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Calibration of a low-cost $PM_{2.5}$ monitor using a random forest model

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ABSTRACT

Background: Particle air pollution has adverse health effects, and low-cost monitoring among a large population group is an effective method for performing environmental health studies. However, concern about the accuracy of low-cost monitors has affected their popularization in monitoring projects.

Objective: To calibrate a low-cost particle monitor (HK-B3, Hike, China) through a controlled exposure experiment.

Methods: Our study used a MicroPEM monitor (RTI, America) as a standard particle concentration measurement device to calibrate the Hike monitors. A machine learning model was established to calibrate the particle concentration obtained by the low-cost $PM_{2.5}$ monitors, and ten-fold validation was used to test the model. In addition, we used a linear regression model to compare the results of the machine learning model. A calibration method was established for the low-cost monitors, and it can be used to apply the monitors in future air pollution monitoring projects.

Results: The values of the random forest model calibration results and observations were more condensed around the regression line $y = 0.99x + 0.05$, and the R squared value ($R^2 = 0.98$) was higher than that for the linear regression ($R^2 = 0.87$). The random forest model showed better performance than the traditional linear regression model.

Conclusions: Our study provided an effective calibration method to support the accuracy of low-cost monitors. The machine learning method based on the calibration model established in our study can increase the effectiveness of future air pollution and health studies.

1. Introduction

Ambient air pollutants have been proven to have adverse health impacts on humans (Brook et al., 2010 ; Atkinson et al., 2010), and better assessments of their health effects require more accurate measurements of air pollution exposure concentrations (White et al., 2012). Previous environmental studies have shown that expensive equipment, such as MicroPEM, have reliable accuracy and a stable performance (Chartier et al., 2017; Cho et al., 2017) and were widely used in particle monitoring and environmental health studies (Chen et al., 2018; Milà et al., 2018); however, challenges remain for their popularization in large-scale $PM_{2.5}$ monitoring. Low-cost air pollution equipment has provided a revolutionary method for performing air quality monitoring, and the advantages of applying low-cost air monitoring technologies and building low-cost sensor-based monitoring networks have been validated by population-based studies by the United States Environmental Protection Agency (US EPA) and European agencies, which have shown massive increases in the spatial and temporal data resolution (USEPA, 2013; Snyder et al., 2013; Borrego et al., 2016). The measurement results from low-cost monitors, especially monitors based on the light scattering method, are easily affected by environmental parameters, such as temperature and relative humidity (Woodall et al., 2017; Castell et al., 2015), and previous studies on low-cost monitors suffered from a lack of calibration; moreover, a sizable fraction of the study papers were commercial or crowdfunded and may have experienced bias (Morawska et al., 2018). Therefore, because of the accuracy and consistency limitations, implementing low-cost sensors among large population groups is difficult.

Several studies have focused on the development and quality of inexpensive air pollutant monitors, although they mainly used the traditional linear regression model to assess the calibration performance (McKercher et al., 2017; Rai et al., 2017). Several studies investigated particle sensors under laboratory conditions to assess the performance of the monitors (Wang et al., 2015; Dacunto et al., 2015;

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Olivares and Edwards, 2015) to calibrate the monitoring concentration of low-cost sensors. However, the measurement principles of these monitors were not consistent, and the monitors suffered significant response factor changes under different meteorological conditions (Morawska et al., 2018). Moreover, the differences generated by different principles and meteorological conditions might not be linear. Therefore, standard air pollution instruments have not been sufficiently verified and nontraditional non-linear regression method should be applied during calibration.

Our study used a MicroPEM monitor (RTI, America) as a standard particle concentration measurement device to calibrate a low-cost particle monitor (HK-B3, Hike, China) through a controlled exposure experiment. We used a machine learning method to establish an accurate calibration function between the two types of monitors and increase the applicability of low-cost Hike monitors.

2. Methods

2.1. Experimental methods

The experiments used a Hike B3 industrial air quality monitor to measure the $PM_{2.5}$ concentration. Hike equipment has primarily been used to measure indoor air quality and pollution monitoring system establishment (Sun et al., 2018), and it can record concentration values through wireless transmission. Sixteen monitors were implemented, and they had a sampling frequency of 10 min. Four MicroPEM™ version 3.2A individual exposure samplers were used as standard controls to exclude the possible effects of outlier values. The sampling frequency of MicroPEM was 10 s, and one of the MicroPEMs was used as a blank control.

The experimental instruments were placed centrally in the 30 m^3 laboratory compartment and started at a unified time. The air inlets of the instruments were approximately 1.2 m above the ground. The Hike instruments were used under indoor condition. Since cigarette smoke accounts for a large contribution to indoor air pollution (Morawska et al., 2018) and served as a test aerosol for instrument calibration, cigarette smoke was used to simulate urban indoor particle pollutants in our study. After the instrument ran stably, cigarettes were lit in the laboratory compartment. MicroPEM monitors were equipped with Teflon filters, and the filters were weighed to calibrate the real-time concentrations of particulate matter. The humidity in the laboratory compartment was regulated by a humidifier. We used Hike equipment to record the temperature and relative humidity of the laboratory cabin. To ensure that the air flow was uniform, all instruments were placed in the middle of the experimental cabin similar to the condition shown in Supplementary Fig. 1. In general, each experiment was completed over 5–6 h. After lighting the cigarette, the instruments required 0.5–1 h to become stable for several minutes. The concentrations of the particles were within the detection limit of the gravimetric control.

2.2. Data processing

Real-time data from MicroPEM were corrected to a zero drift value, and abnormal data caused by instrument defects were deleted. We calibrated the real-time MicroPEM data according to the film weighing data after cleaning up and calculated the average of three real-time MicroPEM data sets collected at the same time point. The average real-time concentration values were used as a standard control. Because the Hike $PM_{2.5}$ monitor sampling frequency was 10 min and the MicroPEM frequency was 10 s, when the $PM_{2.5}$ concentration changed rapidly, the real-time data from the Hike monitors might not change instantaneously. To avoid fluctuations and obtain more accurate data, we removed the first 15 min of data collected after lighting the cigarette. The calibrated real-time MicroPEM data were processed as an average of 5 min or 10 min according to the time point of the real-time data of the Hike $PM_{2.5}$ monitor, and they were matched with the real-time data of the Hike $PM_{2.5}$ monitor.

2.3. Model establishment and validation

We calibrated the real-time Hike $PM_{2.5}$ data according to the temperature and humidity recorded by the MicroPEM monitor using the linear regression method and the random forest method. Formula (1) was used in the linear regression method.

$$Y = \beta1 * X + \beta2 * Temp + \beta3 * RH + \beta0 \tag{1}$$

where Y is the standard control $PM_{2.5}$ concentration, X is the $PM_{2.5}$ concentration recorded by the Hike $PM_{2.5}$ monitor, T is the temperature recorded by the Hike $PM_{2.5}$ monitor, and RH is the relative humidity recorded by the Hike $PM_{2.5}$ monitor.

During data preprocessing via the random forest model, missing data were deleted from the original data set. To obtain a better model fitting, the number of variables (mtry) and decision trees (ntree) corresponding to the maximum model R^2 were selected as model parameters selected for the random forest regression. The trained model was applied to the testing data to assess the model. The accuracy of the model was verified by ten-fold cross validation. To assess the model performance, 90% of the data were randomly chosen as the training data, and the remaining 10% of the data were treated as the testing data set during linear regression and random forest model establishment.

For further analysis, we excluded MicroPEM data with average concentrations higher than 500 $\mu g/m^3$ and reanalyzed the linear regression and random forest models under relatively low concentrations. The training data and testing data were randomly chosen from the data set using a method similar to that described above.

3. Results

Detailed statistics of monitoring and environmental parameters during each experiment are shown in Table 1. The Hike equipment showed higher $PM_{2.5}$ concentrations than the MicroPEM equipment especially under high particle concentration. The environmental temperature ranged from 16.2 to 31.0 °C, and the relative humidity ranged from 5.8 to 79.3%. The particle concentrations from the Hike and MicroPEM equipment are shown in Fig. 1. The horizontal axis is the ordinal number ordered in ascending order according to the standard control concentration, and the vertical axis is the $PM_{2.5}$ concentration. The red spots represent the average concentration from the MicroPEM monitor, and black spots represent that from the Hike monitor. As seen in the plot, the concentrations from the Hike monitor were slightly higher than the standard control among the high-concentration values.

The Spearman correlation coefficients between particle concentrations monitored by the Hike and MicroPEM equipment are shown in Supplementary Fig. 2, where X represents the Hike monitors and mpave represents the average concentration from the MicroPEM monitors. The concentrations between each Hike monitor were highly correlated, and the correlation between the Hike and MicroPEM monitors was also significantly strong.

We performed a linear regression and random forest regression based on the training data set of particle concentrations. The temperature and relative humidity were used as covariates in model establishment. The remaining 10% of the data were used to test the performance of the linear and random forest models, and the results are shown in Fig. 2. The horizontal axis shows the concentration of the model calibration values, and the vertical axis shows the concentration values of observations from the original data set. The linear regression results between the calibrations and observations are also shown in the figure. As shown in Fig. 2, the observation and linear regression calibration values were relatively dispersed, with greater than 95% confidence intervals. The random forest model calibration values and observation values were more condensed around the regression line of $y = 0.99x + 0.05$, and the R squared value ($R^2 = 0.98$) was higher than

Table 1
Basic statistics of the monitoring and environmental parameters during each experiment.

	Variables	Min	1st Qu	Median	Mean	3rd Qu	Max
1st	Standard control $PM_{2.5}$ concentration (μg/m^3)	1.6	3.2	216.5	156.2	297.2	369.7
	Monitoring $PM_{2.5}$ concentration (μg/m^3)	3.0	8.0	379.0	306.3	572.0	688.0
	Temperature (°C)	27.6	29.5	29.9	29.8	30.3	31.0
	Relative humidity (%)	32.5	34.7	35.3	35.4	36.1	39.5
2nd	Standard control $PM_{2.5}$ concentration (μg/m^3)	40.5	54.5	198.3	149.5	217.1	281.5
	Monitoring $PM_{2.5}$ concentration (μg/m^3)	82.0	159.0	499.0	406.5	557.5	843.0
	Temperature (°C)	18.6	19.8	20.4	20.4	20.9	22.5
	Relative humidity (%)	43.9	47.6	49.1	48.9	50.1	52.9
3rd	Standard control $PM_{2.5}$ concentration (μg/m^3)	106.5	561.2	678.0	641.4	760.8	945.3
	Monitoring $PM_{2.5}$ concentration (μg/m^3)	100.0	700.0	767.0	736.9	849.0	996.0
	Temperature (°C)	17.4	19.0	19.7	19.8	20.6	22.5
	Relative humidity (%)	23.2	61.7	66.4	64.2	70.4	79.3
4th	Standard control $PM_{2.5}$ concentration (μg/m^3)	0.0	2.8	6.9	18.8	28.9	80.7
	Monitoring $PM_{2.5}$ concentration (μg/m^3)	0.0	6.0	17.0	37.5	61.0	178.0
	Temperature (°C)	16.2	25.4	27.5	26.9	28.4	29.8
	Relative humidity (%)	5.8	9.4	10.4	10.4	11.6	17.9
5th	Standard control $PM_{2.5}$ concentration (μg/m^3)	44.1	157.3	181.8	222.3	232.5	510.0
	Monitoring $PM_{2.5}$ concentration (μg/m^3)	120.0	282.0	339.0	362.7	411.0	692.0
	Temperature (°C)	27.2	27.7	28.2	28.1	28.6	29.6
	Relative humidity (%)	46.0	46.8	47.7	47.6	48.4	49.3
6th	Standard control $PM_{2.5}$ concentration (μg/m^3)	8.3	504.5	532.3	517.2	674.8	744.6
	Monitoring $PM_{2.5}$ concentration (μg/m^3)	1.0	375.5	482.0	400.7	544.8	761.0
	Temperature (°C)	17.5	19.2	19.9	19.9	20.8	21.9
	Relative humidity (%)	8.0	9.1	10.2	9.9	10.8	11.6
Total	Standard control $PM_{2.5}$ concentration (μg/m^3)	0.0	7.0	65.8	179.5	221.4	945.3
	Monitoring $PM_{2.5}$ concentration (μg/m^3)	0.0	17.0	137.0	263.9	440.0	996.0
	Temperature (°C)	16.2	23.4	27.5	25.8	28.4	31.0
	Relative humidity (%)	5.8	10.5	35.4	31.8	48.3	79.3

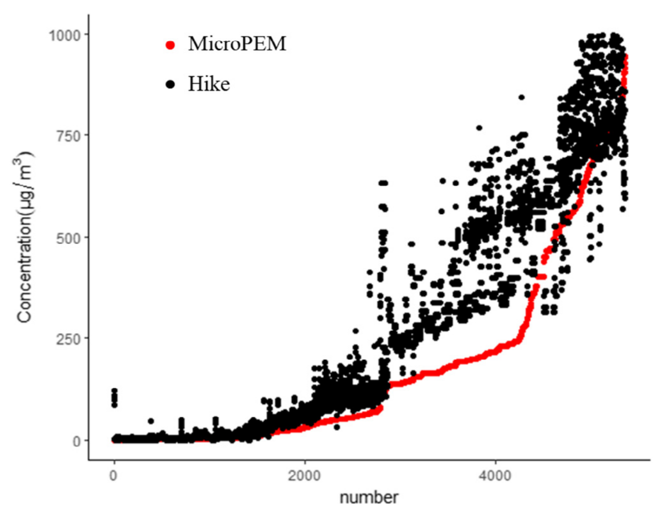

Fig. 1. Monitoring $PM_{2.5}$ concentrations in an ascending sequence.

that of the linear regression ($R^2 = 0.87$), indicating a better fitting performance.

The analysis results under low particle concentration are shown in Fig. 3. The linear regression model showed a similar calibration performance with the basic model, which had a slope of 1.07 and R squared value of 0.87 when applied to the testing data set. The performance of the random forest model increased, and the slope and R squared values were 1.01 and 0.99, respectively, indicating a slight increase of model fitness when focused on the relatively low concentration of particles. A linear regression and random forest regression obtained in our study were conducted for each Hike monitor, and the model performances were similar for each monitor. The relative results are shown in Supplementary Figs. 3 and 4.

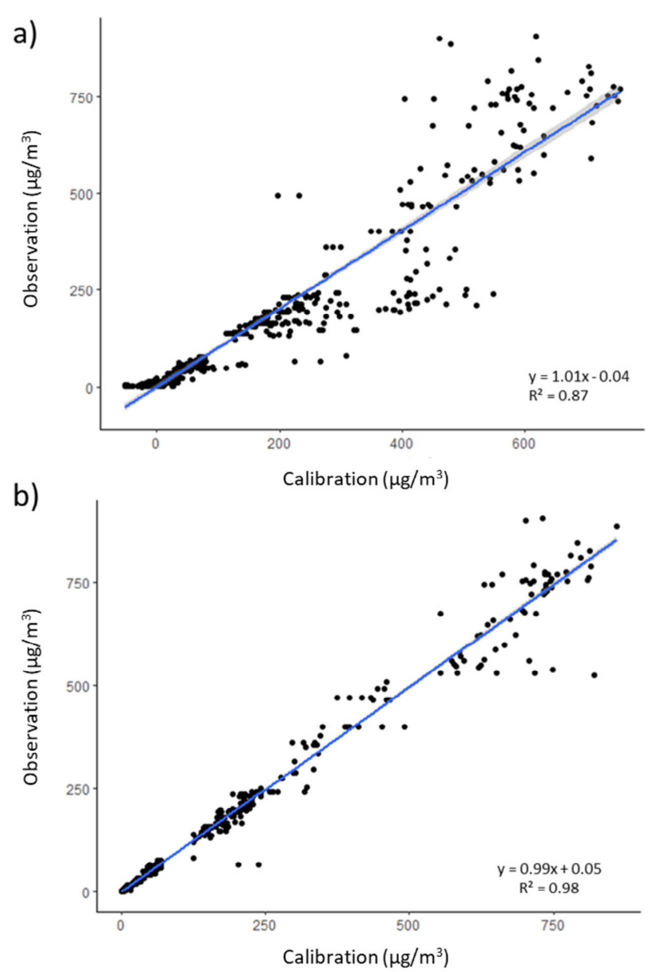

Fig. 2. Model performances of linear regression (a) and random forest regression (b) on concentration calibrations.

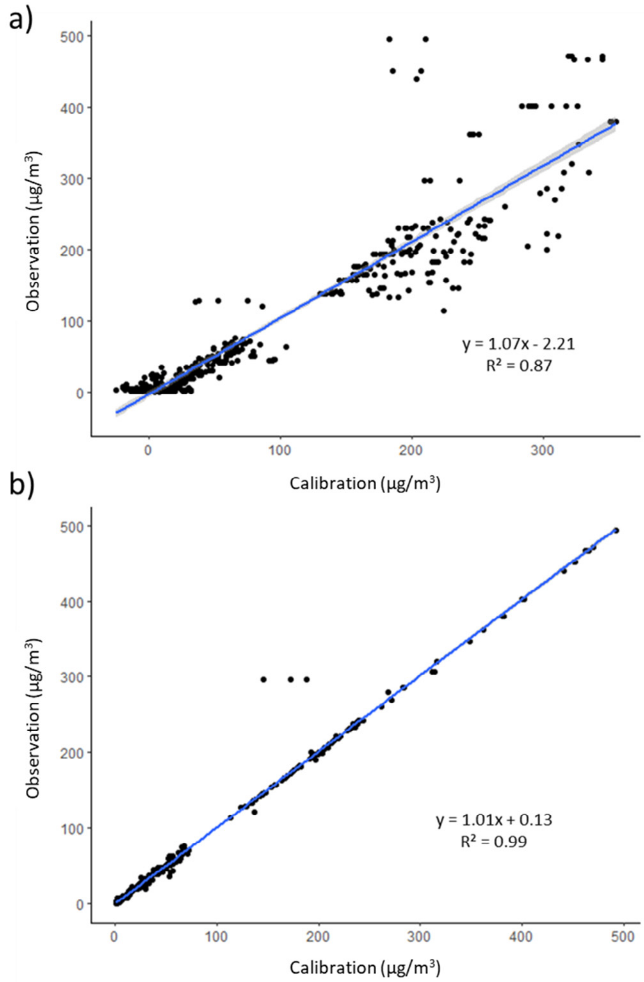

Fig. 3. Model performances of linear regression (a) and random forest regression (b) on concentration calibrations for dataset including $PM_{2.5}$ concentration below 500 μg/m^3.

4. Discussion

Our study used standard particle monitoring instruments to calibrate the concentration values from low-cost monitors at different temperatures, relative humidities and particle concentrations under indoor air pollution conditions stimulated by cigarette smoking. Machine learning techniques (linear regression models and non-traditional random forest model) were applied to obtain the calibration functions, and the machine learning model performances were better than that of the traditional linear regression based on a cross validation. To further complete our result, we reestablished the models under low particle concentrations and obtained a specific model with similar model fitness, indicating the model robustness under different concentration ranges. To the best of our knowledge, this is the first study to apply a random forest model to the calibration of low-cost particle monitors, especially under indoor air pollution conditions. The model established in our study represents a novel method of improving the applicability of low-cost air pollution monitors.

The low-cost instruments in our study were designed to monitor indoor air quality. Since cigarette smoke accounts for a large proportion of indoor air pollution and smoking particles are suitable for calibrating indoor monitors (Morawska et al., 2018), smoking were used to stimulate indoor air pollutant conditions in our study. Previous indoor air monitoring studies mainly used uncalibrated instruments or were focused on a limited range of subjects; thus, they suffered from drawbacks that included low accuracy, low quantity, or insufficient temporal resolution (Dacunto et al., 2015; Olivares and Edwards, 2015). The model established in our study can improve the accuracy of low-cost monitors and contributes to expanding high temporal-spatial resolution networks for indoor air pollution. The particle concentration in our experiment reached 945.3 μg/m^3, which is relatively higher than that of other existing monitor calibration studies (Wang et al., 2015). However, the MicroPEM instrument is generally used for personal exposure, and the instantaneous $PM_{2.5}$ concentration monitored in environmental studies by MicroPEM could reach values higher than 900 μg/m^3 at the individual level (Chartier et al., 2017; Cho et al., 2017). The particle concentrations were consistent with the pollution level at the indoor exposure level, thus better representing our experimental conditions. We also excluded data with particle concentrations higher than 500 μg/m^3 for further analysis, and the calibration results were similar with a slightly higher R^2, indicating a robust statistical analysis.

The calibration model performance could be assessed by variables such as the R squared value and the slope, which are important parameters for measuring model performance, and they were satisfactory compared to other calibration studies. The slopes in our study, including those from the analysis under low concentration, were close to 1, indicating a value between the calibrated and actual concentration values. Austin calibrated two types of sensors using multiple particle sizes at concentrations below 50 μg/m^3, and the linear regression slopes were 5.13 ± 0.05 and 5.25 ± 0.03 for a particle size of approximately 2 μm (Austin et al., 2015). The R squared values of the random forest model established in our study were 0.98 and 0.99 for the basic model and the analysis under low concentrations, respectively. The calibration experiment adjusted the particle concentration among three sensors based on light scattering and found that the R squared value of the pairwise correlation among the three sensors varied from 0.78 to 0.99 and indicated that humidity affected the sensor response (Wang et al., 2015). These results show that the linear regression results in our study have robust model fitness.

The non-traditional random forest model was used in our study to control the influence of environmental parameters, such as temperature and relative humidity, and the calibration results were compared to that of a linear regression model. Previous epidemiology studies reported that meteorological parameters, including environmental temperature and relative humidity, have non-linear relationships with particle concentrations. Based on the haze event observations, $PM_{2.5}$ and PM_{10} concentrations show curved relations under different temperatures and seasons, such as winter and spring (Chen et al., 2017). Temperature and relative humidity were also shown to have non-linear correlations, such as cubic spline or natural spline, with particle concentrations in epidemiologic studies (Kim and Liu, 2014; Villeneuve et al., 2015), which indicated that these meteorological factors are non-linearly associated with monitoring concentrations. Thus, procedures based on a linear regression model may not be sufficient for calibrating particle concentrations under different meteorology conditions. Therefore, a method established based on a non-linear machine learning model could provide a better fit to the meteorological parameters and particle concentrations.

Our study has several advantages. First, we used a machine learning method as well as the traditional linear regression method to calibrate the studied monitor under different meteorology conditions and compared the fitness of each model, and the results demonstrated the reliability of the random forest model. Since indoor air pollution contributed to a large proportion in individual pollution exposure, it is important to established calibration method to ensure the accuracy of indoor air monitoring. Second, the concentration values were highly correlated among monitors, indicating that despite the use of low-cost equipment, stable performance was obtained for each monitor. Third, the temperature and relative humidity in the calibration experiment covered the parameter range under various indoor air conditions among different seasons, which indicates the representativeness of the experiment and supports its further application in air pollutant monitoring projects under actual highly polluted indoor air conditions.

There were also limitations in the study. First, cigarette smoke was used as the particle source in the experiment, and it may differ in terms of the size and components compared with the actual conditions of ambient air pollution. Since Hike instruments have primarily been applied for indoor air quality monitoring, we aimed to simulate indoor air pollution conditions in our study and establish a calibration model, and other indoor air particle pollutant sources such as cooking could be added in the further studies. Our study was a preliminary exploratory experiment to investigate the calibration of low-cost $PM_{2.5}$ monitoring equipment, and further research could be conducted to eliminate the size and component differences between experimental particles and actual ambient particulate matter. Second, calibrated data under various temperatures and relative humidities can be included in subsequent experiments to improve the model fitness. Third, monitoring data in an ambient air pollution exposure project can be applied to the model established in our study to test the model performance.

5. Conclusions

Our study provided an effective calibration method to support the accuracy of low-cost monitors under urban indoor air particle pollution condition. The machine learning method-based calibration model established in our study can increase the effectiveness of future air pollution and health studies, and we aim to use low-cost monitors, such as Hike instruments, to obtain accurate and convenient pollution measurements. Moreover, the results contribute to the establishment of a possible indoor air quality monitoring network.

Author contribution

TL made contributions to the conception and design of the study. YD performed the experiment. JW and YD prepared and cleaned the data. YW performed the statistical analysis and drafted the article. All authors contributed to interpreting the results and critically revising the draft.

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Declaration of competing interest

The authors declare that they have no conflicts of interest.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.envint.2019.105161.

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