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Research article

Electric vehicle attributed future air pollution alleviation: A case study in Guangdong province, China

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ABSTRACT

Electric vehicles (EVs) are advocated to combat the effects of tailpipe emissions. This study synergizes EV charging consumption and charging stations from six cities in Guangdong (GD) province, China, to reveal the potential impacts of EVs on four relevant air pollutants ($PM_{2.5}$, NO_2, SO_2, CO) based on a data-driven attention-based Random Forest model and scenario analysis. Measurements from traffic-affected air pollution monitoring stations show that NO_2 concentrations have a higher mean decrease trend (-2.39 year^{-1}) in the PRD region after EV adoption, followed by $PM_{2.5}$ (-0.29 year^{-1}). In contrast, the environmental benefits of EVs for SO_2 and CO are relatively lower, with decreasing trends of -0.12 year^{-1} and -0.013 year^{-1}, respectively. Pronounced alleviations of these four air pollutants were presented for most districts in other cities under the assumption of conducting comparative EV policy, with mean reductions of -1.86 μg/m^3, -1.08 μg/m^3, -0.17 μg/m^3 and -0.01 mg/m^3 (by 7.8 %, 4.9 %, 1.9 % and 1.4 % with the reference of average values in 2023) for $PM_{2.5}$, NO_2, SO_2 and CO, respectively. Moreover, the concentrations tend to decline as the increase in EV charging consumption and the number of EV charging stations. Results show that a 30 % increase in both EV charging consumption and stations results in a further decline in $PM_{2.5}$ (-0.46 μg/m^3), NO_2 (-0.37 μg/m^3), SO_2 (-0.048 μg/m^3), and CO (-0.0043 mg/m^3) in Guang Dong (GD) province. To the best of our knowledge, it is the first time to assess environmental benefits of EVs with the involvement of actual EV charging demand and charging stations.

1. Introduction

Air pollution is an environmental issue of global concern due to its adverse impact on human health, environmental degradation and climate change (Smith et al., 2009; Kan et al., 2012; Sicard et al., 2016; Tagaris et al., 2009). Air pollution encompasses diverse components, including natural sources like wildfires and volcanic eruptions, as well as those resulting from anthropogenic activities like agricultural processes, industrial and vehicular emissions (Daellenbach et al., 2020; Cofala et al., 2007). Effective mitigation strategies and a comprehensive understanding of the sources and dynamics of air pollution are imperative to safeguard human health and preserve environmental quality. It also aligns with multiple Sustainable Development Goals (SDGs) outlined by the United Nations (https://sdgs.un.org/goals), dedicated to ensuring good health (SDG 3), fostering sustainable cities and communities (SDG 11), and combating climate change and its impact (SDG 13).

The consumption of non-renewable energy sources such as fossil fuels, and various energy-related environmental issues are major challenges with far-reaching impacts. Conventionally fuelled vehicles like using gasoline and diesel are deemed as the primary contributors to non-renewable energy utilization and greenhouse gas emissions with the continuing rise in the quantity of vehicles (Yan and Sun, 2021; Ramli et al., 2019). As reported by Sun and Wang (2018), approximately half of China's overall consumption is attributed to fossil fuels in the

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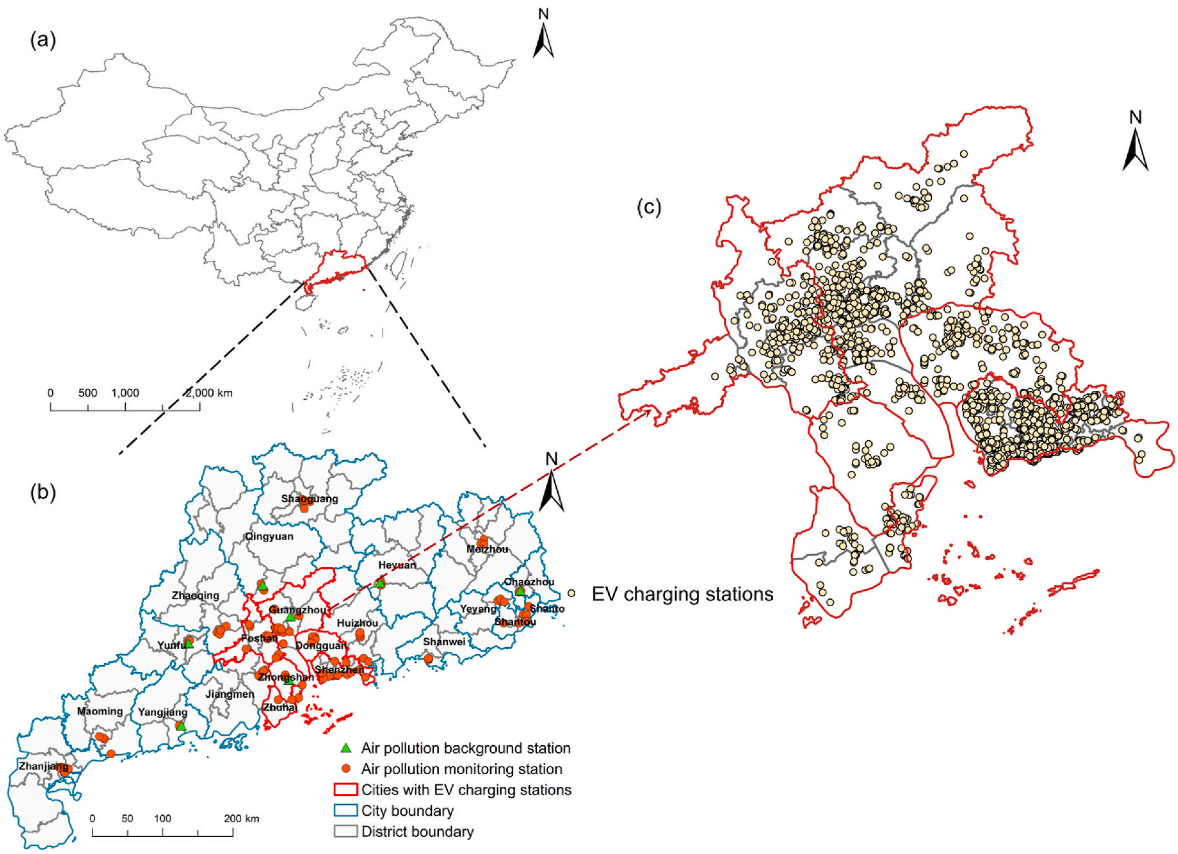

Fig. 1. (a) Study area, (b) spatial location of air pollution monitoring stations and (c) EV charging stations.

transport sector, with new vehicles accounting for 70 % of the annual increase in fossil fuel consumption. The increasing year-on-year demand for vehicle ownership and energy consumption imposes a growing burden on the sustainability of energy resources and the environment. China is a leading contributor to greenhouse gas emissions in the world, responsible for approximately 30 % of global emissions. Among these emissions, around 5 % can be attributed to light-duty vehicles (Sun and Wang, 2018; Qiao et al., 2017).

The implementation of the electric vehicle (EV) strategy is promoted to reduce air pollution and greenhouse gases induced by traffic emissions, which is an effective way for air quality improvement and energy efficiency enhancement. Conventional fuel vehicles emit a variety of harmful compounds through tailpipe emissions, including respirable particulate matter ($PM_{2.5}$), sulfur dioxide (SO_2), nitrogen dioxide (NO_2), volatile organic compounds (VOC), and carbon monoxide (CO), etc., exerting a direct influence on air quality. According to data released by the Shenzhen municipal government in China, vehicular exhaust emerged as the predominant source of $PM_{2.5}$ pollution in Shenzhen, constituting 41 % of the total emissions in 2018 (SZMG, 2018). Thus, the conversion from traditional fuel vehicles to electric vehicles (EVs) has attracted strong support from the governments of China, which is mainly manifested by financial benefits such as fiscal subsidies and tax incentives, expanding the construction of charging facilities, as well as research and development investment (Zhang et al., 2017). With 1.2 million new EVs newly to be registered in 2020, EVs are also proposed as an indispensable countermeasure for achieving carbon neutrality by 2060 (IEA, 2021; The State Council of China, 2021; Wang et al., 2021).

The growth in EV charging demand reflects the increasing adoption of EVs and a decline in the adoption of internal combustion engine vehicles (ICEVs), resulting in lower tailpipe emissions. Several studies have been conducted to quantify the environmental impacts of EV adoption compared to conventional vehicles. For example, Soret et al. (2014) suggest that a reduction of over 10 % NO_x emissions can be attained with vehicle electrification, reaching 40 % in urban areas in Spain. Li et al. (2019) present that the replacement of conventional vehicles with EVs contributes to the mitigation of SO_2 concentrations in China by comparing the well-to-wheel life cycle of different vehicle types. Results show that if the proportion of EVs among passenger vehicles increases by 1 %, SO_2 and NO_x emissions could decrease by 9934 tons and 228 kilotons, respectively. Li et al. (2016) illustrate that the widespread use of EVs can significantly mitigate high pollution episodes by assuming a complete replacement of current light-duty vehicles based on the Community Multi-scale Air Quality model (CMAQ) model in Taiwan, China. Similar implications were also reported by Schnell et al. (2021), the adoption of EVs can effectively mitigate extreme air pollution events in China. Wang et al. (2021) used the COVID-19 full lockdown event to simulate the full switching to EVs, the results show that a reduction in 30 %–80 % of NO_2 and 30 %–70 % of $PM_{2.5}$ across China can be acquired. Even though some pollution may be generated during electricity production and cause environmental injustice where power plants are located (Bai et al., 2021a), the emission mitigation benefits of EVs can be broadened from a long-term perspective with the advancement of clean energy technologies (Li et al., 2018; Philippot et al., 2019), which can also further enhance the environmental conditions and promote human health. However, the majority of studies have concentrated on investigating the influence of EVs on air pollution by assuming the number of EVs in each city, with limited consideration given to actual EV charging consumption in previous studies. This is not capable of providing a factual basis to some extent, which is not conducive to achieving a better understanding of the environmental benefits of EVs.

To fill this gap, the number of EV charging stations and EV charging consumption were synergized and used to provide fact-based insights into the impacts of EVs on air pollution reduction. The purpose of this

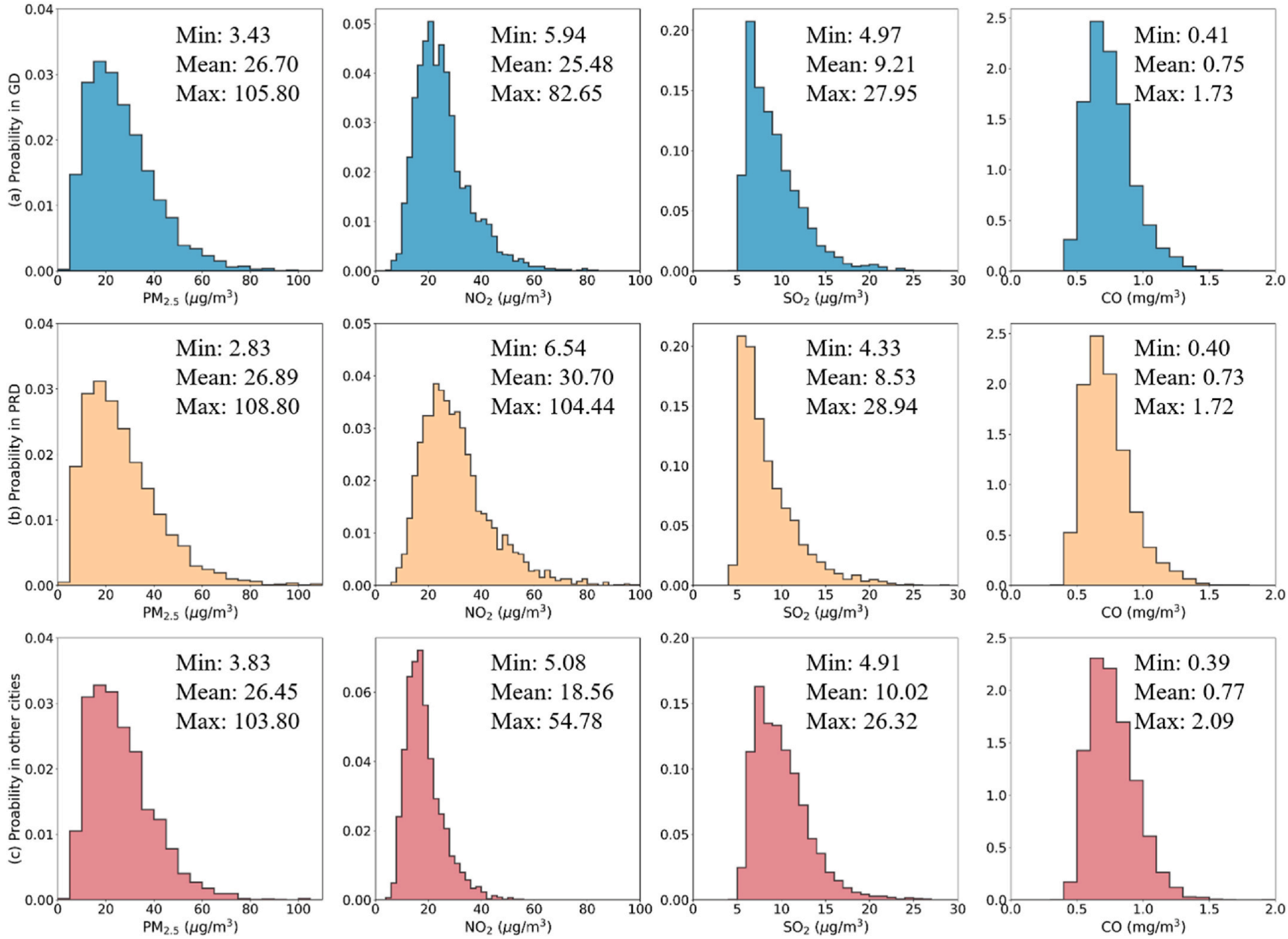

Fig. 2. Descriptive statistics of daily mean concentrations of four air pollutants from ground-based stations in (a) GD province; (b) PRD region and (c) other cities in GD province.

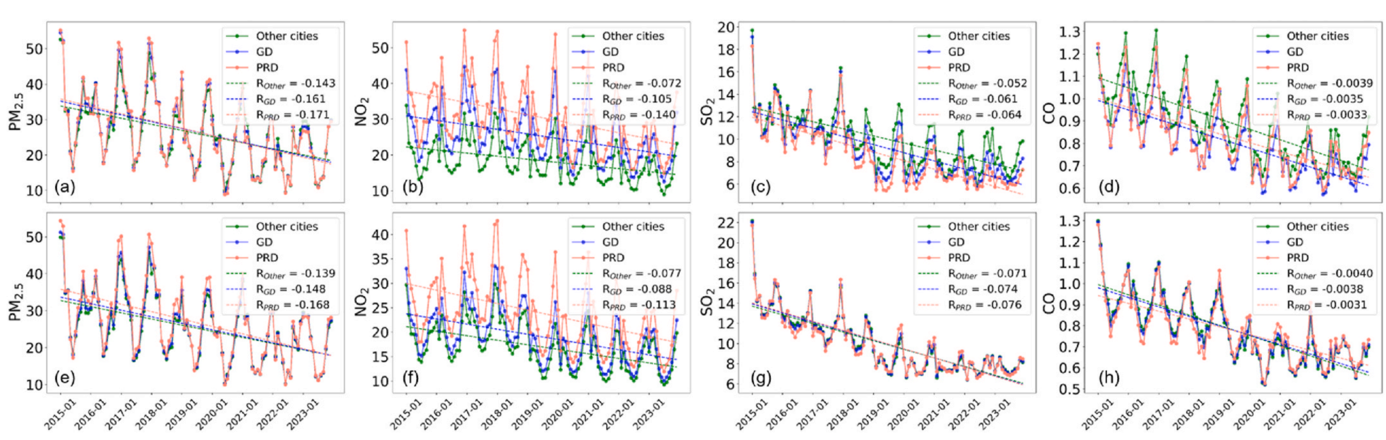

Fig. 3. Linear trends of (a–d) ground-based and (e–f) satellite-based CHAP air pollutants from 2015 to 2023.

study is to underscore the potential of EVs for air pollution abatement in GD province. Quantitative analysis was conducted to quantify the impacts of EV implementation on air pollution between the PRD region and other cities in GD province. Additionally, scenario analysis was also carried out at the district level based on a data-driven ARF model to reveal the prospects of EV implementation in GD province.

2. Data and methods

2.1. Study area

Guangdong (GD) province, nestled in the southeastern part of China, includes a major economic zone Pearl River Delta (PRD) region and other 12 prefecture-level cities (Fig. 1). Geographically, bordered by the

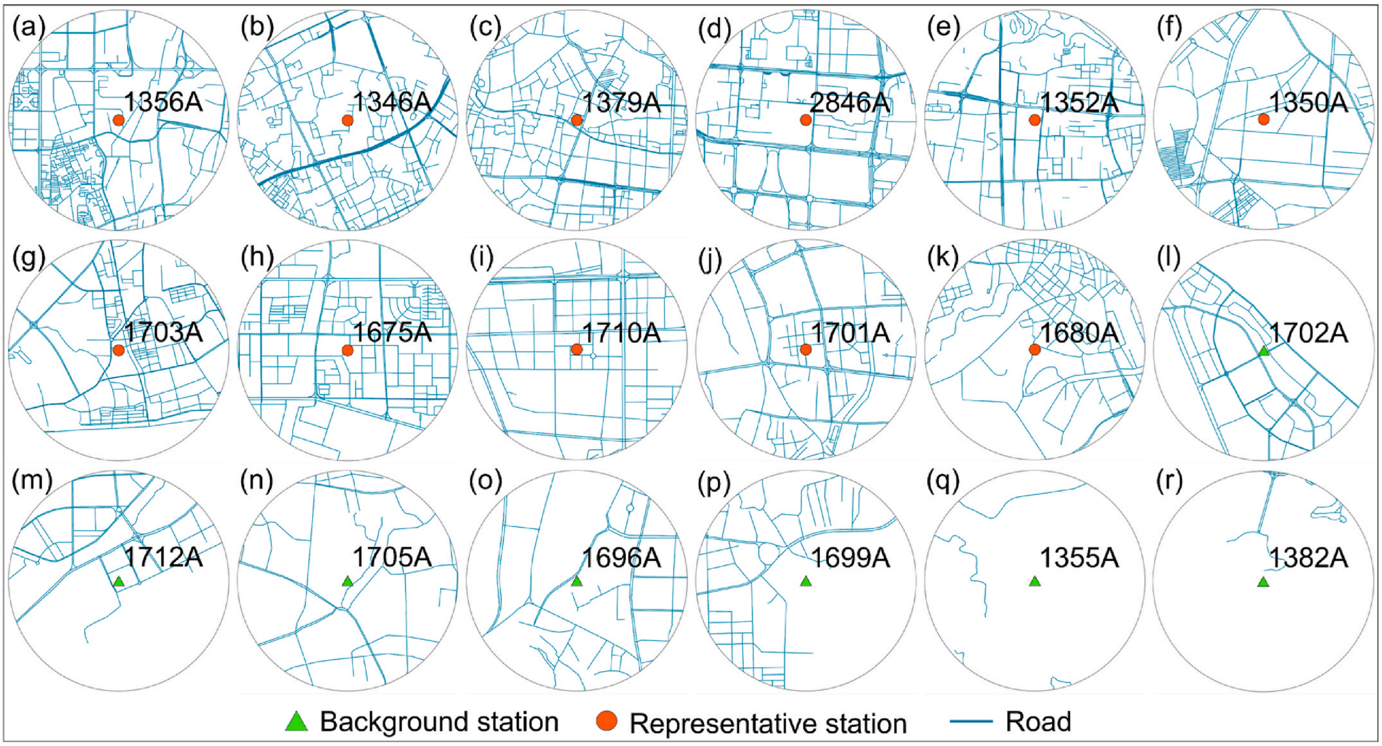

Fig. 4. Representative stations with road networks in (a–f) the PRD region and (g–k) other cities in GD province. Background stations with road networks in (l–p) other cities in GD province and (q–r) the PRD region.

South China Sea and neighbors the special administrative regions of Macau and Hong Kong, GD province covers an area of over 179,000 km^2 and serves as a major gateway to international trade and commerce. It also stands as a pivotal region in China with dense population and high urbanization, renowned for its thriving economy driven by industries such as manufacturing, trade and technology. Inevitably, air pollution has become increasingly serious and attracted extensive concerns due to rapid urbanization and industrialization in GD province. To alleviate air pollution, the PRD Region has been vigorously promoting EVs in the past decade to reduce vehicle emissions and prioritize the implementation of the EV Strategy (State Council of China, 2013).

2.2. Data collection and data processing

2.2.1. In-situ air pollution measurements

According to China's "Air Pollution Prevention and Control Action Plan", over 1436 air pollution monitoring stations were constructed in China by the end of 2014 and the new air quality standard monitoring data was released in real time from 2015 (https://www.gov.cn/xinwen/2015-01/16/content_2805618.htm). Hourly ground-based air pollution concentrations, including $PM_{2.5}$, PM_{10}, O_3, NO_2, SO_2 and CO, are provided by the China Environmental Monitoring Center since 2015 (https://www.cnemc.cn/). The spatial distribution of air pollution monitoring stations is displayed in Fig. 1b. As we aim to investigate the impact of EVs on air pollution in this study, $PM_{2.5}$, NO_2, SO_2 and CO, these four air pollutants, which are highly associated with vehicle emissions, are considered. Hourly ground-based air pollution measurements from 2015 to 2023 were used, which is also consistent with the implementation period of the EVs strategy in GD province.

2.2.2. Satellite-based CHAP air pollution data

The ChinaHighAirPollutants (CHAP, https://weijing-rs.github.io/product.html) data can provide daily averages of $PM_{2.5}$, NO_2, SO_2 and CO with full coverage. The CHAP dataset is derived by using machine learning models based on the synergy of satellite-based observations and ground-based measurements with high spatio-temporal resolution, broader coverage and high quality, which have been elaborated in previous studies (Wei et al., 2021, 2022, 2023a, 2023b). The CHAP dataset has been widely applied in exploring the impacts of air pollution on human health (Yao et al., 2025; Li et al., 2025), or used as comparative data to verify the effectiveness of other studies (Bai et al., 2021b; Lei et al., 2022). Daily $PM_{2.5}$ concentrations at 1 km spatial resolution from 2000 to 2023 can be obtained. For NO_2, SO_2 and CO, daily averaged concentrations from 2019 to 2023 are at 1 km resolution, whereas the spatial resolution is 10 km during 2000–2018. To be consistent with ground-based measurements, daily averages from the CHAP dataset from 2015 to 2023 in GD province were extracted to compensate for ground-based measurements and jointly investigated the EV impacts on air pollution. Daily NO_2, SO_2 and CO data during 2015–2018 are resampled to 1 km to allow for an aligned spatial resolution.

2.2.3. EV charging stations and electricity consumption data

Many EV charging stations have been constructed and scattered all over the city due to the crucial role of EV charging services in promoting EV strategy for environmental pollution reduction. As depicted in Fig. 1c, the spatial distribution of the EV charging stations in six cities in the PRD region is displayed and used in this study, which is provided by our partners. For each EV charging station, EV charging records are composed of station ID, coordinate information and power consumption with an interval of 5 min from December 11, 2022 to January 14, 2023. Abnormal values are identified and removed when the values are over three standard deviations away from the averages of each EV charging station. After data filtering, the number of EV charging stations and the total electricity consumption during this period in these six cities are described in the Supplementary material (Table S1).

2.2.4. Auxiliary data

Auxiliary data, in conjunction with ground-based and satellite-based CHAP air pollution data, are employed to delve into the impacts of EVs,

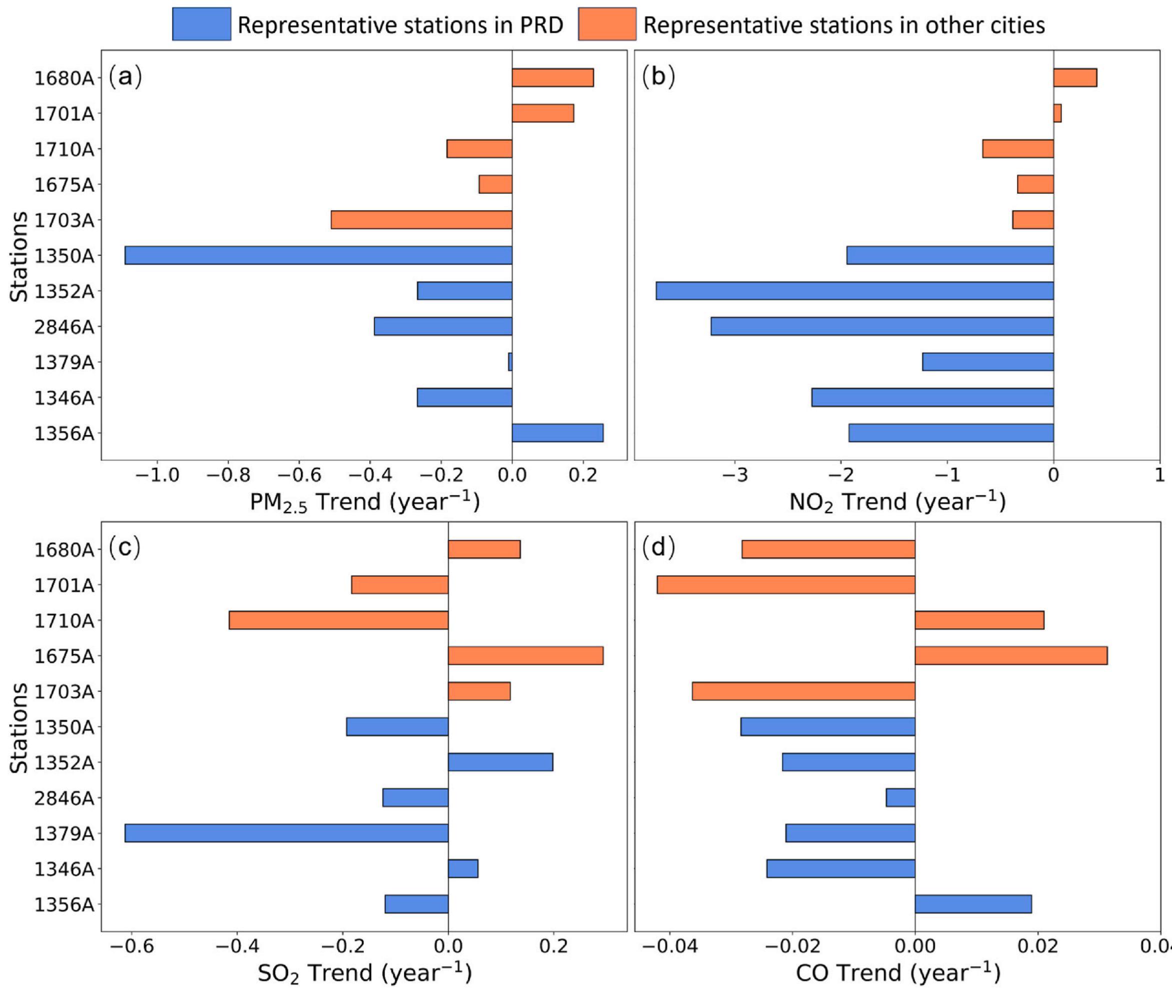

Fig. 5. (a) $PM_{2.5}$, (b) NO_2, (c) SO_2 and (d) CO variation trends of representative stations affected by traffic in the PRD region and other cities during 2015–2023.

Table 1
Comparison of mean variation trends of representative stations in the PRD region ($\overline{\beta}_P$) and other cities ($\overline{\beta}_O$).

	$PM_{2.5}$	NO_2	SO_2	CO
$\overline{\beta}_P$	−0.29	−2.39	−0.12	−0.013
$\overline{\beta}_O$	−0.07	−0.18	−0.03	−0.011

including population density, road density, meteorological factors, greenness, DEM, GDP and the capacity of power plants. Population density data at 1 km resolution in GD province are obtained from the LandScan dataset (https://landscan.ornl.gov/). Road density at 1 km is derived based on the OpenStreetMap and the road types like footbridge and pedestrian are excluded, which are less related to the vehicle emissions. Meteorological data in GD province are extracted from the ERA-5 reanalysis data, including pressure, air temperature, northward/eastward wind speed, total precipitation at 0.1° resolution, and boundary layer height and specific humidity at 0.25° resolution. Greeness is derived from the MODIS 500-m land use product (MCD12Q1) and 90-m DEM data from Shuttle Radar Topography Mission (SRTM) are also used. GDP data at 1 km in China from 1995 to 2020 with 5-year intervals are available at the Resource and Environmental Science Data Platform. Power plant data in 2021 are downloaded from the Global Power Plant Database, including power plant name, latitude, longitude, primary fuel types and capacity (Yin et al., 2021). The power plants with clean energy sources like nuclear, hydroelectric, solar, wind, etc. as the primary fuel types are omitted because generally do not produce direct air pollution.

2.3. Analytical methods

2.3.1. Analysis for traffic-affected air pollution monitoring stations

The transition from traditional ICEV to EV is conducive to reducing air pollution induced by traffic emissions (Soret et al., 2014; Li et al., 2019). To analyze the EV impact on traffic-induced air pollution changes, several in-situ air pollution representative stations affected by traffic were selected. Generally, stations for monitoring traffic-affected air pollution are typically located in transportation hubs or areas with heavy traffic flow. Therefore, we introduced three indices of road networks to explain the complexity of road networks. The three indices are defined as follows: (1) l_i means the total length of road for station i in the 1 km-radius circular area centered at each air quality monitoring station. It is a well-known index that is highly and fundamentally related to traffic flows. (2) n_i is the total number of road intersections for station i; and (3) s_i denotes the number of road segments at all the intersections for station i. n_i is considered as vehicles frequently halt at intersections due to traffic signals, resulting in emission accumulation during idling (Minoura and Ito, 2010). Similarly, s_i can indicate the temporary stopping conditions, as well as the road connectivity along with the road intersections (Wong et al., 2021). Due to the differences in road network complexity in PRD and other cities in GD province (hereinafter other cities), the three indices of each station in PRD and other cities were normalized, respectively.

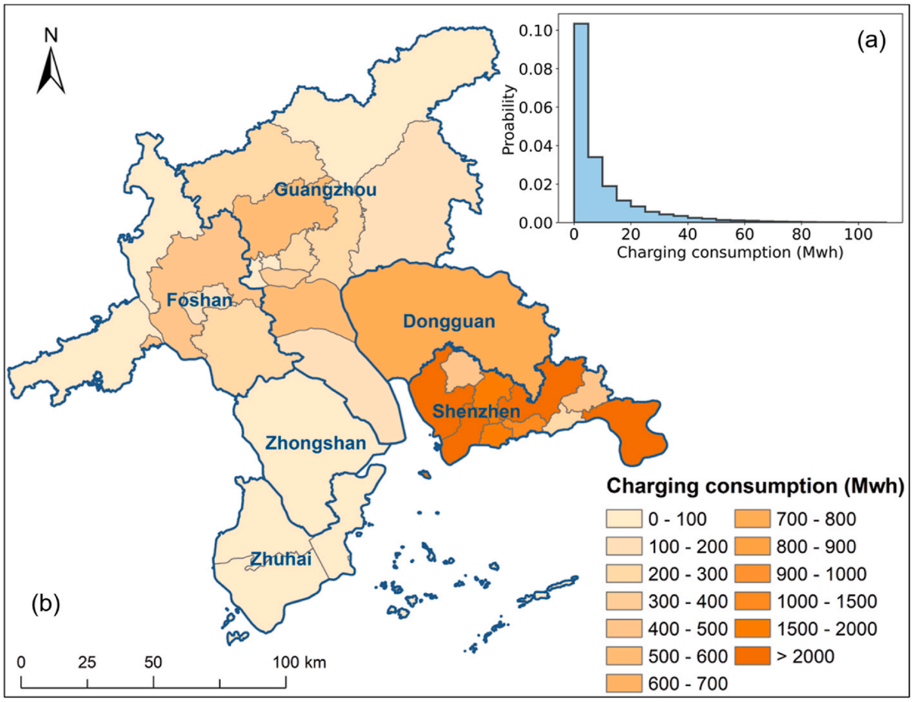

Fig. 6. (a) Density distribution histogram of daily charging consumption (Mwh/daily) for each EV charging station during December 11, 2022–January 14, 2023, and (b) daily mean EV charging consumption (Mwh/daily) in each district.

Table 2
Comparison of validation accuracy of ARF model after the involvement of EV data.

	Validation accuracy (without EV data)			Validation accuracy (with EV data)		
	R^2	RMSE	MAE	R^2	RMSE	MAE
$PM_{2.5}$	0.89	3.25	2.28	0.91	3.19	2.20
NO_2	0.86	3.74	2.88	0.89	3.56	2.66
SO_2	0.83	0.65	0.50	0.84	0.63	0.49
CO	0.79	0.039	0.030	0.80	0.037	0.029

$$Nor_{l_i} = \frac{l_i - min\ (l_i)}{max(l_i) - min\ (l_i)} \tag{1}$$

$$Nor_{n_i} = \frac{n_i - min\ (n_i)}{max(n_i) - min\ (n_i)} \tag{2}$$

$$Nor_{s_i} = \frac{s_i - min\ (s_i)}{max(s_i) - min\ (s_i)} \tag{3}$$

where Nor_{l_i}, Nor_{n_i}, and Nor_{s_i} are the normalized road indices for station i. The three indices are compiled as follows to reflect the characteristics of road networks:

$$RI_i = Sum\{Nor_{l_i}, Nor_{n_i}, Nor_{s_i}\} \tag{4}$$

In this way, stations with higher RI_i can be deemed as representative stations affected by traffic pollution.

Afterwards, yearly averages x_i of representative station i during the year 2015–2023 were calculated based on hourly observations, and the stations with over 30 % missing values were excluded. To reduce the impacts of meteorological factors, measurements from air pollution background stations were involved. Background stations were established by the government or relevant institutes, and used to monitor regional background air quality unaffected by anthropogenic pollution (MEE of State Council of China, 2013). Traffic-related pollution T_i is quantified by deducting the annual averages B_j of the nearest background station j from the representative station values.

$$T_i = x_i - B_j \tag{5}$$

$$\beta = \frac{\sum_{i=1}^{n}(y_i - \overline{y})(T_i - \overline{T})}{\sum_{i=1}^{n}(y_i - \overline{y})^2} \tag{6}$$

where β is the variation trend of representative stations; $\overline{T}$ means mean traffic-related pollution; y_i and $\overline{y}$ are the years 2015–2023 and the corresponding mean value. Finally, comparison of mean variation trends in representative stations between the PRD region ($\overline{\beta}_P$) and other cities ($\overline{\beta}_O$) was conducted to assess the impacts of EVs.

2.3.2. EV-attributed changes derived by the attention-based RF model

Attention-based RF (ARF) proposed by Utkin et al. (2023) was used in this study to investigate the impacts of EVs on air pollution. The self-attention mechanism was introduced and integrated with RF model to promote the capture of the internal correlation from the input data. Self-attention mechanism is an enhanced iteration of the attention mechanism, focusing on highlighting essential features in inputs and within inputs and allocating greater emphasis to these specific factors. (Vaswani et al., 2017). Three main components are composed, namely value (V), key (K), and query (Q) which can be described as:

$$Attention(Q, K, V) = softmax\left(\frac{QK^T}{\sqrt{d_k}}\right)V \tag{7}$$

where d_k means dimensional size of keys. The principle of integrating self-attention mechanism with RF involves leveraging the self-attention mechanism to optimize training parameters and assign weights to decision trees in the RF model.

In this study, the ARF model is mainly used to estimate the variations of air pollution at the district level when the number of EV charging stations and EV charging consumption change based on two simulated scenarios.

Scenario 1. To estimate the variations of air pollution at the district

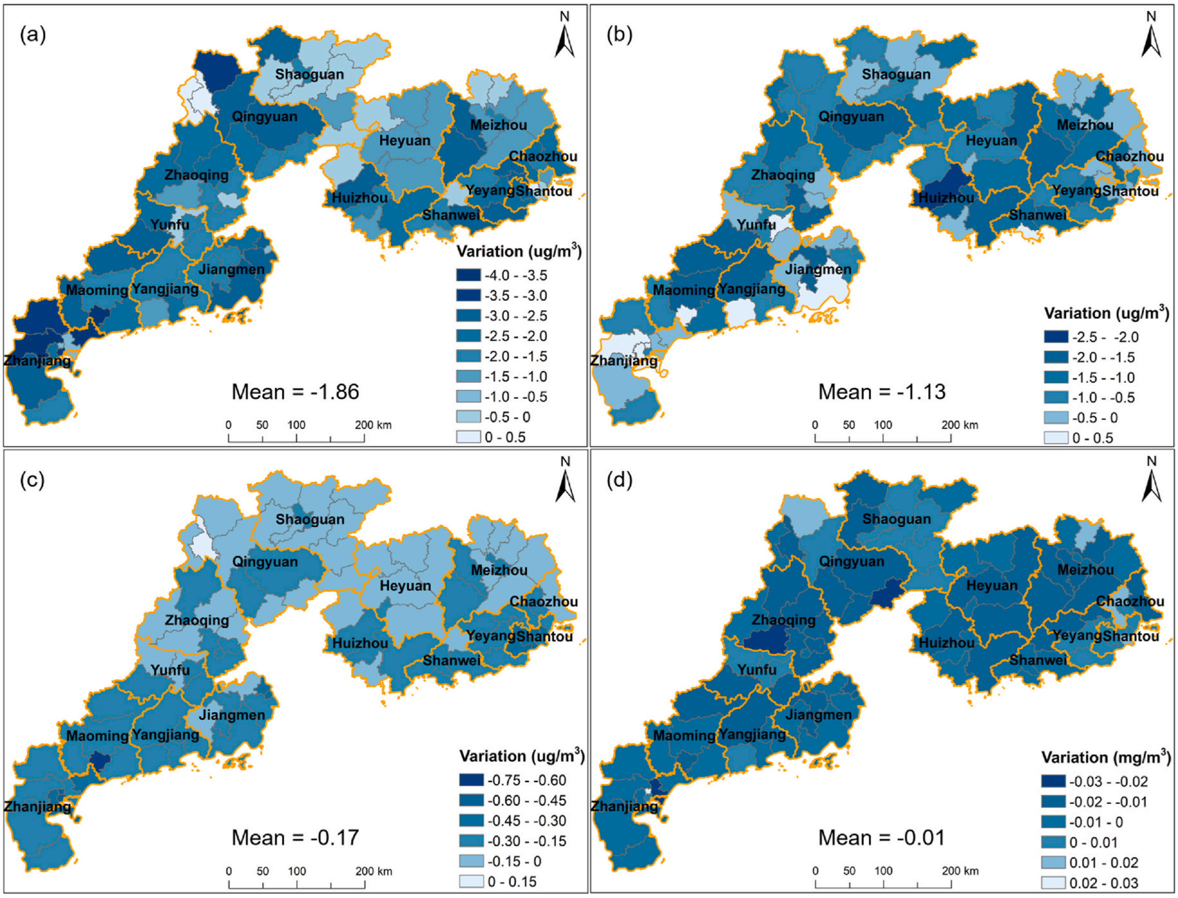

Fig. 7. Variations of (a) $PM_{2.5}$, (b) NO_2, (c) SO_2 and (d) CO based on simulated EV charging consumption and the number of charging stations.

level resulting from the comparative implementation of EV strategy in the remaining cities in GD province, except the six cities mentioned above;

Scenario 2. To derive the variations of air pollution at the district level resulting from the increase in the number of EV charging stations and EV charging consumption.

The meteorological variables, DEM, greenness, population density, road density, GDP, the capacity of power plants, the number of EV stations, EV charging consumption and air pollution concentrations from CHAP were matched spatially and temporally at district level with daily intervals from December 11, 2022 to January 14, 2023. Daily mean SO_2, CO, NO_2, and $PM_{2.5}$ concentrations at the district level are deemed as the ground truth and other factors are used as input data to train the ARF model. Data used for the scenario analysis can be found in Supplementary materials (Table S2). The data with valid EV charging stations and charging consumption acquired in Dongguan, Guangzhou, Foshan, Shenzhen, Zhongshan and Zhuhai are split into training and validation datasets based on 10-fold cross validation. The dataset was divided into ten groups and nine sub-samples were used as training data, remaining sub-sample for validation data. The dataset from other cities is used as a testing dataset and is not involved during the training process. The model performance will be examined using some statistical metrics, including R^2, root mean squared error (RMSE) and mean absolute error (MAE).

For scenario 1, data at the district level in Dongguan, Guangzhou, Foshan, Shenzhen, Zhongshan and Zhuhai were extracted and used as the training dataset. The number of training and validation samples is 1050. Due to the limitation of data availability, the EV charging consumption and the number of EV charging stations are assumed to be 0 first in the remaining cities in GD province, except for the abovementioned six cities, which will be concatenated with other auxiliary data and used as testing data. The number of testing samples is 3290. The estimated air pollution based on the testing dataset will be compared to the CHAP observations to evaluate the model performance. Once a satisfactory model performance is acquired, the pre-trained ARF model can be used to reveal the air pollution variations when the EV strategy was implemented in these areas. How to accurately simulate the number of EV charging stations and EV charging consumption required in these districts is a major concern when using the pre-trained model to examine the impacts of the EV strategy implementation. In this study, the simulated number of EV charging stations and EV charging consumption in these areas were calculated based on the size of population, the number of EV charging stations per capita and charging consumption per capita. Specifically, the size of population for each district was derived from the 1-km population density data. The number of EV charging stations per capita and daily charging consumption per capita were calculated based on the existing EV charging stations and daily charging consumption for each district in the aforementioned six cities. The simulated number of EV charging stations and charging consumption are then substituted for the assumed data when both are 0 and integrated with other data and input into the ARF model. For scenario 2, we aim to assess how the air pollution concentrations in the whole GD province respond when the number of EV charging stations and charging consumption increase by 10 %, 20 % and 30 %, respectively. Finally, for the aforementioned two simulated scenarios, the differences in air pollution concentrations derived from the simulated and assumed data during the same period are considered to be the impacts of EVs.

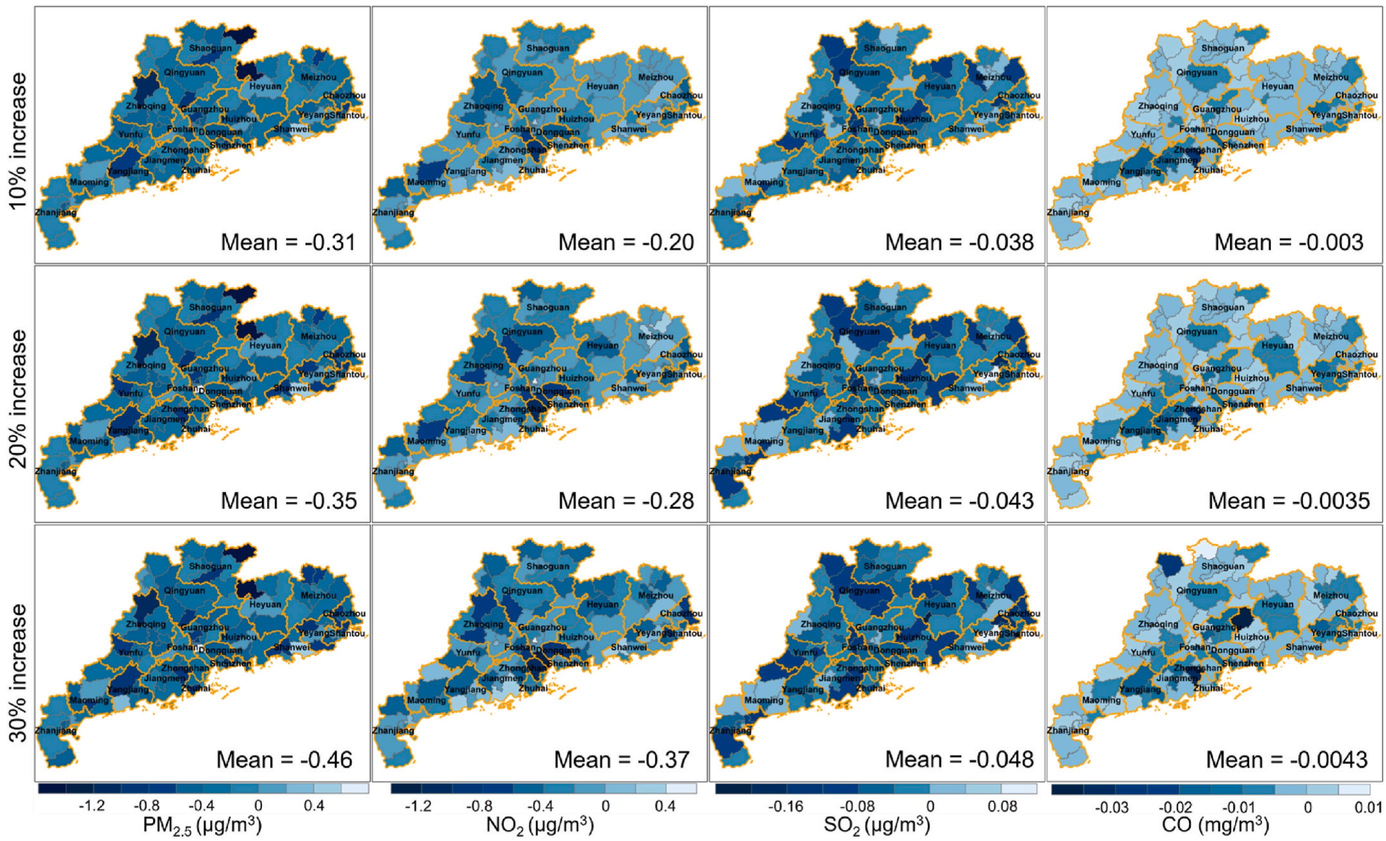

Fig. 8. Variations in $PM_{2.5}$, NO_2, SO_2 and CO when there are 10 %, 20 % and 30 % increases in EV daily mean charging demand.

3. Results and discussion

3.1. Descriptive statistics

Ground-based monitored air pollutant concentrations are generally deemed as the most correct observations with hourly temporal resolution, which can truly reflect the air quality conditions during the study period. We divided the GD province into two regions according to the first-tier EV implementation strategy, namely the PRD region and other cities. To exploit the air pollution injustice in the study area, daily averaged concentrations of $PM_{2.5}$, NO_2, SO_2 and CO during 2015–2023 were derived based on the hourly records and the density distribution histograms of different air pollutants in the whole GD province, PRD region and other cities are depicted in Fig. 2. $PM_{2.5}$ in the whole province, the PRD region and other cities have a similar distribution pattern, with more concentrations around 20–30 μg/m^3. Differently, NO_2 concentrations in other cities are concentrated around 20 μg/m^3, but more data pairs in the PRD region are located around 30 μg/m^3. It indicates that local emissions of NO_2 in the PRD region are the major pollution source for the GD province, affirming the desirability of promoting EV strategy in this region. By contrast, SO_2 and CO in other cities (10.02 μg/m^3 and 0.77 mg/m^3) are slightly higher than those in the PRD region (8.53 μg/m^3 and 0.73 mg/m^3). It may be ascribed to higher industrial emissions and greater reliance on polluting energy sources such as coal in other cities than in the PRD region.

Additionally, pixel-based multi-year mean concentrations of these four air pollutants were calculated to elucidate the spatial characteristics based on daily CHAP values from 2015 to 2023 (Fig. S1). Other cities in the GD province present lower $PM_{2.5}$ concentrations, around 26 μg/m^3 except for two cities in the northern parts of the GD province, which tend to be affected by long-term distance transport in addition to the local emissions (Zheng et al., 2022; Yu et al., 2023). Especially, most NO_2 concentrations in other cities are generally less than 20 μg/m^3, while central areas in the PRD region have significantly elevated values, even higher than 50 μg/m^3. It further implies the principal contributions of local emissions on NO_2 pollution in the GD province. Northern and western areas in GD province have higher SO_2, but lower concentrations are in eastern regions with values of less than 10 μg/m^3. Similarly, northern regions and central areas of the PRD region have higher CO values. Moreover, coastal zones generally show lower concentrations of these four air pollutants, presumably due to the favourable meteorological conditions to facilitate the dissipation and dilution of pollutants (He et al., 2017).

3.2. Comparison between monthly in-situ and CHAP data

Linear trends were derived first based on monthly averaged in-situ and CHAP air pollutant concentrations, respectively (Fig. 3). Pronounced decline trends of these four air pollutants during 2015–2023 can be observed for both ground-based and satellite-based CHAP data. Despite there being slight disparities in the derived varying values between ground-based and satellite CHAP data, consistently varying directions and magnitudes can still be observed in the whole GD province, PRD region and other cities. $PM_{2.5}$ and NO_2 decrease trends are noticeably higher in the PRD region relative to other cities. A lower decline trend of SO_2 is also presented in other cities than in the PRD region, but the discrepancy is comparatively small. However, the downward trend of CO in other cities is higher than that in the PRD region. It implies that conducting the EV strategy may be less efficient in markedly reducing CO concentrations compared to other air pollutants. In addition to vehicle exhaust, industrial emissions are also vital sources of CO pollution. On the other hand, the advancements in vehicle technology, particularly the integration of advanced catalytic converters, have resulted in substantial reductions in CO emissions over time (Yli-Tuomi et al., 2005).

3.3. Trend analysis of representative stations affected by traffic

Summarized road indices of each city in the PRD region and other cities are presented in Fig. S2. The top 10 % of the stations with elevated *RI* in the PRD region and other cities were selected as representative stations mainly affected by traffic, respectively. These stations, along with background stations with surrounding road networks, are displayed in Fig. 4. Variation trends of the representative station affected by traffic during 2015–2023 are derived and shown in Fig. 5. As depicted, representative stations in the PRD region exhibit more pronounced decrease trends than those in other cities. Especially for NO_2, significant decreasing trends in representative stations in PRD can be observed, ranging from around −2 to −3.7 $year^{-1}$. Conversely, the decreasing trends of representative stations in other cities are generally below −1 $year^{-1}$, even with two stations showing increasing variations. This is partly because of the rise in vehicle fleet size, coupled with the absence of EV policy, air pollutants from representative stations in other cities have a greater increase than those in the PRD region. Mean variation trends of representative stations in the PRD region and other cities were also calculated for further comparison. Given the similar meteorological conditions and air pollution control policies in the PRD region and other cities, the comparative analysis of the variation trends of representative stations between the two areas can more directly reflect the impacts of EVs on air pollution. As illustrated in Table 1, notable mean decreasing trends in the four air pollutants are found at representative stations in the PRD region compared to those in other cities. These findings highlight the positive contributions and effectiveness of EVs in reducing air pollution concentrations and improving air quality.

3.4. Potential analysis

Previous studies focused on revealing the current improvement of air quality benefits from EVs (Li et al., 2019; Lyu et al., 2024; Hata et al., 2025), insights into air pollution variations of the cities without EV strategy but are considering the implementations of EVs cannot be provided. In this study, fact-based air pollution variations induced by EVs at a district level were conducted using the ARF model based on CHAP data, EV charging consumption, the number of EV charging stations and other auxiliary data. Fig. 6a shows the density distribution histogram of daily EV charging consumption based on the records of each EV charging station from December 11, 2022 to January 14, 2023. It can be found that the majority of EV charging stations exhibit a consumption of less than 10 Mwh, and the charging consumption of most remaining stations is lower than 40 Mwh. The stations with charging consumption exceeding 50 Mwh occupy a fraction of the total. Daily mean EV charging consumption for each district in PRD six cities during the study period is displayed in Fig. 6b. Districts in Zhuhai and Zhongshan have lower consumption, with values of less than 100 Mwh. Central districts in Guangzhou and Foshan have higher charging consumption (>200 Mwh). The EV charging consumption in most districts in Shenzhen has the highest values with a wide range from around 300 Mwh to over 2000 Mwh. The charging consumption is also consistent with the ranking of EV ownership in these six cities (https://www.sz.gov.cn/cn/xxgk/zfxxgj/zwdt/content/post_10692371.html), indicating that a higher number of EVs typically necessitates increased charging consumption.

As demonstrated in Table 2, considering the number of EV stations and EV charging consumption as predictive variables can improve the model fit by reaching a higher accuracy of the ARF model. It highlights the important significance of EVs on air pollution estimation. A good agreement is also observed between the CHAP data and simulations when the EV charging consumption and the number of EV charging stations are assumed to be 0 (Fig. S3). Nevertheless, a few disparities can be found between the simulated results and the CHAP data. To reduce uncertainty and improve reliability, instead of CHAP values, the simulated results when both EV charging consumption and the number of EV charging stations are 0, are used directly as the reference. The variations of air pollution at the district level are displayed in Fig. 7. It can be found air pollution in most districts presents a further decrease after the EV strategy implementation. $PM_{2.5}$ has a mean reduction of 1.86 μg/m^3. Northeastern regions have a lower decrease (around −0.5 μg/m^3), while western areas have larger reductions, with a range of −4 to −2 μg/m^3. The variations in NO_2 concentrations vary from −2.5 to 0.5 μg/m^3, with only a rare few coastal districts showing increases. And a decrease of exceeding 1 μg/m^3 can be observed in most districts. If implementing the EV strategy, an average decrease of around −0.2 μg/m^3 in SO_2 is observed, with significant reductions in western regions. For CO, the reductions are relatively small, with values lower than −0.02 mg/m^3. In conclusion, the results indicate that the enforcement of policies aimed at expanding the adoption of EVs in GD Province can significantly enhance air quality, especially for $PM_{2.5}$ and NO_2.

As reported by the GD government and related institutions (Guangdong Energy Bureau, 2021), the construction of EV charging stations is ongoing to encourage the usage of EVs. With the increase in charging stations, there will be a corresponding rise in charging consumption. We also simulate the variations of these four air pollutants when the number of EV charging stations and EV charging consumption in each district increased by 10 %, 20 % and 30 %, respectively. Fig. 8 illustrates the variations of air pollution as compared to the values derived from the simulated EV charging consumption and the number of charging stations. As depicted, further decreases in air pollution in most districts can be observed as the increase in EV charging consumption and the number of EV charging stations. Specifically, when there is a 10 % increase in EV charging consumption and EV charging stations, mean $PM_{2.5}$ and NO_2 in GD province tend to decrease by −0.31 μg/m^3 and -0.2 μg/m^3, respectively. Decreases by −0.46 μg/m^3 and -0.37 μg/m^3 are more likely to be reached in terms of 30 % increases in EV charging consumption and stations. Although the decreases in SO_2 and CO are relatively lower, the beneficial impacts of enhancing the adoption of EVs on SO_2 and CO mitigation are still recognized.

3.5. Policy implications and limitations

The results have confirmed the beneficial impacts of EVs on the improvement of air quality in GD province. Moreover, most regions present a continued decrease trend when the number of EV charging stations and EV charging demand increase. It means that the continuous promotion of EV policy is necessary for mitigating air pollution in other cities that do not have high levels of EV facilitation, especially for the regions with high reductions. Targeted incentives such as subsidies, tax breaks and preferential parking for EV holders in pollution hotspots like the PRD region can intensify efforts to promote EV adoption and alleviate local traffic emissions. However, an excessive increase in the construction of charging stations may not guarantee a commensurate decrease in air pollution levels. The charging demands and charging capacity should also be taken into consideration. The results also lay a foundation for urban planners to inform decisions regarding urban development and the integration of industries associated with clean energy.

Nevertheless, there are still some limitations in this study. First, due to the limitation of EV data availability, EV charging demands over a one-month period can be used for the analysis of simulated scenarios. Second, the quantitative analysis is conducted based on a data-driven model in GD province, thus we are cautious about the results in different regions with distinct characteristics. We aim to address these limitations by enhancing our methodology through the comprehensive analysis of multifaceted data in future research endeavors.

4. Conclusions

In this study, the impacts of EVs on four relevant air pollutants ($PM_{2.5}$, NO_2, SO_2 and CO) were qualitatively and quantitatively analyzed in GD province. The main findings are summarized as follows. Results show that local emissions of NO_2 in the PRD region are the major pollution source for the GD province. That is also the partial reason why NO_2 concentrations have higher mean decrease trends (-2.39 year^{-1}) in the PRD region after EV adoption. The evidence is derived from isolating the measurements of traffic pollution-related monitoring stations, which illustrate the positive contributions of EVs to improving air quality. By introducing the number of EV charging stations, EV charging demands, and other auxiliary data, the potential impacts of EVs on air pollution in cities without a strong emphasis on EV strategy implementation were also quantified using the ARF model. Significant reductions can be achieved when these regions have comparative EVs, with a decrease of over -2 μg/m^3 of $PM_{2.5}$ in western areas, as well as exceeding -1 μg/m^3 decline of NO_2 in most districts. Moreover, further enhancements in air quality are exhibited with the increase in the number of EV charging stations and EV charging consumption, as simulated in ambitious scenarios. Specifically, the mean decreases by -0.46 μg/m^3 and -0.37 μg/m^3 in $PM_{2.5}$ and NO_2 in GD province are more likely to be achieved through a 30 % increase in EV charging consumption and the addition of stations. The environmental benefits are still recognized although the decreases in SO_2 (about -0.05 μg/m^3) and CO (around -0.004 mg/m^3) are relatively lower. Our findings can deepen the understanding of EV impacts on air pollution mitigation and enhance the prospective benefits of EVs, which can also provide insightful implications for policymakers in urban planning.

CRediT authorship contribution statement

Xinyu Yu: Writing – review & editing, Writing – original draft, Methodology, Formal analysis, Data curation, Conceptualization. **Man Sing Wong:** Writing – review & editing, Supervision, Methodology, Funding acquisition, Formal analysis, Data curation, Conceptualization. **Kai Qin:** Writing – review & editing, Supervision, Formal analysis, Data curation. **Rui Zhu:** Writing – review & editing, Supervision, Formal analysis, Data curation. **Linlin You:** Writing – review & editing, Supervision, Formal analysis, Data curation. **Jing Wei:** Writing – review & editing, Supervision, Formal analysis, Data curation.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.jenvman.2025.126442.

Data availability

Data will be made available on request.

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