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Rethinking public service facility distribution and management strategies with the consideration of carbon peak – Insights from Suzhou, China

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ABSTRACT

Existing practices have primarily focused on the accessibility and per capita indices of public service facilities (PSFs) in decision-making processes aimed at promoting social equity. However, the national commitment to achieving a carbon peak may induce additional considerations into the planning and policy decisions of PSFs for local governments. By conducting a two-stage simulation of carbon emissions (CEs) and correlation analysis, we identified uncertainties and confirmed the nonnegligible impact of land use structure, particularly PSF distribution, on achieving the urban transport-related carbon peak. Subsequently, we elaborated on the imperative of optimizing PSF distribution for carbon reduction, rather than solely depending on transport management strategies, through a case study of individual medical care travel characteristics. Moreover, a further discussion on the potential trade-offs and synergies between current and low-carbon-oriented PSF planning and policy decisions underscores the necessity of collaboration among decision-makers across pertinent administrative sectors.

1. Introduction

As one of the largest energy-producing and consuming countries, China has officially committed to achieving carbon peak before 2030 and carbon neutrality before 2060. Modern cities are the primary sources of carbon emissions (CEs) (Perera et al., 2021), resulting from massive infrastructure construction, industrial development, and transportation, etc.[1] Nowadays, in China, urban transport has become the second largest source of CEs, which was responsible for 9% of the overall emission.[2] Several studies stated that the transport-related carbon peak time would probably be five years behind China's 2030 target (Chen et al., 2020; Huang et al., 2019). Consequently, it is a considerable challenge for both national and local government decision-makers to promote transport-related carbon peak.

Urban transport-related CEs are jointly affected by various factors, such as land use structure, economic growth, urbanization, and transport management strategies (Arvin et al., 2015; Penazzi et al., 2019). At the national level, the Chinese government is seeking solutions from almost all aspects (Liu et al., 2022). In addition to upgrading the fundamental energy structure, the rapid development of new energy vehicle (NEV) industry is also an influential attempt. However, these macro policies could be inadequate and has potential side effects at the regional level. For instance, since 2020 the subsidy deadline for buying NEVs has been extended for another two years (Hsiao et al., 2023). But a much cheaper daily driving cost would attract more people to use private autobiles, exacerbating traffic congestion. Hence, the achievement of carbon peak requires not only nationalwide strategy guidance, but also regional-level policy optimization from broader perspectives beyond the transport sector itself (Zhang et al., 2019).

In fact, land use, which affects the occurrence, distribution, and flow of urban traffic volume, is deeply correlated with transport-related CEs (Zhang et al., 2018). The optimization of land use structure and relevant policies can help reducing urban transport-related CEs (Muto et al., 2021; Penazzi et al., 2019; Sporkmann et al., 2023; Wang et al., 2022), such as polycentric structure development (Chen et al., 2021), job-housing balances (Andong and Sajor, 2017), and rational land use intensity control (Kang et al., 2023). However, few researches have focused on the impact of specific land-use types and facilities.

Public service facilities (PSFs), such as educational, medical and health, cultural, and sports facilities, primarily tasked with providing various public goods and services to fulfill residents' daily needs (Shi et al., 2020), significantly influence residents' daily decisions regarding destinations and travel modes, sometimes leading to negative

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[1] Global Energy Review: CO2 Emissions in 2021, https://www.iea.org/reports/global-energy-review-co2-emissions-in-2021-2.
[2] Toward Net Zero Emissions in the Road Transport Sector in China, https://wri.org.cn/en/research/toward-net-zero-emissions-road-transport-sector-china.

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Abbreviations

PSF	Public service facility
CEs	Carbon emissions
NEV	New energy vehicle
SDGs	Sustainable Development Goals
OD	Origin-Destination
CBD	Central business district
XGBoost	eXtreme Gradient Boosting
PDP	Partial dependence plot
TAZ	Traffic analysis zone
GDTS	Graded Diagnosis and Treatment System

externalities (DeVerteuil, 2000; Dong et al., 2021; Yang et al., 2022), such as traffic congestion and high CEs around hospitals and schools in many Chinese megacities. Few studies have explored the correlation between CEs and PSF distribution based on activity demand characteristics, emphasizing the need for cross-sector policies to achieve carbon peak. The UN report on Climate and Sustainable Development Goal (SDG) Synergies (2023) addresses the importance of enhancing institutional and policy coordination among different sectors. The incorporation of climate action considerations in policy formulation (i.e., SDG 13) is imperative for advancing other SDGs (Xiao et al., 2023). Therefore, the social equity oriented PSF planning decisions, in line with SDG 10 (Reduced Inequalities), also need to incorporate the perspective of SDG 13.

In this study, we identified uncertainties and pain points of achieving urban transport-related carbon peak in a representative Chinese megacity through a two-stage CE simulation. The distribution of some PSFs was found to be correlated to high CEs. The underlying reasons were discussed through analyzing the related activity demand. We discussed the necessity of optimizing both the distribution of medical facilities and resources by discussing the possible synergies and trade-offs between different goals.

2. Background and related works

2.1. The current planning practices of public service facilities in China

In China, most cities are or were monocentric urban structures, with high-quality PSFs concentrated in the city center (Li et al., 2019; Zhao et al., 2020). The rapid pace of urbanization over the past three decades has led to extensive urban expansion. Consequently, the supply of PSFs often struggles to keep pace with the fast-growing population (Wei et al., 2022). In many cities, both the quantity and quality of PSFs exhibit noticeable spatial disparities (Song et al., 2024; Wei et al., 2022).

As a fundamental aspect of public welfare planning, spatial equity has long been the paramount principle guiding the configuration of PSFs (Hussaini et al., 2023; McAllister, 1976; Peng et al., 2023; Tsou et al., 2005). The existing "Urban Public Service Facility Planning Standards[3]" primarily employ per capita land/facility indicators, which can also be found in relevant national and municipal policies or plans, as summarized in Table A. 1. In most documents, even when low-carbon goals are mentioned, they typically pertain to strategies and recommendations for green buildings and public transport, lacking specific measurements or proposals addressing the CEs associated with PSFs.

[3] https://www.mohurd.gov.cn/gongkai/fdzdgknr/zqyj/201805/20180522_236167.html, public service facilities encompass public cultural amenities, educational facilities (excluding higher education institutions), public sports facilities, healthcare facilities, and social welfare facilities.

2.2. Research perspectives on PSFs

Existing research regarding PSFs has predominantly addressed the themes of accessibility and spatial equity (McAllister, 1976; Tahmasbi et al., 2019; Tsou et al., 2005), location choices (Wang et al., 2021; Yao et al., 2019), and socio-economic impacts (Lee and Kim, 2014; McMillan and Carlson, 1977; Yuan et al., 2020). Additionally, several studies have explored cost efficiency, user satisfaction, and operational service levels (Lo Storto, 2016; Meng et al., 2023).

Numerous studies have quantified social equity by evaluating residents' accessibility to various PSFs and utilized equitable accessibility goals to guide the optimization of their layouts. Achieving social equity in the optimization of PSF layouts also requires consideration of different transport modes and the specific characteristics of diverse population groups (Tahmasbi et al., 2019). Diverse types of PSFs exhibit significant variations in activity and transport demands (Dadashpoor et al., 2016). A comprehensive consideration of the travel demands induced by PSFs, encompassing factors such as time periods, scale, modes, elasticity, and residents' lifestyle preferences, is essential for deriving rational recommendations for the re-optimization of PSF distribution. Regarding specific facility types, urban green spaces, schools, and healthcare facilities have been focal points in relevant research (Rong et al., 2020; Whitehead et al., 2019).

Overall, the research on optimizing PSF distribution has extensively addressed both physical space and service levels. However, there exists a research gap concerning the optimization of PSF layouts aligned with carbon peak objectives. Furthermore, there has been an absence of studies exploring the impact of individual travel demands generated by PSFs on CEs in Chinese megacities.

2.3. Transport-related carbon emission estimation methods

Calculating transport-related CEs is a prerequisite for formulating emission reduction strategies. The precision requirements for data sources vary across different research scales, leading to nuanced emphases in the obtained results. At the macro scale, the assessment of transport-related CEs typically relies on the data of vehicle fuel usage within the study area. This involves employing conversion formulas to translate energy consumption into CEs, thus deriving the overall carbon footprint. Subsequently, methodologies such as scenario simulations are frequently employed to forecast future scenarios, facilitating the informed formulation of carbon reduction policies. Noteworthy models applicable in this context include the Long-range Energy Alternatives Planning System (Ates, 2015; Zhao et al., 2021) and Stochastic Impacts by Regression on Population, Affluence, and Technology (Vélez-Henao et al., 2019). At the micro scale, due to technological limitations, achieving extensive monitoring of CEs remains unfeasible. Some researchers estimated regional totals based on energy consumption, which struggled to identify primary contributors at the micro scale, hindering targeted carbon reduction policies. Others conducted more spatially detailed CE estimation with the help of the implementation of traffic flow simulation and the construction of mobile source emission models, which is highly dependent on data availability. Moreover, some scholars incorporated individual travel demand into CE estimation, aiming to discern the motivations and mechanisms behind residents' trips (Neves and Brand, 2019; Smetschka et al., 2019). The aforementioned CE estimation methods, which inspire our research, are of help to explore the possible carbon peak scenarios and correlated influencing factors. However, further research is needed to provide intuitive insights for relevant policy decision making.

In summary, this study aims to propose an analytical framework of both urban transport-related CE estimation and problem identification, using multi-source data which currently can be obtained without technological difficult. In particular, we comprehensively explored the relationship between PSFs and urban transport-related CEs, providing insights for achieving carbon peak goal from optimizing PSF distribution and management strategies.

3. Methodology

3.1. Analytical framework

Our analytical framework, which is divided into three parts, i.e., macroscopic simulation of CE peak, microscopic CE estimation, and the impact of PSF distribution, is illustrated in Fig. 1. Specifically, employing a two-stage simulation method for urban residents' transport-related CEs (Xu et al., 2022), we identified the correlation between PSF distribution and the CEs generated from urban residents' motorized trips. Subsequently, we attempted to uncover the incentives for high CEs around PSFs by investigating individual activity and travel demand through an Origin-Destination (OD) survey. Eventually, we discussed potential trade-offs, challenges, and possible synergies in PSF planning and management decisions between current and carbon peak goals.

3.2. Two-stage simulation approach

3.2.1. Macroscopic multi-scenario carbon peak simulation

Long-range Energy Alternatives Planning (LEAP) was employed to simulate the carbon peak trends across the whole study area through multi-scenario simulations (Handayani et al., 2022; Shahid et al., 2021). The scenario settings included indicators pertaining to demographics, technological development, land use structure, and transport management strategies. Comprehensive details on the sub-indicators, scenario variables, and parameter settings are provided in Appendix B. Based on existing studies (Xu et al., 2022), we further performed a sensitivity analysis to ascertain the overall impact of land use structure on carbon peak.

A total of 27 scenarios were defined, representing different combinations of technological development (S), transport management strategies (T) and land use structure (L) indicators, i.e., $S^LT^LL^L$, $S^LT^LL^M$, $S^LT^LL^H$, $S^LT^ML^L$, $S^LT^ML^M$, $S^LT^ML^H$, $S^LT^HL^L$, $S^LT^HL^M$, $S^LT^HL^H$, $S^MT^LL^L$, $S^MT^LL^M$, $S^MT^LL^H$, $S^MT^ML^L$, $S^MT^ML^M$, $S^MT^ML^H$, $S^MT^HL^L$, $S^MT^HL^M$, $S^MT^HL^H$, $S^HT^LL^L$, $S^HT^LL^M$, $S^HT^LL^H$, $S^HT^ML^L$, $S^HT^ML^M$, $S^HT^ML^H$, $S^HT^HL^L$, $S^HT^HL^M$, $S^HT^HL^H$. The uppercase letters denote different development states, i.e., Low (L), Medium (M), High (H). For example, T^H represents an ideal combination of transport demand management scheme, such that more residents are willing to use public transport.

3.2.2. Microscopic CE estimation

Most of the time, CEs are not evenly distributed in the urban area. To locate the area with high CE intensity at the zonal level, Motor Vehicle Emission Simulator (MOVES) was employed to simulate CEs during the peak hour. Making use of traffic demand and flow conditions, as well as transport network and signal control, traffic flow simulations were conducted in TransCAD. At this level, CEs are not only correlated with traffic volume, speed, intersection delay, but also the vehicular idling states. Consequently, the vehicle demand from/to origin/destination also affect CE intensity. The input data processing methods can be found in Appendix B. Eventually, link-based CEs were aggregated into traffic analysis zones (TAZs).

3.3. XGBoost and interpretable machine learning methods

eXtreme Gradient Boosting (XGBoost), which uses a gradient boosting framework to sequentially build decision trees and correct errors with each subsequent tree, is a high-performance machine learning algorithm (Chen and Guestrin, 2016). We employed XGBoost to construct a regression model between built environment variables and CE intensity. A hyperparameter set was defined as shown in Table A. 2, and ten rounds of tests were conducted using RandomizedSearchCV in the scikit-learn library to figure out the best-performing set.

Furthermore, we undertook a thorough analysis employing interpretable machine learning methods, which involved calculating the importance ranking of all variables, and generating one-way Partial dependence plots (PDPs). The importance ranking method assesses the significance of input features in predicting the target variable, allowing for the quantification of each built environment variable's contribution to the CE. PDPs, a type of interpretable machine learning method, are valuable graphical tools to interpret the marginal effect of a target predictor on the model prediction (Li, 2022). For complex machine learning models such as XGBoost, PDPs can help researchers unveil non-linear or more intricate relationships between variables and model outcomes. In this study, PDPs were utilized to explore the non-linear relationship between built environment variables, specifically variables related to PSFs, and CE intensity.

4. Case study

4.1. Study area

Suzhou, China, is a modernized and wealthy megacity in the Yangtze River Delta region. Owing to the industrial development in the last thirty years, both GDP and GDP per capita consistently rank at the top ten among all Chinese cities. Besides, Suzhou is also a 2500-year-old city, with plenty of inherited historic and cultural heritages. The total population in this attractive city has increased by 27% during the second decade of 21st century.[4] As shown in Table A. 3 and Figure A. 1, the study area includes five urban districts, namely Gusu (GS) District, Industrial Park (IP), Huqiu (HQ) District, Wuzhong (WZ) District and Xiangcheng (XC) District.

GS is a historic district with an ancient city encircled by canals in the city center. And it is home to an incredible wealth of Suzhou's delicate history dating back thousands of years. Unlike many historical urban areas, as shown in Table A. 3, the overall population density in GS is still very high, despite the stringent control over the development intensity of the ancient city. A considerable number of municipal-level PSFs are also located in this district, attracting activity demand across the city. Consequently, typical urban problems emerged as side effects, e.g., road congestion. Traffic rationing policies, including vehicle and parking restrictions, have been implemented and progressively tightened over the last five years. While strict land use controls and transport demand management strategies have proven effective in reducing overall traffic demand, severe road congestion persists near schools and hospitals during peak hours. And it requires more targeted policy proposals by examining the relationship between residents' activity demand and PSF distribution.

Since the 2000s, the planning perspective of polycentric development has been increasingly recognized as a solution for achieving both social and economic sustainability. According the latest spatial plan,[5] the polycentric structure of Suzhou consists of one core, i.e., the ancient city in GS, along with multiple sub-centers, as shown in Figure A. 1. In the plan, the overall population of the whole study area will continue to increase from 5.15 million to approximately 6.90 million. Therefore, both urban expansion and population growth pose significant challenges to achieving carbon peak, especially when maintaining high economic competitiveness continuous to be government's primary concerns.

4.2. Data collection and processing

The data used for the two-stage CE simulation were estimated and verified based on individual OD survey and roadside traffic surveillance data in 2018, by Suzhou Planning & design research institute co. Ltd. The link-based dataset includes parameters such as free flow speed, road capacity, intersection signal control plans, vehicle type and equivalent

[4] Data source: Suzhou spatial planning (2020–2035).

[5] Data source: Suzhou spatial planning (2020–2035).

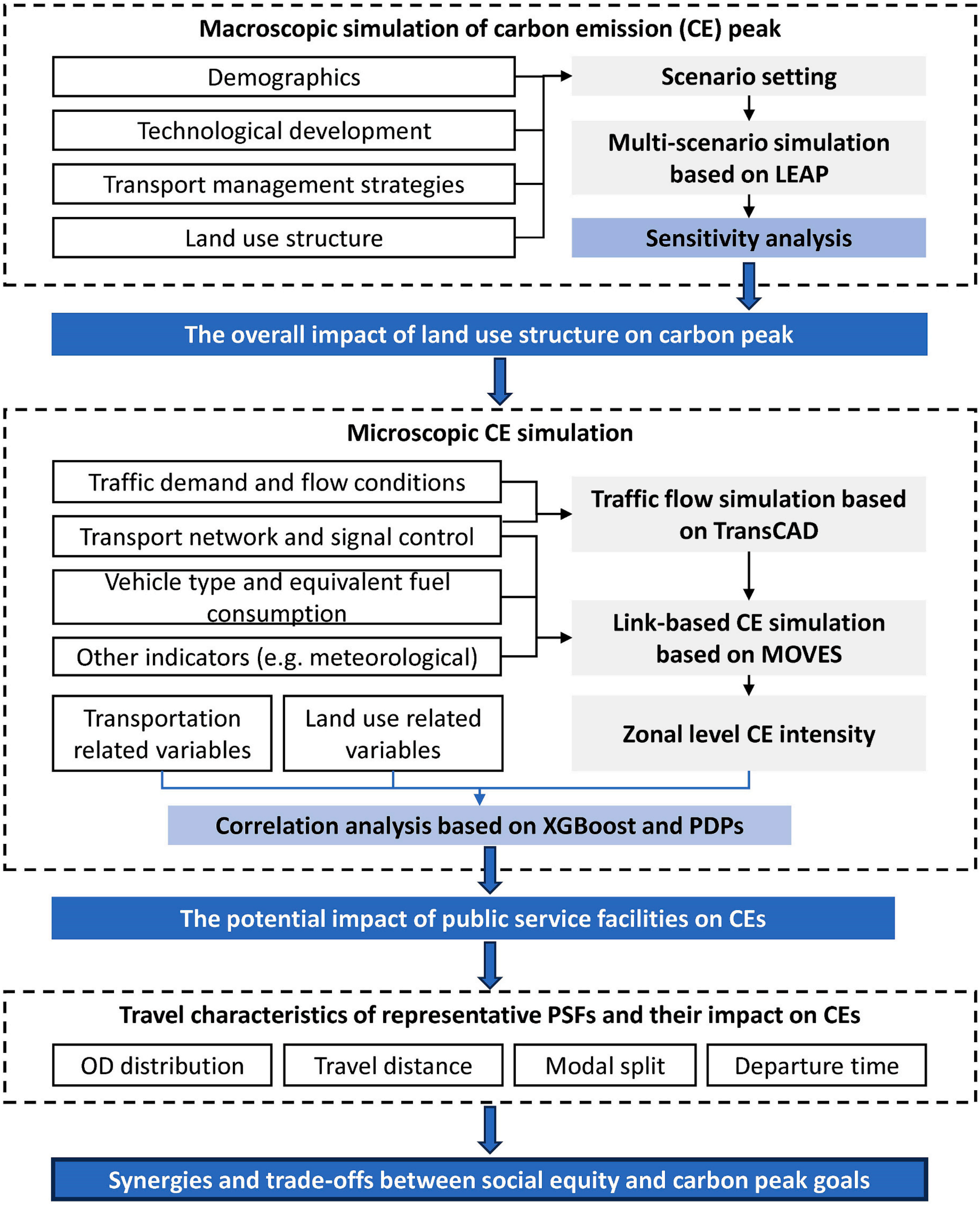

Fig. 1. Analytical framework.

fuel consumption, most of which are predefined in the road network created by the authors' previous transport planning projects. In addition, OD survey data[6] are also used in the analysis of travel characteristics with respect to PSFs.

In the correlation analysis, the TAZ level transport-related CE intensity is considered as the dependent variable. The possible correlated variables include both land use and transport related indicators, such as land use type, development intensity, Point of Interest (POI) data,[7] road network density, etc., as shown in Table A. 4. The results of Pearson correlation analysis of all variables are illustrated in Figure A. 2. Note that during the variable filtering process among the first several rounds of correlation analyses, we discovered the possible correlation of certain PSF agglomeration effect on high CEs, therefore, we subdivided PSF types, following the studies conducted by Huang et al. (2022)Huang

[6] The two latest individual OD survey were conducted in 2013 and 2018 with a 1% sampling rate of approximately 5 million resident population.

[7] POI data were collected from www.amap.com with the same years of traffic flow data.

et al. (2022) and Niu and Silva (2021)Niu and Silva (2021), and created compound variables (see Table A. 5).

4.3. Characteristics of public service facility distribution

In the study area, imbalanced distribution of PSFs can be observed between the central area and new towns, particularly concerning renowned hospitals and key schools. Fig. 2 and Table 1 show the locations and resident population coverage of different level hospitals and schools. For example, although the overall scope of services of all hospitals is fairly good, i.e., 85.57%. The coverage of highest-level (First-class Third-level) hospitals is barely satisfactory. Most of them are located in the city center. These hospitals are much more attractive to potential patients, e.g., the children's hospital and the traditional Chinese medicine hospital. More than two-fifth of the resident population have to travel more than 8 km to reach these facilities, a distance much longer than the average commuting trips. The coverage rate for schools is even lower than that of hospitals, with nearly half of the population having to travel over 8 km to reach key primary and secondary schools.

To be more specific, currently in China, hospitals are classified by a three-level system (i.e., Third-level, Second-level and First-level) according to the Ministry of Health of the People's Republic of China. Additionally, these three levels can be further granted into three subsidiary classes based on periodic evaluations of hospital size, staffing, complexity and possession of various medical resources, etc. As shown in Table 2, Third-level is the highest level, with First-class Third-level hospitals receiving the highest rating. In comparison with primary care provided by First-level hospitals, Third-level hospitals not only provide comprehensive medical care but also conduct researches and training programs. Although residents are encouraged to seek preliminary diagnosis at lower-level medical facilities, they are not obliged and more preferred to get direct treatments from these renowned higher-level hospitals.

In existing municipal medical facility plans, the most pertinent indicators for periodic evaluations are the number of beds and the number of medical practitioners per thousand residents. Although mentioned in official documents,[8] the problem of excessive centralized distribution of high-level hospitals and high-quality medical resources has persisted for years. And this has not been adequately addressed, as larger hospitals are normally more capable of expansion due to their superior resources and social influence.

5. Results

5.1. The overall impact of land use structure on carbon peak

The multi-scenario simulation indicates that Suzhou has the potential to achieve the transport-related carbon peak before 2035 contingent upon promising technological development, a prospective polycentric land use structure, and effective transport management strategies. Each of these aspects is crucial. The carbon peak objective cannot be realized through the contribution of only one factor.

A further sensitivity test was conducted to elucidate the potential impact of land use structure on the achievement of carbon peak at the city level. By keeping technological development at the medium state[9], i.e., S^M, Fig. 3 depicts the results of a sensitivity test of transport management strategies and land use structure, which could vary depending the policies of local governments. The vertical axis of the cumulative histogram represents the overall CE level of the whole city, while the horizontal axis denotes the simulation year. The colored lines depict the CEs generated by different urban transport modes.

In the macroscopic simulation, the average travel distance by different travel modes is chosen to represent the effect of monocentric or polycentric land use structure. For example, according to the results, a shorter average travel distance by automotive, e.g., from current 9 km (e.g., $S^MT^ML^M$) to 7 km (e.g., $S^MT^ML^H$), would effectively reduce the overall CEs by 22.9%. In general, the average travel distance of commuting trips is determined by the distribution of residences and workplaces, while that of other trips is largely affected by PSF distribution. On one hand, a well-balanced job-housing land use structure, as proposed in existing land use plans, would hopefully result in relatively shorter travel distances. However, uncertainties arise from residents' location choice preferences and fluctuations in labor market demands, which would diminish the effect. On the other hand, according to the last two OD surveys conducted in 2013 and 2018, the characteristics of residents' travel decisions that are related to PSFs appear more stable and predictable. This stability is attributed to the current PSF distribution, e.g., CBDs, schools, and hospitals, which are primarily determined by land use plans.

In the simulation, these observations are reflected through parameter settings. For example, the current average travel distance by travel modes is defined based on the lastest OD survey. Predicted values are set based on a joint consideration of current land use plans, travel characteristics/preferences derived from the OD survey, and case studies from similar Chinese megacities. The parameter settings of all the four indicators can be found in Appendix B. As illustrated in Fig. 3, only scenarios characterized by descending cumulative curves, i.e., $S^MT^HL^M$ and $S^MT^HL^H$, demonstrate the pathway toward achieving the carbon peak objective. Even if the transport management strategies are efficient and effective, e.g., T^H, there is still a risk of failure if the indicators of land use structure are unsatisfactory. For instance, a more concentrated distribution of PSFs could exacerbate traffic congestion and higher CE intensity. Moreover, the current master plan anticipates a significant population increase in surrounding districts. In a worst-case scenario, this may lead to higher travel demand and longer distances, causing a substantial rise in CEs. Unlike transport strategies that can adapt changing circumstances, optimizing land use structure, such as PSF distribution, is increasingly crucial.

5.2. The potential impact of public service facilities on carbon emissions

5.2.1. Current carbon emission estimation at the zonal level

Fig. 4 depicts the results in terms of CE per square kilometer of each TAZ in the central area, which normally only contains one or two blocks (see the result for the whole area in Figure A. 3). The darker the color, the higher the CE intensity. Therefore, the constitution of land use type is relatively simple. It is easy to see that TAZs that contain congested expressways and arterial roads generate higher CEs. Road congestion brings not only increased travel time but also higher CEs and air pollution. However, there are also TAZs with noticeable high CE intensities, which mainly contain key schools, high level hospitals, and central business districts (CBDs). By setting the average CE intensity of the whole study area to be 100%, as shown in Table 3, the average CE intensity of TAZs with high-level PSFs is significantly higher than all TAZs with similar facilities, e.g., 170% vs. 115% for schools, and 217% vs. 110% for hospitals. Moreover, the average CE intensity in the ancient city, i.e., 181%, is also much higher than the whole average, due to road congestion and a relatively higher locational aggregation of PSFs. In particular, within the ancient city, the average CE intensity of 5 TAZs with First-class Third-level hospitals reaches 271%. Therefore, under the joint impact of both higher attractiveness and concentrated distribution of high level PSFs on residents' actvity and travel decisions, certain locations in the central area exhibit significantly higher CE intensities.

[8] Suzhou Medical Institution Setup Plan (2016–2020), https://www.suzhou.gov.cn/szsrmzf/zdzxghyjzjhjd/201603/1X8A6II0EVOP2O7JR0M2XOUZKWQJZPRM.shtml.

[9] S^M is defined based on the prediction from China Southern Power Grid New Energy Research (2021).

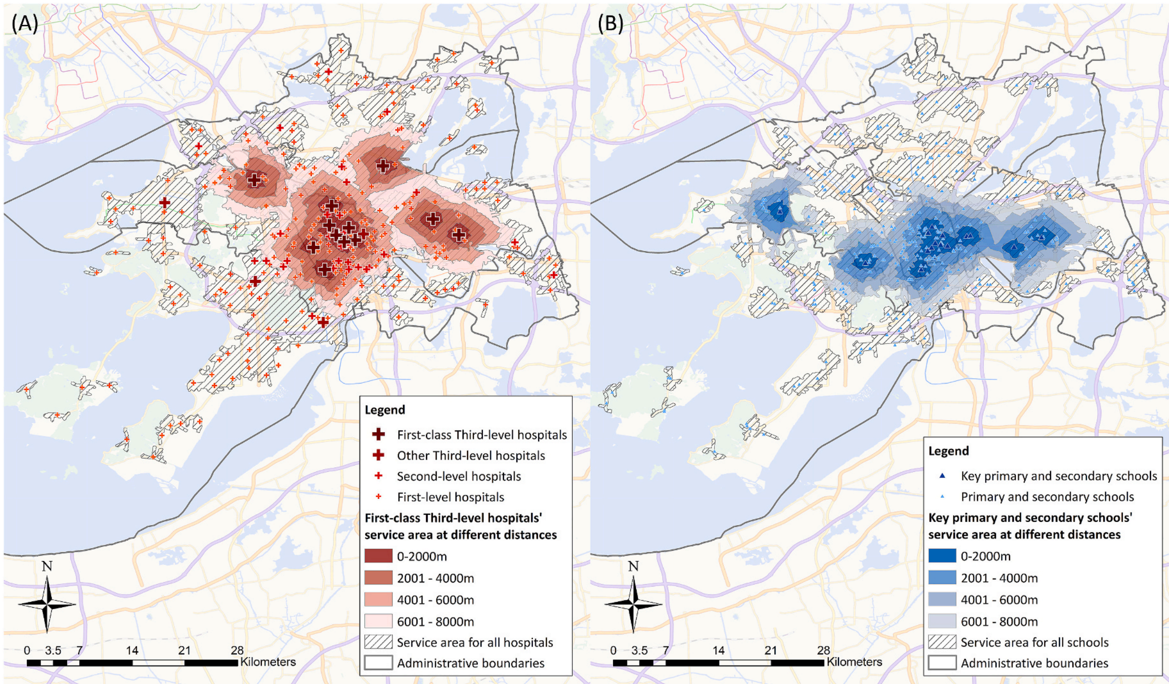

Fig. 2. (A) The distribution and service area of all hospitals of different levels and First-class Third level (highest level) hospitals' service area at different distances, (B) The distribution and service area of all primary and secondary schools, as well as key primary and secondary schools' service area at different distances.

Table 1
The resident population coverages of different level hospitals and schools. [a]

The coverage of First-class Third-level Hospitals				The overall scope of services of all hospitals[b]
2 km	4 km	6 km	8 km	85.57%
9.83%	28.51%	45.94%	59.03%	
The coverage of key primary and secondary schools				**The overall scope of services of schools[c]**
2 km	4 km	6 km	8 km	76.56%
10.72%	27.94%	42.23%	52.44%	

[a] The resident population distribution is estimated based on cellular signaling data aggregated from all the three mobile phone carriers, i.e., China Mobile, China Telecom, and China Unicom.
[b] The overall scope of services of all hospitals are calculated based on current road network. The effective service radii are set to be 2 km, 4 km and 6 km, for First-level, Second-level and Third-level hospitals, respectively.
[c] The overall scope of services of all schools are calculated based on current road network. The effective service radii are set to be 2 km.

Table 2
The number of hospitals by grade in China and Suzhou.

Hospitals	Third-level	Second-level	First-level	Total
Numbers in China*	2548 (11.4%)	9017 (40.3%)	10,831 (48.4%)	22,396 (100%)
Numbers in Suzhou**	18 (4.9%) 13*** (3.5%)	30 (8.2%) 4***(1.1%)	319 (86.9%)	367 (100%)

*Data source: 2019 China Health Statistics Summary.
**Data source: https://www.suzhou.gov.cn/szsrmzf/yljgmdml/xxgkzdly.shtml, and POIs from Amap.com.
***The number of First-class hospitals within Third-level and Second-level ones.

5.2.2. Correlation analysis

A correlation analysis by XGBoost was applied in capturing the relationship between built environment variables and the CE intensity. The resulting optimal R^2 is 0.699, indicating a satisfactory fitting performance. The importance ranking of all variables is depicted in Fig. 5 (A), while Fig. 5 (B) showcases one-way PDPs specifically related to PSFs.

In general, after optimizing the feature set, most remaining features are correlated with CEs. Transport features are highly correlated with CE intensity. The more road sections and traffic volume in a TAZ, the higher the CE intensity, e.g., TAZs with expressways and higher road densities. Besides, since lower speed results of relatively higher CEs per fuel vehicle, TAZs with more road intersections and traffic congestion also generate higher CEs. Related studies also indicate that vehicular traffic congestion, particularly prevalent at intersections characterized by frequent instances of acceleration and deceleration, precipitates an augmented release of CEs (Grote et al., 2016). On the other hand, for the land use features, since floor area ratio (FAR) is normally proportional to OD demand, higher CEs can be found around these areas. It is straightforward to estimate that TAZs with both high values of the above features would generate much higher CEs. However, there is an interesting observation that the overall CE intensity in the ancient city is still high, although the FAR is strictly limited at a lower level, as shown in Fig. 4. High value zones are those TAZs with PSFs, e.g., hospitals and schools. And this can be explained by the top 10 correlated features, e.g. medical POI density (PoiMedical), sports and recreation POI density (PoiSportRecreation), and the proportion of business and public service area (_Pub_Bus_Area).

Indeed, as depicted in Figs. 4 and 5 (B), areas with two or more adjacent PSFs, e.g., commercial centers, medical and recreational facilities, exhibit even higher CEs. This observed agglomeration effect is clear and warrants further investigation into its underlying causes.

5.3. Travel characteristics of representative PSFs and their impact on carbon emissions

Undeniably, there exists a complex non-linear and geographical relationship between urban transport-related CE intensity and the built environment. In this section, we employed individual travel survey data from two OD surveys conducted in 2013 and 2018, to elucidate the

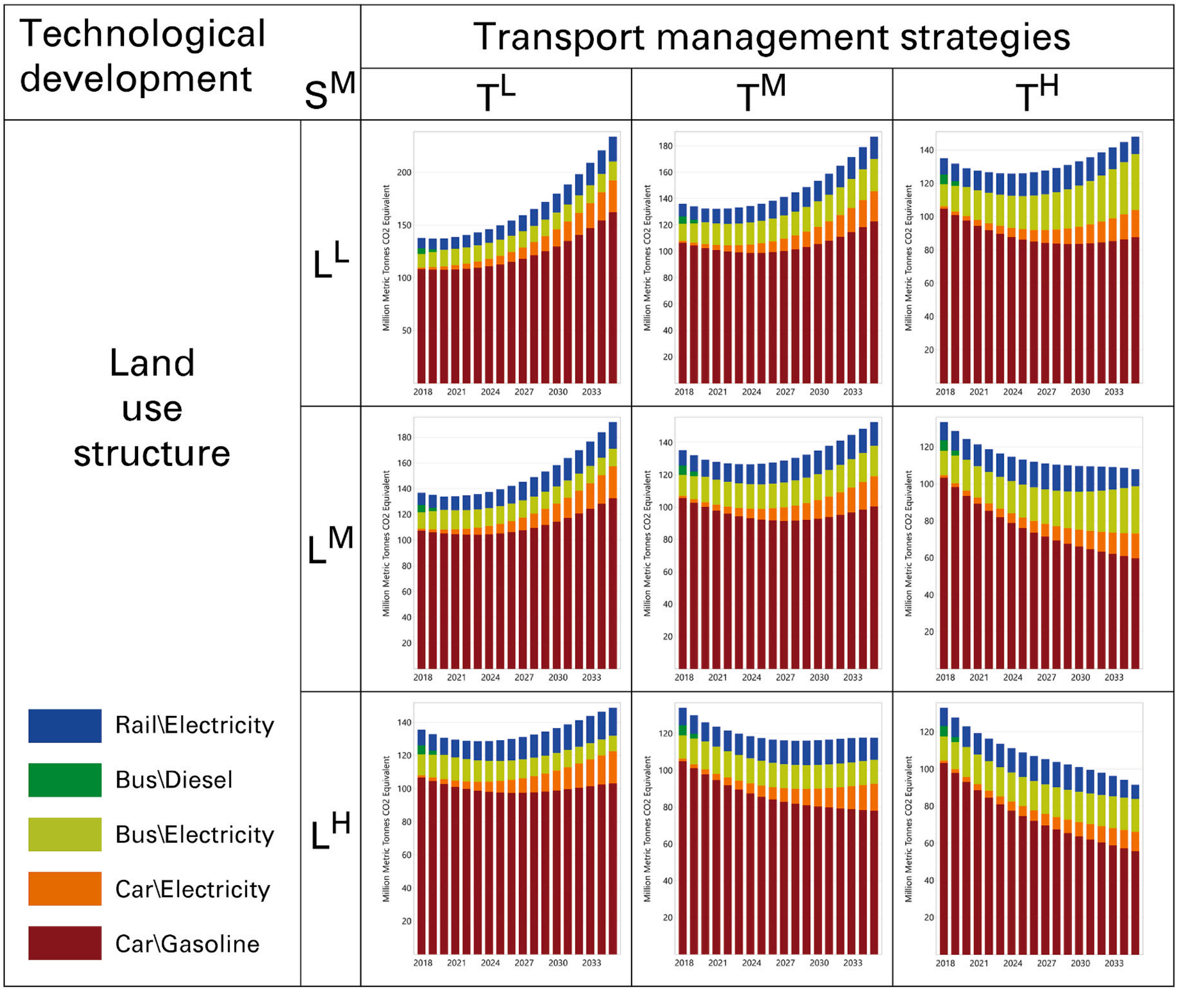

Fig. 3. The sensitivity analysis of the impact of land use structure on carbon emissions.

relationship between travel demand characteristics and PSFs. The objective is to discern the underlying factors contributing to high level transport-related CEs around PSFs. Furthermore, this investigation underscores the imperative of incorporating considerations for carbon peak in the optimization of PSF distribution.

Medical service facilities are indispensable PSFs for residents' everyday life. As illustrated in Fig. 2 (A), the current spatial distribution of medical service facilities is mainly determined by social equity-oriented planning decisions and has historical inheritance. There is a notable spatial agglomeration of high-level hospitals in the ancient city of Suzhou. Despite enhanced public transport services around these hospitals, they stand out as facilities exacerbating transportation issues in major Chinese cities (Song et al., 2019). Table 4 compares the CE intensity, road density, and metro/bus stop density of TAZs with or without high-level hospitals. The CE intensities of TAZs containing high-level hospitals are much higher than the total average. The CE intensities of the TAZs containing four renowned First-class Third-level hospitals are more than a dozen times of the total average. However, there are no obvious connection between CE intensity and road density or metro/bus stop density. Good public transport accessibility doesn't necessarily help to reduce CEs surrounding these hospitals. In fact, when these hospitals are located in the central area, private automotive demand attracted to these hospitals further increases the burden of already overwhelmed road network. Since the land use intensity is highly limited in the ancient city due to heritage preservation purpose, the road capacity is relatively low, and most parking lots are over-loaded during the peak hour. It is straightforward to expect that both the slow speed traffic flow and the queue of idling vehicles would make the emission problem more severe.

According to the two OD surveys, the characteristics of residents' medical care trips are different from that of other trip purposes, in terms of OD distribution, travel distance, modal split, and departure time. It becomes another primary cause of higher CEs.

For the OD demand, as shown in Table 5, among all the observed medical trips on a typical weekday in 2018, despite the average travel distance increasing with the hospital level, 63.3% of residents are drawn to Third-level hospitals. For example, as shown in Fig. 6 (A), the aforementioned four First-class Third-level hospitals attract medical care trips from across the city. Cross-referencing with the hospital distribution in Fig. 2(A) reveals that residents from zones with fewer high-level hospitals directly travel to these renowned First-class Third-level hospitals. In contrast, as shown in Fig. 6 (B), the overall trip distribution displays a noticeable influence of the planned polycentric structure. Fig. 6 (A) and Figure A. 4 illustrate the observed medical care trip attraction and trip distance from aggregated "Large" zones to representative hospitals. Clearly, unlike most trip distribution models suggest (e.g., gravity models), medical care trip demand does not exhibit an inverse relationship with travel distance.

Longer travel distance usually means more motorized trip demand. For the travel mode, although Third-level hospitals are mostly located in the central area with relatively better public transport services, residents are more preferred to use private automotive even if it will probably take more than an hour to get a vacant parking space. As shown in Table A. 6, in both 2013 and 2018, the motorized mode share for medical care,

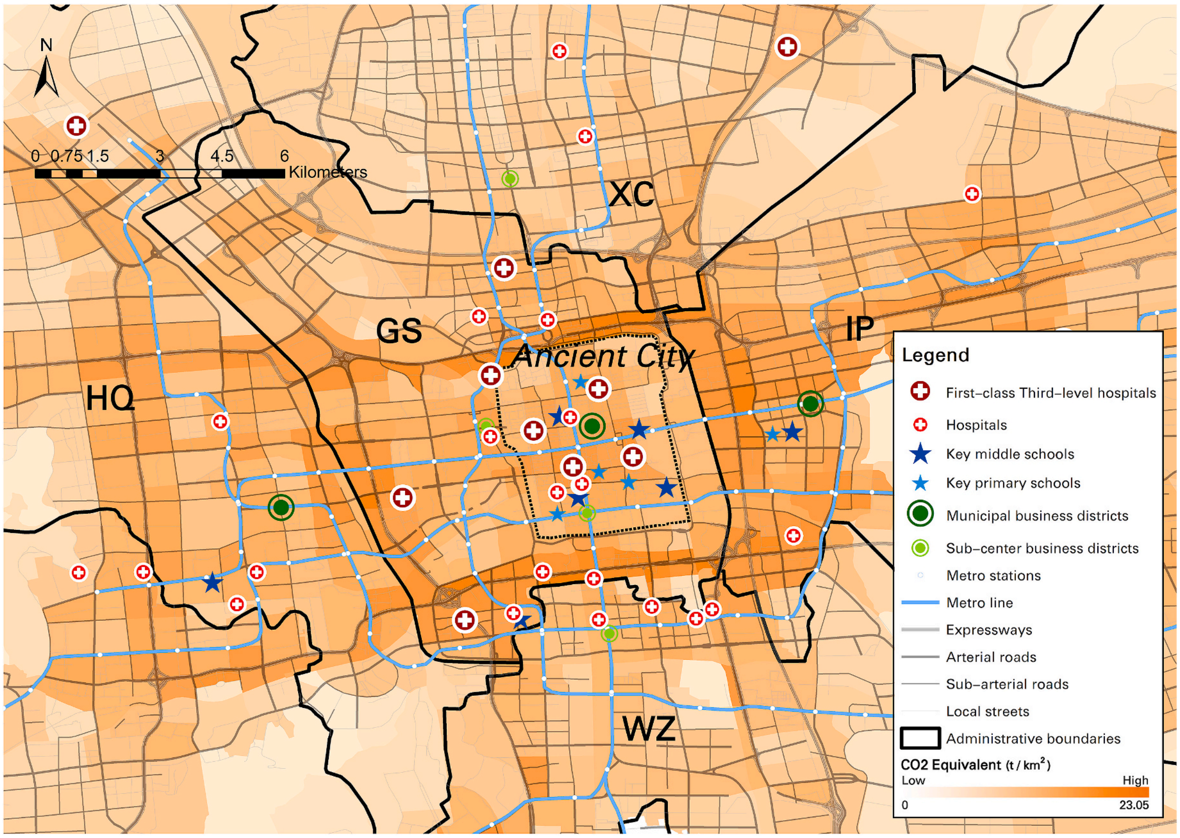

Fig. 4. The CEs and the distribution of some attractive public facilities in the central area.

Table 3
The comparison of average CE intensities.

	Number of TAZs	Average CE intensity
TAZs of the whole study area	1592	100%
TAZs with primary and secondary schools	285	115%
TAZs with key primary and secondary schools	15	170%
TAZs with hospitals	286	110%
TAZs with First-class Third-level hospitals	13	217%
TAZs with schools and First-class Third-level hospitals	4	232%
TAZs within the ancient city	58	181%
TAZs within the ancient city with First-class Third-level hospitals	5	271%

including car and public transport, is much larger than that for all the trip purposes. It is reasonable because prospective patients are more relied on motorized travel modes and companions. And they are less sensitive to monetary cost. Therefore, it is commonly observed that near the entrance of a popular hospital, a long queue for parking is accumulated over a hundred meter along the road side from almost every early morning till the afternoon. When the car driver has to stay in the idling car, the patients get off and start another long journey, i.e., the queue for registration and the queue for medical examination and treatment. It is worthy to note that the car share of medical care trips by aged 20–40 is nearly half. Only a few people were willing to seek medical care by walk or bike. This is due partly to the possibility that they were taking their young children to see the doctor. However, this trend may also signal a growing reliance on private motorized travel modes among younger generations in China. The term “medical tourism” is employed to characterize individuals with economic means opting for extensive travel to access healthcare services (Weisz, 2011). As economic conditions improve, an increasing number of people engage in long-distance, high-carbon mobility to access superior healthcare and other public services.

For the departure time, as shown in Fig. 6 (C), since parking, registration, and examination could be time-consuming, patients are tending to depart from home earlier and earlier, which happens to encounter the morning peak of commuting trips. Eventually, this tragic coincidence translates into more severe congestion and the resultant higher CE level.

6. Discussion

6.1. *The imperative of considering carbon peak goals in the decision-making process of public service facility distribution*

In the previous sections, our estimation results suggest that high transport-related CEs persist in the central area of Suzhou and are closely related to the concentrated distribution of PSFs. This phenomenon is prevalent in many megacities (Figure A. 5), and is consistent with findings in existing researches (Cui et al., 2023; Sun et al., 2021). The underlying reasons are diverse, affected by various factors, introducing uncertainties in achieving the carbon peak goals for local governments. Our study suggests that this phenomenon is not only associated with the rapid urbanization and population growth, the inherit distribution of high-quality PSFs, but also intertwined with residents’ activity preferences and decisions. It could be exacerbated when these PSFs, e.g., renowned hospitals, key schools, are intensively distributed in central areas. Such overconcentration of PSFs could intensify the contradictions (Bendib, 2022).

Considering the direct causes of transport-related CEs, it appears that mitigating regional traffic congestion could be an effective strategy of CE reduction. In practice, several megacities in China have implemented transport demand management schemes in the city centers, e.g., raising parking fees, imposing regional vehicle restrictions. While these initiatives could reduce the overall auto traffic, the effects on alleviating

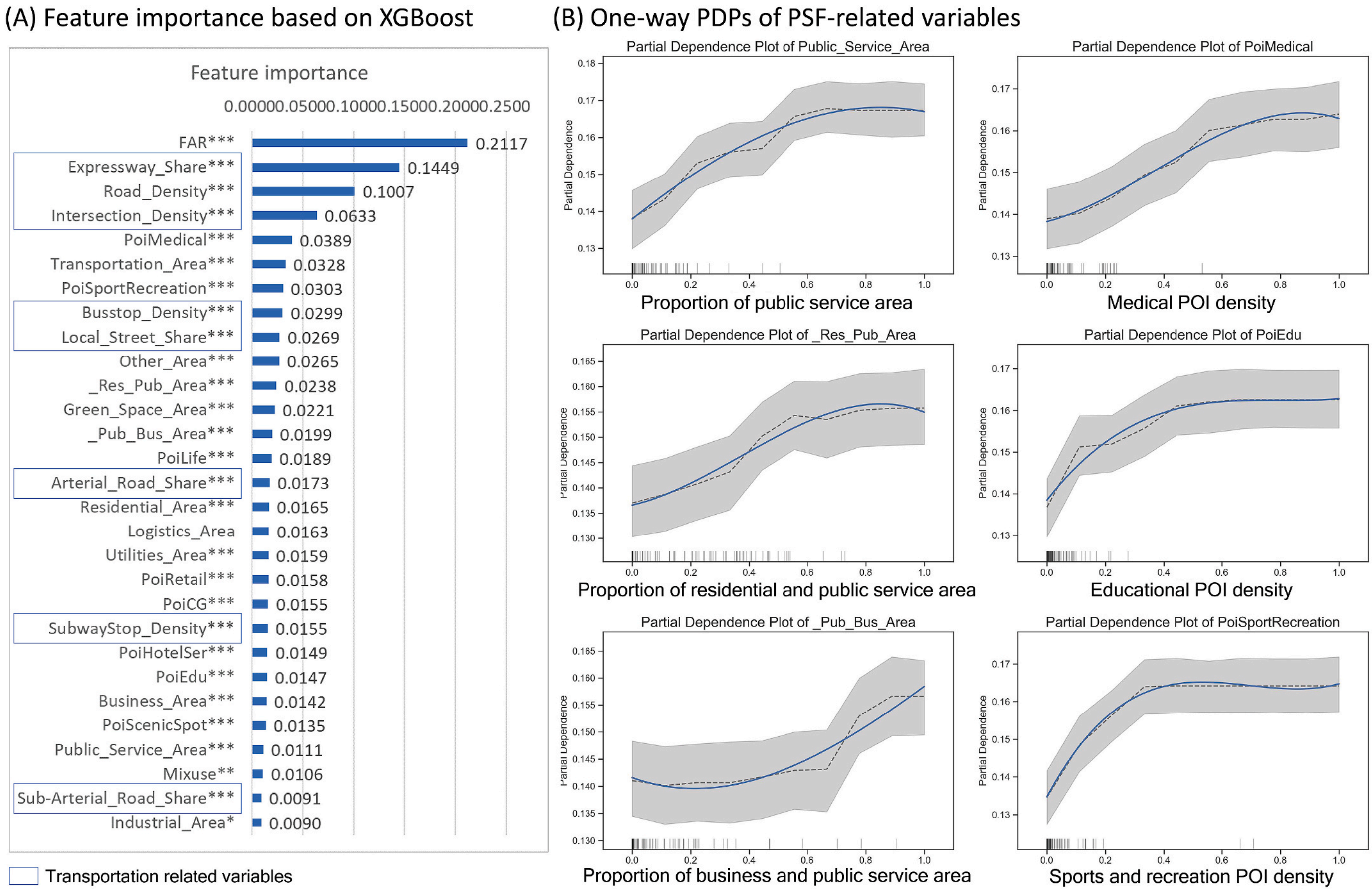

Fig. 5. (A) Feature importance based on XGBoost (Note:"***" represents p-value < 0.001, "**" represents p-value < 0.01, and "*" represents p-value < 0.05 according to Pearson correlation analysis), (B) One-way PDPs of PSF-related variables (Note: In order to clearly display the results, the y-axis values of the PDPs are different. The gray line represents the original curve, while the blue line represents the fitted spline curve. The gray area represents the 95% confidence interval of ICE.).

Table 4
The comparison of CE intensity, road density and metro/bus stop density among TAZs.

Hospitals	Hospital level	CE intensity (kg/km^2)	Road density (km/km^2)	Metro/Bus stop density (number/km^2)
Hospital A*	First-class Third-level	8326.03	46.44	26.51
Hospital B**	First-class Third-level	7767.71	33.98	21.26
Hospital C***	First-class Third-level	7066.58	21.57	12.17
Hospital D****	First-class Third-level	6548.43	13.97	12.41
Averages of TAZs containing Third-level hospitals		3366.18	11.49	7.28
Averages of TAZs containing Second-level hospitals		2363.96	9.79	5.68
Averages of all the TAZs		667.33	3.11	3.92

*The First Affiliated Hospital of Soochow University (Shizi Campus, Headquarter).
**Suzhou Municipal Hospital.
***The Second Affiliated Hospital of Soochow University (Sanxiang Campus, Headquarter) .
****Suzhou Traditional Chinese Medicine Hospital.

congestion around hospitals and schools are marginal. This is attributed to the in-elasticity of motorized travel demand. Taking medical facilities as an example, Chinese residents are willing to and used to taking long distance trips, and enduring long queues for parking and registration, hoping to get medical treatment from renowned hospitals and respected physicians. Therefore, if the ideal hospital is not close, they drive. If the parking queue is long, they travel with companions. If the hospitals are crowded, they choose to go earlier. Time and monetary cost are no longer the primary concerns. When the majority of people are thinking in this way, these automotive travel demand would not be easy to reduce by conventional transport management policies. Even more, some mandatory rationing approaches, e.g., traffic restriction, would make the problem more complicated, e.g., imposing more traffic demand in the bottlenecks of the road network, and damaging the experiences of both medical care and other activity demand. This situation could get worse in many historic cities, such as Suzhou. Subject to the preservation of historical and cultural heritage, both the overall road density and motorized road capacity are low, and the public parking supply within

Table 5
The destinations of residents' medical care trips in 2018 OD survey.

Target hospitals	Percentage of the total medical care trips	Person/Trip[a]	Average travel distance (km)
Third-level	63.3%	1.63	7.62
Second-level	21.5%	1.61	4.01
First-level	15.2%	1.56	3.20
Total	100%	–	–

[a] The value of Person/Trip is equal or greater than 1, indicating that normally patients are used to seek medical treatment with companions, e.g., family members or friends.

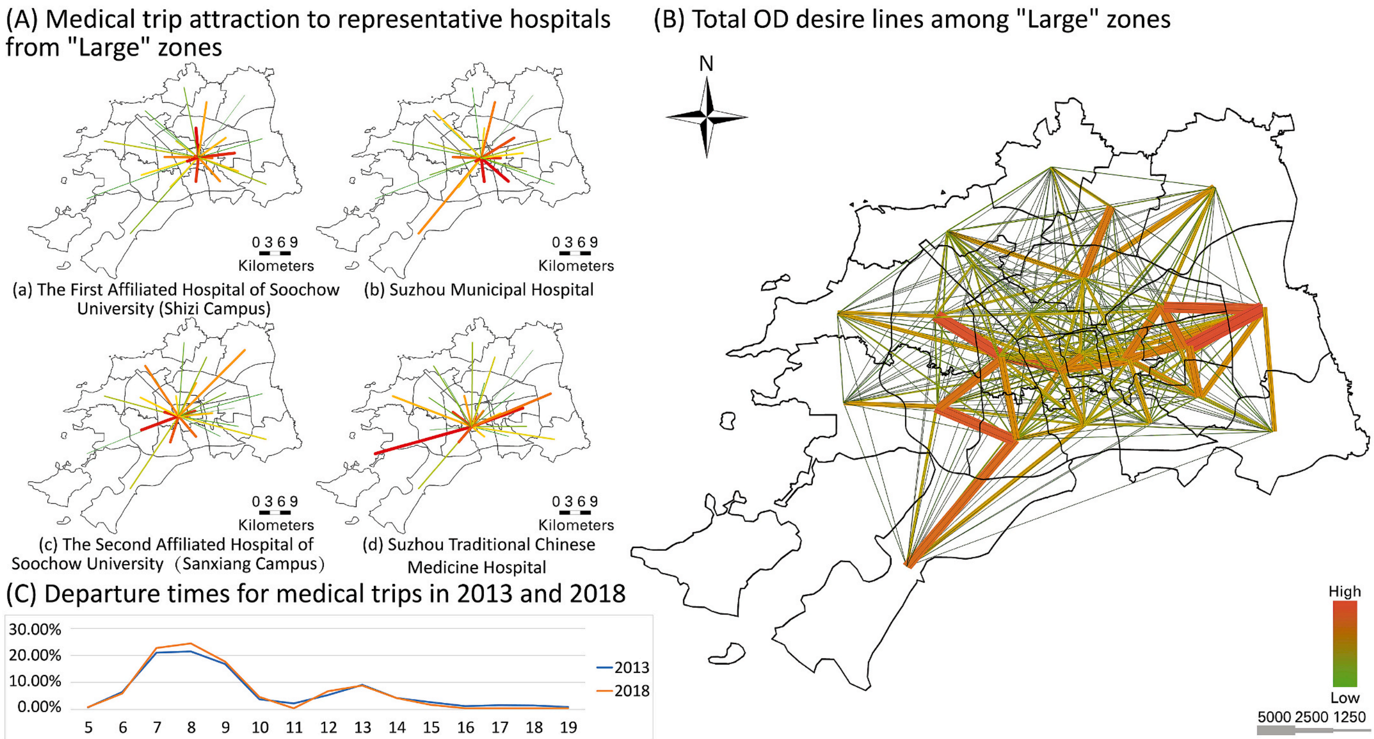

Fig. 6. (A) Medical trip attraction to representative hospitals from "Large" zones, (B) Total OD desire lines among "Large" zones (Note: The thicker the line and the redder the color, the higher the trip demand; the thinner the line and the greener the color, the smaller the travel volume.), (C) Departure times for medical trips in 2013 and 2018.

and around PSFs are insufficient. During the peak hour, a considerable proportion of running vehicles are at lower speed searching for available parking spaces or queuing alongside the road waiting for entering the parking lots. The inefficient use of roads results of unnecessary heavy traffic congestion and much higher CEs. Since 2019, local government has introduced increasingly stringent traffic restriction policies in the

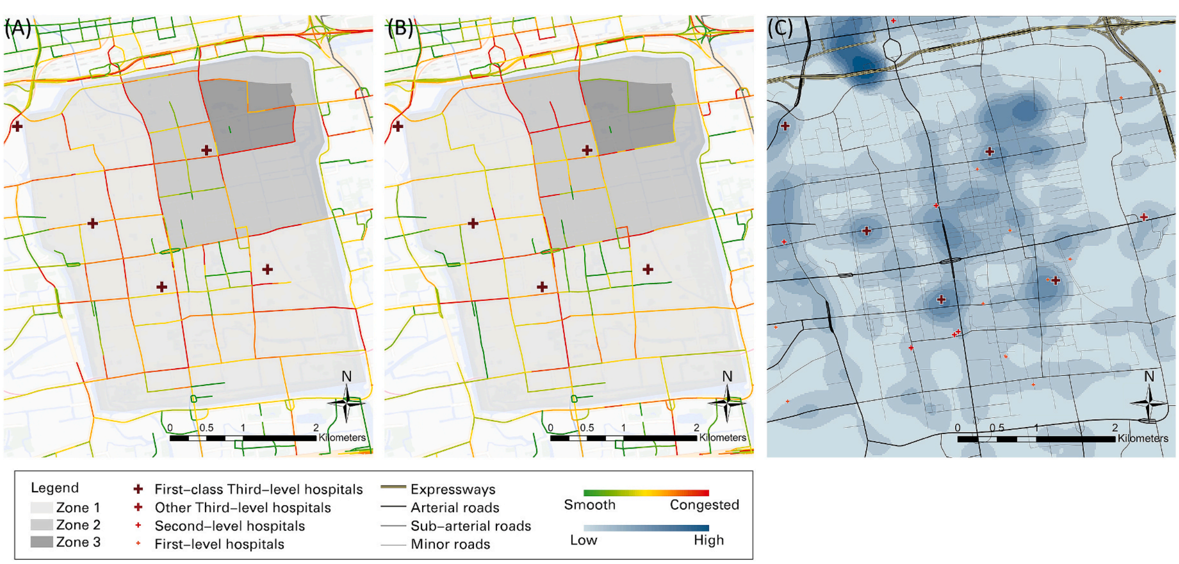

Fig. 7. (A) Traffic conditions during morning rush hour in the ancient city of Suzhou in 2018, (A) Traffic conditions during morning rush hour in the ancient city of Suzhou in 2023, (C) Density map of ride-hailing pick-up and drop-off points during 7–10a.m. on a typical weekday in 2023
Note: Vehicles lacking local licenses face restrictions from 7 a.m. to 9 a.m. and from 4:30 p.m.–7 p.m. on weekdays in Zone 1. In Zone 2, these restrictions extend from 7 a.m. to 7 p.m. daily. Additionally, in Zone 3, all vehicles except those authorized are subject to restrictions from 7 a.m. to 7 p.m. every day.

ancient city, the congestion around most First-class Third-level hospitals has not been mitigated, as shown in Fig. 7(A) and (B). In fact, the introduction of vehicle restrictions may even lead to a surge in demand for taxis/ride-hailing services (Fig. 7 (C)).

Additionally, it is also noted that despite the increasing share of NEVs in the overall vehicle fleet, driven by incentive policies of the NEV industry at both national and municipal levels, such as unlimited license plates and vehicle purchase subsidies, whether it would result of lower CEs remains inconclusive. For example, while purchase subsidies and lower usage costs may incetivize potential residents, particularly younger generations, to shift from public transport, this trend would potentially result of higher automotive demand and heavier traffic congestion in the coming year. When there are still a large proportion of traditional fuel vehicles on roads, the overall CEs could be higher due to the rise of per capita CEs of fuel vehicles. From the perspective of achieving carbon peak at the urban scale, this underscores the potential intricate correlations among relevant influencing factors, such as energy structure, transport management strategies, and land use structure, etc. Endeavoring to attain carbon peak through singular policy dimensions may not only lack precision and efficiency but could also yield unforeseen and undesirable side effects.

Nevertheless, at the current stage, in many Chinese megacities, affected by the characteristics of PSF distribution and residents' activity preferences, further optimizing the PSF and relevant resource distribution seems to be a potential and feasible strategy to effectively reduce the direct or indirect transport-related CEs.

6.2. Trade-offs between different goals

It is widely recognized that urban planning decisions could vary in accordance with different objectives, and there is rarely a decision which can optimize for all objectives simultaneously. Therefore, in practice, trade-offs and possible synergies can be found among objectives and decisions. Currently, the PSF distribution is primarily guided by the principle of social equity, where per capita facility ownership and relatively equal accessibility are typical indicators. Theoretically, these criteria can indirectly contribute to the reduction of transport-related CEs. For instance, evenly distributed medical facilities align with population distribution could reduce the average travel distance of medical care. Enhancing public transport services around tertiary healthcare institutions could promote low-carbon travel demand. However, this decision might not be the first best solution given the objective of carbon peak.

In reality, when multiple types of PSF planning decisions follow similar social equity principles, negative agglomeration effects can emerge. Some strategic plans even suggest the concentration of different types of PSFs. When crucial PSFs are concentrated in highly accessible locations, especially when the peak of activity demand of adjacent facilities overlaps, unexpected congestion effects may occur. Besides, there are also popular planning perspectives of grouping large PSFs together in the newly planned districts, so as to enhance the city image, such as stadiums, theaters, and exhibition centers (Flock, 2023). These attempts may have created another high CE district in addition to the old city center.

Reconciling carbon peak goals and social equity goals involves planning resources towards a balance in efficiency and equity (Wang, 2020). Unilaterally pursuing one goal may inadvertently have significant negative impacts on other objectives. In an extreme hypothetical scenario, if the decision only focuses on CE constraints, attractive PSFs may be planned in proximity to locations close to high-income neighborhood, as low-income groups may have fewer choices for individual motorized vehicles. Conversely, if the focus is on addressing the needs of vulnerable groups, this could attract more long-distance automotive travel demand to these PSFs, thereby increasing the overall CE level. Therefore, decision-makers must carefully consider the relationships between different goals and seek synergies to enhance the overall social welfare.

6.3. Synergies among different sectors

In this study, a possible synergy could be identified in the decision-making process involving collaborative planning of PSF and relevant policies across administrative sectors. Additionally, the study of demand elasticity of management strategies beyond the urban transport system is also inevitable. Under the same PSF layout conditions, the achievement of carbon peak goals significantly hinges on the coordination of PSF associated policies.

Currently in China, there is no family doctor system. In 2017, Graded Diagnosis and Treatment System (GDTS) was proposed by National Health Commission of China. Under an ideal GDTS, prospective patients are willing to select hospitals after taking into account the type, severity of their health conditions, and the stage of medical service, rather than rushing into a few renowned hospitals. After living through three years of the pandemic's impact, the vast majority of residents are highly familiar with the locations of primary medical facilities in their residential vicinity. However, the results do not match the expectations (Fig. 7 (A) and (B)). It seems that the GDTS has not fundamentally shaped residents' preferences and choices on medical care activities (Lu et al., 2019; Shao et al., 2021). Actually, the optimization of medical facility distribution encompasses not only facility itself but also high-quality medical resources, such as medical staff, which are closely binding with renowned hospitals. In recent years, a few First-class Third-level hospitals has established new branches in the newly developed districts. For instance, since 2015, the First Affiliated Hospital of Soochow University (depicted in the bottom-right corner of (Fig. 7 (A) and (B)) initiated the utilization of its new branch outside the ancient city. The congestion is considerably relieved on road sections near the hospital. Since the time adaptability of urban infrastructure plan is much slower than residents' activity decisions, to relieve the impact of revealed negative externalities, such as congestion and high-level CEs around hospitals, more pragmatical approach could lie in the optimized allocation of pertinent medical resources.

In China, achieving carbon peak is a critical national strategic objective. And the objective is usually devolved to local governments, who further decompose it into tasks for relevant administrative sectors. But till now, to the bset of our knowledge, although there are many plans/reports from different sectors advocating low carbon projects or “green" travel modes, few plans or reports explicitly outline how to assess the effectiveness of relevant policy decisions and their feasibility in achieving carbon peak. Some preliminary researches hopefully help the decision makers to understand the necessity and possibility of achieving the carbon peak goal in a collaborative and efficient way among relevant sectors.

Since 2020, Suzhou has initiated the development of a municipal-level transport big data platform, incorporating a sub-module designed to analyze the traffic and parking demand associated with medical care trips to two representative First-class Third-level hospitals. Traffic surveillance data, parking data, and diagnosis data were used to identify the whole activity chain of each medical care trip through data fusion approaches. It is therefore possible to infer the underlying contribution of optimizing the diagnosis and treatment processes to congestion mitigation. Based on that, it is then possible to estimate the contribution to CE reduction. However, the above input data come from various data sources with security and privacy concerns. Without administrative instructions, it is practically challenging to expand the study to the whole city. Fortunately, the aforementioned big data platform and modules received positive reviews from government decision makers. In December 2023, Suzhou started to establish the carbon neutral market, where the CEs of concerned industries will be monitored in an integrated data platform. Almost as the same time, Suzhou Industrial Park was awarded the first batch of national level carbon peak pilot parks. In the proposed carbon peak and carbon neutral policy framework, other than energy, industry, architecture, and transport, public institutions and their affiliated facilities are also included. Although the possible interactions among sectors have not been identified, these actions are recognized as initial steps towards establishing an operational carbon trading system.

In sum, policy coordination relies on collaboration among decision-makers from relevant sectors (refer to Table A. 1[10-15]). Sometimes, it would interfere with their inherent responsibilities. To this end, fundamental research of identifying the diverse demand characteristics associated with these PSFs are essential. In particular, the adoption of a spatial interaction perspective could help to explore the impact of one PSF on the adjacent ones. Furthermore, within the context of long-term SDGs, the connection between increased public spending and the realization of SDGs remains unclear (Cristóbal et al., 2021), prompting the need for further exploration of the synergies and trade-offs among SDGs.

7. Conclusion

In the context of long-term SDGs, specifically SDG 10 (Reduced Inequalities) and SDG 13 (Climate Change), we propose to involve the consideration of carbon peak goals into a collaborative decision-making process of urban PSF distribution. Considering the comprehensive optimization approach within the framework of multi-objective and multi-system urban planning and management, this study stated that it is impractical to universally integrate carbon peak constraint into every planning decision for all PSFs. However, considering the urgency and severity of achieving carbon peak goals at both national and local levels, it becomes imperative not to disregard the direct and latent impacts of PSF and public service resource distribution on transport-related CEs.

Although the proposed framework and available tools are relatively compatible with data input at varying levels of detail, a few simplified assumptions were made in the case study due to data limitations. The auto traffic in the road network is originated from various activity and resultant travel demand with complicated interactions among residents. In the ongoing study, we will further identify the contribution of representative PSFs and their externalities on the other traffic demand in terms of CEs, by analyzing the vehicle OD and parking demand from more data sources. This will also allow us to explore the impact of different types of PSF spatial agglomeration on CEs. Finally, we believe that providing quantitative evidence for the synergies and trade-offs between different objectives would facilitate the collaborative planning and policy decision-making processes of PSF for local governments.

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CRediT authorship contribution statement

Xiaosu Ma: Writing – review & editing, Writing – original draft, Supervision, Project administration, Methodology, Conceptualization. **Yuhan Xu:** Writing – review & editing, Writing – original draft, Visualization, Software, Formal analysis, Methodology, Conceptualization. **Minrong Pan:** Validation, Formal analysis, Data curation. **Ke Jiang:** Investigation, Data curation.

Declaration of generative AI and AI-assisted technologies in the writing process

During the preparation of this work, the author(s) used ChatGPT in order to polish and improve the writing. After using this tool/service, the author(s) reviewed and edited the content as needed and take(s) full responsibility for the content of the publication.

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.

Data availability

The authors do not have permission to share data.

[10] issued by National Development and Reform Commission (NDRC) - Department of Development Strategy and Planning.
[11] issued by Ministry of Housing and Urban-Rural Development of the People’s Republic of China.
[12] issued by Suzhou Municipal Development and Reform Commission.
[13] issued by Shanghai Municipal People’s Government.
[14] issued by Beijing Municipal Commission of Health and Family Planning, Beijing Municipal Commission of Planning and Natural Resources.
[15] issued by Shenzhen Municipal Planning and Natural Resources Bureau, Shenzhen Municipal Civil Affairs Bureau.

Appendix A. Figures and Tables

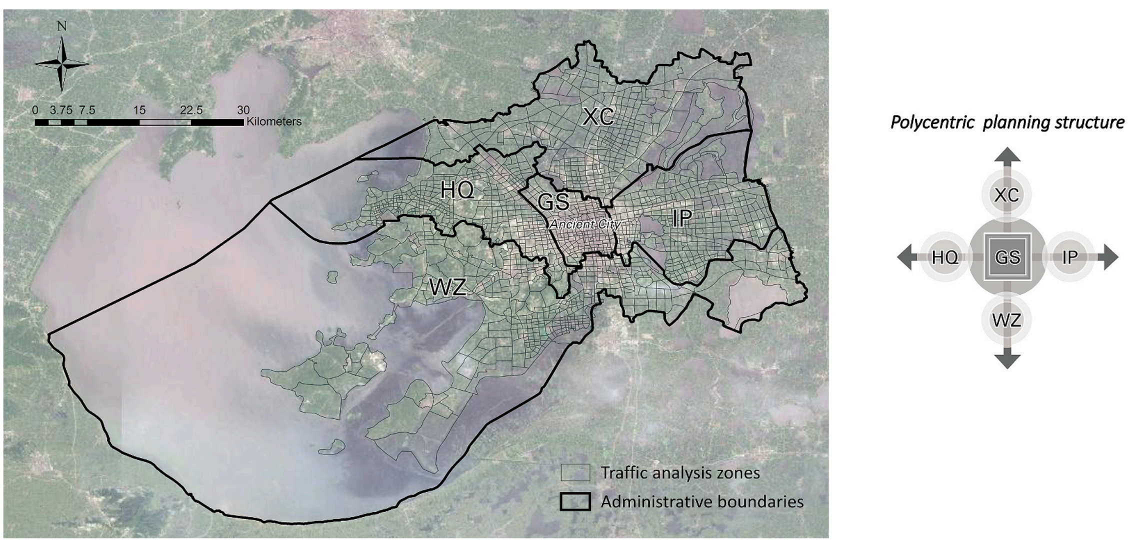


Fig. A. 1. The study area and its proposed polycentric planning structure

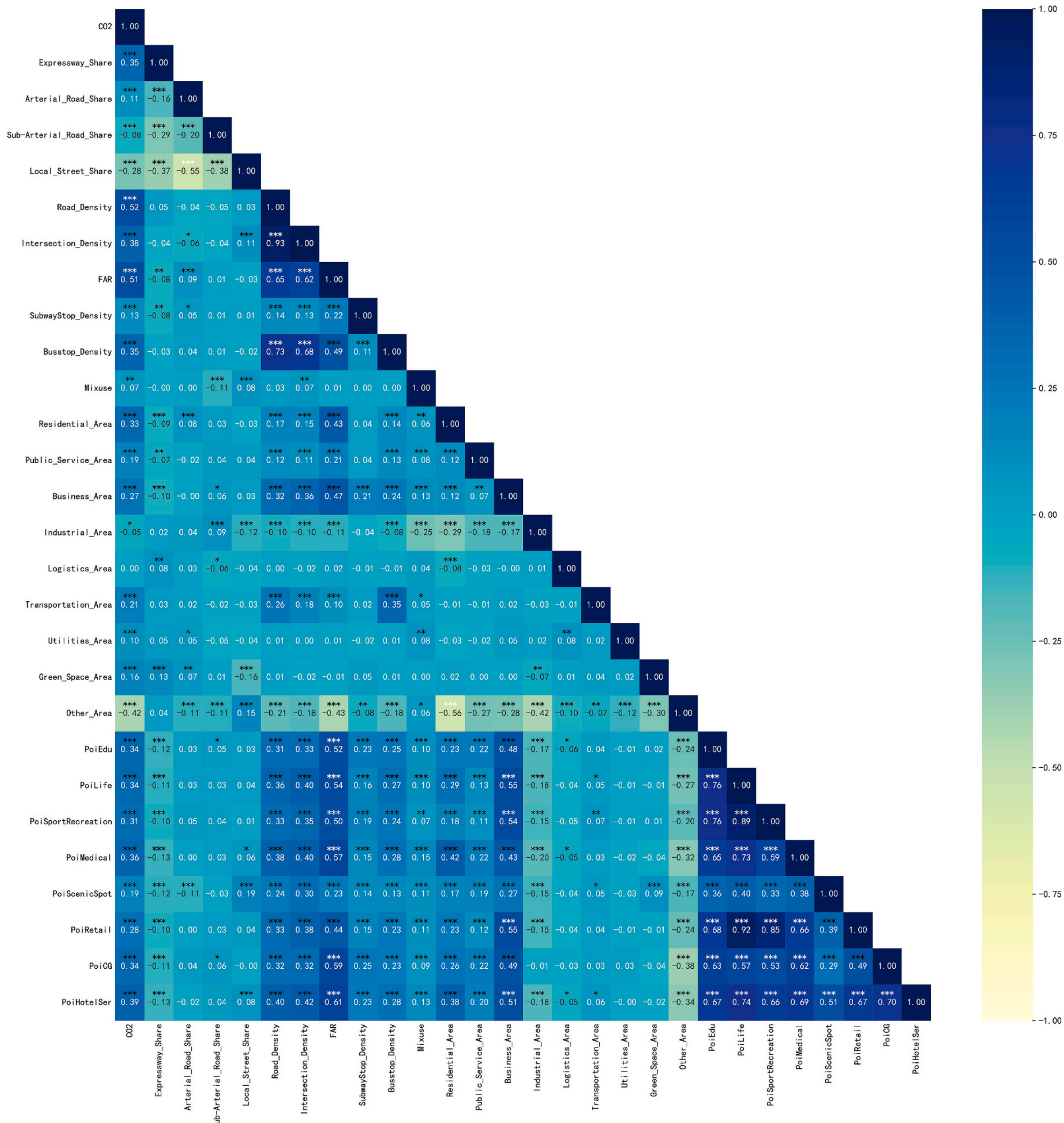


Fig. A. 2. Pearson correlation analysis among CE intensity and possible correlated variables
Note: "***" represents p-value < 0.001, "**" represents p-value < 0.01, and "*" represents p-value < 0.05

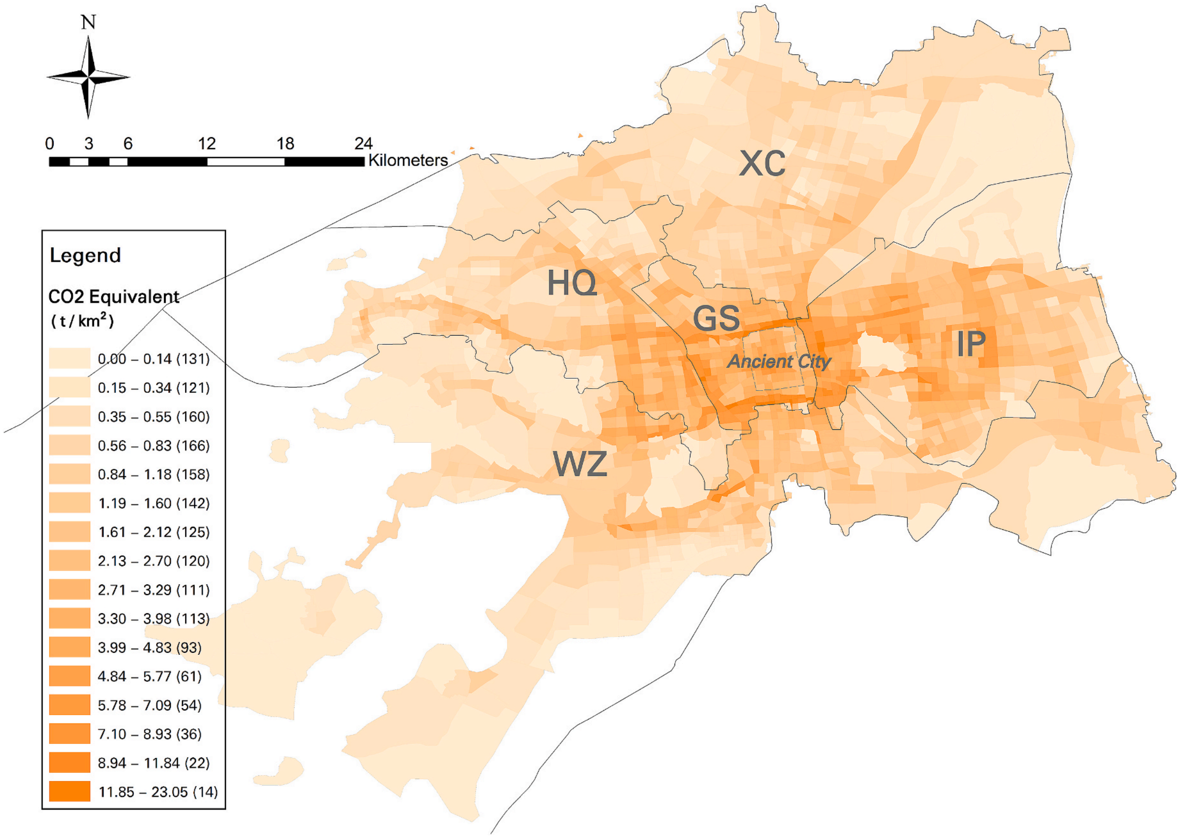
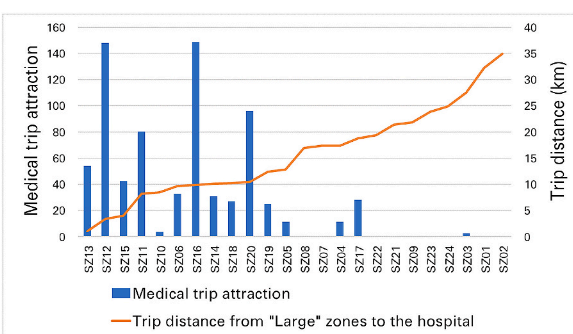
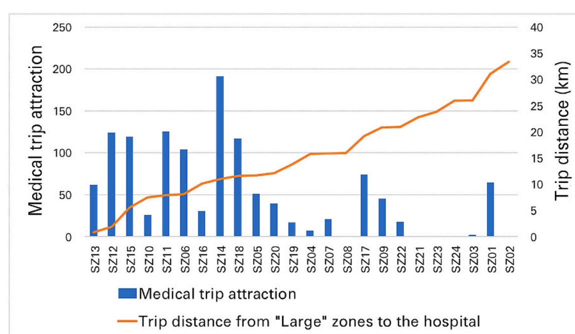


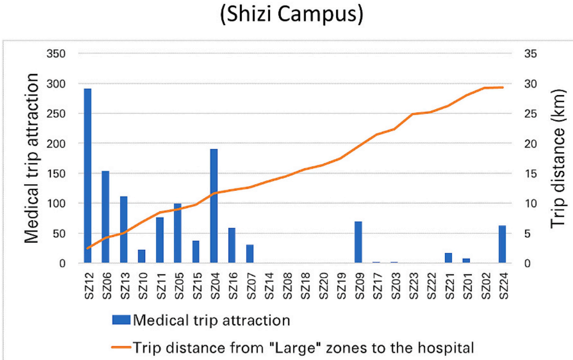
Fig. A. 3. The estimated CEs aggregated at the zonal level



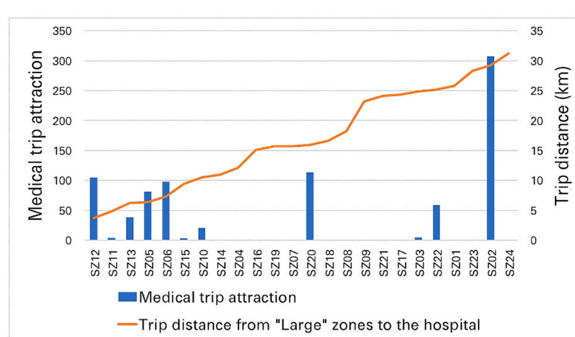
(a) The First Affiliated Hospital of Soochow University (Shizi Campus)



(b) Suzhou Municipal Hospital



(c) The Second Affiliated Hospital of Soochow University (Sanxiang Campus)



(d) Suzhou Traditional Chinese Medicine Hospital

Fig. A. 4. The medical care trip demand and average trip distance from “Large” zones to four representative First-class Third-level hospitals in the ancient city

Fig. A. 5. (A) Road conditions near hospitals during morning rush hour in Chinese megacities. (Source: www.amap.com), (B) Traffic congestion around Suzhou Municipal Hospital.

Table A. 1
Current planning perspectives of PSFs in relevant documents

Documents	Level	Social Equity		Low Carbon Development	
		Social Equity Goals	Per Capita Land/Facility Indicators	Green Building Development	Green Transport
"14th Five-Year" Public Service Plan	National	✓	✓		
Urban Public Service Facility Planning Standards	National	✓	✓	✓	√*
Suzhou's "14th Five-Year" Basic Public Service Plan (2021–2025)	Municipal	✓	✓		√**
Shanghai's "14th Five-Year" Basic Public Service Plan (2021–2025)	Municipal	✓	✓		
Beijing's Special Plan for Medical and Health Facilities (2020–2035)	Municipal	✓	✓		
Shenzhen's Special Plan for Elderly Care Facilities (2021–2035)	Municipal	✓	✓		

*The municipal and district public service centers should comprehensively consider seamless integration with urban public transport, guiding green travel.
**Priority should be given to the development of urban public transport, promoting the integrated development of urban and rural public transport.

Table A. 2
XGBoost Hyperparameter Selection

Hyperparameter	Parameter Set	Final Selected Parameter
max_depth	[2, 3, 4, 5, 6, 7, 8]	5
n_estimators	[30, 50, 100, 300, 500, 1000,2000]	500
learning_rate	[0.1, 0.2, 0.3, 0.4, 0.01, 0.02, 0.03, 0.05, 0.5]	0.02
reg_alpha	[0.0001,0.001, 0.01, 0.1, 1, 100]	0.1
reg_lambda	[0.0001,0.001, 0.01, 0.1, 1, 100]	0.01
subsample	[0.6, 0.7, 0.8, 0.9]	0.6

Table A. 3
Statistical data by districts (2020)*.

District	Area（km^2）	Resident population（thousand person）	Population density（$person/km^2$）	GDP (100 million RMB)
Gusu (GS)	83.42	924.2	11,079	819.90
Industrial Park (IP)	277.96	1134.0	4080	2907.09
Huqiu (HQ)	332.37	832.6	2505	1446.32
Wuzhong (WZ)	2231.69	1389.1	622	1343.78
Xiangcheng (XC)	489.96	891.1	1819	935.66

*Data source: Suzhou statistical yearbook 2021.

Table A. 4
The abbreviations and descriptions of correlated variables

Variables	Abbreviation	Data description and extraction
Transport related indicators		
Expressway length share	Expressway_Share	Divided the length of each type of roads in the TAZ by the total road length of the TAZ
Arterial road length share	Arterial_Road_Share	
Sub-arterial road length share	Sub-Arterial_Road_Share	
Local street length share	Local_Street_Share	
Road density	Road_Density	Divided the total road length in the TAZ by the total area of the TAZ
Intersection density	Intersection_Density	Divided the number of the intersections by the total area of the TAZ
Subway stop density	SubwayStop_Density	Divided the number of the subway stops by the total area of the TAZ
Bus stop density	Busstop_Density	Divided the number of the bus stops by the total area of the TAZ
Land use related indicators		
Floor area ratio	FAR	Divided the gross floor area of the buildings in the TAZ by the total area of the TAZ
Degree of land use mix	Mixuse	Calculated the degree of land use mix according to information entropy (Song et al., 2013)
Proportion of residential area	Residential_Area	Divided the area of each type of land in the TAZ by the total area of the TAZ
Proportion of public service area	Public_Service_Area	
Proportion of business area	Business_Area	
Proportion of industrial area	Industrial_Area	
Proportion of logistics area	Logistics_Area	
Proportion of transportation area	Transportation_Area	
Proportion of utility area	Utilities_Area	
Proportion of green space area	Green_Space_Area	
Proportion of other area	Other_Area	
Educational POI density	PoiEdu	Divided the number of each type of POIs by the total area of the TAZ
Life service POI density	PoiLife	
Sports and recreation POI density	PoiSportRecreation	
Medical POI density	PoiMedical	
Scenic spot POI density	PoiScenicSpot	
Retail POI density	PoiRetail	
Company/Government POI density	PoiCG	
Hotel POI density	PoiHotelSer	

Table A. 5
Public service facility types based on POI data

POI types	POI subtypes
Education	Education
Life service	Life service
Sports and recreation	Sports and recreation
Hospital	Hospital
Scenic spot	Scenic Spot
Retail	Restaurant and shop
Company/Government	Company, finance and insurance, government agency and social group
Hotel	Business residence, accommodation services

Table A. 6
The travel modal split in 2013 and 2018.

Year	2013				2018			
Mode share	Walk/Bike	Car*	Public transport	Other	Walk/Bike	Car*	Public transport	Other
All trips	55.59%	24.76%	18.31%	1.34%	50.95%	30.42%	18.62%	0.02%
All medical care trips	32.89%	37.83%	27.47%	1.81%	30.38%	40.61%	27.79%	1.22%
Medical care trips by age 20–40	5.52%	44.75%	36.46%	13.27%	11.11%	46.67%	31.11%	11.11%

*Car includes both private automotive and taxi, where private automotive share a much larger proportion.

Appendix B Details of the two-stage simulation approach

The contents of this appendix have been partly presented in a conference and included in the conference proceeding (Xu et al., 2022).

8. *Scenario settings of macroscopic carbon peak simulation*

At the macroscopic level, a multi-scenario simulation approach is conducted to find the contributions of four indicators, e.g., demographics, technological development, land use structure, and transport management strategies. As shown in Table B. 1, technological development contains a set of external influencing factors, which are more dependent on technical advancement and national policies. Demographics, land use structure and transport management strategies, on the other hand, are directly affected by the planning decisions of local governments. The transport management strategies are controllable decision-making variables by the government. Note that, in this study, the base year is set to be 2018 so as to avoid the potential impact on traffic demand due to the pandemic since 2020. Besides, in Suzhou, large scale OD survey is conducted every five years, and the most recent one was conducted in 2018.

Table B. 1
Scenario settings

Indicators	Sub-indicators	Scenario Variables
Demographics	Population	Number of residents
	Average trip rate	Number of trips per person
Technological Development	Energy structure	Percentage of coal bituminous
		Percentage of crude oil
		Percentage of natural gas
		Percentage of clean energy
	Vehicle categorization and fuel consumptions	Proportion of electric automotives
		Fuel automotive consumption
		Electric automotive consumption
		Diesel bus consumption
		Electric bus consumption
Transport Management Strategies	Travel modal split	Metro share
		Bus share
		Automotive share
		Non-motorized travel mode share
Land use structure	Average travel distances	Metro average travel distance
		Bus average travel distance
		Automotive average travel distance

8.1. *Scenario settings of demographics*

The population of the study area in 2018 is 5.15 million. The future population and annual growth rate are set according to "Suzhou Master Plan 2020–2035". The total population will reach 6.9 million by 2035. The average trip rate in 2018 was recorded at 2.38 trips per person based on the OD survey, whereas it is predicted to be 2.56 trips per person.

8.2. *Scenario settings of technological development*

The development of technology includes progress in energy and improvement of vehicle efficiency (the distance travelled per use of a quantified energy). To be more specific, progresses in energy (such as adjustment of energy structure and development of clean energy) affect the emissions of electricity generation to a great extent. Electric vehicles (EVs) and metro all use electricity. If more clean energy and fewer fossil fuels are used to generate electricity, the average emission intensity of electricity generation can be reduced, so that indirect emissions of EVs and metro will decline. Additionally, increasing vehicle efficiency can be achieved by improving the design and technology used in automotives and buses.

National Energy Board states that 59% of the electricity in China in 2018 is generated by coal. The remaining is from crude oil (18.9%), natural gas (7.6%) and clean energy (14.5%). The three groups of variables are defined according to "China Southern Power Grid New Energy Research", as shown in Table B. 2.

In 2018, the fuel consumption per hundred kilometers of fuel automotives and buses was 10 L of gasoline and 33 L of diesel, while electric automotives use 20 kW-hours and electric buses use 75 kW-hours per hundred kilometers. This study assumes fuel automotives consume 5 L of gasoline and electric ones consume 12 kW-hours per hundred kilometers,[16] which is set as the upper bound. Lower and medium values are reduced by 10% and

[16] http://csae.sae-china.org/.

20% respectively. All the operating buses in the study area have been electric since 2020. The current energy consumption level of electric buses is set to be 62.5 kW-hours per hundred kilometers.

Suzhou's electric automotives accounted for 0.87% in 2018.[17] In reference to "New Energy Vehicle Industry Development Plan (2021–2035)", electric automotives will make up from "Low" to "High", are 5.18%, 20%, 40%, respectively. The lower bound, 5.18%, is estimated through linear regression.

Table B. 2
Scenario setting of energy structure

Energy Structure	2018	2035		
		Low	Medium	High
Coal Bituminous	59.00%	56.80%	40.00%	30.00%
Crude Oil	18.90%	18.90%	17.00%	10.00%
Natural Gas	7.60%	8.40%	18.00%	22.00%
Zero Carbon Energy	14.50%	15.90%	25.00%	38.00%

8.3. Scenario settings of transport management strategies

In this study, we choose travel modal splits to represent the major implementation effect of transport management strategies. On one hand, according to the last two OD surveys conducted in 2013 and 2018, the automotive trip (including private automotives, taxis and business automotives) has increased from 24.76% to 30.42%. It is worth noting that without strong, deliberate policy intervention, the share of individual motorized travel will keep increasing. On the other hand, the scenarios settings of indicators also take consideration of the planning perspectives from "Suzhou Master Plan 2020–2035", The future travel modal split in 2035 in the simulation is set as shown in Table B. 3. In addition, according to "2018 Urban Metro Transit Statistical and Analysis Report", the energy consumption per passenger-kilometer of metro transit is 0.139 kW-hours in Suzhou. In addition, considering the current metro patronage will increase to a higher level with better metro operational performance, e.g., reduced headway and more dense stations, the energy consumption per passenger-kilometer of metro transit is set to 0.06–0.08 kW-hours.

Table B. 3
Scenario setting of travel mode split

Travel mode	2018	2035		
		Low	Medium	High
Metro	5.07%	15.00%	17.00%	20.00%
Bus	13.55%	8.00%	12.00%	15.00%
Automotive	30.42%	37.00%	31.00%	25.00%

8.4. Scenario settings of land use structure

In this study, at the macroscopic level, the land use structure reflects the impact of urban development structure, e.g., the residence and workplace distribution of polycentric or monocentric structure, on residents' average travel distance. Normally, urban sprawl results in increased travel distance. The land use intensity of the ancient city of Suzhou is highly limited, so according to "Suzhou Master Plan 2020–2035" and other existing detailed plans of districts, the future increased population will live in new districts. Even though polycentric development is encouraged in the land use plan, which could help to reduce the average travel distances, in the scenario setting, this study has to consider every possibility. Therefore, based on 2018 OD survey, the variations of average travel distances for each travel mode are defined as shown in Table B. 4.

Table B. 4
Scenario setting of average travel distance

Average Travel Distance (km)	2018	2035		
		Low	Medium	High
Metro	12.2	14	12.2	10
Bus	6.5	8.5	6.5	4.5
Automotive	9	11	9	7

9. Input data preprocessing in the microscopic CE simulation

At the microscopic level, the unit carbon emission intensity is more correlated with vehicular operating mode, e.g., start/stop, speed. Therefore, this study estimates the link level CE based on current road network configuration, peak hour traffic flow and vehicle speed.

The road network consists of 21,879 links[18] with four types, including expressway, arterial road, sub-arterial road, and local street. The link-based attributes include free flow speed (FFS), road capacity, traffic flow, and intersection signal control settings, which are defined in consistent with reality.

[17] 2018 Suzhou Transportation Development Annual Report.
[18] provided by Suzhou Planning & design research institute co., LTD.

The peak traffic flow were estimated using observed data from real-time traffic surveillance and OD survey.[19]

The average link time and corresponding link speed are estimated by adopting BPR function[20] as shown in Eqn. (1):

$$t = t_0 \times \left[1 + \alpha \cdot (q/c)^{\beta}\right] \tag{1}$$

where t_0 is the free flow travel time; q is the traffic flow and c is the link capacity.

In addition, existing studies indicate idling fuel vehicles generate more carbon dioxide and volatile organic compounds. Therefore, we also estimate the vehicle delay at signalized intersections at the microscopic level. In this study, the HCM delay formula for signalized intersections[21] is adopted as shown in Eqn. (2):

$$d = \frac{0.5C(1-\lambda)^2}{1-[\min(1,x)\lambda]} + 900T\left[(x-1) + \sqrt{(x-1)^2 + \frac{1.2x}{cT}}\right] \tag{2}$$

where C is the cycle length (s); λ is the green ratio; x is the degree of saturation; c is the capacity of the link. T is the analysis time, while in this study, the value is set to 0.25, which means that traffic peak duration is 15 min.

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