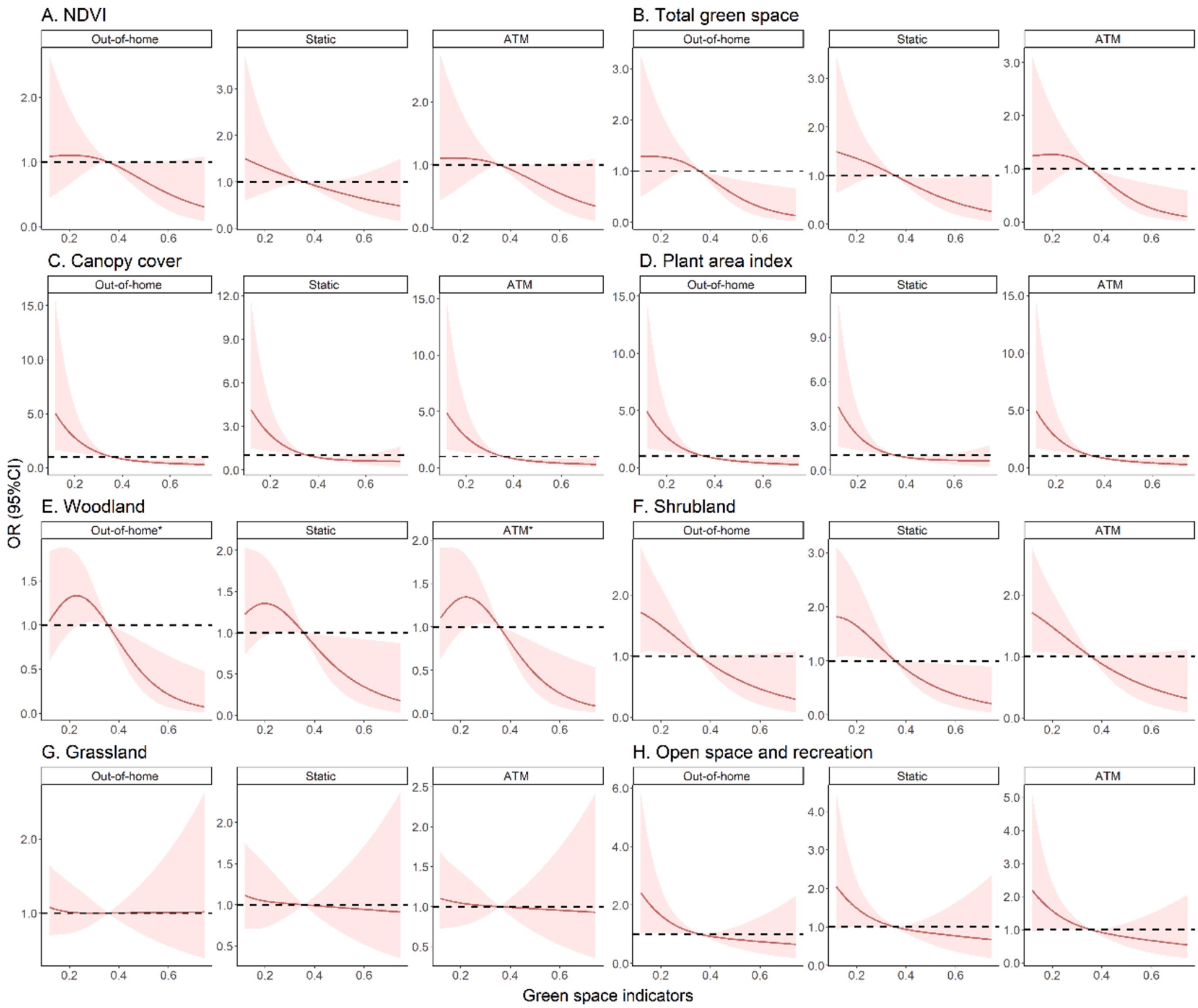

Fig. 3. The estimated dose–response relationship and non-linear trend between out-of-home green spaces indicators and the risk of ARI by different mobility modes using restricted cubic splines. Abbreviations: ARI: acute respiratory illness; ATM: active transportation mode; BMI: body mass index; CI: Confidence Interval; NDVI: Normalized Difference Vegetation Index; OR: Odds Ratio. The green space indicators were normalized to 0–1. Solid lines and shade areas represented the estimates of OR and 95 % CI. The dashed horizontal lines represented the reference line of null association (OR = 1). Knots were placed at the 10th, 50th, and 90th percentiles of time-weighted exposures. *: P < 0.05; **: P < 0.01; ***: P < 0.001. The fully adjusted model was adjusted for age, BMI, gender, education levels, family income, the number of family members, vaccination history, smoking history, population density, frailty status, medical condition, and the indoor absolute humidity.

significant inverse relationships were found for canopy cover, PAI, total green space, shrubland, and open space and recreation in both static and ATM modes during the warm season. In the cool season, higher exposures to total green space, canopy cover, PAI, and woodland in ATM mode were associated with a reduced risk of ARI (Table 3).

A significant inverse linear dose–response relationship was found between the risk of ARI with out-of-home exposures to total green space, canopy cover, PAI, shrubland, and open space and recreation. The relationship between ARI risk and out-of-home woodland exposure was non-linear, initially showing a modest increase in risk before sharply decreasing with greater woodland exposure. This dose–response relationship was more pronounced in ATM mode compared to static mode. No clear dose–response relationship was observed for NDVI, grassland, and ARI. Sensitivity analyses showed a similar association between the green space exposure and ARI episodes, regardless of whether a 100-meter, 500-meter, 1000-meter buffer was used (Supplementary Table 3-6) or when resampling green space indicators, or excluding five participants who reported an ARI episode near the GPS data collection time (Supplementary Table 7).

4. Discussion

To our knowledge, our study is among the first to investigate the relationship between out-of-home green space and ARI. In this two-year prospective cohort study, we found that higher canopy cover and PAI in out-of-home green spaces were negatively correlated with ARI incidence Similarly, total green space, woodland, shrubland, open space and recreation were also negatively correlated with ARI, while out-of-home grassland showed no significant association. These findings suggested that increased outdoor activity in certain types of green spaces may enhance respiratory health among the elderly population in Hong Kong. The strengths of our study lie in the long follow-up period and the use of

Table 2
Association between residential or out-of-home green space indicators and the risk of ARI in warm and cool seasons.

Exposures [a]	Modes	All seasons (n = 134) [b]		Warm season (n = 67)		Cool season (n = 107)	
		OR (95 % CI) [c]	P value	OR (95 % CI)	P value	OR (95 % CI)	P value
NDVI	Residential based	1.07 (0.75, 1.51)	0.722	0.92 (0.72, 1.17)	0.497	1.09 (0.92, 1.29)	0.309
	Out-of-home	0.70 (0.40, 1.21)	0.202	0.79 (0.53, 1.13)	0.204	0.81 (0.62, 1.02)	0.072
Total green space	Residential based	0.93 (0.63, 1.38)	0.732	0.98 (0.67, 1.39)	0.908	1.01 (0.84, 1.20)	0.921
	Out-of-home	0.51 (0.26, 1.02)	0.056	**0.53 (0.31, 0.80)**	**0.003**	0.79 (0.59, 1.01)	0.051
Canopy cover	Residential based	0.67 (0.39, 1.16)	0.151	0.78 (0.55, 1.06)	0.118	0.92 (0.74, 1.13)	0.418
	Out-of-home	**0.36 (0.14, 0.88)**	**0.026**	**0.30 (0.10, 0.60)**	**0.002**	**0.74 (0.56, 0.95)**	**0.020**
PAI	Residential based	0.58 (0.33, 1.02)	0.059	0.80 (0.56, 1.10)	0.168	0.87 (0.68, 1.08)	0.195
	Out-of-home	**0.38 (0.17, 0.84)**	**0.017**	**0.38 (0.15, 0.67)**	**0.002**	**0.67 (0.49, 0.87)**	**0.004**
Woodland	Residential based	1.14 (0.78, 1.68)	0.499	1.26 (0.96, 1.71)	0.099	1.03 (0.84, 1.24)	0.776
	Out-of-home	0.62 (0.38, 1.03)	0.066	0.67 (0.39, 1.01)	0.056	0.83 (0.66, 1.01)	0.062
Grassland	Residential based	0.69 (0.37, 1.26)	0.225	0.80 (0.49, 1.10)	0.164	0.89 (0.65, 1.13)	0.303
	Out-of-home	1.05 (0.66, 1.67)	0.845	0.86 (0.62, 1.18)	0.347	0.93 (0.70, 1.19)	0.568
Shrubland	Residential based	0.81 (0.53, 1.23)	0.324	0.95 (0.69, 1.27)	0.718	0.89 (0.68, 1.12)	0.315
	Out-of-home	0.61 (0.32, 1.18)	0.141	**0.61 (0.39, 0.89)**	**0.014**	0.80 (0.61, 1.01)	0.051
Open Space and Recreation	Residential based	0.85 (0.58, 1.26)	0.426	0.89 (0.60, 1.24)	0.474	1.00 (0.85, 1.17)	0.998
	Out-of-home	0.57 (0.29, 1.11)	0.097	**0.55 (0.33, 0.85)**	**0.007**	0.88 (0.65, 1.13)	0.310

Abbreviations: ARI: acute respiratory illness; BMI: body mass index; CI: Confidence Interval; NDVI: Normalized Difference Vegetation Index; OR: Odds Ratio; PAI: plant area index.
The fully adjusted model was adjusted for age, BMI, gender, education levels, family income, the number of family members, vaccination history, smoking history, population density, frailty status, medical condition, and the indoor absolute humidity.
[a] The green space exposures were normalized to 0–1.
[b] The generalized linear mixed effects model was applied to all seasons with individual random effects.
[c] The OR denoted the change in odds of the outcome per 0.1 unit increase in environmental exposures.

Table 3
Association between green spaces indicators in static and ATM mode and the risk of ARI in warm and cool seasons.

Exposures [a]	Modes	All seasons (n = 134) [b]		Warm season (n = 67)		Cool season (n = 107)	
		OR (95 % CI) [c]	P value	OR (95 % CI)	P value	OR (95 % CI)	P value
NDVI	Static	0.60 (0.31, 1.20)	0.212	0.72 (0.49, 1.01)	0.066	0.85 (0.66, 1.07)	0.164
	ATM	0.70 (0.40, 1.22)	0.207	0.84 (0.58, 1.17)	0.297	0.79 (0.61, 1.00)	0.050
Total green space	Static	0.59 (0.35, 1.02)	0.056	**0.49 (0.27, 0.77)**	**0.002**	0.84 (0.65, 1.05)	0.125
	ATM	0.48 (0.21, 1.07)	0.072	**0.57 (0.35, 0.84)**	**0.006**	**0.75 (0.56, 0.97)**	**0.031**
Canopy cover	Static	**0.50 (0.25, 0.98)**	**0.045**	**0.50 (0.28, 0.78)**	**0.003**	0.84 (0.67, 1.04)	0.116
	ATM	**0.38 (0.17, 0.85)**	**0.018**	**0.30 (0.09, 0.61)**	**0.002**	**0.74 (0.55, 0.95)**	**0.024**
PAI	Static	**0.51 (0.28, 0.94)**	**0.032**	**0.51 (0.29, 0.78)**	**0.002**	**0.80 (0.62, 0.99)**	**0.047**
	ATM	**0.39 (0.18, 0.83)**	**0.017**	**0.37 (0.15, 0.67)**	**0.002**	**0.67 (0.49, 0.87)**	**0.004**
Woodland	Static	0.65 (0.39, 1.07)	0.092	0.72 (0.41, 1.07)	0.110	0.85 (0.67, 1.05)	0.128
	ATM	0.62 (0.38, 1.02)	0.059	0.73 (0.45, 1.05)	0.074	**0.82 (0.65, 0.99)**	**0.045**
Grassland	Static	0.90 (0.54, 1.50)	0.697	0.82 (0.57, 1.16)	0.269	0.90 (0.67, 1.14)	0.372
	ATM	1.00 (0.64, 1.56)	0.998	0.87 (0.62, 1.18)	0.377	0.93 (0.71, 1.18)	0.509
Shrubland	Static	0.61 (0.34, 1.11)	0.095	**0.40 (0.17, 0.69)**	**0.004**	0.86 (0.67, 1.06)	0.147
	ATM	0.61 (0.34, 1.12)	0.094	**0.65 (0.42, 0.93)**	**0.022**	0.79 (0.60, 1.00)	0.051
Open Space and Recreation	Static	0.66 (0.38, 1.13)	0.128	**0.51 (0.27, 0.84)**	**0.009**	0.92 (0.69, 1.18)	0.469
	ATM	0.59 (0.31, 1.10)	0.089	**0.58 (0.35, 0.88)**	**0.010**	0.85 (0.63, 1.10)	0.211

Abbreviations: ARI: acute respiratory illness; BMI: body mass index; CI: Confidence Interval; NDVI: Normalized Difference Vegetation Index; OR: Odds Ratio; PAI: plant area index.
The fully adjusted model was adjusted for age, BMI, gender, education levels, family income, the number of family members, vaccination history, smoking history, population density, frailty status, medical condition, and the indoor absolute humidity.
[a] The green space exposures were normalized to 0–1.
[b] The generalized linear mixed effects model was applied to all seasons with individual random effects.
[c] The OR denoted the change in odds of the outcome per 0.1 unit increase in environmental exposures.

personal GPS trackers for accurate measurement of various outdoor green space exposures.

Previous studies have proposed several possible pathways through which green space may influence respiratory health. Green spaces can mitigate environmental hazards such as the heat island effect and air pollution. They also encourage outdoor activity, which promotes physical health and reduces exposure to indoor pathogens (Yang et al., 2021). Compared to indoor environments, green spaces provide safer settings for social distancing while allowing for recreational and social activities. For instance, one study found that the probability of SARS-CoV-2 transmission indoors was 18.7 times higher than outdoors (Bulfone et al., 2020).

Our findings were consistent with previous studies on green space and respiratory symptoms or infections. An ecological study reported that a 0.1 decrease in NDVI was associated with a 6 % increase in COVID-19 incidence, especially in counties with higher population density (Klompmaker et al., 2021). Similarly, Chen *et al.* found that a 0.1 increase in neighborhood NDVI was associated with a 3.5 % reduction in predicted COVID-19-like illness incidence in urban and rural areas of the US and UK (Chen et al., 2023). A case-crossover study in China reported that the adverse effect of air pollutants on influenza was lessened in areas with higher NDVI (Zhang et al., 2023). Another study involving 563 households in Kuala Lumpur, Malaysia, found that decreased green space was associated with increased respiratory illness rates (LingHoon et al.). In addition, a study in Shanghai, China reported that greater vegetation coverage was associated with a lower risk of respiratory diseases including asthma, bronchitis, and cough over the past five years (Wu et al., 2021).

However, there are studies with conflicting views on the relationship between green spaces and respiratory health. For instance, Huang *et al.* found that while COVID-19 risk was lower in residential and mobility-based NDVI, it was higher in open green spaces in Hong Kong (Huang and Kwan, 2023). Jiang *et al.* reported that while total green space and forests reduced COVID-19 incidence, open spaces might increase it (Jiang et al., 2022). By assessing the availability and connectivity of public green spaces, Pan *et al.* discovered that highly connected green spaces with high-choice measures increased the likelihood of COVID-19 transmission (Pan et al., 2021). These conflicting results may arise from the aggregation of respiratory infections at the administrative unit level, which could be influenced by ecological fallacy. This suggests that while green spaces might improve respiratory health, they could also serve as social venues that increase infection risks during viral outbreaks. Therefore, careful consideration is needed in the design and use of green spaces to balance health benefits with the potential for increased virus transmission (Zhang et al., 2022).

We observed benefits from nearly all types of out-of-home green spaces concerning ARI except for grassland. This can be due to the varying capacities of different vegetation types to absorb contaminants and block pollutants. Previous research has shown that urban trees and shrubs significantly improve environmental quality and respiratory health by filtering air pollutants and airborne pathogens through leaf uptake and surface interception (Nowak et al., 2006). Gases can diffuse into intercellular spaces within leaves and may be absorbed by water films, forming acids or reacting with inner-leaf surfaces. Additionally, trees can intercept airborne particles, further reducing pollution (Smith, 2012). In contrast, grass lacks the height and foliage area necessary to effectively absorb and block pollutants and harmful microorganisms.

Interestingly, we found a significant association between green space and ARI, but not for the residential or out-of-home NDVI measures. This could be due to the fact that a continuous increase in NDVI does not necessarily correspond to a continuous increase in green space. The dose–response curve between NDVI and ARI in our study exhibited a non-linear pattern, with ARI risk initially increasing before decreasing as NDVI increased. For example, an NDVI value of 0.2 might indicate built-up areas rather than less vegetated spaces (Alex et al., 2017). The NDVI, which ranges from 0 to 1, was combined with a raster layer representing mobility trajectories. If a participant spent considerable time in an area with a low NDVI value, they could still experience a relatively high exposure value. This could obscure the perceived differences in true exposure levels along their mobility path, potentially masking significant associations. In the context of measuring mobility-associated exposure, NDVI may be less reliable than the presence of green space. A recent study also applied the DR to extract NDVI, the presence of recreation areas (proxy of green space), and metabolic biomarkers found the significant beneficial relationships only for recreation areas, not NDVI (Letellier et al., 2024).

We found that the health benefits in terms of reduced ARI incidence were more evident in out-of-home green space exposure compared to residential green spaces. This highlights the variability in how green spaces are measured and their health impacts. These two measures capture different aspects of human interaction with green spaces. In densely populated areas like Hong Kong, residential green space is often limited due to crowded living conditions (Yoo and Roberts, 2022). Dynamic evaluation methods that consider individual mobility and geographic context could provide a more accurate and insightful alternative, reducing inferential errors and better tracking daily movements (Kwan et al., 2019). This is consistent with previous findings comparing associations between residential green space and dynamic green space exposure and health (Jankowska et al., 2017; Wang et al., 2021; Yu and Kwan, 2024).

In addition to GPS data, we collected self-reported physical activity data using the Physical Activity Scale for the Elderly (PASE) questionnaire (Han et al., 2020). To further evaluate segmentation, we conducted a correlation analysis between PASE scores and time spent in static, ATM, and PTM modes. The results indicated a positive association between PASE scores and time spent in ATM and PTM modes, with a stronger correlation for ATM. Conversely, there was a negative association between PASE scores and time spent in the static mode (data not shown). These findings suggest that time spent in ATM mode aligns with higher self-reported physical activity, providing additional support for our GPS-based segmentation.

This study has several limitations. First, GPS data was collected over a span of 7 consecutive days which might introduce measurement bias due to changes in individual mobility patterns over the two-year follow-up period. However, older adults have relatively stable mobility patterns and their environmental exposures were less likely to be affected during the week (Yoo and Roberts, 2022). Moreover, it is unrealistic to require participants to wear GPS trackers for longer periods, and most studies have adopted for a 7-day collection period (Kang et al., 2017). Second, the sample size was relatively small, limiting our ability to detect the separate effects of green space in warm and cool seasons. Nevertheless, we still observed a significant inverse association between out-of-home green space and ARI in both seasons. Third, ARI was assessed based on self-reported respiratory symptoms, which may introduce reporting and recall bias, although we provided monthly reminders to participants via phone calls. Fourth, woodland and shrubland may increase allergy exposure and worsen respiratory symptoms in sensitive individuals. The marginally negative association between these green spaces and ARI may reflect a balance between the benefits of greenness and risks posed by plant allergens. However, we did not collect data on plant allergies in Hong Kong, limiting further investigation. Future research should explore the role of plant allergens in this context. Fifth, the canopy cover and PAI data at a 1-km resolution, combined with the 50-meter GPS buffer, may reduce the precision of individual-level exposure assessments compared to finer-resolution NDVI and green space types. However, the aggregation across numerous moving buffers slightly mitigated this limitation, as the sensitivity analysis using the 500-meter and 1000-meter buffers found the similar results. Lastly, although we adjusted for various confounders in our models, some unmeasured factors may still exist.

5. Conclusion

Our study found that exposure to out-of-home green space was associated with a reduced risk of ARI among community-dwelling older adults. This relationship was more evident in the warm season compared with the cool season. The findings suggest that promoting outdoor activities, especially in green spaces, may help mitigate seasonal respiratory illnesses in vulnerable populations. Future studies incorporating biomarkers are needed to further explore the mechanisms linking outdoor environmental exposures to respiratory diseases.

CRediT authorship contribution statement

Qingwei Zhong: Writing – review & editing, Writing – original draft, Visualization, Validation, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Lefei Han:** Writing – review & editing, Writing – original draft, Project administration, Methodology, Investigation, Funding acquisition, Data curation, Conceptualization. **Xinyue Ye:** Writing – review & editing, Supervision. **Lin Yang:** Writing – review & editing, Supervision, Methodology, Data curation, Conceptualization.

Declaration of Competing Interest

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

Acknowledgements

This study is funded by the Early Career Scheme of General Research Fund, from the University Grants Committee of Hong Kong (grant PolyU 251054/16 M), and the Departmental General Research Fund, from Hong Kong Polytechnic University (grant number G-YBFW) and the Shanghai Science and Technology Development Foundation grant number 23YF1421200.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.landurbplan.2025.105336.

Data availability

Data will be made available on request.

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