



## Could greenness modify the effects of physical activity and air pollutants on overweight and obesity among children and adolescents?



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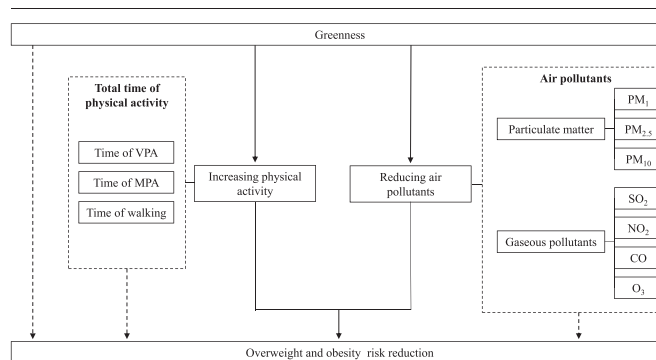
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### HIGHLIGHTS

- Greenness alleviates the negative impacts of air pollution on obesity among children.
- Greenness seemed to work on air pollution directly but not through behavior change to effect on overweight and obesity.
- Reduced levels of air pollution might have a larger impact on schools with a low level of greenness.

### GRAPHICAL ABSTRACT



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### ABSTRACT

Greenness could theoretically increase the impact of physical activity (PA) and reduce the adverse effects of air pollution on overweight/obesity. However, no evidence systematically compares these two pathways, especially in longitudinal studies of children and adolescent's cohort. Greenness, PA, and air pollution were assessed by Normalized Difference Vegetation Index (NDVI), International Physical Activity Short Form, and 7 pollutants (PM<sub>1</sub>, PM<sub>2.5</sub>, PM<sub>10</sub>, SO<sub>2</sub>, NO<sub>2</sub>, CO, and O<sub>3</sub>). Each exposure was divided into low – /high-level groups based on the 50% quantile. Proportional hazards and logistic regression model were used to assess the associations of greenness, PA, pollutants with overweight/obesity. The incidence of overweight/obesity was 1.98% in the national survey, and the cumulative incidence and incidence density were 12.76% and 3.43 per 100 person-year in the dynamic cohort, separately. An increase of 0.1 units in NDVI was associated with a 12% lower risk of overweight/obesity, but no significant link between PA and incidence was observed. The HRs of the high-level of PM<sub>1</sub>, PM<sub>2.5</sub>, PM<sub>10</sub>, SO<sub>2</sub>, NO<sub>2</sub>, CO, and O<sub>3</sub> on the risk of overweight/obesity were 2.21, 2.63, 1.88, 2.38, 1.33, 2.43, and 1.33 in the low-level of greenness, which was higher than those in the high-level of greenness. The AFs of PM<sub>1</sub>, PM<sub>2.5</sub>, PM<sub>10</sub>, SO<sub>2</sub>, NO<sub>2</sub>, CO, and O<sub>3</sub> were 25.58%, 44.37%, 22.96%, 29.15%, 11.55%, 29.50%, and 10.92% in the low-level of greenness, which simultaneously

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was higher than those in the high-level of greenness. Moreover, the risk of overweight/obesity associated with high-level of greenness in the high-level of PM<sub>10</sub>, SO<sub>2</sub>, CO were 0.83, 0.81, and 0.83 respectively. Our findings confirmed that greenness has a moderating effect on the effects of air pollutants on childhood overweight/obesity especially in heavy-industry areas where PM<sub>10</sub>, SO<sub>2</sub>, and CO are the major pollutants, although it did not influence the association between PA and overweight/obesity risks.

## 1. Introduction

As a result of increasing urbanization, economic expansion, obesogenic environmental exposure and the accompanying changes in lifestyles, the global prevalence of overweight and obesity has accelerated. In 2015, around 2 billion people were affected by overweight and obesity globally (Collaborators et al., 2017). For children and adolescents, an eightfold to tenfold increase in the prevalence of overweight and obesity during the past decades (Collaboration, 2017), which caused increased risks of cardiovascular diseases and subsequent huge medical burdens (Wang et al., 2011). In 2014, the global economic impact of obesity was approximately US \$2.0 trillion, which represented 2.8% of the world's gross domestic product (Institute, 2014). Similarly in China, it had the largest number of obesity-afflicted persons across the world (Collaborators et al., 2017; Dong et al., 2019), and the medical burden on overweight and obese people increased from 2.74 billion U.S. dollars in 2003 to 17.57 billion U.S. dollars in 2011 (Qin and Pan, 2016; Zhao et al., 2008).

Evidence showed that children's engagement with greenness had a positive impact on their well-being and health later in life (Sbihi et al., 2015), which would be protective against multiple adverse health outcomes, including overweight and obesity (Schalkwijk et al., 2018; Twohig-Bennett and Jones, 2018). Green space close to children had many specific health benefits, including less noise, more suitable temperature, less stress, greater physical activities, and lower concentration of air pollutants (Tree and forest effects on air quality and human health in the United States, 2014; A Review of the Health Benefits of Greenness, 2015; Sandifer et al., 2015). Previous studies indicated that living in greater green space was associated with a reduced risk of overweight and obesity for children and adolescents (Bao et al., 2021; Wilhelmsen et al., 2017). One possible mechanism was that increased green space or proximity to green spaces provided a setting for PA, resulting in the reduction of risk of overweight and obesity (Fong et al., 2018). Another mechanism from environmental evidence among children emphasized that green space absorbed pollutants, with decreasing risk of overweight and obesity (Huang et al., 2020; Hwang et al., 2019; Franchini and Mannucci, 2018). Two assumptions on how greenness influenced overweight and obesity were thus raised, but both were not fully evaluated with inconclusive findings, which needed to be furtherly confirmed that how greenness affected overweight and obesity by enhancing the effects of PA or alleviating effects of air pollutants or combination of both on children and adolescents' overweight and obesity incidence. In addition, few study assessed the effects of improvements of these two pathways on reducing the likelihood of being overweight and obese in the various greenness levels. As a result, it was unclear which of these two potential paths of improvements should be prioritized for public health gains.

Based on existing researches and two assumptions, our hypothesis was that greenness might decrease the risks of overweight and obesity incidence among children and adolescents by increasing individual PA or/and reducing air pollution around schools where they spent the majority of time in one day. Thus, we used two data sources, a dynamic prospective cohort study combing a national representative study with a large sample of children and adolescents to examine: (1) whether there was a clear separate association between greenness, PA, air pollutants, and overweight and obesity in children and adolescents, (2) whether greenness mitigated the risk of overweight and obesity incidence risk by enhancing the effects of PA, and/or (3) by alleviating the effects of air pollutants and in which components of air pollutant greenness showed greater effects. A further objective was to determine the priority improvement strategy (promoting PA and decreasing air pollutants) across the various green areas for public health practical implementation.

## 2. Methods

### 2.1. Study population

Two data sources were included in the present study, one of which was extracted from a national perspective study with two rounds of follow-up between one year and gathering of a variety of lifestyles information for children and adolescents, and the other of which was based on a 14-year longitudinal dynamic cohort study with collecting of dynamic changes in overweight and obesity for children and adolescents. Our research group participated in the design and implementation of these two surveys, so the comparability of their measured data could be guaranteed.

The national prospective study was conducted in seven provinces (Hunan, Shanghai, Guangdong, Chongqing, Ningxia, Tianjin, and Liaoning) in 2013 to investigate the effectiveness of a lifestyle intervention program on obesity prevention in children and adolescents (the location of 7 provinces was shown in Fig. S1), and the detailed protocols were presented in previous studies (Dong et al., 2017; National School-Based Health Lifestyles Intervention in Chinese Children and Adolescents on Obesity and Hypertension, 2021). In brief, through multi-stage random selection processes, there were 65,347 children and adolescents aged 6 to 18 years from 94 schools were recruited. Finally, a total of 23,732 children and adolescents in the control group who met the inclusion criteria with normal weight at baseline and completed follow-up were included in the study (As shown in the flow chart of Fig. S2). Except for the physical examination (height and weight), data on the consumption of dietary intake, time of sedentary behaviors, and PA from each child and adolescent were collected using standard questionnaires were filled by students. It was endorsed by the Beijing University Health Center Medical Research Ethics Committee (IRB 00001052–13,034).

The 14-year longitudinal cohort study was performed in two cities, Beijing and Zhongshan of China. All children and adolescents (students in schools, excluding drop-outs) aged 6 to 18 years in the two cities completing the annual physical examination census were involved, to link each participant's data to form a longitudinal dynamic cohort. Similarly, the dynamic cohort comprised children and adolescents who weren't overweight or obese at baseline. The endpoint was specified as the moment each student fall off the cohort or they were discovered to be overweight or obese during the follow-up. Despite the fact that our sample contained 14 years of data, the longest follow-up period for each participant was still 12 years. That indicates that when they exited the dynamic cohort, each participant was under the age of 18. Medical specialists from medical facilities carried out the annual physical examination to ensure the quality of the investigation. Data of each child and adolescent were obtained including gender, birth date, test date, height, weight, and school location. Finally, a total of 1,659,076 children and adolescents who met the inclusion criteria with normal weight at baseline and completed follow-up were included in the cohort (Beijing: 1,027,833, Zhongshan: 631,243) (flow chart were presented in Fig. S3). This study has been authorized by the Medical Research Ethics Committee of Peking University Health Center (IRB00001052–20033).

### 2.2. Ascertainment of overweight/obesity

All participants from these two surveys underwent a complete anthropometric evaluation to ascertain their nutritional status and ensure that they were free from visceral diseases. Height (cm) and weight (kg) were measured by a team of trained technicians following a standardized procedure. Height was measured using the portable stadiometer to the nearest 0.1 cm, with the subjects standing straight without shoes and wearing light clothes only. Weight was measured using the lever type weight scale

with a scale precision to nearest 0.1 kg. Both height and weight were measured twice, and the mean values were recorded. The body mass index (BMI) was determined by dividing weight by height squared. Using sex- and age-specific BMI references from International Obesity Task Force (IOTF) (Cole et al., 2000), the BMI was divided into three groups: normal weight, overweight, and obesity. In the national prospective study, the incidence rate of overweight and obesity was calculated by:

$$\frac{\text{Number of new overweight and obesity}}{\text{Total number of participants without overweight and obesity at baseline}} \cdot \text{In the dynamic cohort, the incidence rate of overweight and obesity was reported by cumulative incidence } \left( \frac{\text{Number of new overweight and obesity from 2005 to 2018}}{\text{Number of participants without overweight and obesity from 2005 to 2018}} \right) \text{ and incidence density } \left( \frac{\text{Number of new overweight and obesity from 2005 to 2018}}{\text{Total person time of participants without overweight and obesity from 2005 to 2018}} \right).$$

### 2.3. Greenness assessment

The Landsat 5 Thematic Mapper satellite pictures were used to quantify the greenness around schools in a normalized differential of vegetation index (NDVI) with a resolution of 30 m by 30 m (<http://earthexplorer.usgs.gov>). The NDVI was computed by dividing the difference in the amount of the two observations between spectral reflectance measurements in almost infrared and in red regions of the electromagnetic spectrum. NDVI was calculated by:  $NDVI = \frac{NIR-RED}{NIR+RED}$ , where NIR presented the land surface reflectance of near-infrared; RED presented the surface reflectance in red regions of the electromagnetic spectrum. The NDVI values varied from  $-1$  to  $+1$ , with higher values denoting more greenness. The amounts of greenness exposure of each child and adolescent were determined based on NDVI values around schools from the previous year at the time of the survey. The temporal resolution of NDVI is 16 days, indicating that the NDVI of each year includes 23 NDVI values. The average one-year NDVI values were calculated based on the 23 NDVI values. The average one-year NDVI values were computed and allocated to each participant as the exposure substitutes in 500 m and 1000 m of circular buffers surrounding every school center. For each year, we calculated the average one-year NDVI of each school. The average one-year NDVI exposure of each school one year prior to the endpoint was utilized as the greenness exposure. Finally, the  $NDVI_{500m}$  values were utilized as the greenness measurement at the school level, while  $NDVI_{1000m}$  values were analyzed for sensitivity. The Beijing and Zhongshan NDVI distributions were displayed in Fig. 2 in 2016. The NDVI was classified into low- and high-level groups of greenness based on the 50th values as the bound for grouping of greenness (national survey: 0.24; dynamic cohort: 0.25).

### 2.4. Physical activity (PA)

Only the national prospective study collected the information of PA for each child and adolescent using a standard questionnaire. The International Physical Activity Short Form (IPAQ-SF) was used to estimate the past seven days' PA. The daily average and the weekly frequency and duration of these activities were requested to report: VPA (vigorous-intensity PA, activities which lead individuals to breathless, sweat, and intense tiredness such as running, basketball, soccer, swimming, aerobics, or heavyweight carrying.), MPA (moderate-intensity PA, activities that induce humans to swim moderately, such as biking, table tennis, and badminton, dance, but not walking), and walking (including at school, at home). The time spent in walking, MPA, and VPA was coded as a total. The time of PA was classified into low- and high- level groups based on the 50th values as the bound (national survey: VPA, 25.71; MPA, 25.71; Walking, 30.00; Total time, 98.57).

### 2.5. Fine particulate matter ( $PM_x$ ) exposure assessment

In the present study, fine particles were composed of three sizes of diameters. The designations  $PM_{1.0}$ ,  $PM_{2.5}$ , and  $PM_{10}$  were pollutant diameters that were at or below  $1 \mu m$ ,  $2.5 \mu m$  or below, and at or above  $10 \mu m$ , respectively.  $PM_x$  was calculated at one kilometer in spatial resolution utilizing a space-time extremely randomized trees (STET) model which is new tree-

based ensemble approach for regression, and combined the remote satellite sensing, meteorology, multi-resolution emission inventory, and land utilization data (Wei et al., 2019; Wei et al., 2021a; Wei et al., 2020; Wei et al., 2021b). The  $PM_x$  data included  $PM_{1.0}$  (2013–2018),  $PM_{2.5}$  (2000–2018) and  $PM_{10}$  respectively (from 2013 to 2018), which were collected from the CHAP dataset (<https://weijing-rs.github.io/product.html>). The address-specific annual average concentrations of  $PM_x$  were calculated and linked to individual data using the school address with the translation of latitude and longitude. The yearly average concentrations of  $PM_{1.0}$ ,  $PM_{2.5}$ , and  $PM_{10}$  for each survey year (one year before the date at the year of the survey) were used to represent the long-term  $PM_x$  exposure of each child and adolescent (As shown in Fig. 2). The  $PM_x$  was classified into low- and high- level groups of  $PM_x$  based on the 50th values as the bound for grouping of  $PM_x$  (national survey:  $PM_1$ ,  $51.81 \mu g/m^3$ ,  $PM_{2.5}$ ,  $65.10 \mu g/m^3$ ,  $PM_{10}$ ,  $101.63 \mu g/m^3$ ; dynamic cohort:  $PM_1$ ,  $25.68 \mu g/m^3$ ,  $PM_{2.5}$ ,  $60.00 \mu g/m^3$ ,  $PM_{10}$ ,  $83.19 \mu g/m^3$ ).

### 2.6. Gaseous pollutant ( $SO_2$ , $NO_2$ , $CO$ , and $O_3$ ) exposure assessment

Four compounds of gas pollutants, Sulfur dioxide ( $SO_2$ ), Nitrogen dioxide ( $NO_2$ ), nitric oxide (CO), and ozone ( $O_3$ ), at a 10-km resolution were included in our study, also collected from the CHAP dataset that were generated from big data utilizing the extended STET model (Wei et al., 2022). In short, we trained STET models individually with 10-fold cross-validation (10-CV) in the high-resolute surface of  $SO_2$ ,  $NO_2$ , CO, and  $O_3$  from 2013 to 2018 years with full coverage utilizing meteorological data, surface stress, satellite remote sensing products, and emission inventory. And the out-of-sample 10-CV method was utilized in near-face gaseous pollutants to assess model overall performance. Similarly, long-term gas pollutant exposure was evaluated using the annual average gaseous pollutant concentration for each study year. The data on gas pollutants were matched to the school address for each child and adolescent (As shown in Fig. 2). The bound for grouping of gaseous pollutant was used to classify low- and high- level groups (national survey:  $SO_2$ ,  $34.50 \mu g/m^3$ ,  $NO_2$ ,  $45.42 \mu g/m^3$ , CO,  $1.19 mg/m^3$ ,  $O_3$ ,  $80.22 \mu g/m^3$ ; dynamic cohort:  $SO_2$ ,  $11.34 \mu g/m^3$ ,  $NO_2$ ,  $41.12 \mu g/m^3$ , CO,  $0.96 mg/m^3$ ,  $O_3$ ,  $93.01 \mu g/m^3$ ).

### 2.7. Statistical analysis

For categorical variables, the frequencies were computed and continuous variables were given as mean standard deviation (SD). In the current study, we conducted a two-tiered analysis strategy based on Fig. 1. In the first stage, a separate association between NDVI, PA, air pollutants, and overweight and obesity risks among children and adolescents was assessed using a logistic regression model. Stratified analysis was performed to estimate the effects of PA and air pollutants on overweight and obesity incidence by low- and high-level groups of NDVI. In the second stage, we validated the factors (air pollutants) that showed significant differences in the low- and high-level group of NDVI in the first stage with dynamic queues.

The benefits of improving greenness level and improvements in  $PM_x$  and gaseous pollutants around the school in reducing overweight and obesity risks in children and adolescents were assessed using the dynamic cohort. Firstly, the separate association between  $PM_x$ , gaseous pollutant, NDVI, and overweight and obesity incidence among children and adolescents were assessed using restricted cubic spline (RCS) with 3 knots coupled with proportional hazards model (Cox model). The hazard ratio (HR) with both qualitative and quantitative results was calculated after adjusting for age, sex, height, weight, and city (Beijing and Zhongshan). Secondly, the Cox models with adjusting confounders were used to assess the effects of  $PM_x$ , gaseous pollutant on overweight and obesity incidence in the low- and high-level group of NDVI (stratification variables). Determining the temporal sequence of the health impacts of greenness and air pollutants is challenging, therefore we additionally assess the effects of greenness on the risk of overweight or obesity in low- and high-level  $PM_x$  and gaseous pollutant groups.

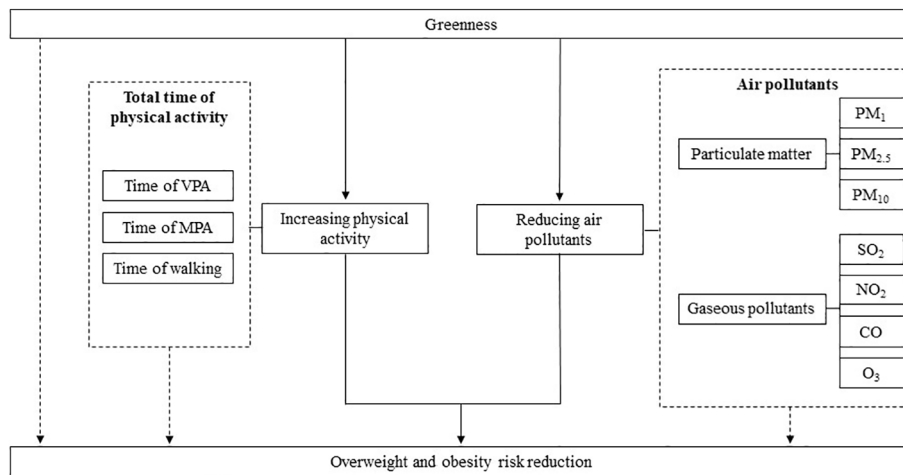


Fig. 1. Potential mechanisms of greenness on overweight and obesity through increasing PA or reducing air pollution Note: VPA, vigorous-intensity physical activity; MPA, moderate-intensity physical activity; PM<sub>1</sub>, PM<sub>2.5</sub>, and PM<sub>10</sub> denote pollutants with diameters of 1 μm or less, 2.5 μm or less, and 10 μm or less, respectively; SO<sub>2</sub>, Sulfur dioxide; NO<sub>2</sub>, Nitrogen dioxide; CO, nitric oxide; O<sub>3</sub>, ozone; dotted arrow denotes direct effects; solid arrow denotes indirect effects.

Thirdly, when the association is significant, we assessed the benefits of improvements in PA or PM<sub>x</sub> and gaseous pollutants around the school in reducing overweight and obesity risk in children and adolescents by different greenness levels. Taking air pollutants as the example, Attributable fraction (AFs) of overweight and obesity risks attributed to PM<sub>x</sub> and gaseous pollutants in the low-level and the high-level group of NDVI. We also examined the AFs of overweight and obesity risks ascribed to low-level groups of

NDVI in the low- and high-level group of PM<sub>x</sub> and gaseous pollutants, given the hazy temporal sequence of pollutants and greenness. The AFs of overweight and obesity attributed to specific environmental factors were calculated by:  $AF = 1 - \frac{(1-S_0)}{(1-S_t)}$ , where S<sub>0</sub> denoted the counterfactual survival function for the event if the exposure were eliminated from the population at baseline and S<sub>t</sub> denoted the factual survival function (Chen et al., 2010; Sjolander and Vansteelandt, 2017). To estimate the overall AFs of

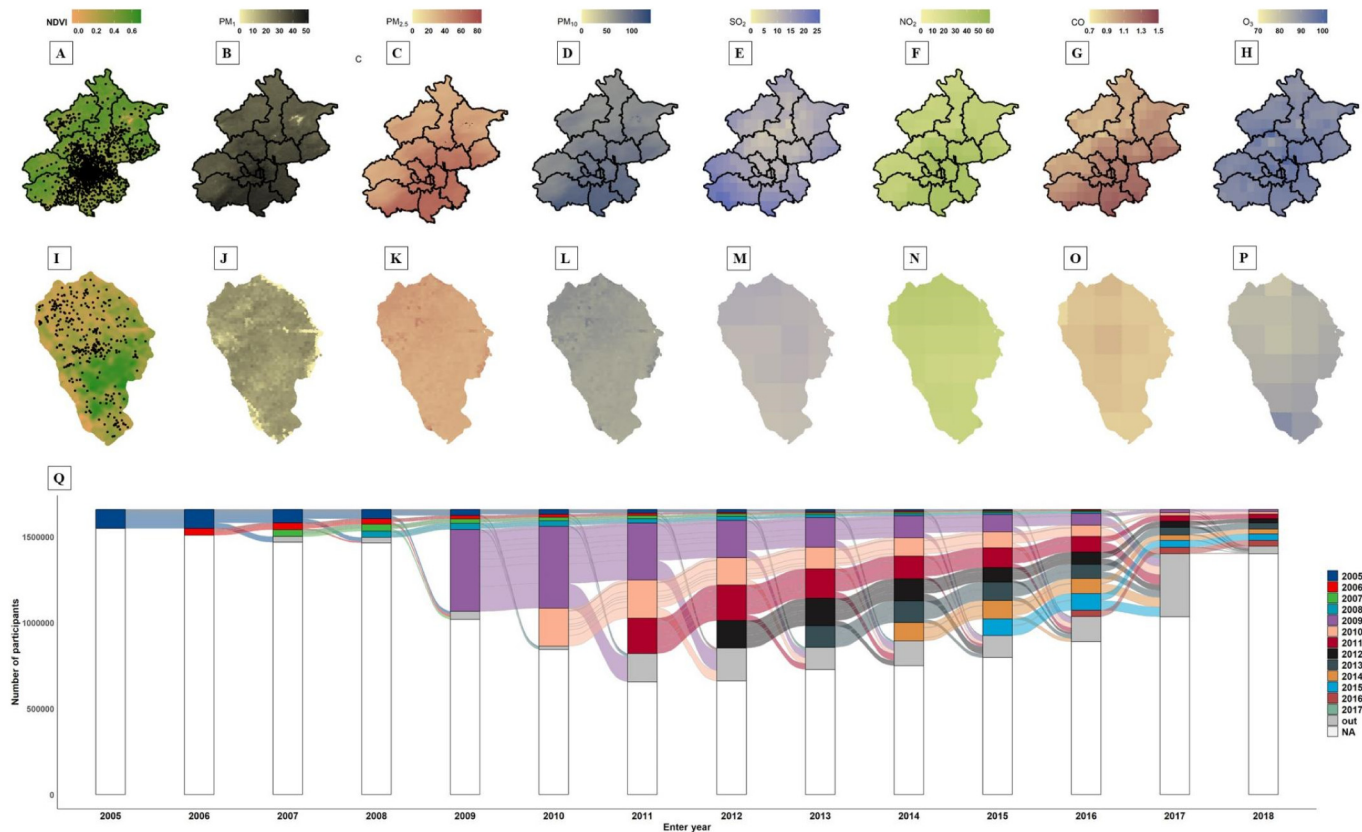
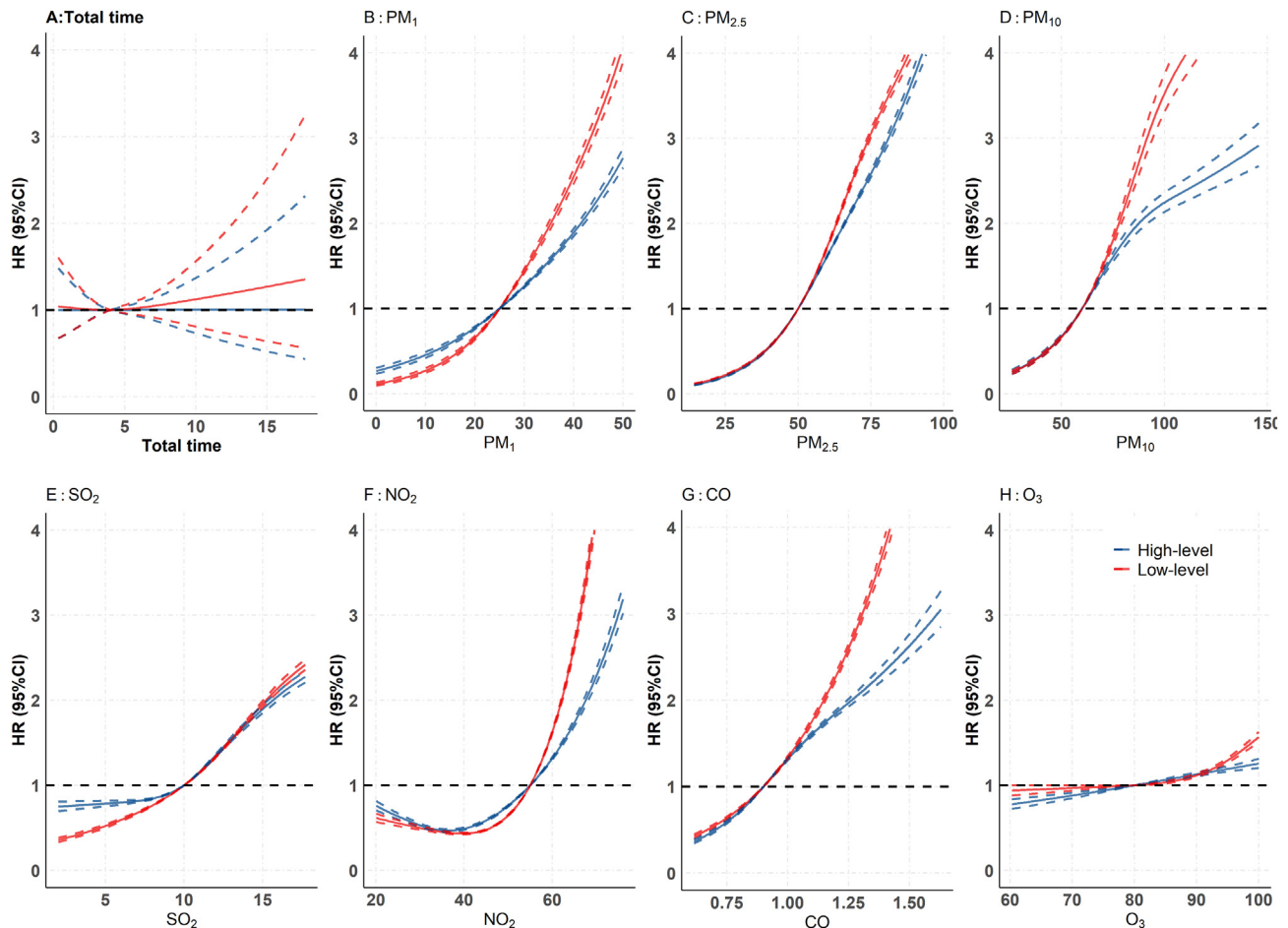


Fig. 2. Location of survey schools in Beijing and Zhongshan and their air pollutants concentration distribution and mean NDVI levels, and participants dynamic change in the cohort. Note: Subfigure A and I represented the mean NDVI levels in 2016 from Beijing and Zhongshan, respectively. Black dots were the location of schools. Subfigure B (PM<sub>1</sub>), C (PM<sub>2.5</sub>), D (PM<sub>10</sub>), E (SO<sub>2</sub>), F (NO<sub>2</sub>), G (CO), and H (O<sub>3</sub>) represented the air pollution concentration in 2016 in Beijing, and Subfigure J (PM<sub>1</sub>), K (PM<sub>2.5</sub>), L (PM<sub>10</sub>), M (SO<sub>2</sub>), N (NO<sub>2</sub>), O (CO), and P (O<sub>3</sub>) represented the air pollutants concentration in 2016 in Zhongshan, respectively. The subfigure I showed the flow of participants in this dynamic cohort study with integrating children from Beijing and Zhongshan. NA, Not Applicable; Out, participants who quitted the dynamic cohort study.



**Fig. 3.** Nonlinear association between PA, air pollutants and NDVI and Overweight/obesity incidence in the low- and high-level group of greenness Note: The restricted cubic spline (RCS) with 3 knots combined with proportional hazards model (COX model) was used to assess the effects of air pollutants (Total time for subfigure A;  $PM_{10}$  for subfigure B,  $PM_{2.5}$  for subfigure C,  $PM_{10}$  for subfigure D,  $SO_2$  for subfigure E,  $NO_2$  for subfigure F, CO for subfigure G,  $O_3$  for subfigure H) on Overweight/obesity incidence in the low-level group (Red lines) and the high-level group of greenness (Blue lines). HR, hazard ratio.

the whole dynamic cohort, the number of people in the dynamic cohort with different survival times was weighted to calculate the overall AF (weighted). The 95% confidence interval of weighted AFs was calculated based on the Monte Carlo method. The benefits of decreasing  $PM_x$  and gaseous pollution and boosting greenness level on the overweight and obesity incidence were demonstrated by weighted AFs.

Additional evaluations were conducted to determine the benefits of greenness surrounding school improvement across various PA and air pollution levels. Based on the substantial association between overweight and obesity incidence and exposures (PA and air pollution levels), we calculated the AF of greenness in the high- and a low-level group of exposures in this study.

All analyses were performed using R (version 4.0.3). The “rms”, “survival”, and “AF” were used to fit the Cox model, RCS model, and calculate the AFs, respectively. Statistical significance was defined as a two-sided  $p$ -value of less than 0.05.

## 2.8. Results

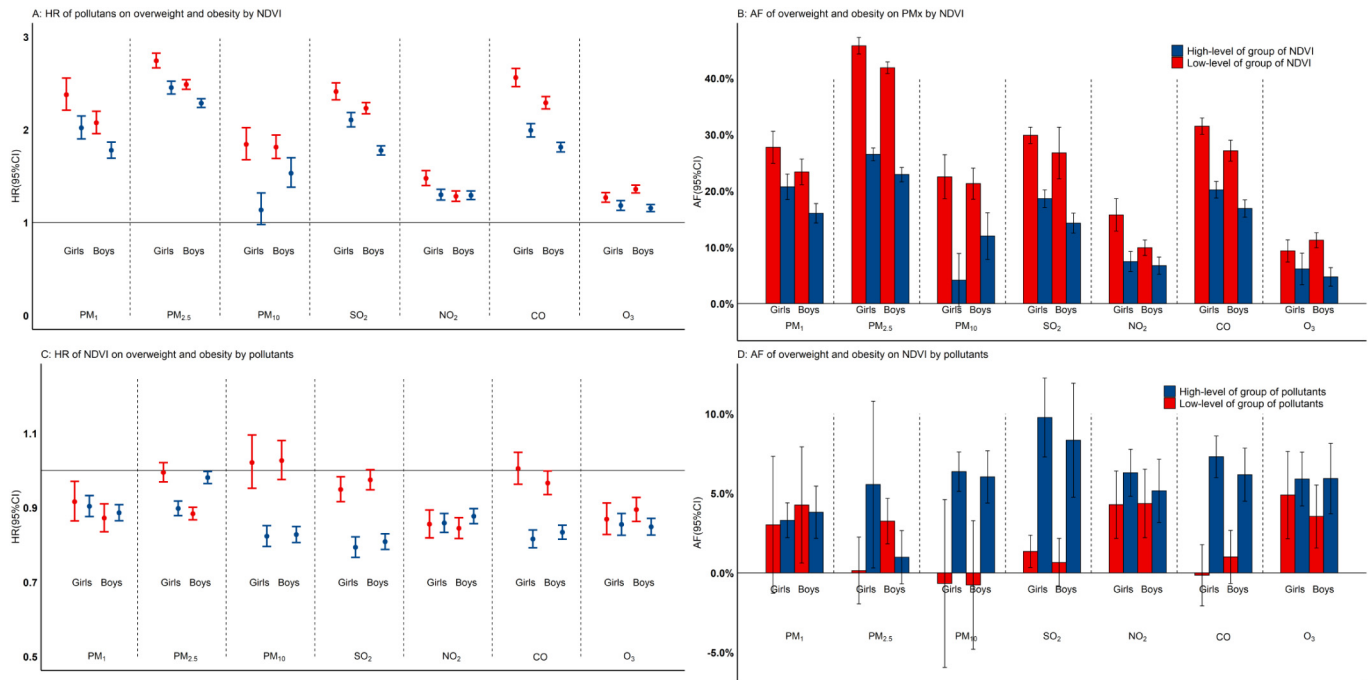
### 2.8.1. Separate association between greenness, PA, air pollutants, and overweight and obesity

A national study with a 1-year follow-up included a total of 23,732 children and adolescents with 471 (1.98%) new overweight or obesity during the followed-up (Table S1). And 14-year follow-up dynamic cohort included 1,659,076 children and adolescents with 171,757 (cumulative incidence: 12.76%; incidence density: 3.43 per 100 person-year) new overweight or obesity during the 14-year follow-up (Table S2). Table 1

illustrated the separate association between greenness, PA, and air pollution, and the risk of overweight and obesity. A statistically significant negative association was observed between greenness around schools and overweight and obesity in children and adolescents, which indicated that an increase of 0.1 units in NDVI exposure in children and adolescents was associated with a lower incidence of obesity and overweight with an adjusted HR of 0.88 (95%CI: 0.77–0.99). The negative association was also witnessed in the dynamic cohort with adjusted HR of 0.82 (95%CI: 0.81–0.82). No statistically significant association was found between the PA and overweight and obesity risks using VPA, MPA, walking time, and total time. However, a significantly increased risk of overweight and obesity in children and adolescents was substantial for all air pollutants except  $O_3$  concentrations. For example, in the national study, for every ten-unit (10  $\mu\text{g}/\text{m}^3$ ) increase in  $PM_{10}$ ,  $PM_{2.5}$ ,  $PM_{10}$  exposure, there were 1.19 (95% CI:1.10–1.28), 1.05 (95%CI:1.01–1.11) and 1.07 (95%CI:1.04–1.10) times increase in the risks of overweight and obesity in children and adolescents. Table 1 also showed the results of exposures in the two cohorts.

### 2.8.2. Association between PA and overweight and obesity modified by greenness levels

No change was observed between PA and overweight and obesity when stratified by greenness levels (Table 2). Specifically, a 30-mins increase for VPA exposures was not associated with a significant increase in the risks of overweight and obesity in children and adolescents with the adjusted HR of 0.99(95%CI:0.92–1.07) in a low-level group of greenness, and the adjusted HR was 0.97(95%CI:0.88–1.06) in a high-level group of greenness. Similar



**Fig. 4.** The HR and AF of air pollutants and NDVI on overweight and obesity incidence by sex. Note: AF, attributable fraction. HR of PM<sub>x</sub> concentration on overweight and obesity risk was calculated using Cox models after adjusting confounders in the low-level group (Red dot) and the high-level group of greenness (Blue dot) by sex (subfigure A). We calculated the AF of overweight and obesity risks attributed to air pollutants in the low-level (Red bar) and the high-level group (Blue bar) of NDVI (subfigure B). HR of NDVI on overweight and obesity was calculated using Cox model after adjusting confounders in low- and high-level group of air pollutants by sex (subfigure C). AF of overweight and obesity risks attributed to NDVI in the low- and high-level of air pollutants was calculated by sex (subfigure D).

results were observed for MPA and walking, even for the total time of PA. Moreover, the RCS results did not show a significant association between the PA and overweight/obesity risks (Fig. 3), thus, we did not perform any further analysis on PA.

### 2.8.3. Association between air pollutants and overweight and obesity modified by greenness levels

Difference was witnessed between air pollutants and overweight and obesity when stratified by greenness levels (Table 2). In comparison to the high-level NDVI group, a slight greater association between air pollutant concentrations and overweight/obesity risks in the low-level NDVI group was observed. Specifically, in the national study, a 10-unit increase (10 g/m<sup>3</sup>) for PM<sub>10</sub> exposures were associated with a 17% increase in the risks of overweight and obesity in children and adolescents with the adjusted HR of 1.17 (95%CI:1.06–1.29) in the low-level group of greenness, but the adjusted HR was 1.12 (95%CI:0.97–1.29) in the high-level group of greenness. Similar results were observed for PM<sub>2.5</sub>, PM<sub>10</sub>, SO<sub>2</sub>, CO, and O<sub>3</sub>, except for NO<sub>2</sub>. For NO<sub>2</sub>, in the high-level group of greenness, there was a higher risk of overweight and obesity associated with NO<sub>2</sub> compared to the low NDVI group (adjusted HR: 1.26 vs. 1.00). However, in the dynamic cohort, a 10-unit increase (10 g/m<sup>3</sup>) for NO<sub>2</sub> exposures was associated with a 65% increase in the risks of overweight and obesity in children and adolescents with the adjusted HR of 1.65 (95%CI:1.66–1.72) in the low-level group of greenness, but the adjusted HR was 1.22 (95%CI: 1.20–1.24) in the high-level group of greenness. The results of sensitivity analysis which used the NDVI<sub>1000</sub> as the greenness assessment were shown in Table S3. The sensitivity analysis results were similar with the main analysis. The same results of the dynamic cohort were also shown in both boys and girls (Table S4).

Meanwhile, Fig. 3 (from Subfigure B to H) and Fig. 4 (Subfigure A) demonstrated the modified impacts of greenness surrounding schools on the effects of air pollution on the risk of overweight and obesity in the dynamic cohort. The following findings are based on the dynamic cohort. According to stratified analyses based on greenness, high levels of air

pollutants were associated with an elevated risk of overweight and obesity, and the effects of air pollutants were higher in the low-level NDVI group. In the low-level NDVI group, higher quantities of air pollutants were associated with an increased risk of overweight and obesity, compared to the high-level NDVI group. The HRs of the high-level group of PM<sub>1</sub> on the risk of overweight and obesity were 2.21 (2.11–2.31) and 1.87 (1.80–1.94) in the low- and high-level group of NDVI, HRs were 2.63 (2.58–2.67) and 2.34 (2.30–2.38) for PM<sub>2.5</sub>, and HRs were 1.88 (1.78–1.99) and 1.42 (1.31–1.55) for PM<sub>10</sub>. For the gaseous pollutants, the HRs of the high-level group of SO<sub>2</sub> on the overweight and obesity risk were 2.38 (2.33–2.44) and 1.89 (1.85–1.93), HRs were 1.33 (1.28–1.37) and 1.29 (1.25–1.33) for NO<sub>2</sub>, HRs were 2.43 (2.38–2.49) and 1.89 (1.85–1.93) for CO, and HRs were 1.33 (1.30–1.37) and 1.15 (1.12–1.19) for O<sub>3</sub>. The same results were also shown in both boys and girls (Table S5).

The AF of the high-level group of air pollutants was computed to examine the putative advantages of improved air pollutants in lowering the risk of overweight and obesity in the low- and high-level greenness groups (Subfigure B in Fig. 4). Reducing air pollution resulted in a potential decrease in overweight and obesity, with the theoretical advantages being higher in regions with a low level of greenness. For example, in the low-level group of NDVI, 25.58% (23.6–27.56%) of overweight and obesity event cases could be ascribed to the high-level group of PM<sub>1</sub>, and 17.82% (16.37–19.26%) to the low-level group of NDVI. In the low-level group of NDVI, 44.37% (43.44–45.30%) could be ascribed to high PM<sub>2.5</sub>, whereas in the high-level group of NDVI, 24.18% (23.23–25.14%) could be related to high PM<sub>2.5</sub>. High PM<sub>10</sub> may account for 22.96% (20.32–25.60%) in the low-level NDVI group, and 10.47% (6.85–14.09%) in the high-level NDVI group. The AFs of SO<sub>2</sub> on overweight and obesity were 29.15 (24.69–33.62) and 15.91 (14.45–17.36) in the low- and high-level NDVI groups, respectively. The NO<sub>2</sub> AFs was 11.55 (10.36–12.75) and 6.91 (5.66–8.15) in the low- and high-level NDVI groups, CO AFs was 29.5 (27.7–31.29) and 18.26 (17–19.51), and O<sub>3</sub> AFs were 10.92 (9.84–12.01) and 4.92 (3.44–6.41) in the low- and high-level NDVI groups, respectively (Table S5).

**Table 1**  
The effects of Greenness, air pollutants, and PA on overweight and obesity in children and adolescents in China.

Effects	Stratum	National survey with 1-year follow-up			Dynamic cohort with 14-year follow-up			
		HR (95%CI) of	high-and low-level groups		HR (95%CI) of	high-and low-level groups		
Greenness & Overweight/obesity	Greenness (per 0.1 unit)	0.88(0.77–0.99)	high-level (>0.24)	1	0.82(0.81–0.82)	high-level (<0.25)	1	
			low-level (<0.24)	0.66(0.56–0.78)		low-level (<0.25)	0.79(0.79–0.8)	
Physical activity & Overweight/obesity	VPA (per 30 min)	0.99(0.93–1.07)	high-level (>25.71)	1	-			
			low-level (<25.71)	1.01(0.85–1.21)				
	MPA (per 30 min)	1.01(0.94–1.08)	high-level (>25.71)	1	-			
			low-level (<25.71)	0.98(0.81–1.17)				
	Walking (per 30 min)	1.01(0.97–1.05)	high-level (>30.00)	1	-			
			low-level (<30.00)	1.02(0.86–1.21)				
	Total time (per 30 min)	1.00(0.98–1.03)	high-level (>98.57)	1	-			
			low-level (<98.57)	0.89(0.74–1.08)				
	Air pollutants & Overweight/obesity	PM <sub>1</sub> (per 10 µg/m <sup>3</sup> )	1.19(1.10–1.28)	low-level (<51.81)	1	1.56(1.54–1.58)	low-level (<25.68)	1
				high-level (>51.81)	1.24(1.05–1.46)		high-level (>25.68)	2.03(1.97–2.09)
PM <sub>2.5</sub> (per 10 µg/m <sup>3</sup> )		1.05(1.01–1.11)	low-level (<65.10)	1	1.45(1.45–1.46)	low-level (<60.00)	1	
			high-level (>65.10)	1.17(1.07–1.27)		high-level (>60.00)	2.54(2.52–2.57)	
PM <sub>10</sub> (per 10 µg/m <sup>3</sup> )		1.07(1.04–1.10)	low-level (<101.63)	1	1.17(1.16–1.18)	low-level (<83.19)	1	
			high-level (>101.63)	1.53(1.31–1.80)		high-level (>83.19)	1.22(1.19–1.26)	
SO <sub>2</sub> (per 10 µg/m <sup>3</sup> )		1.07(1.03–1.12)	low-level (<34.50)	1	1.86(1.84–1.88)	low-level (<11.34)	1	
			high-level (>34.50)	1.43(1.22–1.68)		high-level (>11.34)	2.01(1.98–2.04)	
NO <sub>2</sub> (per 10 µg/m <sup>3</sup> )		1.16(1.04–1.29)	low-level (<45.42)	1	1.43(1.42–1.45)	low-level (<41.12)	1	
			high-level (>45.42)	1.13(0.96–1.34)		high-level (>41.12)	1.36(1.33–1.39)	
CO (per 0.1 mg/m <sup>3</sup> )	1.06(1.03–1.09)	low-level (<1.19)	1	1.24(1.24–1.25)	low-level (<0.96)	1		
		high-level (>1.19)	1.32(1.12–1.55)		high-level (>0.96)	2.15(2.12–2.19)		
O <sub>3</sub> (per 10 µg/m <sup>3</sup> )	0.97(0.83–1.14)	low-level (<80.22)	1	1.14(1.13–1.15)	low-level (<93.91)	1		
		high-level (>80.22)	1.50(1.24–1.82)		high-level (>93.91)	1.27(1.25–1.29)		

Note: PA, Physical activity. VPA, vigorous-intensity physical activity; MPA, moderate-intensity physical activity; reference is the Q1.

**2.8.4. Effects of greenness on the risk of overweight and obesity modified by which components of air pollutants**

The impacts of greenness on the risk of overweight and obesity were also evaluated, as shown in Fig. 4 (Subfigure C to Subfigure D), taking into account the hazy temporal sequence of greenness and air pollutants and the components of air pollutants. For PM<sub>10</sub>, SO<sub>2</sub>, CO, the greenness showed greater effects in the high level of these pollutants, compared with the low-level. The NDVI rise was related to a reduced risk of overweight and obesity in the low-level group of air pollutants, and the NDVI exhibited lower HRs on overweight and obesity in the low-level group of air pollutants. The HRs of the high-level group of NDVI on the overweight and obesity risk was 0.87(0.84–0.90) and 0.90(0.88–0.92) in the low- and high-level group of PM<sub>1</sub>, HRs were 0.93(0.92–0.95) and 0.98(0.96–0.99) in PM<sub>2.5</sub> groups, HRs were 1.01(0.97–1.05) and 0.83(0.82–0.85) in PM<sub>10</sub> groups. In the gaseous pollutants' groups, the HRs

were 0.98(0.96–1.00) and 0.81(0.79–0.82) in SO<sub>2</sub>, HRs were 0.84(0.82–0.86) and 0.88(0.86–0.89) in NO<sub>2</sub>, HRs were 0.98(0.95–1.00) and 0.83(0.82–0.85) in CO, and HRs were 0.89(0.86–0.91) and 0.86(0.84–0.87) in O<sub>3</sub>. The same results were also shown in both boys and girls (Table S6).

Furthermore, the effects of increased greenness on the risk of overweight and obesity were not uniform across all air pollution categories. For example, in low- and high-level PM<sub>1</sub>, AFs were 4.48(0.93–8.03) and 3.47(2.04–4.90), in PM<sub>2.5</sub> groups, AFs were 1.91(–0.26–4.07) and 1.17(–0.78–3.13), and in PM<sub>10</sub> groups, AFs were –0.29(–4.23–3.66) and 5.95(4.55–7.36). Low- and high-level SO<sub>2</sub> groups had AFs of 0.53(–0.84–1.90) and 8.73(5.50–11.97), NO<sub>2</sub> groups had AFs of 4.60(2.68–6.52) and 5.35(3.61–7.08), CO groups had AFs of 0.66(–0.78–2.10) and 6.44(5.01–7.88), and O<sub>3</sub> groups had AFs of 4.01(2.28–5.74) and 5.76(3.78–7.73). The advantages of increased greenness

**Table 2**  
Association between physical activity and air pollutants and overweight/obesity risk (hazard ratio, HR, 95% CI) by greenness.

Factor	Stratum	National survey with 1-year follow-up	Dynamic cohort with 14-year follow-up	
Physical activity	VPA	Low-level group of greenness	0.99(0.92–1.07)	
		High-level group of greenness	0.97(0.88–1.06)	
	MPA	Low-level group of greenness	1.03(0.95–1.11)	
		High-level group of greenness	1.02(0.94–1.11)	
	Walking	Low-level group of greenness	1.03(0.98–1.08)	
		High-level group of greenness	1.02(0.97–1.08)	
	Total time	Low-level group of greenness	1.02(0.99–1.05)	
		High-level group of greenness	1.01(0.98–1.05)	
	PM <sub>1</sub>	Low-level group of greenness	1.17(1.06–1.29)	1.69(1.66–1.72)
		High-level group of greenness	1.12(0.97–1.29)	1.42(1.40–1.45)
PM <sub>2.5</sub>	Low-level group of greenness	1.08(1.01–1.16)	1.45(1.44–1.46)	
	High-level group of greenness	1.01(0.92–1.11)	1.44(1.44–1.45)	
PM <sub>10</sub>	Low-level group of greenness	1.05(1.01–1.10)	1.19(1.18–1.20)	
	High-level group of greenness	1.05(1.00–1.11)	1.13(1.12–1.14)	
Air pollutants	SO <sub>2</sub>	Low-level group of greenness	1.11(1.04–1.17)	
		High-level group of greenness	0.95(0.88–1.02)	
	NO <sub>2</sub>	Low-level group of greenness	1.00(0.87–1.15)	
		High-level group of greenness	1.26(1.06–1.51)	
	CO	Low-level group of greenness	1.10(1.06–1.15)	
		High-level group of greenness	0.99(0.95–1.04)	
	O <sub>3</sub>	Low-level group of greenness	1.02(0.79–1.33)	
		High-level group of greenness	0.84(0.67–1.06)	

were seen across all pollutants, albeit they varied depending on pollutant levels, particularly for boys in PM<sub>1</sub> and PM<sub>2.5</sub> (Subfigure D in Fig. 4 and Table S6).

### 3. Discussion

Using both nationwide prospective survey and longitudinal dynamic cohort, this study could be the first report to systematically examine the association between greenness, PA, air pollutants, and overweight and obesity incidence in children and adolescents, as well as the modifying effects of greenness on the effects of PA and air pollutants on overweight and obesity incidence. The effects of greenness on overweight and obesity incidence were achieved by alleviating the effects of air pollutants, rather than enhancing the effects of PA. We observed a strong association between greenness, air pollutants, and overweight and obesity, but short-term PA did not seem to play a significant role in incidence under the context of China. High greenness around schools could reduce the risks of overweight/obesity incidence by offsetting the negative effects of air pollution on overweight/obesity, and therefore benefits gained more in reducing incidence by improving air pollution in low-greenness areas. Greenness showed greater effects in lowering the impact of air pollution in heavy-industry areas where PM<sub>10</sub>, SO<sub>2</sub>, and CO are the major pollutants. Our findings were of great public health significance, supporting the urgent need for effective air pollution mitigation strategies for the reduction of incidence, and providing an effective way by increasing the greenness areas around the schools to mitigate such damage effects of air pollution.

The greater greenness was significantly associated with lower overweight and obesity incidence, which is consistent with most prior researches on the protective effect of greenness among adults and children (Bao et al., 2021; Persson et al., 2018; Pereira et al., 1966; Paul et al., 2018; Matthew et al., 2014). Besides BMI, a study on the association between greenness and obesity was reinforced by the study on waist circumference (Taren et al., 2015). However, still, a few studies reported positive or null associations (Wilhelmsen et al., 2017; Potestio et al., 2009; Lovasi et al., 2013; Lovasi et al., 2011), which were inconsistent with our current findings. These variations might contribute to the buffer of greenness exposure assessment (i.e., 500 m and 1000 m), different evaluations of greenness (i.e. NDVI and Enhanced Vegetation Index), and adjustment of covariates (i.e. gender, food intake, height, and weight). Several potential mechanisms were proposed to explain the association between greenness and overweight and obesity: encouraging physical activity and reducing the harm of air pollutants (Markevych et al., 2017). Considering our data availability, we systemically verify these two hypotheses.

The association between PA and overweight/obesity incidence was not significant in our study, moreover, the greenness does not enhance the effect of PA on incidence as expected. The possible reasons might be: 1) The non-significant association between PA and overweight/obesity limited the modification of greenness. We originally hypothesized that the greenness provided a setting for students to engage in PA, which might boost PA levels according to the previous publications (Lachowycz and Jones, 2011) (Markevych et al., 2016). However, this association was inconsistent, the negative and null relationship also existed (Pescatello et al., 2021; Kemper and Monyeki, 2019; Janssen and Leblanc, 2010; Chen et al., 2020), and our study supported the null relationship. 2) The positive impacts of greenness on PA were obscured by lacking leisure time and intense educational pressure. The high academic pressure in China drives students to spend more than 9 h per day indoor studying, which occupies leisure time for PA, as the consequence, the small amount of time spent on PA does not result in much energy expenditure (Heneberg, 2014). In addition, the low incident with 471 overweight and obesity during one-year follow-up might also be an important reason why this study did not find a relationship between PA and overweight/obesity risks. Further well-captured and accurate variables of physical activity are needed in future studies to validate our hypothesis.

The present study confirmed that the association between air pollutants and overweight/obesity incidence existed, and greenness alleviated the

effects of air pollutants on incidence. Although numerous studies have explored the association between a single or two pollutants and overweight/obesity, none have explored the association between multiple components of air pollutants and incidence systematically and comprehensively and included particulate matter (PM<sub>1</sub>, PM<sub>2.5</sub>, PM<sub>10</sub>) and gaseous pollutant (SO<sub>2</sub>, NO<sub>2</sub>, CO, O<sub>3</sub>) simultaneously. Our study validated that increased PM<sub>10</sub>, PM<sub>2.5</sub>, PM<sub>10</sub>, SO<sub>2</sub>, NO<sub>2</sub>, CO, and O<sub>3</sub> exposures were associated with a greater risk of incidence in a large sample with 1.65 million students. The biochemical mechanisms behind the influence of ambient air pollutants on childhood overweight and obesity have lately gotten a lot of attention. In animal studies, air pollutants were proven to enhance oxidative stress, adipose tissue inflammation, and hormone disruption, all of which contribute to metabolic dysfunction and obesity (Xu et al., 2011; Xu et al., 2010; Liu et al., 2014; Haberzettl et al., 2016). Air pollution exposure causes oxidative stress, which increases the development of white adipocytes, which store additional energy in the form of triglycerides, and decreases the differentiation of brown adipocytes, which release energy as heat (Xu et al., 2011; Lin et al., 2016). However, considerable uncertainty remains, and further study is required to better understand the molecular pathways. A potential mechanism for the modifying effects of greenness by alleviating the effects of air pollutants could be supported by our findings. Vegetation might efficiently absorb the air pollutants, and the capacity of removal depends on the enzymatic system specific for each vegetal species (Timm et al., 2014; Nowak et al., 2006; Chaparro and Terradas, 2009). In detail, the plants remove atmospheric PM via adsorptive effects, and remove gaseous pollutants by absorbing effects with the opening of stomata at night (Wannomai et al., 2019; Chen et al., 2017), i.e. the urban trees can remove air pollutants including PM and gaseous pollutants effectively (Pace et al., 2018; Koricho et al., 2020; Fares et al., 2016). Notably, in such an environment, where air pollution is severe as in China, the effect of greenness on lessening the negative effects of air pollution might be more effective.

More specially, greenness showed larger effects in alleviating the impact of air pollutants in high-pollution areas, especially in heavy-industry areas where PM<sub>10</sub> (over 83.19 µg/m<sup>3</sup>), SO<sub>2</sub> (over 11.34 µg/m<sup>3</sup>), and CO (over 0.96 mg/m<sup>3</sup>) are the major pollutants. Our study provided a sensible recommendation for reducing overweight/obesity incidence caused by air pollutants through improving school greenness. The intervention for schools, in which children spent most time out from home, might be more cost-efficient in reducing obesity incidence than in the community. The current findings, therefore, implied that improving greenness levels might be one of the most effective means of reducing overweight and obesity risks in similar contexts suffering from high pollution.

There were four significant strengths in the current study. Firstly, a comprehensive pollutant assessment method covered seven types of air pollutants, which increased the reliability of the results. Secondly, a large sample size from both a national prospective study with accurate measurement for PA and a longitudinal dynamic cohort with repeated BMI measurements over 14 years to determine overweight/obesity incidence. Thirdly, data were extracted from the national prospective study covering seven provinces and the longitudinal dynamic cohort from two cities with drastically varying amounts of greenness and air pollution. The varying greenness and air pollutants provided the chance of stratified analyses by greenness. Finally, the cohort data from Beijing and Zhongshan cities which closed to the census with a 14-year follow up validated the findings in the national prospective study with a one-year follow-up. Validation in a long-term dynamic cohort improved the reliability and portability of this study. Thus, we simultaneously used two data sources to confirm that the modifying effect of greenness on reducing effects of air pollution on incidence.

Several limitations should also be noted. Firstly, the greenness around schools was assessed by NDVI from the satellite data. The indicator of NDVI could not distinguish the different types of vegetation and could be sensitive to atmospheric effects, clouds, and types of soil (Markevych et al., 2014; Weier, 2000), which would overestimate its effect on overweight/obesity. Secondly, our PA assessment is based on IPAQ-SF, which



might lead to biased assessment due to inaccurate responses by children. A previous study showed that participants who were less PA were more likely to report more PA in the self-reported questionnaire than that measured by the accelerometer (Colley et al., 2018). Therefore, our non-significant association of PA and incidence might be attributed to the types and duration of PA measurement, and further research with precise PA measurement will be needed. Thirdly, the air pollutants satellite-driven might lead to exposure misclassification. However, in the large sample ecological study, satellite-driven pollutants assessment was an effective assessment of air pollutants exposure. And the modeling framework that was developed to estimate the air pollutants performed well. Additionally, the lack of follow-up for the students who transferred to another school in both two data sources. Some students transferred from other schools since entering the cohort. Thus, each student's location was assumed with an unchanged status throughout the follow-up.

#### 4. Conclusion

In conclusion, by using two prospective studies with a large sample size and new overweight/obesity determination, we confirmed that greenness did not considerably improve the health benefits of PA on reducing childhood overweight and obesity risks, but it did greatly minimize the negative impacts of air pollution on increasing childhood overweight and obesity risks. This showed that the pathway of greenness-air pollution-obesity might be the major mechanism driving the effect of greenness on childhood overweight and obesity. Moreover, the greenness showed greater effects in the areas where PM<sub>10</sub> (over 83 µg/m<sup>3</sup>), SO<sub>2</sub> (over 11 µg/m<sup>3</sup>), and CO (over 0.96 mg/m<sup>3</sup>) were the major pollutants. This study provided us with clear evidence that we were able to compensate adequately for the detrimental effect of air pollution on childhood overweight and obesity by improving the greenness near schools, particularly in high-pollution areas. Thus, such results implied that policymakers should promote greenness surrounding schools and neighborhoods. Reduced levels of air pollution might have a larger impact on schools with a low level of greenness.

#### CRedit authorship contribution statement

Dr. LC conceptualized and designed the study, completed the statistical analyses, drafted the initial manuscript, and reviewed and revised the manuscript; Prof. YS and YHD contributed to the conceptualization and design of the study, supervised the data collection, the statistical analyses and initial drafting of the manuscript, and reviewed and revised the manuscript; Dr. DG, TM, MMC, YHL, YM, BW, JJ, and XJW assisted with the statistical analyses and reviewed the manuscript. Dr. JBZ, SC, LJW, XTL, XHG, and SZH conducted the data collection, and reviewed and revised the manuscript. Dr. JW provided the data of air pollutants. All authors read and approved the final version of the manuscript.

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#### 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.

#### Appendix A. Supplementary data

Supplementary data to this article can be found online at <https://doi.org/10.1016/j.scitotenv.2022.155117>.

#### References

- Bao, W.W., et al., 2021. Greenness surrounding schools and adiposity in children and adolescents: findings from a national population-based study in China. *Environ. Res.* 192, 110289.
- Chaparro, L., Terradas, J., 2009. Report on Ecological services of urban forest in Barcelona.
- Chen, L., Lin, D.Y., Zeng, D., 2010. Attributable fraction functions for censored event times. *Biometrika* 97 (3), 713–726.
- Chen, B., et al., 2017. Effects of different plant configuration modes in urban park green spaces on p(PM<sub>2.5</sub>)reduction.
- Chen, P., et al., 2020. Physical activity and health in Chinese children and adolescents: expert consensus statement (2020). *Br. J. Sports Med.* 54 (22), 1321–1331.
- Cole, T.J., et al., 2000. Establishing a standard definition for child overweight and obesity worldwide: international survey. *BMJ* 320 (7244), 1240–1243.
- Collaboration, N.C.D.R.F., 2017. Worldwide trends in body-mass index, underweight, overweight, and obesity from 1975 to 2016: a pooled analysis of 2416 population-based measurement studies in 128.9 million children, adolescents, and adults. *Lancet* 390 (10113), 2627–2642.
- Collaborators, G.B.D.O., et al., 2017. Health effects of overweight and obesity in 195 countries over 25 years. *N. Engl. J. Med.* 377 (1), 13–27.
- Colley, R.C., et al., 2018. Comparison of self-reported and accelerometer-measured physical activity in Canadian adults. *Health Rep.* 29 (12), 3–15.
- Dong, Y., et al., 2017. National blood pressure reference for Chinese Han children and adolescents aged 7 to 17years, p. 897.
- Dong, Y., et al., 2019. Economic development and the nutritional status of Chinese school-aged children and adolescents from 1995 to 2014: an analysis of five successive national surveys. *Lancet Diabetes Endocrinol.* 7 (4), 288–299.
- Fares, S., et al., 2016. Particle deposition in a peri-urban Mediterranean forest. 218, pp. 1278–1286.
- Fong, K.C., Hart, J.E., James, P., 2018. A review of epidemiologic studies on greenness and health: updated literature through 2017. *Curr. Environ. Health Rep.* 5 (1), 77–87.
- Franchini, M., Mannucci, P.M., 2018. Mitigation of air pollution by greenness: a narrative review. *Eur. J. Intern. Med.* 55, 1–5.
- Haberzettl, P., et al., 2016. Exposure to fine particulate air pollution causes vascular insulin resistance by inducing pulmonary oxidative stress. *Environ. Health Perspect.* 124 (12), 1830–1839.
- Heneberg, P., 2014. Energy expenditure of hunter-gatherers: when statistics turns to be unreliable. *Endocr. Metab. Immune Disord. Drug Targets* 14 (2), 152–158.
- Huang, S., et al., 2020. Ambient air pollution and body weight status in adults: a systematic review and meta-analysis. 265(Pt A).
- Hwang, S.E., et al., 2019. Ambient air pollution exposure and obesity-related traits in Korean adults. 12, pp. 1365–1377.
- Institute, M., 2014. Overcoming obesity: an initial economic analysis.
- Janssen, I., Leblanc, A.G., 2010. Systematic review of the health benefits of physical activity and fitness in school-aged children and youth. *Int. J. Behav. Nutr. Phys. Act.* 7, 40.
- Kemper, H.C., Monyeki, K.D., 2019. The Amsterdam Growth and Health Longitudinal Study: how important is physical activity in youth for later health? (ELS 33). *Cardiovasc. J. Afr.* 30 (3), 138–141.
- Koricho, H.H., et al., 2020. Understanding the ecosystem services of urban forests: implications for climate change mitigation in the case of Adama City of Oromiya region state, Ethiopia.
- Lachowycz, K., Jones, A.P., 2011. Greenspace and obesity: a systematic review of the evidence. *Obes. Rev.* 12 (5), e183–e189.
- Lin, Y., et al., 2016. Inhaled SiO<sub>2</sub> nanoparticles blunt cold-exposure-induced WAT-browning and metabolism activation in white and brown adipose tissue. *Toxicol. Res. (Camb.)* 5 (4), 1106–1114.
- Liu, C., et al., 2014. Air pollution-mediated susceptibility to inflammation and insulin resistance: influence of CCR2 pathways in mice. *Environ. Health Perspect.* 122 (1), 17–26.
- Lovasi, G.S., et al., 2011. Is the environment near home and school associated with physical activity and adiposity of urban preschool children?. 88(6), pp. 1143–1157.
- Lovasi, G.S., et al., 2013. Neighborhood safety and green space as predictors of obesity among preschool children from low-income families in New York City. 57(3), pp. 189–193.
- Markevych, I., et al., 2014. A cross-sectional analysis of the effects of residential greenness on blood pressure in 10-year old children: results from the GINIplus and LISAPlus studies. *BMC Public Health* 14, 477.
- Markevych, I., et al., 2016. Neighbourhood and physical activity in German adolescents: GINIplus and LISAPlus. 147(may), pp. 284–293.
- Markevych, I., et al., 2017. Exploring pathways linking greenspace to health: theoretical and methodological guidance. *Environ. Res.* 158, 301–317.
- Matthew, et al., 2014. Food environment, walkability, and public open spaces are associated with incident development of cardio-metabolic risk factors in a biomedical cohort.
- Nowak, D.J., et al., 2006. Air pollution removal by urban trees and shrubs in the United States. 4(3–4), pp. 115–123.
- Pace, R., et al., 2018. Modeling ecosystem services for park trees: sensitivity of i-tree eco simulations to light exposure and tree species classification. 9, p. 2.
- Paul, et al., 2018. Association of residential greenness with obesity and physical activity in a US cohort of women. 160, pp. 372–384.
- Pereira, G., et al., 1966. The association between neighborhood greenness and weight status: an observational study in Perth Western Australia. 12.
- Persson, et al., 2018. Urban residential greenness and adiposity: a cohort study in Stockholm County.
- Pescatello, L.S., et al., 2021. Best practices for meta-reviews in physical activity and Health Research: insights from the physical activity guidelines for Americans advisory committee scientific report. *J. Phys. Act. Health* 1–9.
- Potestio, M.L., et al., 2009. Is there an association between spatial access to parks/green space and childhood overweight/obesity in Calgary, Canada? 6(1) p. 77–77

- Qin, X., Pan, J., 2016. The medical cost attributable to obesity and overweight in China: estimation based on longitudinal surveys. *Health Econ.* 25 (10), 1291–1311.
- Sandifer, P.A., Sutton-Grier, A., Ward, B.P.J.E.S., 2015. Exploring connections among nature, biodiversity, ecosystem services, and human health and well-being: opportunities to enhance health and biodiversity conservation. 12, pp. 1–15.
- Sbihi, H., et al., 2015. Greenness and incident childhood asthma: a 10-year follow-up in a population-based birth cohort. *Am. J. Respir. Crit. Care Med.* 192 (9), 1131–1133.
- Schalkwijk, A.A.H., et al., 2018. The impact of greenspace and condition of the neighbourhood on child overweight. *Eur. J. Public Health* 28 (1), 88–94.
- Sjolander, A., Vansteelandt, S., 2017. Doubly robust estimation of attributable fractions in survival analysis. *Stat. Methods Med. Res.* 26 (2), 948–969.
- Taren, S., et al., 2015. Green space and child weight status: does outcome measurement matter? Evidence from an Australian Longitudinal Study. 2015, pp. 1–8.
- Timm, et al., 2014. Reforestation as a novel abatement and compliance measure for ground-level ozone. 111(40), pp. 4204–4213.
- Twohig-Bennett, C., Jones, A.J.E.R., 2018. The health benefits of the great outdoors: a systematic review and meta-analysis of greenspace exposure and health outcomes. 166(OCT.), pp. 628–637.
- Wang, Y.C., et al., 2011. Health and economic burden of the projected obesity trends in the USA and the UK. *Lancet* 378 (9793), 815–825.
- Wannomai, T., et al., 2019. Removal of trimethylamine from indoor air using potted plants underlight and dark conditions.
- Wei, J., et al., 2019. Satellite-derived 1-km-resolution PM1 concentrations from 2014 to 2018 across China. *Environ. Sci. Technol.* 53 (22), 13265–13274.
- Wei, J., et al., 2020. Improved 1 km resolution PM2.5 estimates across China using enhanced space-time extremely randomized trees. *Atmos. Chem. Phys.* 20, 3273–3289.
- Wei, J., et al., 2021. Reconstructing 1-km-resolution high-quality PM2.5 data records from 2000 to 2018 in China: spatiotemporal variations and policy implications. *Remote Sens. Environ.* 252, 112136.
- Wei, J., et al., 2021. The ChinaHighPM10 dataset: generation, validation, and spatiotemporal variations. *Environ. Int.* 146, 106290.
- Wei, J., et al., 2022. Full-coverage mapping and spatiotemporal variations of ground-level ozone (O3) pollution from 2013 to 2020 across China. *Remote Sens. Environ.* 270, 112775.
- Weier, J., 2000. H.D. Measuring vegetation (NDVI & EVI). Available from <http://earthobservatory.nasa.gov/Features/MeasuringVegetation/>.
- Wilhelmsen, C.K., et al., 2017. Associations between green area in school neighbourhoods and overweight and obesity among Norwegian adolescents. 7.
- Xu, X., et al., 2010. Effect of early particulate air pollution exposure on obesity in mice: role of p47phox. *Arterioscler. Thromb. Vasc. Biol.* 30 (12), 2518–2527.
- Xu, Z., et al., 2011. Ambient particulate air pollution induces oxidative stress and alterations of mitochondria and gene expression in brown and white adipose tissues. *Part Fibre Toxicol.* 8, 20.
- Zhao, W., et al., 2008. Economic burden of obesity-related chronic diseases in mainland China. *Obes. Rev.* 9 (Suppl. 1), 62–67.
- Tree and forest effects on air quality and human health in the United States. *Environ. Pollut.* 193 (oct), 119–129.
- A review of the health benefits of greenness. *Curr. Epidemiol. Rep.* 2(2), 131–142.
- National school-based health lifestyles intervention in Chinese children and adolescents on obesity and hypertension. *Front. Pediatr.* 9, 615283.