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Mapping Air Pollution Concentrations on Sidewalks in Central Business Districts Based on Mobile Monitoring

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Abstract

Air pollution on urban sidewalks poses a huge threat to human health. We conducted an air pollution mobile monitoring campaign to measure PM2.5 levels on sidewalks in the Futian Central Business Districts area of Shenzhen, using portable air pollution sensors. The campaign involved collecting data during peak commuting times to capture variations in air quality. Calibration of the AirBeam3 devices against a standard instrument ensured data accuracy. Using GIS spatial analysis, we mapped air pollution patterns and identified notable differences between weekdays and weekends, with concentrations ranging from 3-9 $\mu g/m^3$. Our findings indicate higher pollution levels on weekdays, particularly in the afternoon, correlating with increased traffic and economic activity. The study also highlights spatiotemporal heterogeneity, with morning pollution concentrations more pronounced in the northern financial district and afternoon levels higher in the southern area, characterized by commercial facilities. These patterns suggest that regional industrial distribution and traffic flow significantly influence air quality. By understanding the dynamics of pollution in urban environments, this research contributes to the development of effective strategies for improving air quality and public health in densely populated city centers.

1. Introduction

Rapid urbanization and industrialization have made urban air pollution a critical environmental issue (Du et al., 2019; S. Wang et al., 2020). Road traffic emissions are a major contributor to this pollution and are closely linked to various health conditions (Jandacka et al., 2017; Tobías et al., 2020). To monitor air pollution and mitigate its negative impact on social development, governments worldwide have established networks of fixed-site monitors, including roadside stations, to measure air quality (Lim et al., 2019). However, due to the high costs of equipment and operation, these stations are often sparsely distributed.

Since air pollutant concentrations can vary significantly over short distances and time periods, static networks alone cannot fully characterize the urban environment. Consequently, there is growing interest in using mobile monitoring to study the spatial distribution of air pollution. For example, Shi et al. (2018) used trams to collect long-term street-level $PM_{2.5}$ data in Hong Kong, identifying key building design factors affecting pollution dispersion. DeSouza et al. (2020) identified $PM_{2.5}$ hotspots using low-cost sensors mounted on trash trucks. Automobiles are the most commonly used vehicles for mobile air pollution sensing, as seen in studies from the United States (Messier et al., 2018; Miller et al., 2020), Europe (Shah et al., 2023), and China (C. Huang et al., 2022; G. Huang et al., 2023; Shi et al., 2016). Additionally, bicycles equipped with low-cost sensors are frequently used to monitor roadside air pollution (Hassani et al., 2023; von Schneidemesser et al., 2019).

Previous research using mobile monitoring has made significant progress, yet certain gaps remain. Firstly, most studies have utilized vehicles as the primary mobile monitoring platforms. While vehicle-mounted sensors can monitor urban road air pollution on a large scale, they are limited to specific routes and cannot capture pollution levels on sidewalks. Walking is a crucial mode of travel, especially in central business districts (CBDs), where sidewalks are close to traffic (Rakowska et al., 2014) but often lack sufficient physical protection (Lv et al., 2021). Consequently, pedestrians are exposed to high pollution levels. Furthermore, some studies have monitored air pollution at specific sidewalk locations, such as bus stops (Xing et al., 2019) and intersections (Z. Wang et al., 2021) or in limited areas (Alas et al., 2022), they fail to fully capture regional spatiotemporal variations in pedestrian-level pollution. Understanding these patterns is crucial for urban planners to propose interventions that reduce pollution and protect pedestrians.

To address these gaps, this study focuses on the Shenzhen CBD, measuring PM2.5 levels on sidewalks to study spatial-temporal heterogeneity. The objectives are: (1) to use low-cost sensors for mobile monitoring of sidewalk air pollution, and (2) to employ GIS for data aggregation and spatial analysis to investigate spatiotemporal patterns.

2. Method

2.1. Study Area

Shenzhen, a prominent mega-city in southern China's Guangdong Province, borders Hong Kong to the south and covers an area of 1,997.47 square kilometers. With a resident population of 17,790,100, Shenzhen is one of China's three major national financial centers. This study focuses on the Futian CBD area, chosen for its high pedestrian traffic and significant air pollution exposure risks. Air pollution data was collected from walkable roads in the CBD.

2.2. Data Collection Campaign

In this study, we focused on particulate matter with a particle size of less than 2.5 micrometers ($PM_{2.5}$) as a representative air pollutant, given its prominence in near-road environments. We measured $PM_{2.5}$ using the low-cost AirBeam3 air quality monitor, which has been widely used in previous research (Johnston et al., 2019; Song & Kwan, 2023). The device features a Plantower PMS7003 sensor for $PM_{2.5}$, as well as a relative humidity and temperature sensor and a GPS locator, enabling meteorological data collection and spatial analysis. The temporal resolution of AirBeam3 data varies with the recording duration: data is recorded every second for sessions under 2 hours, averaged every 5 seconds for sessions between 2 and 9 hours, and averaged every minute for sessions exceeding 9 hours.

The data collection campaign took place from July 1 to July 8, 2024, during sunny weather. Eight research assistants were recruited to walk the sidewalks and collect air pollution data. Prior to the campaign, our team provided training on the monitoring routes and instrument usage, as shown in the **Figure 1** (a). PM2.5 measurements were taken from 7:30 to 9:30 a.m. and 5:30 to 7:30 p.m., coinciding with peak commuting times and higher pollution levels. The instrument was worn on a lanyard around the chest, positioning the PM sensor intake and exhaust ports away from the direction of travel to minimize wind interference, as shown in the **Figure 1** (b).

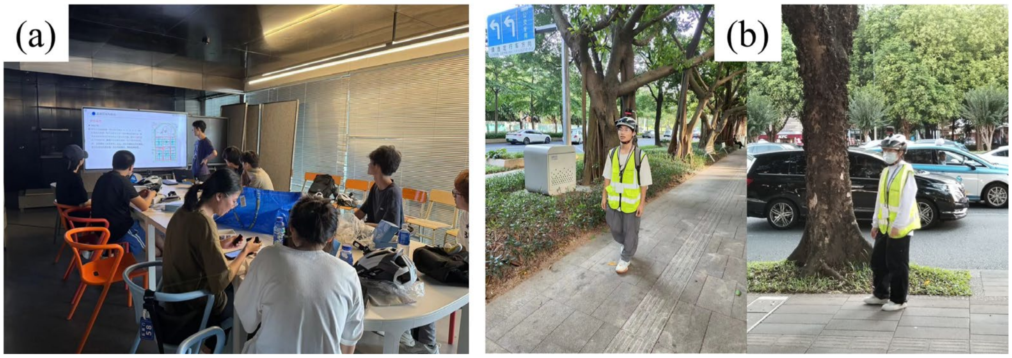

Figure 1: Photos from: (a) Training for research assistants; (b) The process of monitoring

2.3. Instruments Calibration

We conducted a laboratory comparison between the low-cost PM2.5 instruments and a regulatory instrument to calibrate the AirBeam3. The eight AirBeam3 devices, labeled A through H, were placed side by side. The standard instrument used was the Profiler Model 212 (MetOne Instruments, Inc.), a robust optical particle counter widely used in air monitoring (Brattich et al., 2020). The calibration involved generating a PM2.5 linear calibration equation between the AirBeam3 and the standard instrument, following a method from previous studies (Zhou & Lin, 2019). Each AirBeam3 was tested and calibrated using 5 minutes average values over a 24-hour period. The fitting equation is shown in the Equation (1):

$$Y = \beta_1 X + \beta_0 \tag{1}$$

where Y is the PM concentrations recorded by the standard instrument, and X is PM concentrations recorded by the AirBeam3 sensors.

3. Results

3.1. Results of Instrument Calibration

The coefficient of determination (R^2) was used to assess the relationship between the instruments. **Figure 2** shows that R^2 values between the AirBeam3 devices and the standard instrument ranged from 90.8% to 96.5%, indicating a strong linear correlation. Thus, the eight linear equations derived were used for data calibration.

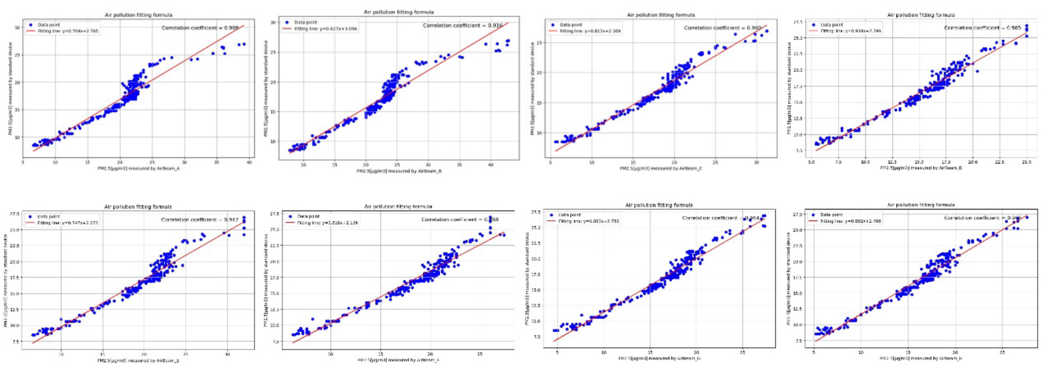

Figure 2: Measurement comparison between eight AirBeam3s and the standard instrument

3.2. Air Pollution Data Aggregation and Mapping

After data collection and calibration, air pollution data points were aggregated at the sidewalk segment level. To determine the spatial resolution (or segment length), we used semi-variogram modeling in GIS. The semi-variogram, a function of distance, increases over a certain range until reaching stability. We divided the time periods into four categories: weekday mornings, weekday afternoons, weekend mornings, and weekend afternoons.

The semi-variogram results, as shown in the **Figure 3**, indicating that the major range for morning data (17.4m on weekdays and 9.4m on weekends) is larger than for afternoon data (1.64m on weekdays and 1.50m on weekends). This indicates that morning data points are spatially correlated over a greater distance. To ensure consistent spatial resolution, we chose a 10m section of the road as the study unit.

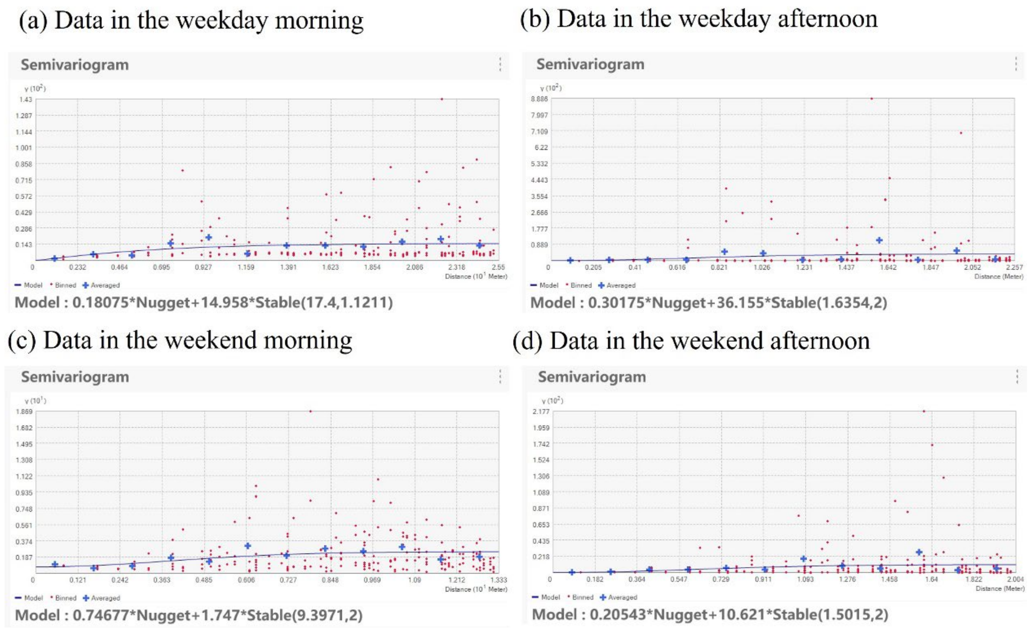

Figure 3: The semi-variogram models and the corresponding major ranges of the $PM_{2.5}$ datasets

After data aggregation, PM2.5 distribution maps in **Figure 4** illustrate the spatial and temporal variations in air pollution. Table 1 presents the descriptive statistics of air pollution on sidewalks in the Futian CBD area. The results indicate that average air pollution concentrations are higher on weekdays than on weekends. The highest average concentrations were recorded on weekday afternoons, while the lowest were observed on weekend mornings.

(a) (b) (c) (d)

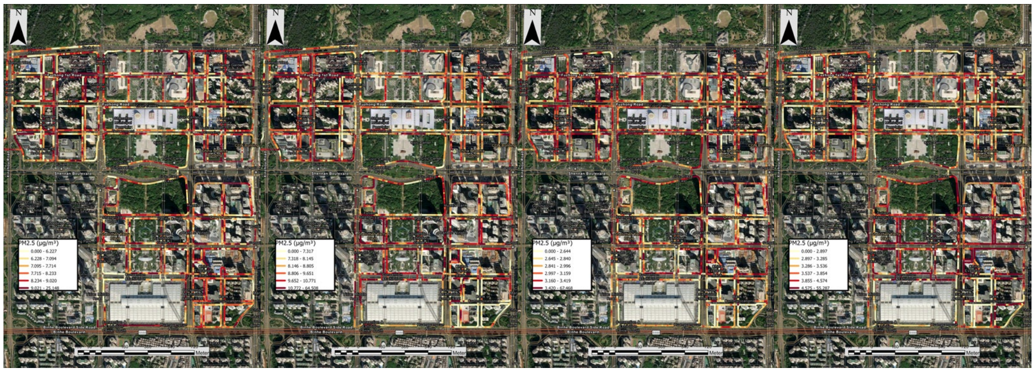

Figure 4: $PM_{2.5}$ distribution maps in the: (a) weekday morning; (b) weekday evening; (c) weekend morning; (d) weekend evening

Time	Mean ($\mu g/m^3$)	Min ($\mu g/m^3$)	Max ($\mu g/m^3$)	Std ($\mu g/m^3$)
Weekday morning	7.5	2.14	25.1	2.06
Weekday afternoon	8.8	3.61	64.5	3.26
Weekend morning	3	2.37	67.5	2.14
Weekend evening	3.84	2.4	55.4	2.36

Table 1: Descriptive statistics of air pollution on sidewalks

3.3. Hotspots Analysis

To better demonstrate the spatial-temporal heterogeneity of air pollution, a hotspots analysis was conducted, with results shown in the figure. As shown in the **Figure 5**, the study area exhibits a higher number of hotspots compared to cold spots, indicating a pronounced clustering of high pollution on sidewalks in the CBD. Hot and cold spots are less evident on weekend mornings, likely because lower traffic and pedestrian flow result in fewer emissions, leading to a more balanced air pollution distribution. In contrast, on weekend evenings, increased economic activities in the CBD area leads to more noticeable concentrations of air pollutants.

(a) (b) (c) (d)

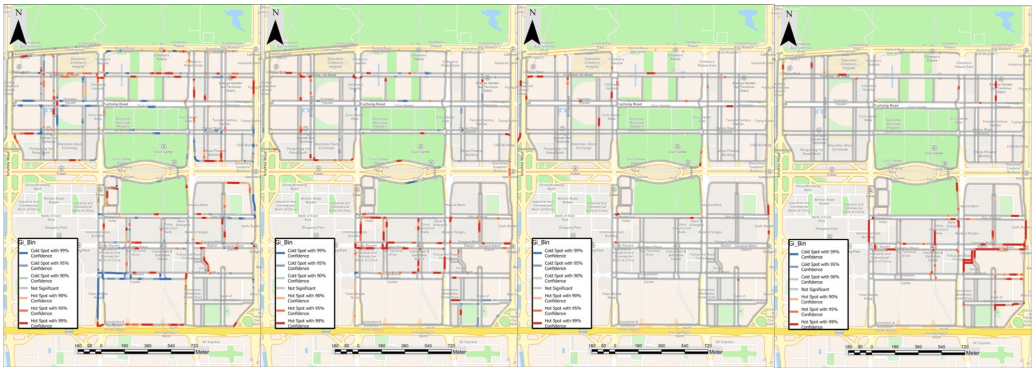

Figure 5: Hotspots analysis results in the: (a) weekday morning; (b) weekday evening; (c) weekend morning; (d) weekend evening

In addition to temporal variations, spatial heterogeneity was also observed. In the morning, pollutant concentrations are more pronounced in the northern part of the study area. This area, north of Shennan Boulevard, is dominated by financial facilities like the Shenzhen Stock Exchange and Ping An Financial Building, attracting significant morning rush hour traffic and emissions. In the afternoon, higher pollutant concentrations shift to the southern part of the study area, which features large restaurants and shopping centers such as Shenzhen One Avenue and the Leader Exhibition Center. These are key destinations for after-hours pedestrian and vehicular traffic. Thus, the spatial and temporal changes in economic activities influence regional air pollution concentrations.

4. Discussion

Our study offers valuable insights for local urban planning and environmental management practices. First, considering the temporal variability of air pollution concentrations, it is necessary to take tailored traffic control policies for weekdays and weekends to mitigate the exacerbation of air pollution caused by traffic congestion. Second, the spatial heterogeneity of air pollution concentrations highlights the limitations of relying solely on fixed monitoring stations to capture small-scale pollution variations. To address this, governments could implement regular mobile air pollution monitoring on highly polluted roads, complementing fixed station data to more effectively enhance urban air quality. In the future, our research will focus on exploring the influence of urban built environment factors on the spatial and temporal variations of sidewalk air pollution, enabling more targeted and effective interventions.

5. Conclusions

In this study, we conducted an air pollution monitoring campaign in the Futian CBD area of Shenzhen, measuring PM2.5 levels on sidewalks using portable sensors. After calibrating the data, we mapped air pollution on weekdays and weekends. We found that mean PM2.5 concentrations ranged from 3-9 μg/m³ across different time periods. Using GIS spatial analysis, we examined the spatial and temporal heterogeneity of air pollution, suggesting links to regional industrial distribution and traffic flow variations. The study results can inform air pollution interventions on regional sidewalks.

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