

Electronic Supplementary Material

Recognition of children's movement patterns during recess for characterizing particle exposure doses

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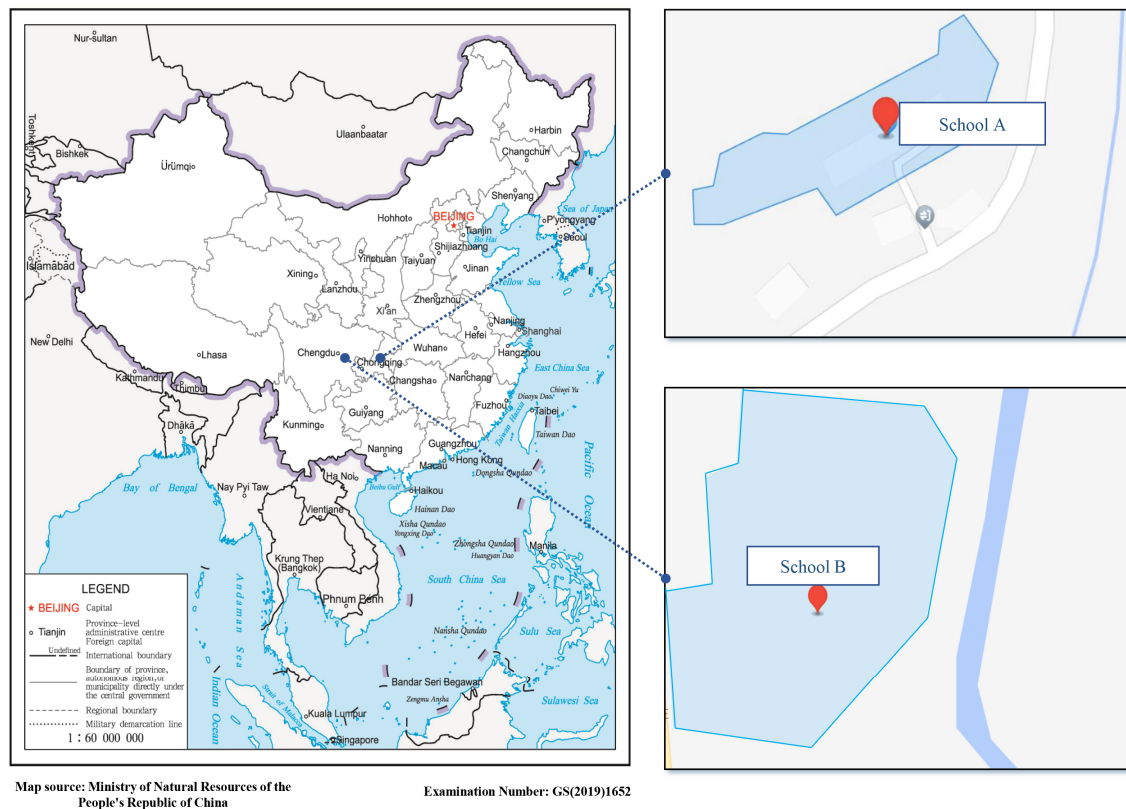


Fig. A1 Location of schools

Table A1 Characteristics for the participant classrooms

School Name	Location	Classroom area(m ²)	Window and door area(m ²)	Year	Number of students	Occupancy density (m ² /person)	Layout	
							number of rows	number of columns
School A	rural area	49.17	13.64	Year 2	20	2.46	4	5
				Year 3	12	4.10	4	3
				Year 6	36	1.37	6	6
School B	urban area	49.02	18.24	Year 1	42	1.17	6	7
				Year 4	42	1.17	6	7
				Year 5	42	1.17	6	7

Text A1

Linear regression models were required to minimize this measurement error among BLATN monitors (Kumar et al., 2024, 2023). The linear regression models were developed as the below equation:

$$PM_{2.5(SDS029)} = m \times PM_{2.5(BLATN)} + c \quad (A1)$$

Where PM_{2.5} (SDS029) and PM_{2.5} (BLATN) are the PM_{2.5} concentrations monitored by high-end instrument and portable PM_{2.5} monitors, m and c are the slope and intercepts, respectively, of the linear regression model (see Table A2). After applying the coefficients of linear regression models, the monitored data using portable PM_{2.5} monitors were compared with the high-end instrument. The measurement errors of our PM_{2.5} monitors were reduced to 3% of the measurement concentrations compared with high-end equipment. Finally, the developed linear regression models were used to improve the quality of monitored PM_{2.5} data during the experimental campaign.

Table A2 Summary of coefficients of linear regression for monitored PM_{2.5} during colocation study

Instrument Number	Slope (<i>m</i>)	Intercept (<i>c</i>)
<i>BLATN</i> 1	0.779	7.358
<i>BLATN</i> 2	0.722	4.573
<i>BLATN</i> 3	0.782	5.100
<i>BLATN</i> 4	0.691	5.140
<i>BLATN</i> 5	0.713	2.037
<i>BLATN</i> 6	0.662	2.996

Table A3 Internal and distortion parameters of the camera

Type of parameters	Name	Value
Radial distortion	k_1	-0.367
	k_2	0.159
	k_3	-0.037
Tangential distortion	p_1	-0.000493
	p_2	-0.000867
Internal reference matrix	f_x	378
	f_y	433
	u_0	367
	v_0	247

Text A2

Based on the similar triangles in the schematic diagram, the formula can be obtained from the variables on the left and right sides of the pinhole plane:

$$\frac{\tan \alpha}{\tan \beta} = \frac{\frac{P_p}{2f}}{\frac{B_p}{2f}} = \frac{P_p}{B_p} \quad (\text{A2})$$

$$\tan \beta = \frac{\frac{1}{2}R}{Z} \quad (\text{A3})$$

From the above two equations, we can derive:

$$Z = \frac{\frac{1}{2}R \cdot P_p}{B_p \cdot \tan \alpha} \quad (\text{A4})$$

Where α is 1/2 of the Vertical Field of View (VFOV), which can be calculated from the focal length and the height of the sensor:

$$VFOV = 2\arctan\left(\frac{H}{2f}\right) \quad (\text{A5})$$

Where H is the height of the sensor, which is 9.6 mm, and f is the camera focal length, which is 4 mm. Further, the following equation can be obtained:

$$Z = \frac{\frac{1}{2}R \cdot P_p}{B_p \cdot \tan \alpha} = \frac{\frac{1}{2}R \cdot P_p}{B_p \cdot \tan\left(\arctan\left(\frac{H}{2f}\right)\right)} = \frac{R \cdot f}{\frac{B_p \cdot H}{P_p}} \quad (\text{A6})$$

Where R is the actual height of the children, which is 139.5 cm based on the average height of boys and girls aged 7–12 according to GB/T26158-2010 Human Dimensions of Chinese Minor (Standardization Administration of China, 2010). B_p is the pixel height of the children in the image; P_p is the pixel height of the image.

The pixel coordinates output from YOLO are used as the real-time coordinates of the moving children (u, v). The pixel coordinates corresponding to the origin of the image coordinate system are used as the centre point (u_0, v_0). The real-time coordinates (X, Y) of the moving children are calculated as follows by using the pixel coordinate difference between the two coordinates and the transformation relationship between different coordinate systems:

$$X = \frac{Z}{f_x} \cdot (u - u_0) \quad (\text{A7})$$

$$Y = \frac{Z}{f_y} \cdot (v - v_0) \quad (\text{A8})$$

If $u > u_0, v > v_0$, then X and Y are positive; otherwise, they are negative.

Text A3

MAE takes the absolute errors of individual instances before collective summation and division by several instances (Bell et al., 2020). *MAPE*, the mean absolute value of the ratio of the estimation error to the real value, is more conducive to understanding the results of the assessment because of its expression in the form of a percentage (Bell et al., 2020; Zhang et al., 2020). *RMSE* is used to represent the sensitivity of variation to large errors (He et al., 2020; Sangsuwan and Ekpanyapong, 2024). The formulae for the three indicators are shown below:

$$MAE = \frac{1}{A} \sum_{a=1}^A |s_a^g - s_a^e| \quad (\text{A9})$$

$$MAPE = \frac{1}{A} \sum_{a=1}^A \frac{|s_a^g - s_a^e|}{s_a^g} \quad (A10)$$

$$RMSE = \sqrt{\frac{\sum_{a=1}^A (s_a^g - s_a^e)^2}{A}} \quad (A11)$$

Where A is the number of people to be measured, s_a^g is the ground truth speed of person a , and s_a^e is the estimated speed of person a .

Table A4 Statistical results of activity speeds of different age groups

Group	n	Mean speed (m/s)	Median speed (m/s)	Range of average speed (m/s)
Lower age group	22264	0.52	0.42	0.01-5.78
Middle age group	21192	0.50	0.40	0.01-6.08
Upper age group	22760	0.47	0.37	0.01-6.07

Table A5 Two-by-two comparison results obtained using the Nemenyi test

Nemenyi test			
Parameter	Group	Group	p-value<0.05
Speed	Lower age group	Middle age group	<0.001
	Lower age group	Upper age group	<0.001
	Middle age group	Upper age group	<0.001

Table A6 Two-by-two comparison results for different groups by using the Nemenyi test

Nemenyi test			
Activity intensity	Group	Group	p-value<0.05
LPA	Lower age group	Middle age group	<0.001
	Middle age group	Upper age group	<0.001
	Lower age group	Upper age group	<0.001
MPA	Lower age group	Middle age group	0.82
	Middle age group	Upper age group	0.02
	Lower age group	Upper age group	0.06
VPA	Lower age group	Middle age group	0.33
	Middle age group	Upper age group	0.02
	Lower age group	Upper age group	0.33

Table A7 Two-by-two comparison results for different groups by using the Nemenyi test

Nemenyi test				
	Activity level	Group	Group	p-value<0.05
Duration	LPA	Lower age group	Middle age group	0.338
		Lower age group	Upper age group	<0.001
		Middle age group	Upper age group	<0.001
	MPA	Lower age group	Middle age group	0.029
		Lower age group	Upper age group	<0.001
		Middle age group	Upper age group	0.245

Table A8 Inhalation doses in each age group and the relative differences between groups

Parameter	Dose ($\mu\text{g}\cdot\text{kg}^{-1}$)		Group	Group	Relative Difference
Lower age group	Autumn	2.42	Middle age group	Lower age group	14.67%
	Winter	8.18			
Middle age group	Autumn	2.05	Upper age group	Lower age group	30.64%
	Winter	7.03			
Upper age group	Autumn	1.65	Upper age group	Middle age group	18.72%
	Winter	5.77			

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