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Spatial heterogeneity in health risks of illness-related absenteeism associated with $PM_{2.5}$ exposure for elementary students

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ABSTRACT

Little is known about the impact of socio-economic and environmental factors on the associations between $PM_{2.5}$ exposure and health risk for elementary students. We estimated the space variability of effects of $PM_{2.5}$ on daily illness-related absence rate for 2278 elementary schools from 97 counties across Jiangsu Province with data collected in the 2016-17 academic year. We evaluated the effects at school- and county-scales and examined the role of socio-economic and environmental factors with generalized addictive models (GAM). With an inter-quartile range (IQR, 32 μg/m^3) increase in $PM_{2.5}$ concentration, the relative risk of absence rate for a given school ranged between 1.00 and 2.81. Factors including high economic development level, low health expenditure, dense road network, dense population and low vegetation coverage drove strong effects for schools/counties. For the implementation of efficient clean air policies and public health interventions, we should concern about not only high-polluted areas but also areas under specific socio-economic and environmental conditions.

1. Introduction

According to the Global Burden of Disease Study 2015, fine particulate matter ($PM_{2.5}$) is the fifth-ranked risk factor for death. $PM_{2.5}$ caused approximately 4.2 million deaths worldwide, of which 1.1 million were in China (Cohen et al., 2017). Deaths related to $PM_{2.5}$ exposure were mainly due to diseases including lower respiratory tract infections, lung cancer, ischemic heart disease, cerebrovascular disease and chronic obstructive pulmonary obstruction (Cohen et al., 2017). By 2019, ambient particulate matter pollution has risen to the fourth place in the global ranking of risk factors by the total number of deaths (Murray et al., 2020).

Children are more vulnerable to $PM_{2.5}$ pollution, in view of their immature organ development, imperfect defense and immune mechanism, and insufficient protective measures and awareness, etc (World Health Organization (WHO), 2018; Gent et al., 2003). Children's exposure to $PM_{2.5}$ could lead to a series of health risks such as obesity, intellectual disability, impaired cardiopulmonary function and respiratory system damage. High-level childhood exposures to $PM_{2.5}$ are associated with lifelong health consequences (World Health Organization (WHO), 2018).

Studies estimating the impacts of air pollution exposure in school children confirmed the positive associations between exposure to air pollutants and illness-related absence and the impact of $PM_{2.5}$ was the most consistent across studies (Watanabe et al., 2021; Mendoza et al., 2020; Adar et al., 2015). Even low levels of $PM_{2.5}$ exposure can increase the risk of illness-related school absence (Mendoza et al., 2020; Adar et al., 2015), and the health risk varied among regions with different socioeconomic characteristics, requiring exploration at finer spatial scales (Mendoza et al., 2020). With records of absenteeism due to illness, comprehensive risk assessments of extensive health damage and ancillary social effects caused by air pollution on children can be taken (Ransom and Pope, 1992). However, relevant evidence was mainly collected from developed countries (Mendoza et al., 2020; Ransom and Pope, 1992; Park et al., 2002; Rondeau et al., 2005). Limited studies conducted in developing countries ignored the confounding effects of

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regional socio-economic and environmental factors (Chen et al., 2018; Liu and Salvo, 2018; Zhang et al., 2018), which could lead to biases in risk assessment. Additionally, current studies focused on the time series analysis of the relationship between pollution exposure and illness-related absence, ignoring the potential spatial differences in the exposure-response process. With the same 10 μg/m^3 increase in $PM_{2.5}$ concentration, related average public death toll in China, Europe, and the United States increased by 0.54%, 1.23%, and 0.98%, respectively (Akyuz et al., 2020; Yang et al., 2012; Chen et al., 2011). Consistent evidence exists that the socioeconomic and environmental factors are associated with the spatial differences in public health responses to $PM_{2.5}$ exposure (Akyuz et al., 2020). Therefore, it is necessary to pay attention to the spatial heterogeneity in illness-related school absenteeism associated with $PM_{2.5}$ exposure for primary students and explore the potential causes.

Thus, we collected daily illness-related absence records from 2278 elementary schools across 97 counties in Jiangsu Province and estimated the association between daily absence rate and $PM_{2.5}$ exposure. Our objective was to explore the spatial distribution of comprehensive illness-related absence risks associated with $PM_{2.5}$ exposure for elementary students and examine the influence of socio-economic and environmental variables on the distribution. Our results are expected to provide insights into the identification and governance of potential high-risk areas.

2. Methods and materials

2.1. Location and participants

Jiangsu Province located on the east coast of mainland China. It is one of the major Chinese economic hubs with a dense population. The industrialization and economic development levels are relatively developed in Jiangsu but notably different among cities and even among counties. $PM_{2.5}$ pollution has long been a severe environmental problem in Jiangsu. The influence of socioeconomic and other environmental factor on the health impacts of $PM_{2.5}$, however, was barely studied. The annual growth number of elementary students in Jiangsu has been ranking first in the country in the past ten years (http://tj.jiangsu.gov.cn/). Considering the vulnerability of school-age children, our study planned to focus on the relationship between $PM_{2.5}$ exposure of elementary students in Jiangsu Province and their school absence due to illnesses.

2.2. Data source and variables

We collected absenteeism records from the student health monitoring system of the Jiangsu Provincial Center for Disease Control and Prevention (JS CDC). The dataset included location information (city, district, school) about where the absence happened and the date and reasons (sick leave or not) of an absence. We eliminated records that were not illness-related, such as those caused by physical injuries. We also deleted records when there were >20 students from the same class requesting a leave simultaneously in that some of them may just try not to be infected. If a student asks for sick leave for multiple consecutive days, there was only one record in the health monitoring system when the first day of absence took place. Data of schools where student population statistics could not be identified were excluded as well. We identified 693,081 illness-related absence records from 2278 elementary schools, 97 counties across Jiangsu Province during the 2016-17 academic year (September 2016–June 2017) and calculated daily absence rates at the school level based on these data.

We extracted $PM_{2.5}$ concentrations of each school from the China-HighAirPollutants (CHAP) dataset developed by Wei et al. (2013–2020) (Wei et al., 2021). The daily $PM_{2.5}$ concentrations at a high resolution of 1-km were predicted from the Moderate Resolution Imaging Spectroradiometer (MODIS) Multi-Angle implementation of Atmospheric Correction (MAIAC) aerosol products using artificial intelligence (Wei et al., 2020, 2021). The missing concentration data was replaced by the interpolated values generated based on measurements from a routine monitoring network. Daily relative humidity and temperature data of 22 monitoring stations in Jiangsu were obtained from the National Meteorological Data Center. We retrieved the meteorology estimates of each school with ordinary Kriging interpolation.

We collected socio-economic factors at the county level, including Gross Domestic Product (GDP), disposable income per capita, health expenditure, energy and environmental expenditure. We also gathered demographic variables of 1-km resolution, including Normalized Difference Vegetation Index (NDVI), population density and road density. The socio-economic data came from the Statistical Bulletin of National Economic and Social Development and the Jiangsu Provincial Bureau of Statistics (http://tj.jiangsu.gov.cn/). Density information of the road network was extracted from the OpenStreetMap (https://www.openstreetmap.org/). Population density were from Socioeconomic Data and Applications Center in the National Aeronautics and Space Administration's Earth Observing System Data and Information System (https://sedac.ciesin.columbia.edu/data/sets/browse). NDVI information was extracted from the MODIS (https://ladsweb.nascom.nasa.gov).

2.3. Statistic analysis

We first examined the spatial distribution and aggregation characteristics of absenteeism rate, $PM_{2.5}$ exposure and socio-economic factors. Moran's I and the High/Low Clustering analysis were used for global spatial autocorrelation test, and hotspot analysis based on Getis-Ord Gi* statistic was conducted for cluster analysis. Among them, Moran's I was applied to determine whether there were spatial differences in attribute values; the High/Low Clustering analysis was used to quantify the intensity of high or low value spatial clustering for the study area. Local spatial autocorrelation analysis was performed through hotspot analysis to further identify locations of statistically significant hot spots and cold spots.

The association between $PM_{2.5}$ exposure and illness-related school absence was further estimated with generalized additive model (GAM). The over-dispersed Poisson distribution was used to reflect the daily illness-related absenteeism rate because the daily absence rates were pretty low (Putila and Guo, 2011). We applied LOESS local smoothing function to allow for the undetected spatial influential factor(s) (Chen et al., 2015).

In the basic model, we controlled for the current day's relative humidity (RH) and temperature with 3 degrees of freedom (df) for both variables via a natural cubic spline. A dichotomous variable indicating whether the day is the first day after a public holiday was included to illustrate the holiday effect. We estimated the relative risk (RR) to represent the additional risk of illness-related absenteeism related to an IQR increase in $PM_{2.5}$ concentration and calculated its 95% confidence interval (95% CI). The basic equation is as follows:

$$Ln(Absence.rate) = \beta_1 PM_{2.5} + \beta_2 Holiday + ns(Temp, df = 3) + ns(RH, df = 3) + s(longitude, latitude) + e_{error} \tag{1}$$

$$RR = \exp(IQR * (Estimate \pm 1.96 * SE)) \tag{2}$$

In equation (1), Absence. rate was daily illness-related absence rate of a given school on that day; $PM_{2.5}$ was the corresponding daily $PM_{2.5}$ concentration; Holiday was used to indicate if this was the first day following a public holiday; Temp and RH were the daily averages of temperature and relative humidity; s() represented the LOESS function with longitude and latitude being the paired spatial coordinate; ns was natural cubic spline and df was the degree of freedom; e_{error} represented the error term. In equation (2), RR was the relative risk of illness-related absence; IQR was the interquartile range of $PM_{2.5}$ concentration in Jiangsu Province during the study period; Estimate was β_1 extracted from equation (1); SE was standard error.

We checked the multicollinearity among socio-economic and environmental factors by calculating the condition index through the Kappa function and detected very weak multicollinearity. We then added these factors into the basic model to detect their confounding effects. Separate models were created across various spatial scales, including region-, county- and school-levels, to screen high-risk areas and identify their common spatial features. We further conducted subgroup analyses by stratifying the socio-economic and environmental variables. We estimated the RR separately in areas where the level of a given socio-economic or environmental condition was higher than its 90th (or 75th) percentile or lower than its 10th (or 25th) percentile (top and bottom 10% or 25%).

3. Results

3.1. Absenteeism distribution and socio-economic status

The cumulative number of absence days for elementary students in southern Jiangsu (Suzhou, Wuxi, Changzhou, Nanjing, Zhenjiang) was much higher than that in central and northern Jiangsu. The average illness-related daily absence rate of elementary schools in Nantong, central Jiangsu 0.526% [standard deviation, SD, 0.453%] was the highest, followed by that 0.391% [0.519%] of students in Nanjing, southern Jiangsu. The highest level of $PM_{2.5}$ pollution during the study period occurred in Xuzhou, northern Jiangsu, with 60.97[6.38] μg/m^3 (Fig. 1). The spatial difference of $PM_{2.5}$ concentration in other regions was less obvious.

As shown in Figs. S1 and S2, the GDP, disposable income per capita, energy and environmental expenditure, population density and road density in southern Jiangsu were higher than those in central and northern Jiangsu overall. In contrast, the NDVI in central and northern Jiangsu was higher than that in the south.

3.2. Spatial autocorrelation

Moran I's index estimation and High/Low Clustering analysis were applied to test global spatial autocorrelation. We found that, except for energy and environmental expenditure and health expenditure, the rest demographic variables exhibited significant positive spatial autocorrelation. The rest demographic variables also clustered with high values at the global level with Z-score exceeding 1.96 and p-value lower than 0.05 from both analyses (Table S1, Fig. 2). Hot spot analysis was then applied to test local spatial autocorrelation. Hot spots of absence rate distributed in Nanjing (southern Jiangsu), Nantong (central Jiangsu), Yangzhou (central Jiangsu) and Huai'an (northern Jiangsu). Hot spots of GDP, disposable income per capita and population density were mainly in southern Jiangsu, especially in Nanjing, Suzhou and Wuxi. Hot spots of NDVI scattered in northern Jiangsu and central Jiangsu while cold spots mainly distributed in southern Jiangsu. For $PM_{2.5}$ concentration, the hot spots concentrated in northern Jiangsu and the junction of Taizhou (central Jiangsu), Changzhou (southern Jiangsu), Wuxi (southern Jiangsu) and Zhenjiang (southern Jiangsu).

3.3. $PM_{2.5}$ and illness-related absenteeism

With the basic model, we found that the overall impact of $PM_{2.5}$ pollution on illness-related absence was robust with RR being 1.035 (95% CI: 1.025-1.044). After controlling for the county- and school-level demographic variables, the RR increased to 1.045 (95% CI: 1.036-1054). Elementary students in southern Jiangsu suffered the most from $PM_{2.5}$ pollution with a relative risk of 1.059 (95% CI: 1.049-1.069) while the risk disappeared in northern Jiangsu (Table 1).

To explore the spatial distribution of the health risks, we constructed exposure-response models for each of the 97 counties and 2278 school (Fig. 3). The significant positive impacts of $PM_{2.5}$ on illness-related absenteeism were detected in a total of 23 (23.711%) counties, with

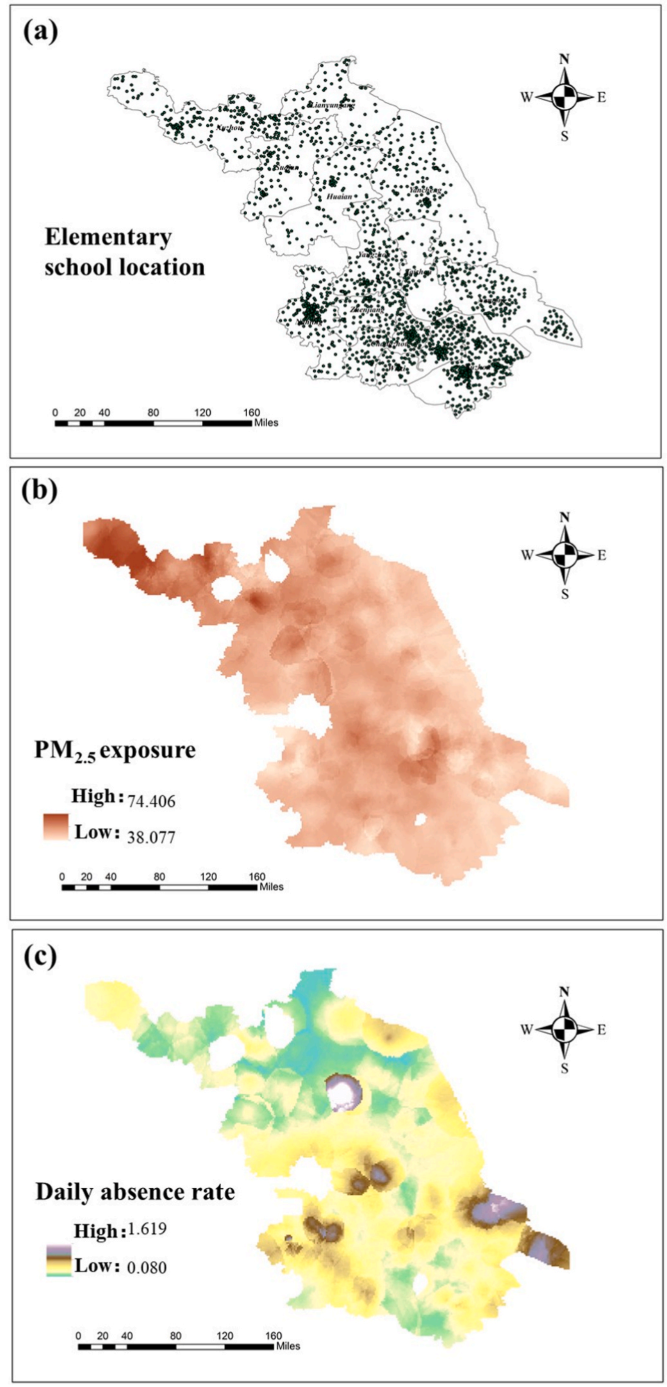


Fig. 1. The location of elementary schools in Jiangsu Province, the spatial difference of $PM_{2.5}$ pollution (μg/m^3) and school absence (%) due to illness during the 2016-17 academic year.

relative risk ranging between 1.053 and 1.180 (Mean 1.093, SD 0.030). These counties were concentrated in southern Jiangsu, especially in Suzhou City, while only four counties (Haizhou, Tongshan, Haimen and Guangling) located in northern Jiangsu and central Jiangsu. At the school level, we detected a total of 307 (13.477%) elementary schools in the province where illness-related absenteeism was remarkably related to $PM_{2.5}$ exposure. The range of relative risks at school level was 1.000-2.814 (mean 1.273, SD 0.222). The overall health risk was higher than those at county levels. The proportion of significantly and adversely affected elementary schools in southern Jiangsu also reached 18.33%, far exceeding that in northern (8.38%) and central Jiangsu (9.11%)

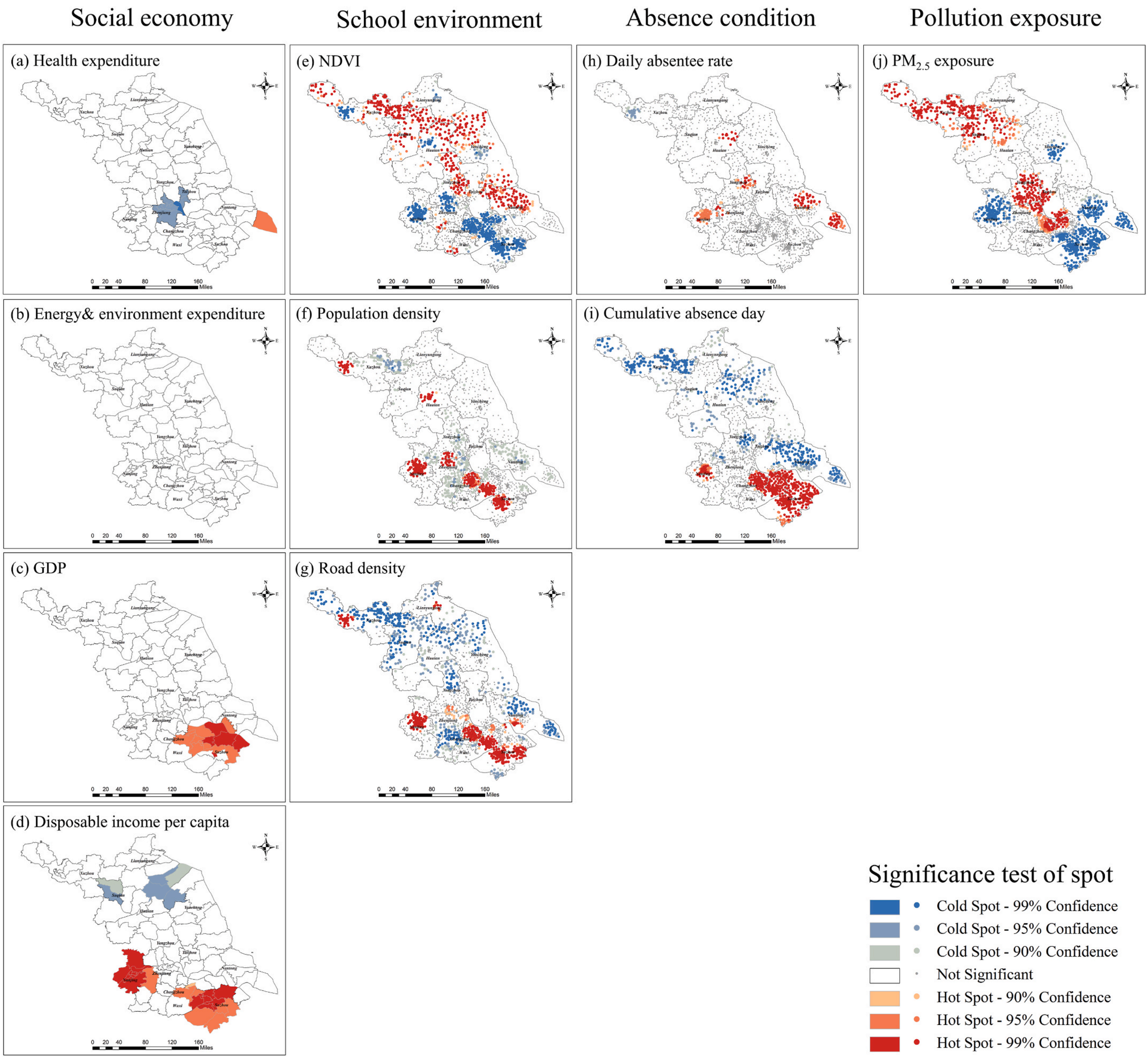


Fig. 2. Hot spot analysis of demographic variables and $PM_{2.5}$ concentrations during the 2016–17 academic year in Jiangsu province. * Red dots represent areas where high values are clustered, and cold dots represent areas where low values are clustered. (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

(Table S2).

3.4. Potential socio-economic and environmental impacts

Furthermore, to characterize areas with higher risks, we performed subgroup analysis based on the top/bottom 10% and 25% data stratified according to certain social-economic and environmental factor in turn (Fig. 4). The analyses proved that students in areas with higher GDP and disposable income per capita suffered more from $PM_{2.5}$ exposure. The illness-related absence risk associated with $PM_{2.5}$ for students in area with the top 10% GDP was higher than that of students in areas with the top 25% GDP, while the risk was insignificant for students in area with GDP of the bottom 10% and 25%. It was worth noting that though students in areas of the top 10% or top 25% of energy and environmental expenditure levels bore higher health risks (Fig. 4), increasing energy and environmental expenditures was able to reduce the risk of illness-related absenteeism overall across Jiangsu Province (Table 1). Risk of illness-related absenteeism were also robust in areas with denser population and road but insignificant vice versa. In contrast, students in areas with lower local medical expenditure and lower NDVI levels were more susceptible to $PM_{2.5}$ pollution. For medical expenditure, students in areas with lower health care spending tended to have a higher risk of illness-related absenteeism.

4. Discussion

Using ~0.7 million illness-related records obtained from 2278 elementary schools, this work explored the characteristics of areas where elementary students bore high health risks of illness-related absence due to $PM_{2.5}$ exposure. Risk of illness-related school

Table 1
Relative risk (RR) of illness-related school absenteeism rate associated with $PM_{2.5}$ with and without the control of socio-economic and environmental factors.

	JS [a]	JS-with control [b]	Northern JS [c]	Central JS	Southern JS
RR (95% CI [d])	1.035 (1.025,1.044)	1.045 (1.036,1.054)	0.997 (0.978,1.016)	1.028 (1.006,1.050)	1.059 (1.049,1.069)
$PM_{2.5}$	0.001*** (0.000)	0.001*** (0.000)	0.000 (0.000)	0.001* (0.000)	0.002*** (0.000)
Temperature, df = 1	−0.145*** (0.022)	−0.186*** (0.020)	−0.313*** (0.044)	−0.116* (0.045)	−0.217*** (0.020)
Temperature, df = 2	0.111 (0.070)	−0.083 (0.063)	0.238 (0.123)	−0.258* (0.117)	−0.247*** (0.056)
Temperature, df = 3	−0.518*** (0.025)	−0.551*** (0.026)	−0.175*** (0.052)	−0.473*** (0.058)	−0.625*** (0.026)
RH, df = 1	−0.115*** (0.021)	−0.167*** (0.021)	0.091 (0.050)	−0.261*** (0.038)	−0.118*** (0.017)
RH, df = 2	−0.237 (0.092)	−0.307** (0.092)	0.541** (0.207)	−0.347** (0.122)	−0.295*** (0.067)
RH, df = 3	−0.068** (0.021)	−0.079** (0.021)	0.053 (0.057)	−0.022 (0.038)	−0.054** (0.018)
Public holiday	0.292*** (0.008)	0.283*** (0.008)	0.183*** (0.021)	0.201*** (0.021)	0.313*** (0.009)
GDP		0.000*** (0.000)	0.002*** (0.000)	0.002*** (0.000)	0.000*** (0.000)
Disposable income per capita		0.000** (0.000)	−0.000* (0.000)	−0.000*** (0.000)	−0.000*** (0.000)
Energy & Environment expenditure		−0.005** (0.002)	−0.575*** (0.027)	0.000 (0.013)	−0.028*** (0.003)
Health expenditure		−0.052*** (0.003)	−0.027*** (0.008)	−0.236*** (0.024)	−0.007 (0.004)
Population density		0.000*** (0.000)	−0.000*** (0.000)	−0.000 (0.000)	0.000 (0.000)
NDVI		1.261*** (0.059)	1.765*** (0.131)	2.380*** (0.184)	0.223** (0.076)
Road density		0.000* (0.000)	−0.000*** (0.000)	−0.000*** (0.000)	0.000*** (0.000)

*$p < 0.05$, **$p < 0.01$, ***$p < 0.001$.
[a] JS, global model for Jiangsu Province, basic model, controlling for temperature, RH, and a binary indicator indicating if it was the first day after holiday.
[b] JS-with control, global model for Jiangsu Province, based on the basic model, further controlling for socio-economic and environmental factors.
[c] Northern/Central/Southern JS, global model for different parts of Jiangsu Province, with control for socio-economic and environmental factors.
[d] 95%CI is the upper and lower limit of the 95% confidence interval of the RR.

absenteeism associated with $PM_{2.5}$ exposure was significant in Jiangsu Province overall while differences in risks were also obvious among counties/schools. With exposure-response models stratified according to socio-economic and environmental conditions, we found shared characteristics of surrounding environment and socioeconomics in areas with high risks.

We confirmed the risk of illness-related absenteeism associated with $PM_{2.5}$ exposure for elementary students in Jiangsu Province, eastern China. Consistent with research constructed in southern China (Chen et al., 2018) and northern China (Liu and Salvo, 2018), about 13.477% of primary schools and 23.711% of counties in Jiangsu province suffered from the risk of illness-related absence associated with $PM_{2.5}$ exposure. The overall relative risk was 1.035 across the province with each IQR increase (32 $\mu g/m^3$) in $PM_{2.5}$ concentration. A study conducted in Washington found that after converting to ultra-low sulfur diesel, a drop of 10 $\mu g/m^3$ in $PM_{2.5}$ concentration was associated with a reduction of 8% in school children's absenteeism (Adar et al., 2015). In Utah, per 1 $\mu g/m^3$ increase in $PM_{2.5}$ exposure was also detected to be associated with an absence rate ratio of as high as 1.02[6]. Compared with our study, we found that the impact of $PM_{2.5}$ exposure on the illness-related absence of children in the US was higher than that in China. Liu et al. revealed that the sensitivity of elementary students from America, Canada and Europe to $PM_{2.5}$ was higher than that of students from China (Liu and Salvo, 2018). It was speculated that children in China could have formed long-term adaptation because of frequent and severe air pollution exposure. Parents' low tolerance for children's school absence may also mask part of illness-related absenteeism risks in China (Liu and Salvo, 2018).

Spatial heterogeneity of absence risk resulting from $PM_{2.5}$ exposure was also explicit in Jiangsu Province. The higher accumulative absenteeism rate was mainly distributed in southern Jiangsu, where students also suffered from higher illness-related absenteeism risks related to $PM_{2.5}$ exposure when compared with students in central and northern Jiangsu. Distribution of factors such as GDP, disposable income per capita, energy and environmental expenditure, road density and population density were similar, displaying high-high clustering in southern Jiangsu. In comparison, $PM_{2.5}$ concentration, together with NDVI, was obviously higher in central and northern Jiangsu than in southern Jiangsu. We noticed that the overall relative risk of illness-related absenteeism increased to 1.045 (95% CI: 1.036-1.054) across Jiangsu Province when controlling the socio-economic and environmental variables. The spatial differences of socio-economic and environmental factors may as well be responsible for the different risks in various areas.

Some studies conducted in developed countries listed evidence of more adverse health influence of air pollution on people in areas of less unfavorable socio-economic conditions (Meng et al., 2012; Green et al., 2004; O'Connor et al., 2008), but the result in our study was the opposite. Studies conducted in the United States reported that schools with more students from low-income families or in low socio-economic areas tended to have higher illness-related absenteeism rates (Meng et al., 2012; Simons et al., 2010). However, in our study, students in areas with higher levels of economic development suffered a higher risk of illness-related school absence due to $PM_{2.5}$ exposure, and such risks disappeared in areas with lower socio-economic development levels (RR < 1). A study conducted in China showed that high levels of socio-economic development, urbanization and air pollution might jointly lead to an increased risk for children suffering from asthma, rhinitis, and respiratory symptoms (Norbäck et al., 2018). Again, we speculated that the long-term adaptability of children in heavier

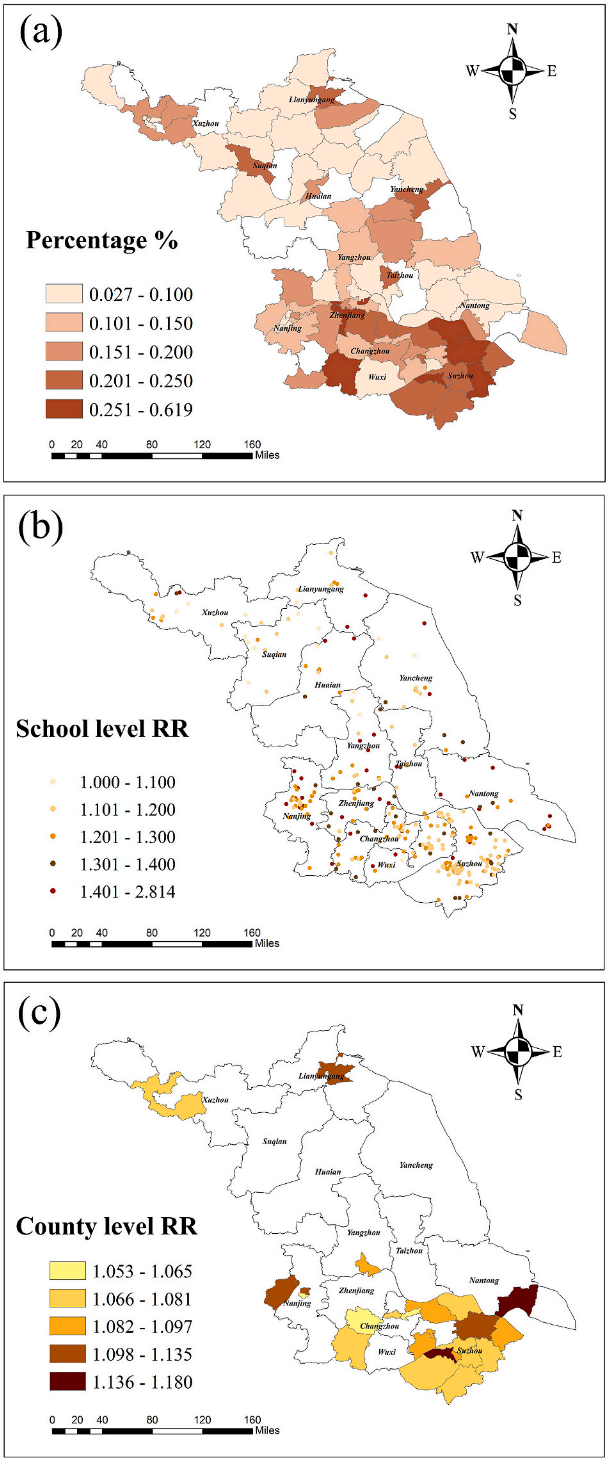


Fig. 3. Schools and counties with significant risks of illness-related school absenteeism rate associated with $PM_{2.5}$. (a) Proportion of significantly influenced schools in each county; (b) relative risk distribution of significantly influenced schools; (c) relative risk distribution of significantly influenced counties.

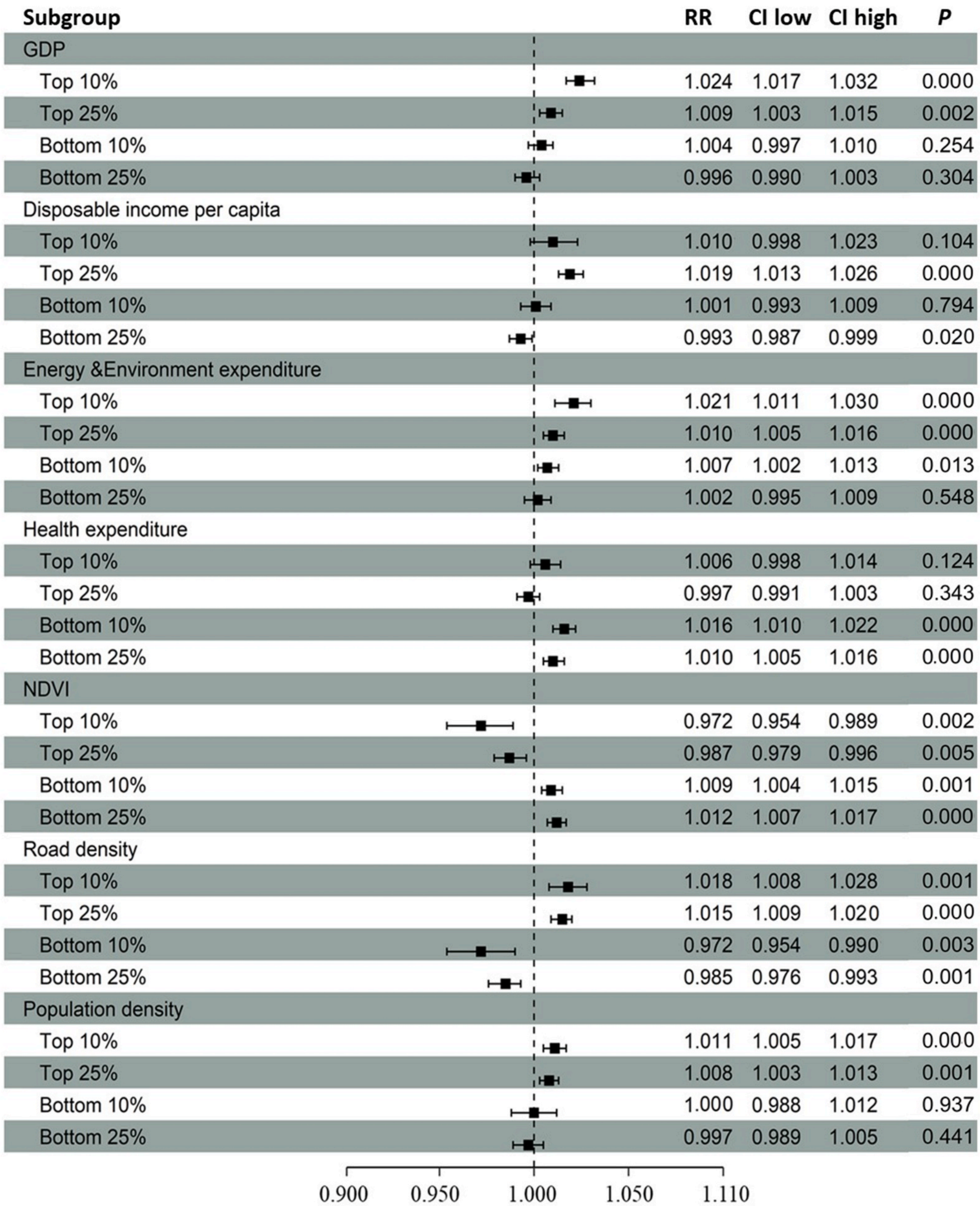
polluted areas and the higher tolerance of parents in economically developed areas for children's absenteeism may also be the underlying explanations (Liu and Salvo, 2018). A cross-sectional survey covering ten cities in China indicated that socio-economic level might be related to more rhinitis and confirmed asthma, yet further investigation is needed (Zhang et al., 2013).

Road density also has proven effects on the health risks related to $PM_{2.5}$ exposure. Schools around major roads faced great threats of traffic-related pollutants potentially causing damages to children's health (Meng et al., 2012). On one side, particulate matter from vehicle exhaust may contain more hazardous components such as heavy metals; on the other, risk associated with $PM_{2.5}$ may increase due to synergistic effects of $PM_{2.5}$ and other vehicle emissions (Lv et al., 2019; Gupta, 2020). Adoption to clean fuel used in school buses was able to lower the absenteeism especially for those with asthma (Adar et al., 2015). A study covering seven cities in China indicated that both high levels of economic development and proximity to major roads were associated with more frequent asthma, rhinitis and dry cough for children (Norbäck et al., 2018). In contrast, studies in the US found the contribution of sound socio-economic conditions to the decreased air pollution related health effects (Green et al., 2004). One possible explanation could be that, the road density around schools was higher in areas with stronger economies in China (Zhang et al., 2015), leading to more traffic-related air pollution exposure for school-age children in these areas; whereas, schools with higher proportion of students participating in free and reduced-price meal programs were more likely to located near busy roads in the US (Green et al., 2004).

Neighborhood environmental differences among schools, such as NDVI, is an important factor affecting the exposure-response relationship related to $PM_{2.5}$. The absenteeism risk brought about by $PM_{2.5}$ existed only in areas with low NDVI and the risk was robust. Green space, especially tree coverage, was deemed to mitigate $PM_{2.5}$ pollution at the neighborhood scale (Dadvand et al., 2012). The personal $PM_{2.5}$ exposure levels in sites with high NDVI could therefore be lower than measurements from routine monitoring stations or concentrations estimated based on MODIS. Evidence from Barcelona emphasized that increasing green vegetation coverage around elementary schools alleviated air pollution exposures for school children (Dadvand et al., 2015). The relatively higher NDVI in northern Jiangsu partly explained the lower risk of illness-related absenteeism there. However, it should be vigilant that there was a positive association between NDVI and illness-related absenteeism overall. Whether NDVI places positive or negative influence on health effects is conditional upon other restrictions including the type of vegetation (Lovasi et al., 2013; Gernes et al., 2019; Dadvand et al., 2014; Fuertes et al., 2016). The government should be cautious on evaluating the benefits of enhancing the vegetation coverage of green spaces surrounded by schools.

Additionally, the positive role of government public financial expenditures should be affirmed (Yip et al., 2019). Pupils in areas with lower health expenditures had higher risks of absenteeism related to $PM_{2.5}$ exposure overall. Therefore, low-income families in areas with low medical expenditures might avoid the extra expenses of taking time off to go to the hospital, which led to the underestimation of absence risks. The government needs to increase health expenditures to help school children receive equal access to higher-quality health services. Increasing regional energy and environmental protection expenditures also reduced the adverse effects of $PM_{2.5}$ pollution for elementary children. Considering the clean air policy promoted by the Chinese government in the past ten years, increasing energy and environmental protection expenditures is helpful to control $PM_{2.5}$ pollution, thereby reducing the exposure risk of all citizens, especially school children (Xiao et al., 2020).

This is the first research assessing the county-, and even school-level differences of the illness-related absenteeism risk associated with $PM_{2.5}$ exposure. With risk estimation for 2278 schools from 97 counties in Jiangsu Province, we found that the health risk from $PM_{2.5}$ was robust for students in about 13.5% of primary schools and 23.7% of counties. The relative risk of illness-related absenteeism associated with an increase of IQR (32 μg/m^3) in $PM_{2.5}$ concentration ranged from 1.00 to 2.81. After detecting the high-risk areas, we further characterized the socio-economic and environmental conditions of these areas. We found that GDP, disposable income per capita, health expenditures, road and population density and NDVI are significantly and positively associated



Subgroup	RR	CI low	CI high	P
GDP				
Top 10%	1.024	1.017	1.032	0.000
Top 25%	1.009	1.003	1.015	0.002
Bottom 10%	1.004	0.997	1.010	0.254
Bottom 25%	0.996	0.990	1.003	0.304
Disposable income per capita				
Top 10%	1.010	0.998	1.023	0.104
Top 25%	1.019	1.013	1.026	0.000
Bottom 10%	1.001	0.993	1.009	0.794
Bottom 25%	0.993	0.987	0.999	0.020
Energy &Environment expenditure				
Top 10%	1.021	1.011	1.030	0.000
Top 25%	1.010	1.005	1.016	0.000
Bottom 10%	1.007	1.002	1.013	0.013
Bottom 25%	1.002	0.995	1.009	0.548
Health expenditure				
Top 10%	1.006	0.998	1.014	0.124
Top 25%	0.997	0.991	1.003	0.343
Bottom 10%	1.016	1.010	1.022	0.000
Bottom 25%	1.010	1.005	1.016	0.000
NDVI				
Top 10%	0.972	0.954	0.989	0.002
Top 25%	0.987	0.979	0.996	0.005
Bottom 10%	1.009	1.004	1.015	0.001
Bottom 25%	1.012	1.007	1.017	0.000
Road density				
Top 10%	1.018	1.008	1.028	0.001
Top 25%	1.015	1.009	1.020	0.000
Bottom 10%	0.972	0.954	0.990	0.003
Bottom 25%	0.985	0.976	0.993	0.001
Population density				
Top 10%	1.011	1.005	1.017	0.000
Top 25%	1.008	1.003	1.013	0.001
Bottom 10%	1.000	0.988	1.012	0.937
Bottom 25%	0.997	0.989	1.005	0.441

Fig. 4. Relative risk of illness-related school absenteeism rate associated with $PM_{2.5}$ for elementary schools grouped according to socio-economic and environmental factors.
* Top or bottom 10% (25%), schools locating in areas where the level of a given socio-economic or environmental factor was higher than its 90th (or 75th) percentile or lower than its 10th (or 25th) percentile. CI low/high represented 95% CI.

with the illness-related absenteeism risk associated with $PM_{2.5}$.

This study had several advantages. We explored the $PM_{2.5}$-related health impacts with up to ~0.7 million illness-related school absence records, a large sample size representative enough to display the exposure-response relationship. In addition, this study made use of the modeled $PM_{2.5}$ concentration data with a high spatial resolution of 1-km, allowing us to improve the accuracy of exposure assessment. Finally, as far as we know, this is the first study exploring the spatial heterogeneity of $PM_{2.5}$-related health threats in school-aged children in countries with severe air pollution problems like China. Limitations also existed. Firstly, with data of only one year, we were not able to conduct time series analyses to explore the moderating effects of socio-economic and environmental factors on illness-related absenteeism risk associated with $PM_{2.5}$ exposure as time went by. Secondly, the socio-economic data are collected from yearbook of a city or county. Systematic differences could exist between areas in data processing before data collection. Thirdly, with no high-resolution data of other air pollutants, the interaction effects between pollutants were not considered. Finally, here we only consider the spatial change in PM2.5 concentrations, which may not be able to fully explain the PM2.5-related health effects. We would dig into the impact of PM2.5 component in future studies.

The study verifies that $PM_{2.5}$ exposure poses widespread risks of illness-related absenteeism to elementary students and the risks vary on school- and county-levels. Students in areas with higher levels of economic development, denser road network and lower green space coverage may have higher risks. To deal with health risks related to $PM_{2.5}$ exposure, the government may need to focus on not only areas with high pollution, but also areas with specific socio-economic and environmental characteristics. In addition, public financial expenditure and school site selection are effective interventions regarding alleviation of health impacts of $PM_{2.5}$ on elementary students. This provides evidence for identifying areas where students suffer from higher risks by spatial characteristic indicators and the governments' intervention measures should focus on.

CRediT author statement

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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.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.envres.2022.113473.

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