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Coupling mobile phone data with machine learning: How misclassification errors in ambient PM2.5 exposure estimates are produced?

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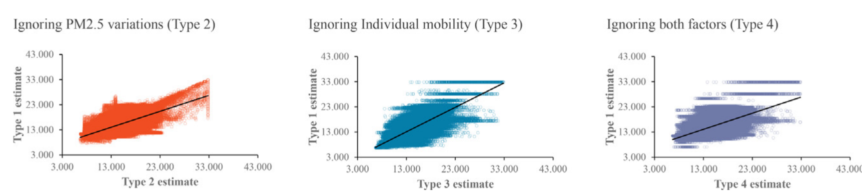
HIGHLIGHTS

- First study coupling mobile phone location data and machine learning approach to examine exposure misclassification errors.
- Ignoring individual mobility and PM2.5 variations leads to misclassification errors.
- A larger misclassification error in the estimate neglecting PM2.5 variations than that ignoring individual mobility
- High economic-status group suffer from a larger misclassification error.

GRAPHICAL ABSTRACT



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ABSTRACT

Background: Most studies relying on time-activity diary or traditional air pollution modelling approach are insufficient to suggest the impacts of ignoring individual mobility and air pollution variations on misclassification errors in exposure estimates. Moreover, very few studies have examined whether such impacts differ across socioeconomic groups.
Objectives: We aim to examine how ignoring individual mobility and PM2.5 variations produces misclassification errors in ambient PM2.5 exposure estimates.
Methods: We developed a geo-informed backward propagation neural network model to estimate hourly PM2.5 concentrations in terms of remote sensing and geospatial big data. Combining the estimated PM2.5 concentrations and individual trajectories derived from 755,468 mobile phone users on a weekday in Shenzhen, China, we estimated four types of individual total PM2.5 exposures during weekdays at multi-temporal scales. The estimate ignoring individual mobility, PM2.5 variations or both was compared with the hypothetical error-free estimate using paired sample *t*-test. We then quantified the exposure misclassification error using Pearson correlation analysis. Moreover, we examined whether the misclassification error differs across different socioeconomic groups. Taking findings of ignoring individual mobility as an example, we further investigated whether such findings are robust to the different selections of time.

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Results: We found that the estimate ignoring PM2.5 variations, individual mobility or both was statistically different from the hypothetical error-free estimate. Ignoring both factors produced the largest exposure misclassification error. The misclassification error was larger in the estimate ignoring PM2.5 variations than that ignoring individual mobility. People with high economic status suffered from a larger exposure misclassification error. The findings were robust to the different selections of time.

Conclusions: Ignoring individual mobility, PM2.5 variations or both leads to misclassification errors in ambient PM2.5 exposure estimates. A larger misclassification error occurs in the estimate neglecting PM2.5 variations than that ignoring individual mobility, which is seldom reported before.

1. Introduction

Air pollution has attracted considerable concerns from the public and scholars. An accurate estimate of air pollution exposure is essential to understand socioeconomic disparities in such exposure and the effect of air pollution on human health, which thereby supports policy making in air pollution regulations and public health interventions. Individual exposure is determined not only by air pollution variations but also by individual mobility, thereby increasing the difficulty of generating accurate estimates. Hence, the exposure may be biasedly estimated if the two determinants are not properly considered. Despite some efforts (Yoo et al., 2015; Nyhan et al., 2016; Shafran-Nathan et al., 2018), however, how ignoring air pollution variations and individual mobility produces misclassification errors in exposure estimates has not been well understood.

Several studies have highlighted the importance of incorporating individual mobility and air pollution variations in exposure estimates. Overall, many studies suggest that ignoring the two aforementioned determinants can produce misclassification errors in exposure estimates (Nyhan et al., 2016; Tang et al., 2018; Shafran-Nathan et al., 2018; Tayarani and Rowangould, 2020), whilst few studies report no misclassification errors (Kwan et al., 2015). In particular, Yoo et al. (2015) reported a substantial difference in exposure estimates when air pollution variation was not properly captured and respondents spent much time out of their homes. Similarly, combining the activity data and hourly NO2 concentrations, Shekarrizfard et al. (2016) found that the average exposure during mobility is higher than that at home location. This finding emphasizes the importance of considering individual mobility in exposure estimates. By contrast, few studies indicate that incorporating individual mobility and air pollution variations has no effect on improving the accuracy of exposure estimates. In particular, a study conducted in Franklin County, USA, reported that no significant difference exists between home- and people-based exposure estimates (Kwan et al., 2015).

Although findings from the limited studies tend to be consistent, further investigations are required due to the following reasons. Firstly, regarding the consideration of air pollution variations, the traditional approaches including land use regression and interpolation may not well capture the spatiotemporal variations of air pollution concentration. These methods usually assume a linear relationship between air pollution concentration and the corresponding predictors (Jerrett et al., 2005; Setton et al., 2011; Park and Kwan, 2017; Culyba et al., 2018). However, such relationship is likely to be non-linear (Di et al., 2016; Li et al., 2017; Zhao et al., 2019), especially when air pollution is modelled at a fine spatiotemporal scale. Therefore, the traditional modelling approaches may not accurately reflect air pollution variations, which thereby may not be sufficient to demonstrate the significance of considering air pollution variations in exposure estimates. Although some studies have used dispersion models (Gerharz et al., 2009; Smith et al., 2016; Shafran-Nathan et al., 2018; Reis et al., 2018), such modelling approaches are usually time-consuming and have a high requirement of data input, parameter setting and computing resources.

Secondly, most studies rely on time-activity diary to derive individual mobility, which may not be sufficient to examine the impact of ignoring individual mobility on exposure misclassification errors. Individual mobility information is usually derived from the time-activity data that heavily relies on the recall and memory of the respondents (Buonanno et al., 2014; Smith et al., 2016; Culyba et al., 2018; Tang et al., 2018). There are also some studies deriving mobility information from the simulated movement data at the population level (Setton et al., 2011; Dhondt et al., 2012; Park and Kwan, 2017). Such processing may produce the bias in the characterization of individual mobility (i.e. information on time, location and activity) that an individual goes through.

Thirdly, few studies examine the effects of ignoring individual mobility and air pollution variations across multi-temporal scales. Most studies focus on the examination at a daily scale (Setton et al., 2011; Park and Kwan, 2017; Shafran-Nathan et al., 2017; Tang et al., 2018). One of the problems of single-scale examinations is temporal uncertainty, that is, the findings may be different when the impacts of ignoring the determinants of exposure estimates are examined at different temporal scales. The knowledge on whether such effects exist at other temporal scales (e.g. weekly) is scarce. For studies on air pollution-related health effects or socioeconomic disparities, it is crucial to determine the extent to which the average concentration at a certain temporal scale can be a proxy of the true individual exposure. However, such multi-temporal examinations are limited.

Lastly, only few studies have examined the differential impacts of ignoring individual mobility and air pollution variations according to socioeconomic characteristics. Blanchard et al. (2018) suggested that women residing in the most deprived blocks suffer from larger misclassification errors in exposure estimates. However, such studies are quite limited. Differential effects can cause differential misclassification errors in exposure estimates across socioeconomic groups, which will produce the bias in the estimate of air pollution effect. However, whether the influences of disregarding individual mobility and air pollution variations on exposure misclassification errors vary across different socioeconomic groups is still unclear.

To fill the gaps above, coupling mobile phone location data with a geo-informed backward propagation neural network model we developed, this study aims to examine how ignoring individual mobility and PM2.5 variations produces misclassification errors in ambient PM2.5 exposure estimates. In addition, this work analysed whether the impacts of ignoring the two determinants on exposure misclassification errors differ amongst people with different economic statuses. Finally, as the day, week, month, season and year that contain the day of available mobile phone data were selected for the multi-temporal examinations, taking the findings of ignoring individual mobility as an example, this study tested whether such findings are robust to the different selections of time.

2. Materials and methods

2.1. Research area

Main built-up areas in Shenzhen are selected as research area in the present study. Shenzhen, located in the southeast of Guangdong

Province, China, is one of the four first-tier metropolises in China. It covers a total area of around 1953 km^2 and is home to around 15 million people. Areas in Yantian and Dapeng were excluded in the present study because these two districts are mostly covered by mountains. Accordingly, areas in the total of 8 districts were selected. They are Futian, Luohu, and Nanshan, which are downtown areas. Baoan, Longhua, and Longgang are suburbs, while Guangming and Pingshan are rural areas. The annual mean PM2.5 concentration in Shenzhen was 36.39 $\mu g/m^3$ in 2012, which is more than three times higher than the value stated in the air quality guidelines of World Health Organization at 12 $\mu g/m^3$ (World Health Organization, 2006) (Fig. 1).

2.2. Data

2.2.1. Mobile phone location data

Mobile phone location dataset on a weekday (March 23, 2012) in Shenzhen, China, was provided by the largest mobile phone operator in Shenzhen for academic purposes. The use of this dataset in the present study has got the ethical approval from the Human Research Ethics Committee, The University of Hong Kong (No. EA2003008). The initial number of mobile phone users is 12.4 million, which represents a considerable proportion of Shenzhen's population (approximately 15 million). Each time-location record in the dataset contains information: 1) user ID, which has been anonymously processed 2) date and time and 3) geospatial locations (i.e. longitude and latitude coordinates) of the corresponding mobile phone tower that provides mobile phone services. Time-location information was continuously recorded at approximately one-hour intervals as long as the mobile phone was active. It should be noted that the mobile phone location dataset has been encrypted to protect the privacy of mobile phone users before the permitted use in the present study.

On the basis of studies using mobile phone data to understand human behaviour (Järv et al., 2015; Yu et al., 2018), we assume that a time series of locations of mobile phone towers that a user is connected to represent the user's movement trajectory (i.e. user's footprint in space and time). If a mobile phone user was located in the service area (usually represented by the Thiessen polygon) of a mobile phone tower nearest to the user, then the location of this tower was recorded in the user's movement trajectory. Hence, the accuracy of estimated locations of mobile phone users is highly dependent on the service area of mobile phone towers. In our study, a total of 5908 mobile phone towers are located in the entire city of Shenzhen. The average service area of mobile phone towers was 0.28 km^2 (standard deviation $= 0.58$ km^2).

The dataset we obtained in the present study has been processed. For more details of data processing, please refer to Zhou et al. (2018). Briefly, activity locations, namely home and workplace, were identified in accordance with the place-starting time-duration model (Long and Thill, 2015). Home location was identified based on the location records from 0 am to 6 am with time spent at this location for more than 4 h. In a similar manner, workplace was identified according to the location records of two periods (i.e. 8 am–12 am and 2 pm–6 pm) with time spent at this location for more than 5 h. After processing, there were nearly 1.3 million phone users with continuous and non-continuous 24-hour location records left. According to the results of validation (Zhou et al., 2018), there was high agreement in the spatial distributions of residents derived from mobile phone location data and statistical data with R^2 equal to 0.80. A similar pattern of results can be observed in the spatial distributions of workers ($R^2 = 0.69$). To well meet the research design for the present study, we derived the location records of phone users with the continuous 24-hour location records, which left the number of mobile phone users by 757,143. Also, mobile phone users with location records outside Shenzhen were excluded. We finally acquired 755,468 mobile phone users for the examination of exposure misclassification errors in the present study.

2.2.2. Hourly PM2.5 concentrations derived from Geo-BPNN model

We estimated the hourly PM2.5 concentrations at 1 km^2 spatial resolution from March 9, 2012 to December 31, 2013 using a geo-informed backward propagation neural network model (i.e. Geo-BPNN hereinafter). BPNN model is superior in modelling the complex and nonlinear relationships between a number of predictors

Fig. 1. Research area.

and outcome variable (s) (Hecht-Nielsen, 1992). It has been suggested that BPNN has good model performance and thus has been widely used in PM2.5 estimates (Gupta and Christopher, 2009; Di et al., 2016; Dong et al., 2020). More details of using Geo-BPNN model to estimate PM2.5 concentrations can refer to our previous study (Guo et al., 2020). Briefly, our Geo-BPNN model consists of an input layer, two hidden layers and an output layer. In the input layer, there are 27 variables including the gap-filled MAIAC (i.e. Multi-Angle Implementation of Atmospheric Correction) AOD (i.e. aerosol optical depth), hourly traffic flow, meteorological factors, land use indicators, urban form, elevation and spatiotemporally informative terms. The details of filling the gaps in the original MAIAC AOD can refer to our previous research (Guo et al., 2020). These variables (Table S1) were selected based on previous studies (Just et al., 2015; Li et al., 2017; Wei et al., 2019; Yao et al., 2019).

The number of hidden layers and neurons are two of the most important parameters influencing the BPNN model performance. Usually, it is preferable to construct neural network with not too many hidden layers to avoid the potential model over-fitting problem (Schalkoff, 1997). According to Fletcher and Goss (1993), the neural network can perform well if the number of neurons in the hidden layer ranges from $(2\sqrt{n}+u)$ to $(2n+1)$, where n and u denote the number of input variable and output variable, respectively (Corresponding values are equal to 27 and 1 in the present study, respectively). Therefore, in this study, we trained six Geo-BPNN models with different specifications in the number of hidden layer (1 and 2, respectively) and neurons (40, 45 and 50, respectively) in each layer in order to determine the best model for PM2.5 estimates (Table S2). With respect to training algorithm, we selected the Levenberg-Marquardt algorithm which is robust and has been used in many studies (Feng et al., 2015; Di et al., 2016; Zhou et al., 2020). The epochs and learning rate were finally set to 5000 and 0.0001, respectively, based on multiple attempts.

The Geo-BPNN model with 2 hidden layers (each with 45 neurons) was selected for estimating hourly PM2.5 concentrations at 1 km^2 grid cells in the present study. We used the sample-based tenfold cross-validation which has been widely used in AOD-based PM2.5 estimate studies (Li et al., 2017; Yao et al., 2019). This can be briefly described as: 1) We averagely and randomly split the data into 10 subsets 2) For each subset, we made its predictions using the model trained from the remaining nine subsets 3) We iterated this process to all subsets and hence obtained a series of data pairs of PM2.5 observations and predictions 4) We finally did a regression on the data matchups and calculated statistics including R^2 and RMSE (root mean square error). The statistical indicators of R^2 and RMSE were equal to 0.69 and 13.25 μg/m^3, respectively, indicating relatively satisfactory PM2.5 estimates. Fig. 2 shows the spatial distributions of the estimated PM2.5 concentrations on March 23, 2012 in Shenzhen.

2.2.3. Housing price as a proxy of economic status

Housing price was used as a proxy of mobile phone user's economic status. We collected the data of housing price of 6811 residence communities from the Fangtianxia (https://sz.esf.fang.com/), one of the largest Real Estate Network platform that provides an extensive map-based search of housing properties. Each housing price record comprises information such as the residence community's average housing price, total housing price and geographic location (i.e. latitude and longitude coordinates). As in many studies (Xu et al., 2018; Xu et al., 2019), we assume that people who live in residence communities with high average housing prices are more likely to be rich. Hence, we attributed the average housing price of the residence community nearest to a phone user's home location to the user as a proxy of the user's economic status.

2.3. Assessing the four types of individual total exposures at multi-temporal scales

The four types of individual total exposures include (1) Type 1 estimate (i.e. the hypothetical error-free exposure), which considers the individual mobility (using hourly activity locations) and spatiotemporal variations of PM2.5 concentrations (using hourly PM2.5 concentrations); (2) Type 2 estimate, which considers the individual mobility but not the spatiotemporal variations of PM2.5 concentration (using the average concentration of residential committee during a period, e.g. daily average concentration); (3) Type 3 estimate, which considers the spatiotemporal variations of PM2.5 concentration but not the individual mobility (using home locations); (4) Type 4 estimate, which neither considers the individual mobility nor the spatiotemporal variations of PM2.5 concentration.

The Type 1 daily total exposure was estimated through combing the estimated hourly PM2.5 concentrations and hourly mobile phone location data. The hourly PM2.5 exposure in a certain activity location of a mobile phone user was extracted from the PM2.5 concentration map at the corresponding hour. Then, the Type 1 daily total exposure of a mobile phone user was calculated by summing up the hourly PM2.5 exposures during the day. The Type 2 daily total exposure was calculated by adding up the daily average concentrations of the residential committees where a mobile phone user's activity locations are located. The Type 3 daily total exposure was calculated by summing up the estimated hourly PM2.5 concentrations in the home location of a mobile phone user. The Type 4 daily total exposure was calculated by adding up the mean daily concentrations of the residential committee where a mobile phone user lives in. Assuming that an individual's daily mobility pattern generally remains constant in a certain period (especially on weekdays) due to the multiple constraints (i.e. capacity, coupling and authority constraints) placed on individuals' spatiotemporal behaviours (Ilägcrstrand, 1970), we further calculated the four types of total PM2.5 exposures during a week, a month, a season and a year, respectively. We excluded weekends and holidays in the multi-temporal calculations, because our mobile phone data source is available on a weekday but individuals' mobility patterns between weekday and weekend are likely to be different (Liu et al., 2009; Dewulf et al., 2016; Siła-Nowicka et al., 2016). It should be noted that the periods selected to calculate the four types of total PM2.5 exposures across multi-temporal scales were the day, week, month, season and year that contain (or within) the day when mobile phone data is available. Hence, the examination in the present study may not be robust to the different selections of time. As a response, a day, week and month were thereby random selected in accordance with the season to calculate the Type 1 and Type 3 total exposures in the sensitivity analysis, with the consideration of the seasonal variation of PM2.5 pollution (Wang et al., 2014; Li et al., 2017). The Type 1 and Type 3 total exposures during each of three other seasons were also calculated to evaluate the robustness of the findings.

2.4. Statistical analysis

Firstly, paired sample t-test was used to determine whether there are significant differences amongst the four types of exposure estimates. This is to examine the importance of considering individual mobility and PM2.5 variations on individual exposure estimates. The level of statistical significance in paired sample t-test was set to 5%. We compared the differences between the Type 1 estimate (i.e. hypothetical error-free exposure) and three other estimates at multi-temporal scales (daily to annual) instead of the solely examination at a daily scale in most previous studies (Shekarrizfard et al., 2016; Park and Kwan, 2017; Yu et al., 2018). The calculation of the four types of exposure estimates and the selection of the time for the multi-temporal analysis have been specified in Section 2.3.

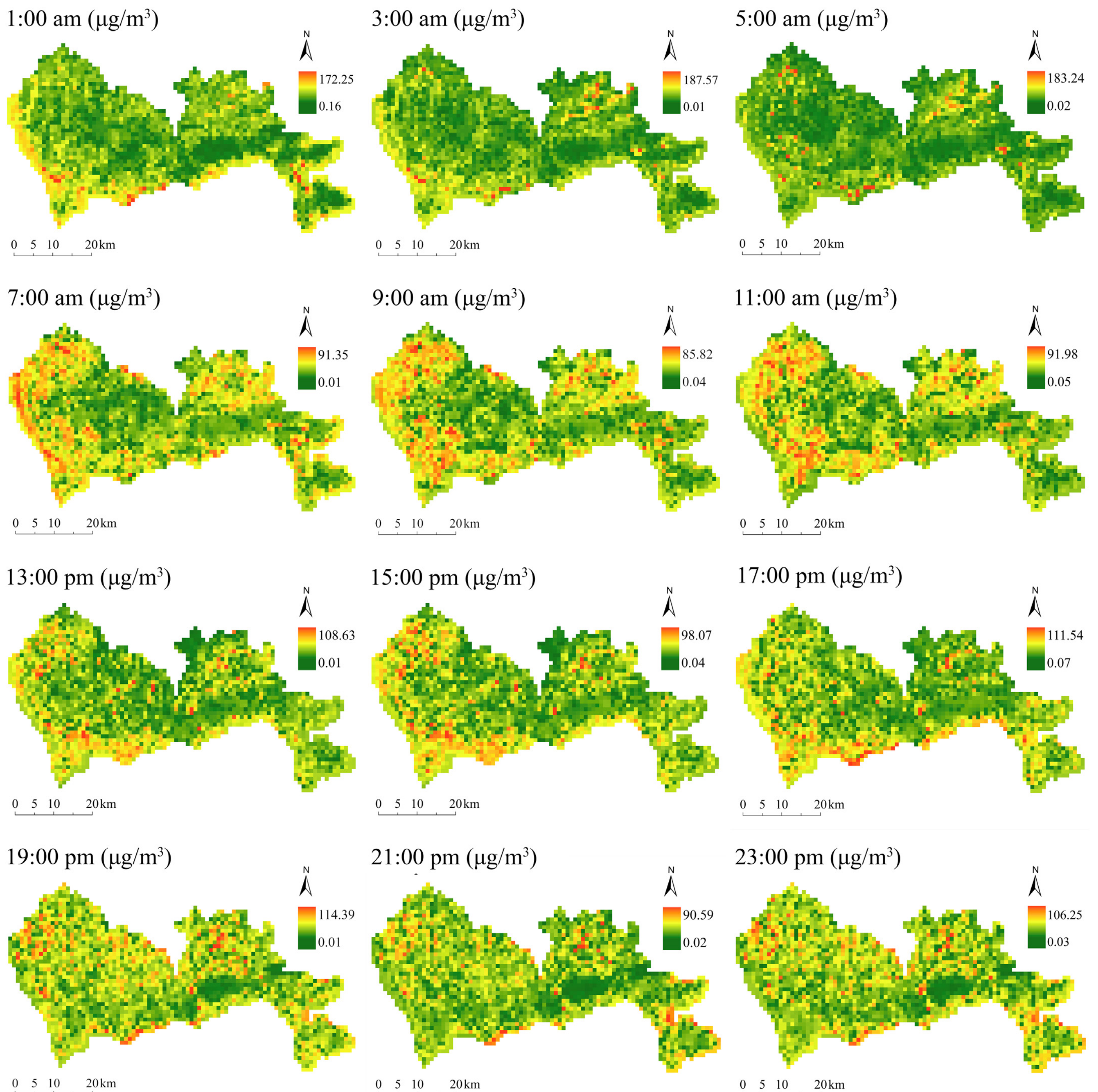

Fig. 2. Spatial distributions of the estimated PM2.5 concentrations in Shenzhen.

Secondly, Pearson correlation analysis was used to quantify the exposure misclassification error in terms of the four types of exposure estimates. The Pearson correlation coefficient (i.e. correlation coefficient hereinafter) quantifies the closeness of each of three other estimates to the Type 1 estimate (i.e. the hypothetical error-free exposure). This coefficient measures the misclassifications in PM2.5 exposure estimates if PM2.5 variations (i.e. Type 2 estimate), individual mobility (i.e. Type 3 estimate) or both (i.e. Type 4 estimate) are ignored. The higher the correlation coefficient (ranges from 0 to 1), the smaller the misclassification error. We set the level of statistical significance in Pearson correlation analysis to 5%.

Thirdly, we tested the differential effects of ignoring individual mobility, PM2.5 variations or both on the basis of economic status. One-way ANOVA was used to determine whether the paired differences between the Type 1 estimate (i.e. the hypothetical error-free exposure) and each of the three other types of estimates significantly vary amongst different economic-status groups. Then, the Pearson correlation coefficients were used to measure the exposure misclassification error in the low, middle and high economic groups, respectively. This is to examine which economic-status group exhibits the highest misclassification error when individual mobility, PM2.5 variations or both is ignored in exposure estimates.

Lastly, we performed the sensitivity analysis. Our examination at multi-temporal scales may not be robust to the different selections of time. Therefore, taking the impact of ignoring individual mobility as an example (Type 1 & Type 3 total exposures), a day, week and month were further random selected on a seasonal basis considering the seasonal variations of PM2.5 pollution (Wang et al., 2014; Li et al., 2017). Meanwhile, each of three other seasons was also selected for the further examination.

3. Results

3.1. Descriptive analysis

Table 1 presents the summary statistics of the four types of exposure estimates. In general, there were differences between the Type 1 estimate and each of three other estimates at all temporal scales. The mean value of the total daily exposure of the Type1 estimate was 0.695×10^3 μg/m^3, which was slightly lower than that of the Type 3 estimate (ignoring individual mobility) but higher than those of the Type 2 (ignoring PM2.5 variations) and Type 4 (ignoring individual mobility and PM2.5 variations) estimates. With respect to the weekly examination, the mean value of the total weekly exposure of the Type 1 estimate was 3.803×10^3 μg/m^3, which was lower than that of the Type 2, Type 3 or Type 4 estimate. A similar pattern can be observed in the results at the monthly or seasonal scale. Regarding the annual examination, as shown in Table 1, the mean value of the total annual exposure of the Type 1 estimate was the highest amongst the four (288.035×10^3 μg/m^3), followed by that of the Type 4, Type 2 and Type 3 estimates.

3.2. Comparison of exposure estimates

3.2.1. Boxplots of the four types of exposure estimates

The boxplots of the four types of exposure estimates at multi-temporal scales are displayed in Fig. 3. In general, the median values of the four types of exposure estimates were close to each other at all temporal scales, whereas the lengths of boxes (i.e. range between the first and third quartiles) varied across exposure estimates. As shown in Fig. 3(a), the length in the Type 3 daily estimate that ignored individual mobility was 0.346×10^3 μg/m^3, which was larger than that in the Type 1 daily estimate at 0.329×10^3 μg/m^3 (i.e. the hypothetical error-free exposure). The same pattern was observed in the results at the weekly, monthly or seasonal scale (Fig. 3(b–d)) but not at the annual scale (Fig. 3(e)).

Moreover, we observed that the length of box was smaller in the Type 2 estimate that ignored PM2.5 variations than in the Type 1 estimate at all temporal scales. In particular, the length in the Type 2 annual estimate was 45.481×10^3 μg/m^3, which was considerably smaller than 66.048×10^3 μg/m^3 in the Type 1 annual estimate (Fig. 3(e)). Furthermore, we found that the lengths between the minimum and maximum estimates were considerably larger in the Type 1 and Type 3 estimates than in the Type 2 and Type 4 estimates. For example, the lengths between the minimum and maximum estimates in the Type 1 and Type 3 weekly estimates were around 8.661×10^3 μg/m^3, which was larger than 8.200×10^3 μg/m^3 in the Type 2 and Type 4 weekly estimates (Fig. 3(b)).

3.2.2. Paired sample t-test to examine whether differences amongst exposure estimates exist

Table 2 presents the results of the paired sample *t*-test that assessed the differences amongst the four types of exposure estimates. In general, ignoring individual mobility (i.e. Type 2), PM2.5 variations (i.e. Type 3) or both (i.e. Type 4) led to a statistically significant difference amongst the exposure estimates. The Type 2 daily exposure estimated without considering PM2.5 variations was found to be statistically different from the Type 1 estimate (i.e. the hypothetical error-free exposure) with p value = 0.000 (Table 2). This result is true for the difference between the Type 1 and Type 2 estimates at a weekly, monthly, seasonal or annual scale (Table 2).

Significant differences were observed in exposure estimates with and without the consideration of individual mobility (Type 1 and Type 3 estimates). For example, the annual exposure estimate considering individual mobility (Type 1) was found to be significantly different from the annual estimate ignoring such determinant (Type 3) with p value = 0.000 (Table 2). Regarding the exposure estimate that ignored individual mobility and PM2.5 variations simultaneously, such estimate was significantly different from the Type 1 estimate which considered the two determinants simultaneously at each of the temporal scales (Table 2).

3.2.3. Pearson correlation analysis to quantify exposure misclassification errors

Table 3 shows the Pearson correlation analysis to quantify the exposure misclassification error. The Pearson correlation coefficient provides the information regarding how the exposure estimate ignoring individual mobility (i.e. Type 2), PM2.5 variations (i.e. Type 3) or both (i.e. Type 4) was close to the Type 1 estimate (i.e. the hypothetical error-free exposure). Overall, ignoring individual mobility and PM2.5 variations simultaneously resulted in the largest misclassification error in exposure estimate. The correlation coefficient between the Type 1 and Type 4 daily estimates was 0.732 ($p = 0.001$), which was lower than the coefficient of 0.800 ($p = 0.001$) between the Type 1 and Type 2 daily estimates or the coefficient of 0.839 ($p = 0.001$) between the Type 1 and Type 3 daily estimates (Table 3). Fig. 4(a–c) presents the scatter plots of the Type 1 daily estimate and three other types of daily estimates. A similar pattern of results was observed at the weekly, monthly, seasonal or annual scale (Table 3, Fig. 4(d–o)).

It should be also noted that ignoring PM2.5 variation (i.e. Type 2) produced a larger misclassification error than ignoring individual mobility (i.e. Type 3). In particular, the correlation coefficient between the Type 1 and Type 2 seasonal estimates was 0.672 ($p = 0.001$, Fig. 4(j)), which was lower than the coefficient of 0.837 between the Type 1 and Type 3 seasonal estimates ($p = 0.001$, Fig. 4(k)).

3.3. Differences amongst exposure estimates according to economic status

Fig. 5 exhibits the differences amongst exposure estimates in accordance with economic status. In general, people with high

Table 1
Descriptive analysis of the four types of exposure estimates (10^3 μg/m^3).

	Daily	Weekly	Monthly	Seasonal	Annual
	Mean (SD)	Mean (SD)	Mean (SD)	Mean (SD)	Mean (SD)
Type 1	0.695 (0.220)	3.803 (0.896)	15.144 (2.678)	45.765 (8.418)	238.025 (49.427)
Type 2	0.679 (0.194)	3.892 (0.860)	15.413 (2.488)	47.547 (7.833)	222.029 (37.087)
Type 3	0.700 (0.236)	3.822 (1.037)	15.197 (3.161)	46.071 (10.188)	218.474 (46.848)
Type 4	0.683 (0.213)	3.909 (0.981)	15.454 (2.921)	47.726 (9.375)	222.203 (42.222)

Type 1: Consider individual mobility, consider PM2.5 variations. Type 2: Consider individual mobility, not consider PM2.5 variations. Type 3: Not consider individual mobility, consider PM2.5 variations. Type 4: Not consider individual mobility, not consider PM2.5 variations.

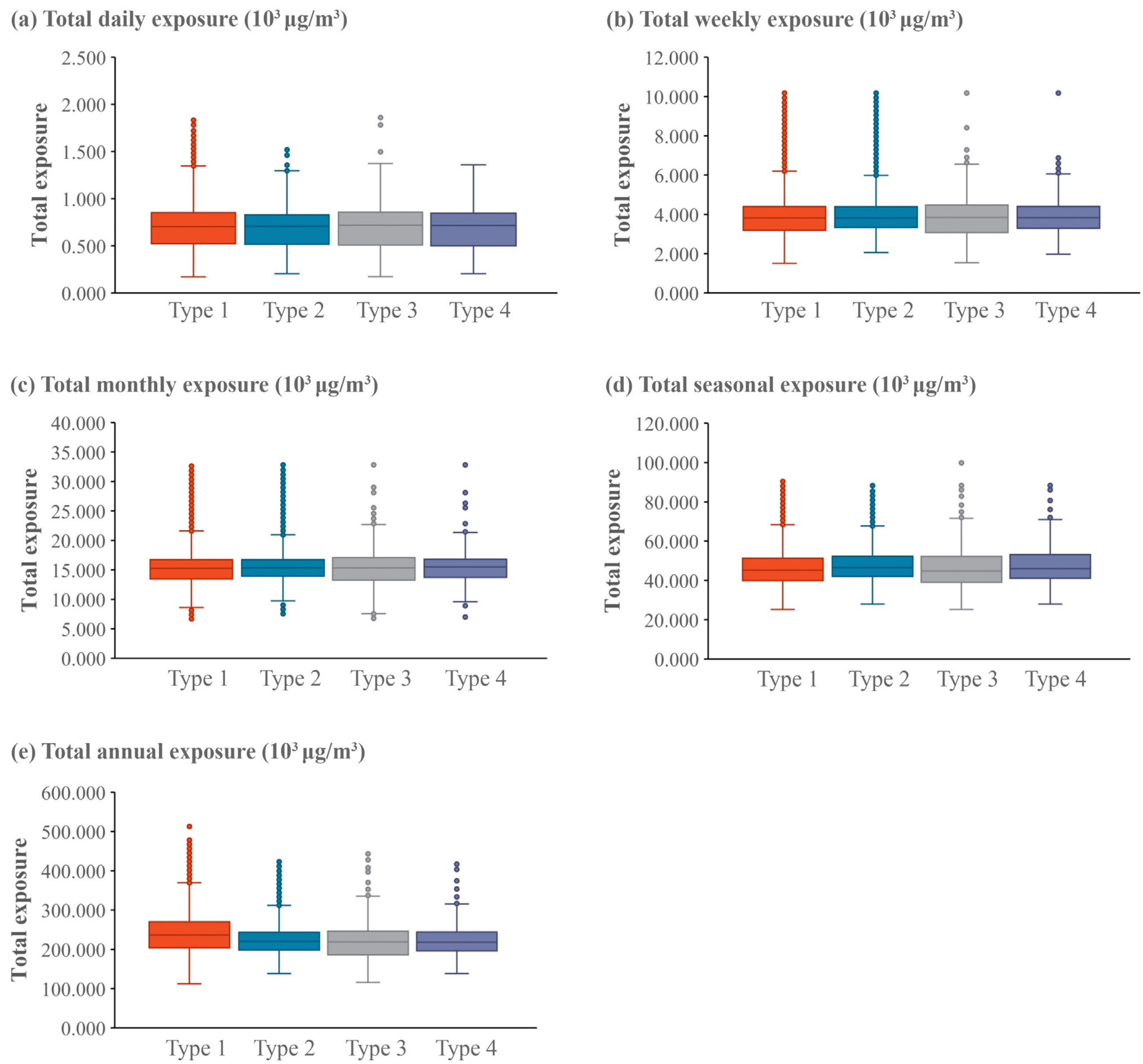

Fig. 3. Boxplots of the four types of PM2.5 exposures estimated at multi-temporal scales. Type 1: Consider individual mobility, consider PM2.5 variations; Type 2: Consider individual mobility, not consider PM2.5 variations; Type 3: Not consider individual mobility, consider PM2.5 variations; Type 4: Not consider individual mobility, not consider PM2.5 variations.

economic status showed the lowest correlation between the Type 1 estimate (i.e. the hypothetical error-free exposure) and each of three other types of estimates. In other words, people living in areas with higher residential property prices suffered from a larger exposure misclassification error. When PM2.5 variations were ignored, as shown in Fig. 5(a), the difference between the

Table 2
Paired sample *t*-test between the error-free estimate and three other types of estimates.

	Type 1 & Type 2		Type 1 & Type 3		Type 1 & Type 4	
	t value	p-value	t value	p-value	t value	p-value
Daily	105.263	0.000	−31.759	0.000	64.451	0.000
Weekly	−129.135	0.000	−32.127	0.000	−124.772	0.000
Monthly	−113.621	0.000	−26.098	0.000	−105.658	0.000
Seasonal	−234.398	0.000	−47.67	0.000	−206.568	0.000
Annual	381.156	0.000	493.681	0.000	326.339	0.000

Type 1: Consider individual mobility, consider PM2.5 variations. Type 2: Consider individual mobility, not consider PM2.5 variations. Type 3: Not consider individual mobility, consider PM2.5 variations. Type 4: Not consider individual mobility, not consider PM2.5 variations.

Table 3
Pearson correlation analysis to quantify misclassification errors in exposure estimates.

	Type 1 & Type 2		Type 1 & Type 3		Type 1 & Type 4	
	Coefficient	p-value	Coefficient	p-value	Coefficient	p-value
Daily	0.800	0.000	0.839	0.000	0.732	0.000
Weekly	0.771	0.000	0.866	0.000	0.696	0.000
Monthly	0.683	0.000	0.825	0.000	0.588	0.000
Seasonal	0.672	0.000	0.837	0.000	0.575	0.000
Annual	0.679	0.000	0.746	0.000	0.587	0.000

Type 1: Consider individual mobility, consider PM2.5 variations. Type 2: Consider individual mobility, not consider PM2.5 variations. Type 3: Not consider individual mobility, consider PM2.5 variations. Type 4: Not consider individual mobility, not consider PM2.5 variations.

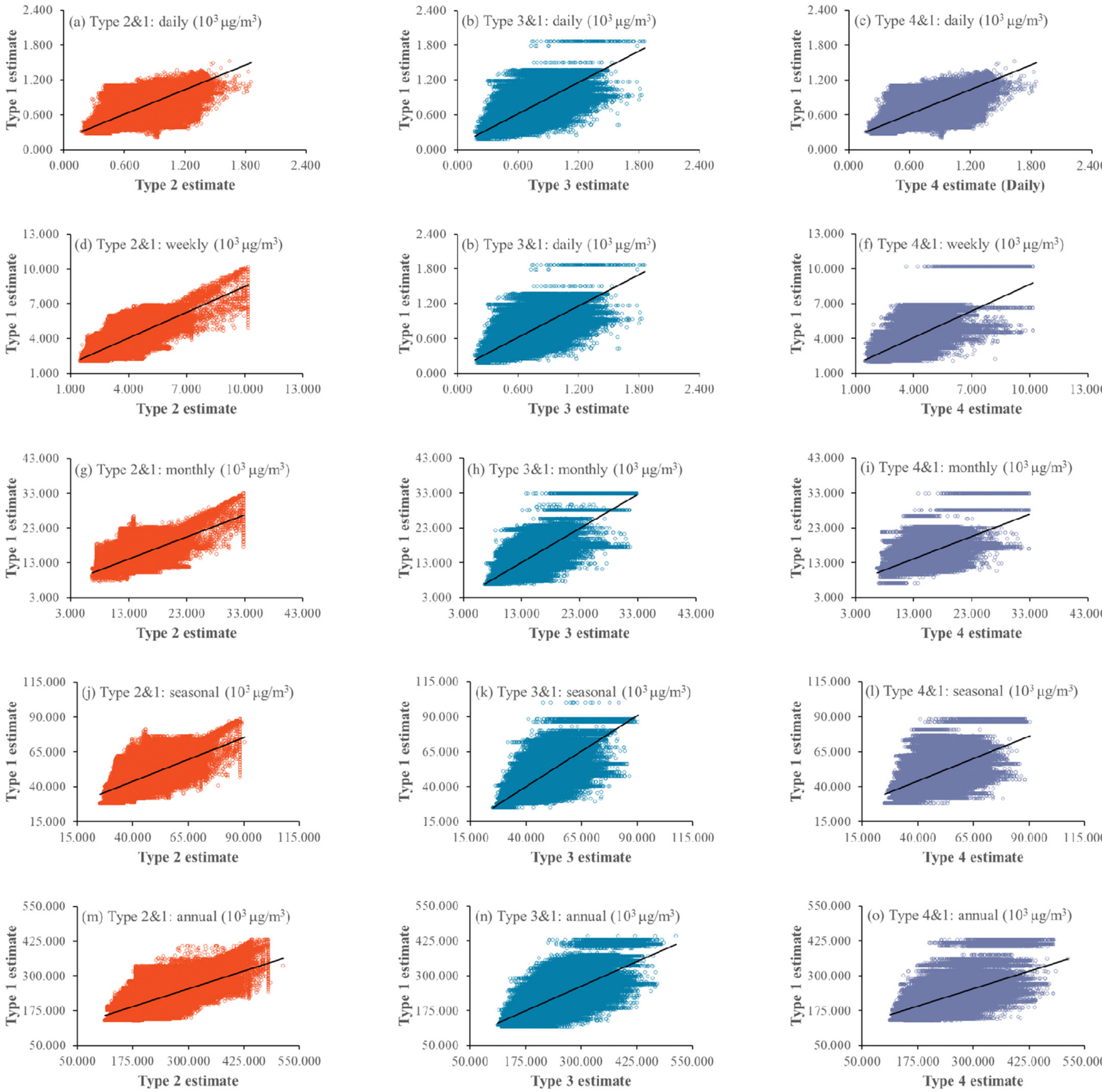

Fig. 4. Scatter plots of the error-free estimate and three other types of estimates.

Type 1 and Type 2 daily estimates significantly varied across different economic-status groups (p-trend = 0.000); the correlation coefficient between the two types of exposure estimates was 0.779 (p = 0.000) in the high economic-status group, which was lower than 0.794 (p = 0.000) and 0.785 (p = 0.000) in the low and middle economic-status group, respectively; a similar pattern was observed in the results of four other temporal scales (Fig. 5 (b–e)).

When individual mobility was ignored (i.e. Type 3), the difference between the Type 1 (i.e. the hypothetical error-free exposure) and Type 3 daily estimates significant differed among the three economic-status groups with p-trend value = 0.000 (Fig. 5(f)); the correlation coefficients between the Type1 and Type 3 daily estimates were 0.854 (p = 0.000) and 0.831 (p = 0.000) in the low and middle economic-status groups, respectively, which were higher than 0.791 (p = 0.000) in the high economic-status group (Fig. 5(f)); similarly, as shown in Fig. 5(g–j), people with high economic status also exhibited the lowest correlation between the Type 1 and Type 3 estimates at each of four other temporal scales. When individual mobility and PM2.5 variations were simultaneously ignored in exposure estimates (i.e. Type 4), the lowest correlations between the Type 1 and Type 4 estimates at all the temporal scales were still observed for people with high economic status (Fig. 5(k–o)).

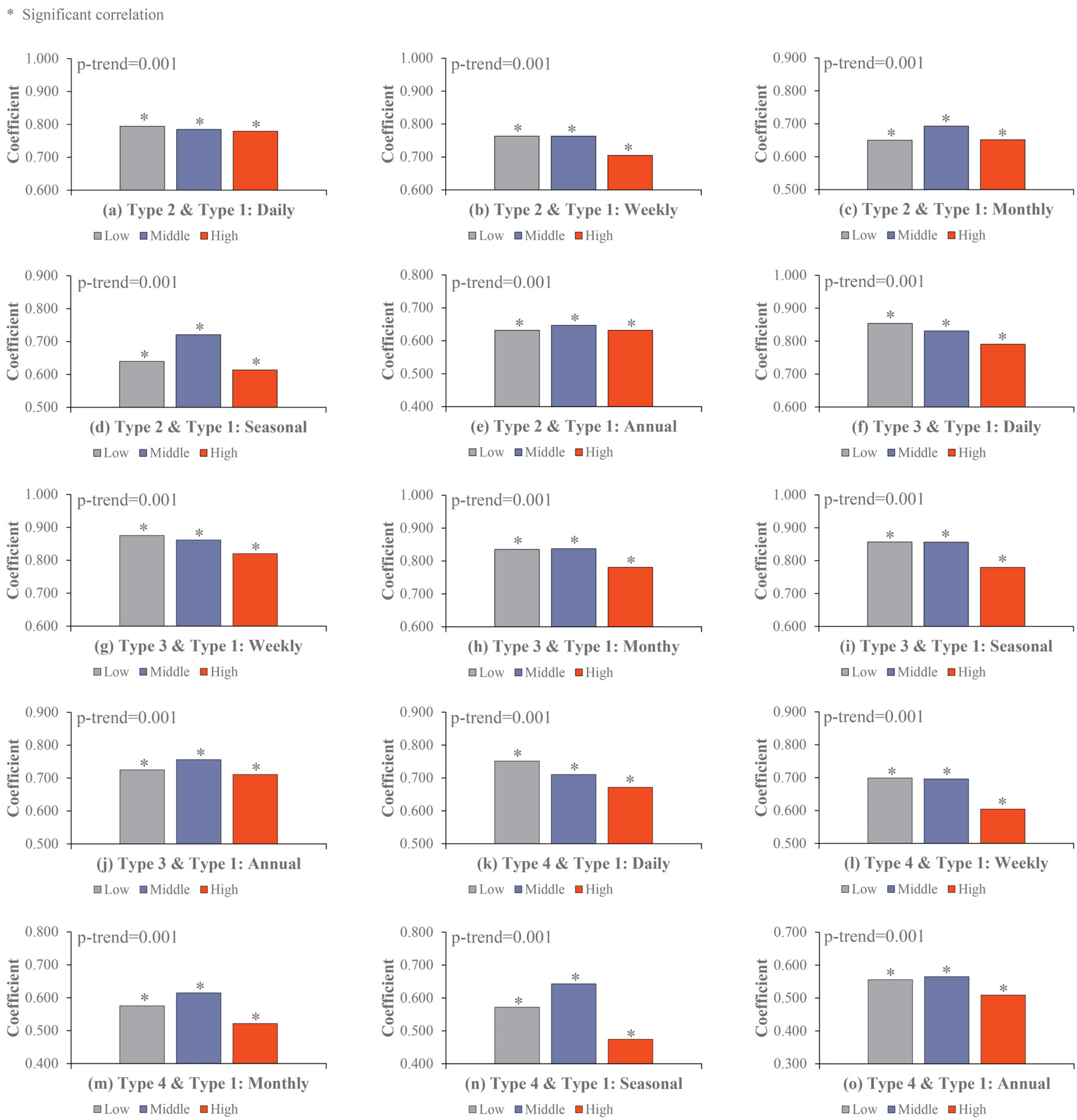

Fig. 5. Pearson correlation coefficients between the error-free estimate and three other types of estimates in the low, middle and high economic stratums.

3.4. Sensitivity analysis

The results of the sensitivity analysis of the different selections of time are shown in Table 4. In general, the findings that ignoring individual mobility can lead to misclassification errors in exposure estimates were not sensitive to the different selections of time. According to the results of the paired sample *t*-test, the Type 1 daily estimate (i.e. the hypothetical error-free exposure) was significantly different from the Type 3 daily estimate (i.e. ignoring individual mobility) in each of the random selected days ($p \le 0.000$). The value of Pearson correlation coefficient (quantify exposure misclassification errors) ranged from 0.421 to 0.891 ($p = 0.001$). Similarly, significant differences between the Type 1 and Type 3 estimates were also observed in the random selected weeks and months and in each of three other seasons.

4. Discussion

4.1. New insights from this study

An accurate estimation of air pollution exposure is essential to investigate the socioeconomic disparities in air pollution exposure and its

Table 4
Sensitivity analysis of the different selections of time (Type 1 & 3 estimates as example).

	p-value (paired *t*-test)	Pearson coefficient		p-value (paired *t*-test)	Pearson coefficient
Day 1	0.000	0.859	Month 1	0.000	0.861
Day 2	0.000	0.874	Month 2	0.000	0.838
Day 3	0.000	0.891	Month 3	0.000	0.830
Day 4	0.000	0.421	Month 4	0.000	0.630
Week 1	0.000	0.896	Spring	0.000	0.837
Week 2	0.000	0.876	Summer	0.000	0.841
Week 3	0.000	0.843	Autumn	0.000	0.668
Week 4	0.000	0.852	Winter	0.000	0.648

Type 1: Consider individual mobility, consider PM2.5 variations. Type 3: Not consider individual mobility, consider PM2.5 variations.

effect on human health. Individual mobility and air pollution variation are the two determinants of exposure estimates. However, how ignoring the two determinants produces misclassification errors in exposure estimates has not be well understood. In an attempt to remedy the issue, we coupled mobile phone location data (not call detail records of mobile phone data) and a machine learning approach to investigate the effect of ignoring individual mobility, PM2.5 variations or both on exposure misclassification errors.

We found the robust evidence that the misclassification error is larger in the estimate ignoring PM2.5 variations than the estimate ignoring individual mobility, which is seldom reported before. Usually, previous studies either emphasize the necessity of considering individual mobility in exposure estimates (Setton et al., 2011; Buonanno et al., 2014; Blanchard et al., 2018) or discover that the misclassification error is larger in the estimate disregarding individual mobility than the estimate that does not consider air pollution variations (Shafran-Nathan et al., 2018). This suggests that the role of air pollution variations in the occurrence of exposure misclassification errors receives insufficient attention. The large misclassification error caused by ignoring air pollution variations obtained in the present study highlights that air pollution variations should also be well considered in exposure estimates, which thereby supports a more accurate estimate of air pollution-related health effect.

We found that the impact of ignoring PM2.5 variations, individual mobility or both significantly varies across different economic-status groups. That is, people with high economic status suffer from a larger exposure misclassification error. Consequently, ignoring each determinant may result in the differentially misclassified exposure estimates of socioeconomic subgroups. On the one hand, the differential impacts of ignoring the determinants on exposure misclassification errors may distort (or confound) the statistical associations between air pollution exposure and health outcomes in epidemiological studies. On the other hand, because some studies reported that people with high economic status are disproportionately exposed to air pollution (Blanchard et al., 2018; Guo et al., 2020), the differential influences may mask the pattern of the socioeconomic disparities in air pollution exposure if the exposure of high economic-status group is underestimated. The findings of the present study highlight that the differential effects of ignoring the determinants across socioeconomic groups should be well considered in exposure estimates to promote the scientific examination in relation to air pollution.

4.2. Strengths of the present study

This study demonstrates several strengths. Firstly, we combine the machine learning approach (i.e. Geo-BPNN) and remote sensing data to estimate PM2.5 concentrations at finer spatial and temporal scales (hourly at 1 km^2 spatial resolution), which can well examine the effect of ignoring PM2.5 variations. Remote sensing data, which have high spatiotemporal coverage and resolutions, have been widely used as the key data input in air pollution modelling. Machine learning has been widely utilized in air pollution modelling (Di et al., 2016; Li et al., 2017) because of its ability to model the complex and nonlinear associations between the predictors (e.g. traffic flow) and the outcome variables (e.g. PM2.5 concentrations). Such a modelling approach is superior not only because of its high practicality, but also because of its effective characterization of air pollution variations at finer spatio-temporal scales, which to a large extent overcomes the limitations of the insufficient characterization of air pollution variations in traditional modelling methods used in previous studies.

Except the Geo-BPNN, we further selected the random forest (RF) model, i.e. another commonly used machine learning method in the field of PM2.5-AOD studies (Hu et al., 2017; Wei et al., 2019; Dong et al., 2020), to estimate PM2.5 concentrations and then compared the four types of exposure estimates. A similar pattern of results was observed, which indicates that the findings that ignoring individual mobility, PM2.5 variations or both leads to misclassification errors, were robust to PM2.5 estimates from different machine learning models. More details of the RF model and corresponding analysis results can be found in the Supplementary Material (i.e. Text S1, Tables S3 and S4).

Secondly, this study is one of the earliest attempts to use mobile phone big data (not call detail records) to derive the information on individual trajectories, which can well suggest the effect of ignoring individual mobility on exposure misclassification errors. This dataset opens up new opportunities for capturing individual mobility. On the one hand, the high and increasing penetration rate of mobile phone users offers a new large-scale population-representative dataset of individual mobility. Mobile phone location dataset, which to a large extent can be a proxy of the entire population, is not limited to a small sample size or a certain socioeconomic subgroup. Therefore, this dataset is suitable to analyze not only the effect of ignoring individual mobility on the exposure misclassification error, but also the differential effects according to socioeconomic characteristics. On the other hand, the continuous information of geospatial locations on an hourly basis benefits the examination at multi-temporal scales, which has not been investigated in previous studies.

4.3. Limitations and prospects

Several limitations and future directions should also be noted. Firstly, this study does not incorporate other factors that can affect exposure estimates, such as indoor air pollution, window type and infiltration efficiency in different microenvironments (Tang et al., 2018; Ścibor et al., 2019), because of the unavailability of such data at present, which may introduce bias to the estimated individual exposures (Shekarrizfard et al., 2016; Shafran-Nathan et al., 2017). Secondly, our mobile phone data source is available only on a weekday. The findings of this study may not be suitable for weekends or holidays because there might exist the differences between the weekday and weekend mobility patterns of individuals (Liu et al., 2009; Dewulf et al., 2016; Siła-Nowicka et al., 2016).

Thirdly, although PM2.5 concentrations are modelled at the highest spatial resolution that the current satellite-based approach can access, similar to previous studies (Yoo et al., 2015; Yu et al., 2018), PM2.5 estimates in this study may still be insufficient to capture the spatial variation of PM2.5 pollution, which in turn may still be insufficient to demonstrate the necessity of considering air pollution variations in exposure estimates. As an alternative, future research can turn to deep learning approaches for improved PM2.5 estimates. Deep learning is an advanced machine learning approach capable of comprising multiple processing layers to represent the observed data that involves not only a number of predictors but also the multiple levels of abstraction. Thus, a few attempts have used deep learning methods, such as the deep belief network (Li et al., 2017), to estimate daily PM2.5 concentrations. These studies suggest improved PM2.5 estimates by deep learning approaches compared to the traditional machine learning methods (Li et al., 2017; Sun et al., 2019; Wang and Sun, 2019). Hence, we are certain that the results in the present study can be enhanced in terms of the PM2.5 estimates by employing deep learning approaches in the future.

Fourthly, the findings of the present study are related to the specificity of the study location (i.e. Shenzhen). Shenzhen has its unique characteristics such as urban structure (i.e. polycentric and ribbon urban form), population distribution pattern and land use layout. These characteristics shape the mobility patterns of residents in Shenzhen, which may be different from those residing in other Chinese or Western cities. However, there does exist the substantial variations of air pollution concentrations, which do not depend on the study location. Hence, if individual mobility and PM2.5 variations are ignored, there still exist the misclassification errors in exposure estimates, which may make our findings suitable elsewhere.

Fifthly, because the accuracy of the estimated locations of the mobile phone users heavily depends on the service area of mobile phone towers, like prior studies (Silm and Ahas, 2014; Yu et al., 2018), the accuracy of the estimated locations in the present study (the average area $= 0.28\ km^2$) may not be sufficient to illustrate the necessity of considering individual mobility in exposure estimates. A potential solution is to install a specially designed application on the respondent's mobile phone to collect the large-scale location dataset with a high spatial resolution (Fan et al., 2015), if the respondent consent is available. Lastly, the large scale individual-level mobile phone location data, which has been used to analyze the effect of ignoring individual mobility in the present study, has been seldom utilized to investigate socioeconomic disparities in air pollution exposure. Future studies can address this gap to advance the research on exposure disparity from a location (i.e. home)-based paradigm to a people-based one.

5. Conclusions

Misclassification errors in exposure estimates occur if individual mobility, air pollution variations or both is ignored. The error produced by disregarding air pollution variations is larger than that produced by ignoring individual mobility. Not only individual mobility but also air pollution variations should be considered in the estimate of individual exposure to air pollution. Future studies estimating the effect of air pollution exposure on human health should well consider socioeconomic differences, because such differences can cause uncertainty in health estimates through the differential influences of ignoring exposure assessment determinants on exposure misclassification errors across different socioeconomic groups.

CRediT authorship contribution statement

Huagui Guo: Conceptualization, Data curation, Methodology, Formal analysis, Writing - original draft. **Qingming Zhan:** Funding acquisition, Investigation. **Hung Chak Ho:** Methodology, Writing - review & editing. **Fei Yao:** Resources, Writing - review & editing. **Xingang Zhou:** Resources, Writing - review & editing. **Jiansheng Wu:** Funding acquisition, Investigation. **Weifeng Li:** Methodology, Writing - review & editing.

Declaration of competing interest

All authors declared no conflicts of interests.

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Appendix A. Supplementary data

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