Journal of Transport Geography 112 (2023) 103697

Contents lists available at ScienceDirect

Journal of Transport Geography

journal homepage: www.elsevier.com/locate/jtrangeo

Do shared *E*-bikes reduce urban carbon emissions?

Qiumeng Li [a,*], Franz Fuerst [b], Davide Luca [a,c]

[a] Department of Land Economy, University of Cambridge, 16-21 Silver Street, Cambridge, UK
[b] Department of Land Economy, Trinity Hall, University of Cambridge, 16-21 Silver Street, Cambridge, UK
[c] International Inequalities Institute, London School of Economics and Political Science, London, UK

ARTICLE INFO

Keywords:
Micro-mobility
Sharing economy
E-bikes
Substitution effects
Carbon emissions
Urban context

ABSTRACT

Under the threat of climate change, many global cities nowadays are promoting shared commuting modes to reduce greenhouse gas emissions. Shared electric bikes (e-bikes) are emerging modes that compete with bikes, cars, or public transit. However, there is a lack of empirical evidence for the net effect of shared e-bikes on carbon emissions, as shared e-bikes can substitute for both higher carbon emissions modes and cleaner commuting modes. Using a large collection of spatio-temporal trajectory data of shared e-bike trips in two provincial cities (Chengdu and Kunming) in China, this study develops a travel mode substitution model to identify the changes in travel modes due to the introduction of shared e-bike systems and to quantify the corresponding impact on net carbon emissions. We find that, on average, shared e-bikes decrease carbon emissions by 108–120 g per kilometre. More interestingly, the reduction effect is much stronger in underdeveloped non-central areas with lower density, less diversified land use, lower accessibility, and lower economic level. Although the actual carbon reduction benefits of shared e-bike schemes are far from clear, this study bears important policy implications for exploring this emerging micro-mobility mode to achieve carbon reduction impacts.

1. Introduction

Significant carbon emissions have long been a challenge for cities due to the high dependence of transportation on fossil fuels and a car-dependent lifestyle (Sloman and Hopkinson, 2020). Many global cities have introduced a variety of policies to promote sustainable transportation to reduce carbon emissions in cities and combat the challenges of climate change. Reducing carbon emissions in urban transport is particularly important for cities in developing countries. By 2050, two-thirds of the world's population will live in urban areas, while about 95% of urban expansion in the coming decades will take place in developing counties (United Nations, 2019). China is the largest developing country undergoing rapid urbanisation. As more and more people move to cities in China, the challenges of urban congestion and emissions pollution will become even more acute.

One of the major developments in green and shared urban transportation in recent years is shared electric bikes (e-bikes) sharing systems, a novel type of micro-mobility service. Developed based on bike-sharing, an earlier form of shared micro-mobility service, e-bike sharing has gradually become the focus of governments and companies (Kr-asia, 2020), as it is accessible on an "as-needed" basis and can offer travel at higher speeds with less physical effort than shared bikes, i.e. exclusively human-powered bicycles which we will refer to simply as bikes throughout this article. With considerable capital investments being poured into their development, shared e-bikes continue to land in new cities and the market is growing exponentially (Elliott Ramos, 2021).

However, whether shared e-bikes can help to achieve carbon reduction in cities is yet under debate. Shared e-bikes can either replace the unsustainable commuting modes that rely on fossil energy (e.g., by car) or substitute for some even cleaner commuting modes (e.g., by bike). Compared to cars or public transit, shared e-bike trips are more flexible and solve last-mile connectivity problems. Meanwhile, some citizens may be attracted to shared e-bikes because it is easier to travel longer and overcome road barriers than by using bikes (P Rérat, 2021). Since e-bikes are greener than cars but have greater carbon emissions than bikes, the net substitution effect of shared e-bikes on carbon emissions is ambiguous, since it depends on the forms of transportation combinations they substitute.

A few past studies have used either simulations or surveys to investigate this research question (Bucher et al., 2019; McQueen et al., 2020; Wamburu et al., 2021), but there is still a lack of direct empirical evidence. In addition, existing studies have discussed the impact of various

* Corresponding author.
E-mail addresses: ql303@cam.ac.uk (Q. Li), ff274@cam.ac.uk (F. Fuerst), dl622@cam.ac.uk (D. Luca).

https://doi.org/10.1016/j.jtrangeo.2023.103697
Received 3 October 2022; Received in revised form 18 July 2023; Accepted 4 September 2023
Available online 13 September 2023

factors (e.g., weather and temperature) on the adoption of shared e-bikes (Bucher et al., 2019), while a few studies have explored the impact of the built environment (e.g., land use and accessibility) on the net carbon emissions of shared e-bikes. Specifically, the substitutional choices between alternative transportation modes are expected to vary in different urban contexts, which will result in spatial heterogeneities in the associated carbon emissions reductions. For example, in more compact and accessible neighbourhoods, people are expected to prefer walking or cycling, so e-bikes are more likely to substitute for green transport modes than cars in those areas. Therefore, there are two knowledge gaps: the first one is whether shared e-bikes can help to achieve carbon reduction in cities, and the second one is in which urban built environments the development of e-bike sharing will be more effective in reducing carbon emissions, which has not been explored.

To bridge these two knowledge gaps in the literature, we use China, one of the largest e-bike sharing markets in the world, as the case study. Using complete daily trip-level shared e-bike data from one of the largest shared micro-mobility companies in two provincial cities (Chengdu and Kunming) in China, this study investigates the net effect of adopting shared e-bikes on urban carbon emissions, after considering their substitutions for alternative commuting modes. We first present a travel mode substitution model to identify the changes in commuting modes due to the introduction of shared e-bike services and quantify the corresponding changes in carbon emissions per kilometre. Then we analyse the correlations between these changes in carbon emissions and the urban features, to reveal what kind of places contribute to the carbon reduction effect of shared e-bikes.

2. Literature review

The literature review is developed from two aspects of research. Firstly, it discusses the debate about whether shared e-bikes can bring about carbon emissions reduction. Secondly, it examines the factors that may influence the carbon emissions reduction of shared e-bikes, as well as the spatial heterogeneity of their carbon emissions reduction effects.

2.1. The carbon reduction potential of e-bike sharing

The popularity of e-bike sharing has also triggered discussions on its role in the sustainable development of cities, especially in carbon emission reduction. Most studies have explored the environmental benefit of bike sharing (D'Almeida et al., 2021; Fishman et al., 2014; Kou et al., 2020; Wang and Sun, 2022). However, for e-bike sharing, knowledge about the environmental impact of this emerging micro-mobility mode is scarce. Although for-profit companies assert that e-bike sharing can reduce carbon emissions (Hellobike, 2020), scholars have not reached a consensus that shared e-bikes have an environmental benefit. Whether developing e-bike sharing services has a net positive effect on reducing carbon emissions depends on what modes of transportation they have substituted for. Based on a meta-analysis of published articles from China, Europe, North America, and Australia, Bigazzi and Wong (2020) reported that the highest proportion of alternative transport modes replaced by e-bikes is public transit (33%), followed by bikes (27%), cars (24%) and walking (10%), and this result varies across different countries. The carbon emissions of e-bikes are higher than conventional bikes, slightly lower than public transit, and much lower than cars(McQueen et al., 2020). Therefore, to quantify the net impact of e-bike sharing on carbon emissions, the first step is to understand what transportation modes are more likely to be replaced by shared e-bikes.

Some studies stated that e-bikes, as a promising carbon-efficient alternative to cars, have the potential to reduce carbon emissions by changing unsustainable travel habits (Haustein and Moller, 2016; Winslott Hiselius and Svensson, 2017; Harvey and Guo, 2018; Moser et al., 2018). It has been found that car trips are the main mode replaced by e-bikes in North America and Australia (MacArthur et al., 2014, 2018; Johnson and Rose, 2013). Mcqueen et al. (2020) stated that e-bikes reduced the share of car trips in all journeys by about 10 percentage points and lowered carbon emissions by 225 kg per year in North America. Some researchers estimated the car kilometres substituted by e-bikes among surveyed users (Cairns et al., 2017; Moser et al., 2018). Bucher et al. (2019) simulated the reduction in greenhouse gas emissions by e-bikes under different transportation and weather scenarios, based on car trip information. The study found that the reduction of emissions could reach up to about 10% of the overall greenhouse gas emissions in Switzerland. In the summarised study of Berjisian and Bigazzi (2019), the net carbon reduction per e-bike in use was estimated at around 460 kg p.a,

However, some studies have challenged the green mode shift effect of e-bike trips. In the Netherlands e-bikes have only significantly reduced conventional bicycle trips, and not the other transport modes like cars, thereby bringing adverse effects (De Haas et al., 2022); Jones et al., 2016). Bieliński et al. (2021) pointed out that shared e-bikes have a significant substitution effect for public transport instead of car trips in Tricity, Poland. Studies in several Chinese cities have suggested that e-bikes can be an affordable alternative to public transit (Cherry and Cervero, 2007; Montgomery, 2010; Cherry et al., 2016). Sun et al. (2020) found that e-bikes substitute more conventional bike use than car use in Netherland, but they still have a net gain in environmental sustainability, because the share of bike kilometres is significantly smaller than that of cars.

The research mentioned above, along with other relevant studies, primarily employs simulations and surveys to investigate the potential environmental impact and behavior change associated with shared e-bikes. The most common method is the intercept survey-based method (Cairns et al., 2017; Cherry et al., 2016; Fyhri et al., 2017; Lin et al., 2017; McQueen et al., 2020; Moser et al., 2018). The arguments are based on a similar question: "If the target mode (e.g., shared bike or e-bike) was unavailable, what kind of transportation would you choose?" Due to limitations of questionnaire sample size on the analysis of individual systems, samples could not be fully representative of the overall users (Fukushige et al., 2021; Kou et al., 2020), which may cause bias and validity problems for the analysis of net carbon emissions changes attributable to shared e-bikes. The findings of these surveys show diverse results of the substitution effects, which vary according to their different questionnaire design, sampling rules, and local contexts.

In summary, the potential environmental benefits of shared e-bikes remain unclear. While some studies suggest that e-bike sharing can reduce carbon emissions by replacing car trips, others argue that it may only substitute for low carbon travel modes, leading to adverse effects. To quantify the net impact of e-bike sharing on carbon emissions, it is essential to understand what transportation modes are more likely to be replaced by shared e-bikes. However, previous studies primarily relied on surveys, which may have limited sample sizes and potential biases. This study is based on large-scale shared e-bike trip data from two entire city samples, providing more empirical evidence for revealing the carbon reduction effect of shared e-bikes.

2.2. Factors influencing the carbon reduction potential

The relationship between environmental potential and shared e-bikes depends on people's travel substitution choices, so the factors affecting the travel choice are worth to be identified in another line of research. Land use is the most crucial factor in travel choice. In the early research, Cervero and Kockelman (1997) proposed the '3D' elements – density, diversity, and design – and demonstrated that high-density, diverse land uses and road network design helped to reduce the commute frequency, as well as reduce car travel, and thus reduce carbon emissions. Furthermore, Cervero (2002) put forward the '5D' elements – density, diversity, design, distance to transit, and destination accessibility. Ewing and Cervero (2010) added another two 'Ds', demand management and demographics, to compose a '7D' concept, but this is less related to the attribute of land use. Density is the essential variable. Boarnet et al. (2008) found that in a higher density region, citizens prefer to walk, especially in a high-density retail area, contributing to carbon reduction. Moilanen (2010) found that employment density was proportional to non-car transport choices. Diversity is another important factor. Peng (1997) indicated that the job-housing rate had a U-shaped relationship with car travel distance per capita, meaning that the job-housing balance could reduce car usage and bring environmental benefits. Frank et al. (2008) also found that road connectivity and land use mixed degree promoted the probability of walking.

As for the factor influencing bike sharing behavior, extensive studies have explored the influence of the built environment, weather, environment, and other factors on bike usage(Eren and Uz, 2020; Li et al., 2020; Mattson and Godavarthy, 2017; Nankervis, 1999; Spencer et al., 2013; Winters et al., 2010). There are few studies specifically address factors influencing the environmental potential of e-bikes. According to a survey in Sacramento, Fukushige et al. (2021) found that long e-bike sharing trips and trips originating from non-commercial areas have a higher propensity to reduce car use, while trip distances <1 mile are more likely to replace walking,. Sun et al. (2020) showed that e-bike riders would be more likely to substitute cars in less urbanized areas. Philips (2020) also pointed out that e-bikes could have the most potential to reduce carbon emissions in rural and sub-urban areas, because many low-carbon transportation options are already available to people living in developed area.

Previous studies have identified factors that influence travel choices, particularly the role of land use in reducing travel carbon emissions. But the factors affecting the environmental potential of e-bikes still need further research. Specifically, it is unclear what kind of geospatial context would enhance the carbon reduction potential of e-bikes. This study aims to answer these questions by examining the relationship between the carbon reduction potential of shared e-bike and built environment characteristics from the disaggregated perspective in cities.

3. Research strategy

Ascertaining the carbon emissions reduction potential of shared e-bikes involves the construction of a valid counterfactual. In other words, if there were no shared e-bike available for a trip, what alternative mode would a traveller choose? Fig. 1 illustrates the stepwise procedure of our empirical analysis. Firstly, according to the key indicators mentioned in previous studies, such as distance, time, and transit coverage of a trip, a travel mode substitution model is established to simplify the complex problem of substitution and to make it measurable. Four potential substituted modes (driving, public transit, walking and cycling) are included in our analysis.

The distance and duration of route of each trip can be crawled using the Amap developer platform API[1] by inputting the time, origin, and destination (OD) coordinates of each e-bike sharing trip (Fig. 2). In terms of the information available on potential substituted transportation modes, we crawled the duration and distance of alternative modes for the same OD locations via Amap API, and retrieved information about whether the OD locations lie within the coverage of public transit. The above information can be used in the travel mode substitution model to measure which mode is more likely to be replaced by a given shared e-bike trip, and to hence estimate the net carbon emissions change. The net carbon emissions reduction effect of e-bike sharing in a place depends on the different substituted combinations. How much net carbon emissions are reduced or increased by shared e-bikes substituting for other transportation modes can be calculated by multiplying by the carbon emissions coefficient of each substituted mode. The change in net carbon emissions of each trip with its origin in the grid are aggregated to the same grid. Finally, impact analysis models are built to unpack the urban features that influence the carbon emissions reduction effect of shared e-bikes. The net carbon emissions per kilometre in each grid are put into the models as the Y variable. Land-use variables of each grid, like density and diversity, are put into the models as X variables. In the sensitivity analysis module, this paper assesses the impact of extreme parameters in the substitution model on the effectiveness of shared e-bikes in reducing carbon emissions and the relationship between factors and emission reduction. By altering these parameters, the study evaluates the sensitivity of these outcomes to parameter changes.

3.1. Travel mode substitution model

This section estimates the substitution of individual e-bike trips for other modes based on the distance, time, and transit coverage of the trip. The method is designed to identify the mode of transportation with the highest probability of being replaced or complemented by a shared e-bike trip (Fig. 3).

Firstly, trip distance is a determining factor for measuring the choice of different travel modes (Fig. 4) (De Sá et al., 2015; Ermagun and Samimi, 2018; Fitch et al., 2021; Kim et al., 2020; Kong et al., 2020; Lee et al., 2021). For example, if a trip taken by e-bike has a significantly long distance, the motivation to replace a bike trip with an e-bike ride will be lower than replace a car trip. For the relationship between non-motorised travel and motorised travel, Zhang and Mi (2018) set a threshold (e.g.,1 km) for the trip distance: if the distance is less than the threshold, people prefer to choose walking or cycling as an alternative; if above the threshold, people are inclined to choose a motorised trip, because for long trips, travellers would have taken a car. This paper sets the first threshold (D_{t1}) based on the relationship between the distance and frequency of various transportation means in the empirical data. (In the robustness section, we will also test the sensitivity of results to alternative thresholds.) For trips with a travel distance (D) lower than the first threshold (D_{t1}), we assume that people will be more likely to choose non-motorised modes, such as walking or cycling. This paper sets 500 m as the threshold (D_{t2}) of a comfortable walking distance (Gehl and Koch, 2011; Li et al., 2019) to distinguish walking and cycling. Most walkers feel tired when they walk further than 500 m (Gehl and Koch, 2011).

For trip distances (D) above the first threshold (D_{t1}), people are more likely to choose motorised modes, such as cars or public transit. The accessibility of public transit is a critical aspect affecting people's choices (Liao, 2021). This paper combines the method of the substitution relationship between public transit and cars in Kong et al. (2020), using transit coverage of the trip to distinguish between public transit and driving. The transit coverage analysis includes two steps: spatial coverage and time cost. In transit spatial coverage analysis, if both the trip origin and destination (OD) are within the buffer of transit stops, then the areas are considered to be accessible for a transit trip. Previous studies usually set the buffer at 400 m around stops (Demetsky and Bin-Mau Lin, 1982; Murray et al., 1998; Hawas et al., 2016). Following these existing studies, this paper sets the 400 m buffer as the transit coverage area. If the conditions for spatial coverage are met, we consider the time cost. Different transit stops have different operation times. If users have to wait for a long time or spend long time to transfer different buses line, they may not choose transit for the trip. According to the result of existing studies (Salonen & Toivonen, 2013; Schwieterman, 2019), the mean travel time difference between cars and public transit is around 20 min. The paper set 20 min as the travel time difference threshold (T_t) of public transit and car trips, in line with the time difference parameter measured in previous study. If there is no transit available within a given spatial buffer or cost too much time above the threshold, people will choose to use the car, otherwise, they will choose public transit. Besides spatial coverage and time cost, the service quality of public transit also affects people's choices. Many aspects determine service quality, such as safety, crowdedness, privacy, etc. It is important to note that data on service quality is not available, hence our study does not take this

[1] https://lbs.amap.com/api/webservice/guide/api/newroute

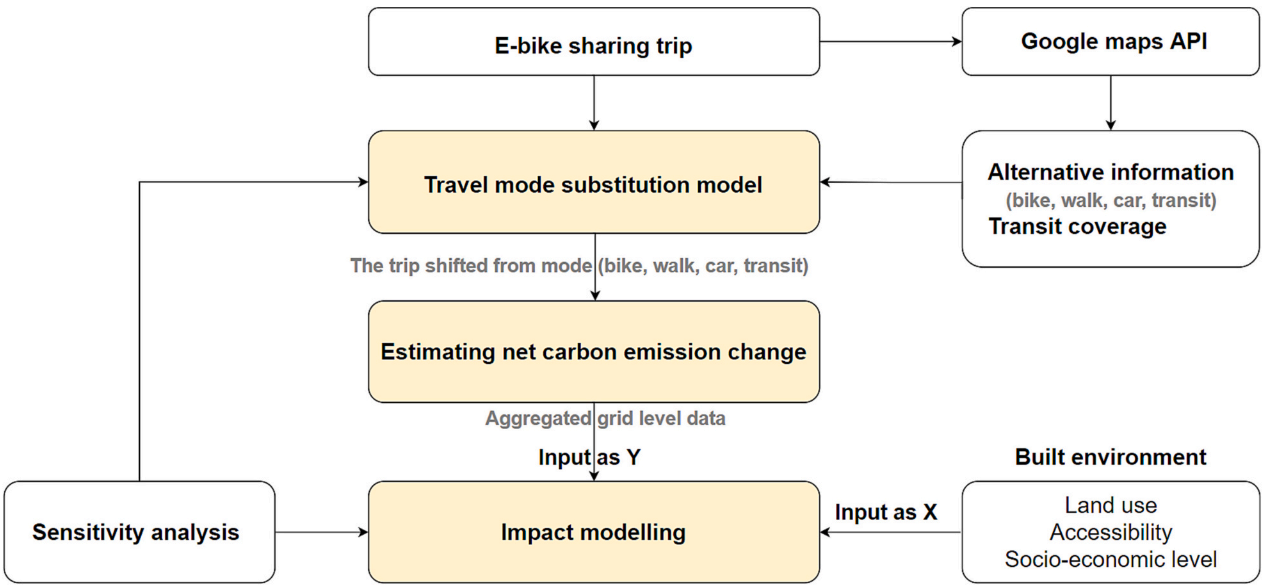

Fig. 1. Carbon emissions modelling steps for shared e-bikes.

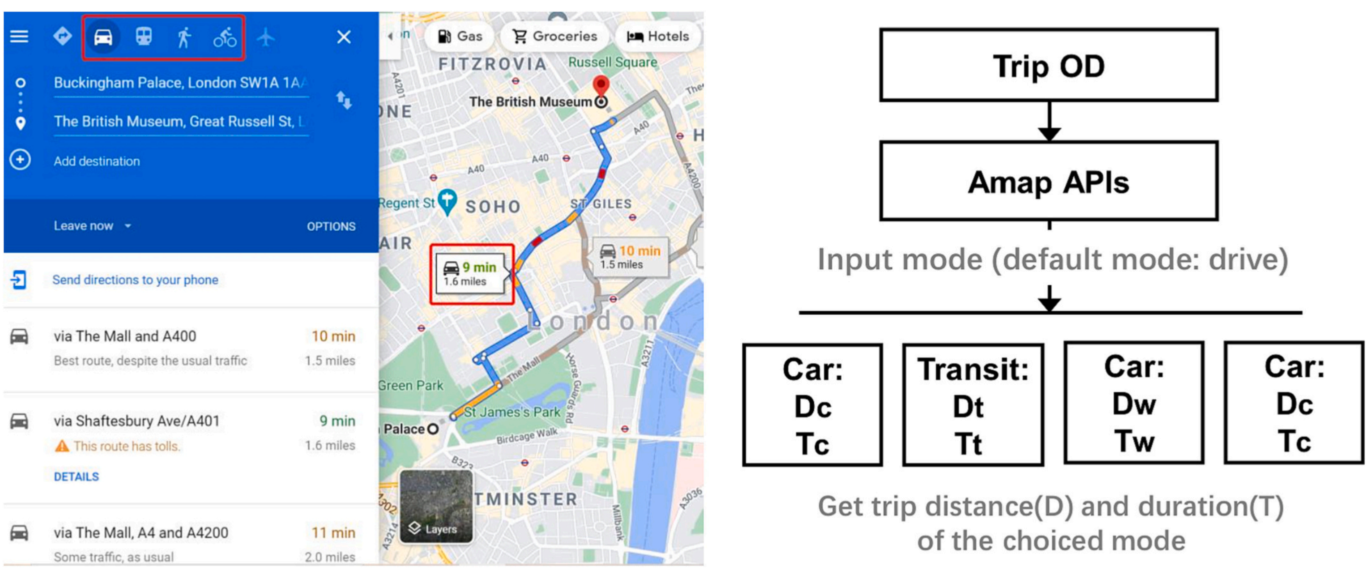

Fig. 2. The process of crawling potential substituted mode information from the Amap developers API.

unobserved factor into account, at least not explicitly.

3.2. Carbon emissions analysis

To analyse net carbon emissions changes, we develop a comprehensive measure of different substitution combinations. Taking the carbon analysis of a 100*100 m grid sample as an example (Fig. 5), and assuming that 10 e-bikes launch their trips from that specific origin (the white grid), the paper will first use the method described in Section 3.1 to infer which transport mode has been replaced by each e-bike trip. We will then take the carbon emissions parameters (Table 1) of the substituted transport mode and multiply it by the distance by the corresponding mode crawled from the map API. The emission parameters are for operational CO_2 emissions of the transport modes. Carbon dioxide (CO_2) is the primary greenhouse gas emitted around the world, accounting for about 80% of total greenhouse gas emissions.[2] Finally, we will subtract the carbon emissions generated by shared e-bikes from the carbon emissions generated by the replaced original mode trips to obtain the change in net carbon emissions. The specific formula designed in the paper is as follows:

$$E_i = \left(E_{drive}\sum_{d=1}^{a} D_d + E_{transit}\sum_{e=1}^{b} D_t + E_{active}\sum_{f=1}^{c} D_f\right) - E_{ebike}\sum_{i=1}^{n} D_j \tag{1}$$

$$E_{drive} = p \cdot \rho \tag{2}$$

where $E_i$represents the total carbon emissions reduction of shared e-bikes in spatial grid ***i***, ***n*** is the number of e-bike sharing trips originating in grid area ***i***, ***a*** is the number of substituted car trips, ***b*** is the number of substituted public transit trips, and ***c*** is the number of substituted active mode trips (walking or cycling). If $E_i$is greater than zero, it means that

[2] https://www.c2es.org/content/international-emissions/

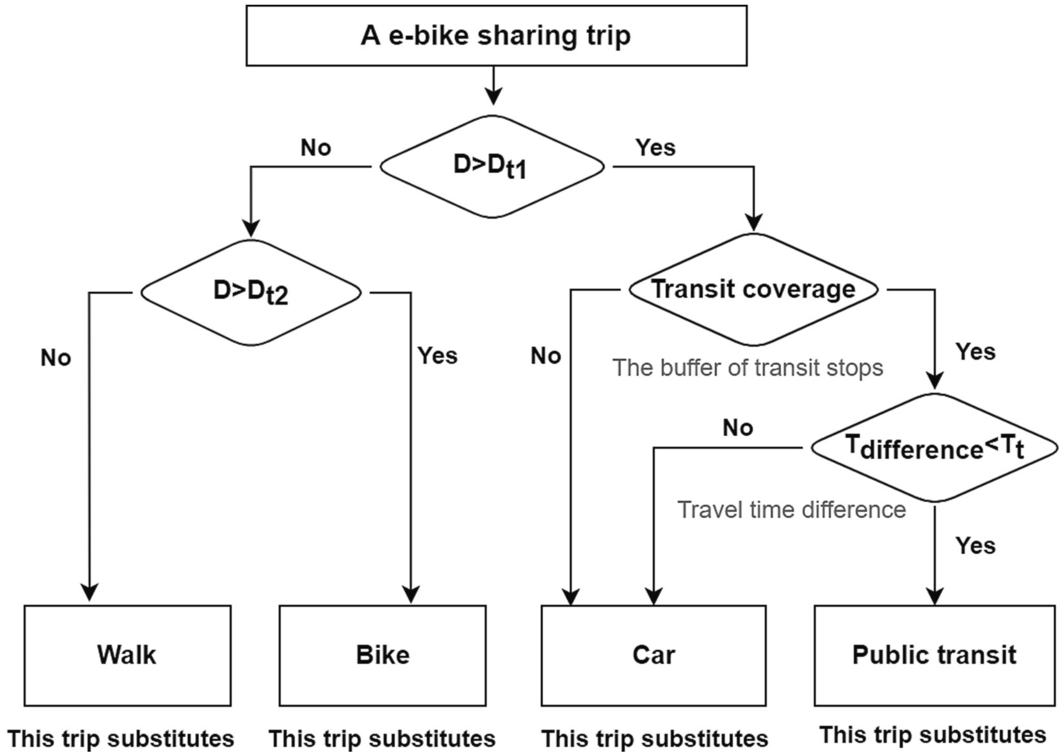

Fig. 3. Travel mode substitution model.

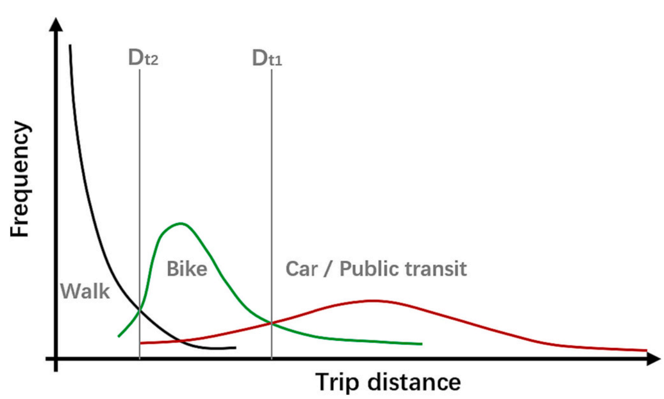

Fig. 4. The conceptual relationship between travel distance and frequency of different travel modes.

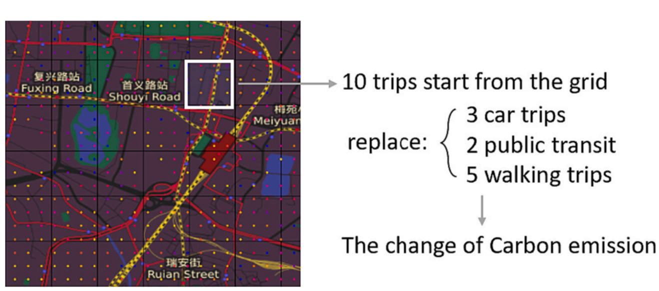

Fig. 5. A grid sample for measuring the net carbon emission.

shared e-bikes starting within this grid, decrease the carbon emissions and have a positive impact on the environment. If E_i is almost equal to zero, it means that shared e-bikes have no environmental benefit. If E_i is less than zero, it means shared that e-bikes have a negative effect on the environment. For trips with the same origins and destinations, the distances travelled by cars, buses and bikes may not be the same.

Table 1
Carbon emission parameter.

Mode	Carbon emission parameter	Value	Unit	Reference
Car	E_{drive}	223.9	g CO_2/P·km	(Zhang and Mi, 2018)
Public Transit	E_{bus}	26.0	g CO_2/P·km	(Yang and Zhou, 2020)
	E_{Metro}	20.9	g CO_2/P·km	(Yang and Zhou, 2020)
E-bike	E_{ebike}	4.9	g CO_2/mile	(McQueen et al., 2020)
Walking/bike	E_{active}	0	g CO_2/P·km	(Mcqueen et al., 2020) (Zhang and Mi, 2018)

When calculating carbon emissions, the travel distance of each transport mode is based on the real route distance crawled by Amap API, rather than the straight-line Euclidean distance of OD points, to improve the accuracy of the calculation. The definitions of other variables are as below:

E_{drive}: per kilometre carbon emissions parameter of a car trip (g CO_2/P·km).

$E_{transit}$: per kilometre carbon emissions parameter of public transit (g CO_2/P·km).

E_{active}: per kilometre carbon emissions parameter of walking or cycling (g CO_2/P·km).

E_{ebike}: per kilometre carbon emissions of a shared e-bike trip (g CO_2/P·km).

D_j: distance of trip j by a shared e-bike (km).

D_d: distance of trip d by driving (km).

D_t: distance of trip t by public transit (km).

D_f: distance of trip f by walking/cycling (km).

p: Petrol consumption per unit of distance travelled (L/km).
ρ: The density of petrol (kg/L).

3.3. Modelling the impact of carbon emission changes

To explore the interaction between urban structure and the carbon reduction effect of shared e-bikes, this paper takes land use, accessibility, and socio-economic factors into account, based on land use-transport interaction theories (Wegener and Fuerst, 2004). We develop an empirical regression model where the dependent variable is the average net carbon emissions of all trips originating from each 100*100 m grid. We regress such measure on the independent and control variables listed in Table 2. We first use a simple ordinary least squares estimator (OLS), and then a more complex Spatial Durbin Model (SD) to avoid errors caused by spatial interdependence between carbon emissions reduction effect of shared e-bikes and the spatial lags of both the outcome and urban features. The spatial lag regression formula is listed as follows:

$$y_i = log\left(\frac{E_i}{N_i}\right) \tag{3}$$

$$y_i = \lambda \boldsymbol{w}_i \boldsymbol{y} + \boldsymbol{x}_i \boldsymbol{\beta} + \boldsymbol{w}_i \boldsymbol{X} \boldsymbol{\theta} + \varepsilon_i \tag{4}$$

where y_i represents the net carbon emissions per kilometre in spatial unit $\boldsymbol{i}$ in log form, and N_i is the total distance of e-bike sharing trips in grid area $\boldsymbol{i}$. When y_i is above zero, this means that the shared e-bikes reduce the carbon emissions in unit $\boldsymbol{i}$; otherwise, the net carbon emission in unit $\boldsymbol{i}$ increases. w_i is the spatial weights vector, and the neighbourhoods are based on the rule of Queen's case. λ is the spatial lag coefficient of $\mathbf{y}$, and $\boldsymbol{\theta}$ is the vector of coefficient of $\boldsymbol{x}_i$. $\boldsymbol{x}_i$ is the collection of independent variable *j*, including land use characteristic, accessibility and economic activity level, and control variables, including population density, average trip duration of shared e-bikes, which is calculated as the count of trips divided by the count of shared e-bikes in grid $\boldsymbol{i}$. $\boldsymbol{X}$ is the matrix of explanatory variables and $\boldsymbol{\theta}$ is a vector of parameters. ε indicates the unobserved error.

It is well documented in the extant literature that the built environment shapes travel behaviours and vice versa (Ewing and Cervero, 2010). In this paper, four measures are used to describe the built environment: land use diversity, land use intensity, road density, and the number of public transit stations and stops. Land use intensity is measured by the floor area ratio (FAR). The road density index is represented by the reciprocal of block size. For the socio-economic aspect, this paper uses the night light index as a proxy of the economic activity level of areas. When an area has a high night light index, this generally indicates there are a lot of commercial activities, relatively high economic income, and development. Many studies have found a closer connection between light and economic activity (Mellander et al., 2015). The land diversity level is calculated by the degree to which there is a mixture of diverse POI types. POIs were crawled from the Amap. In this paper, the initial twenty POIs are reclassified into eight more general categories (Table A1), according to previous studies (Liu and Long, 2016; Kong et al., 2020). Generally, the diversity level can be presented by the Shannon entropy index (Shannon, 1948), which can be formulated follows:

$$\mathrm{D} = -\sum_{j}^{c} h_j log_n h_j, \tag{5}$$

where D is the entropy index, which range from 0 to 1. $h_j$is the proportion of the j$^{\text{th}}$ type of normalized POI, and n is the number of categories. A value of 1 represents extreme diversity of land function, whereas a value of 0 indicates there is only one type of POIs in specific unit.

Table 2
Descriptive statistics.

		Mean	Std dev	Min	Max
Dependent variables					
The net carbon emissions reduction per kilometre in each grid		165.87	264.72	−4.87	3289.25
Independent variables					
Land use characteristic	Land use diversity	0.63	0.29	0	1.10
	Land use intensity	1.46	1.46	0	18.43
Accessibility	Road density index	10.34	18.72	0.04	193.67
	Counts of public transit stations and stops	0.71	1.35	0	6
Economic activities	Nighttime light index	29.04	13.76	3.47	77.02
Control variables					
Population density (X 10000 per m_2)		71.16	41.31	0	203.75
Average trip duration (in minutes)		12.69	4.78	3.19	135.23

4. Data and study area

China has the largest number of shared e-bikes in the world. After the dockless shared bike race that took China by storm from 2016 to 2018, many tech companies are now betting on a similar yet different business: e-bikes (Krasia, 2020). Electric bike-sharing systems emerged in 2017 and rose to prominence after 2019. From 2019 to 2022 there has been a rapid development period for shared e-bikes. Due to policy restrictions in most of the big cities in China, shared e-bikes mainly operate in small cities and counties. Kunming and Chengdu are among the few big cities where government policies encourage the use of shared e-bikes. This paper chooses the urban main area of Kunming and three sub-centre districts of Chengdu (Fig. 6) as the study area (shared e-bike systems were launched in Pidu, Wenjiang and Shuangliu districts, and were not allowed to launch in the city centre of Chengdu). Kunming has a population of over 5 million people, and the three sub-centre districts of Chengdu have a population of over 2.5 million people.

Compared to previous studies based on traditional survey data analysis (Cherry et al., 2016; Lin et al., 2017), this paper analyses the carbon emissions reduction effect of shared e-bikes based on big data analysis. The e-bike sharing trip data is the most important input in this study. Data from 4 million recorded trips are collected in two cities, including user attributes (user id, gender, and age), trip attributes (start and stop time, date, and location) and bike id (Table 3). The time span of the data covers two weeks in March 2021. All users are anonymous so that privacy is protected. Bike-sharing trip data was also collected in 2020 and Taxi trip data in 2018 from Meituan and DIDI companies, to analyse the difference in distance distributions between cycling and driving, which could give reference for the distance threshold setting in the travel mode substitution model. Apart from the absence of user attributes, the bike-sharing trip data and shared ride-hail trip data includes attributes that are similar to Table 3. These attributes include date, starting coordinates, ending coordinates, start time, end time, and so on.

5. Results

To explore whether shared e-bikes reduce carbon emissions and in what kind of urban context shared e-bikes are more effective at reducing carbon emissions, we analysed the competition between potential substituted travel modes by shared e-bikes, the spatial patterns of the changes in net carbon emissions attributable to shared e-bikes, and the impacting factors with a view towards choosing the optimal deploying strategy for shared e-bikes to boost reductions in carbon emissions. Hence, our analysis focuses on the impact of the urban features of starting locations on the carbon emissions reduction effect of shared e-bikes.

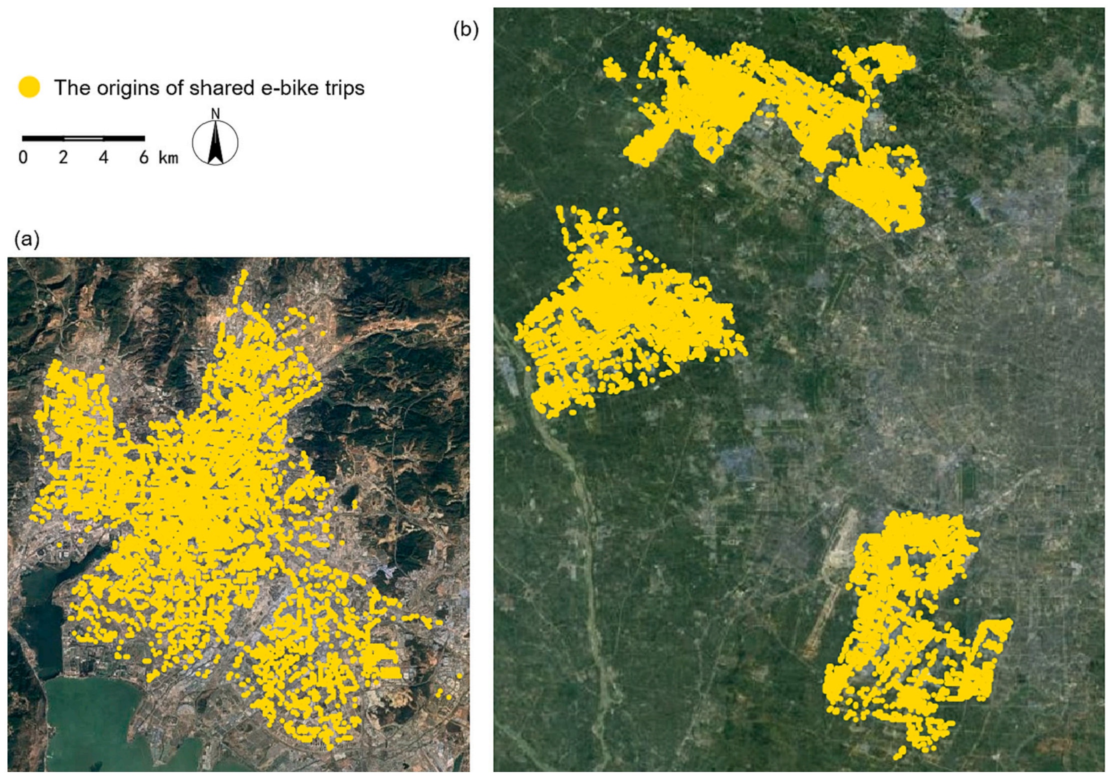

Fig. 6. The study area and spatial distribution of origins of shared e-bike trips in (a) Kunming and (b) Chengdu.

Table 3
Example of e-bike sharing trip records.

Order id	City	Date	User id	Bike id	Gender	Age	Register date	Origin (X,Y)	Destination (X,Y)	Start Time	End Time
Trip No. 1	Kunming	2021-03-02	8979	7865	Female	28	2020-08-02	25.02, 102.42	24.32, 102.13	12:50	13:02

5.1. Mode substitution

Shared e-bike trips with a distance longer than 10 km or a duration longer than 3 h were deleted. After data cleaning, there were 2,463,596 trips in Kunming and 1,322,749 trips in Chengdu. Fig. 7 shows the relationship between the time and distance of using other travel modes with the same starting and ending points as the e-bike sharing trips, by crawling data from Amap API. Based on the travel duration and frequency distribution of transportation modes over different distances, the competition between different travel modes lies mainly in the distance interval from 1 km to 3 km. We use the distance distributions of shared bikes and ride-hail trips to represent the distance distributions of bikes and cars (Fig. 8). Based on the positional coordinates of the origin and destination, the shortest path distance for each shared bike trip and shared ride-hail trip is calculated. Subsequently, the distance distributions are plotted to depict the travel frequencies corresponding to different distances for shared bikes and shared ride-hail trips. A travel distance of around 1600 m is a critical value in Chengdu. When the distance is <1600 m, the probability of people using non-motorised tools such as bikes is higher; when the distance is longer than 1600 m, the

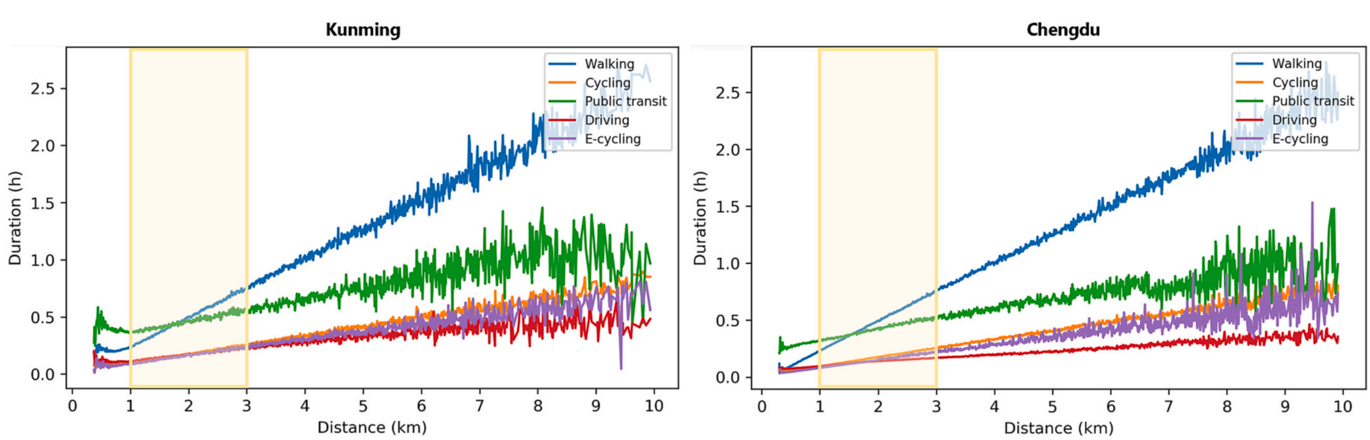

Fig. 7. Travel duration of different transportation means regards to different travel distances (The data is crawled from Amap developer platform API).

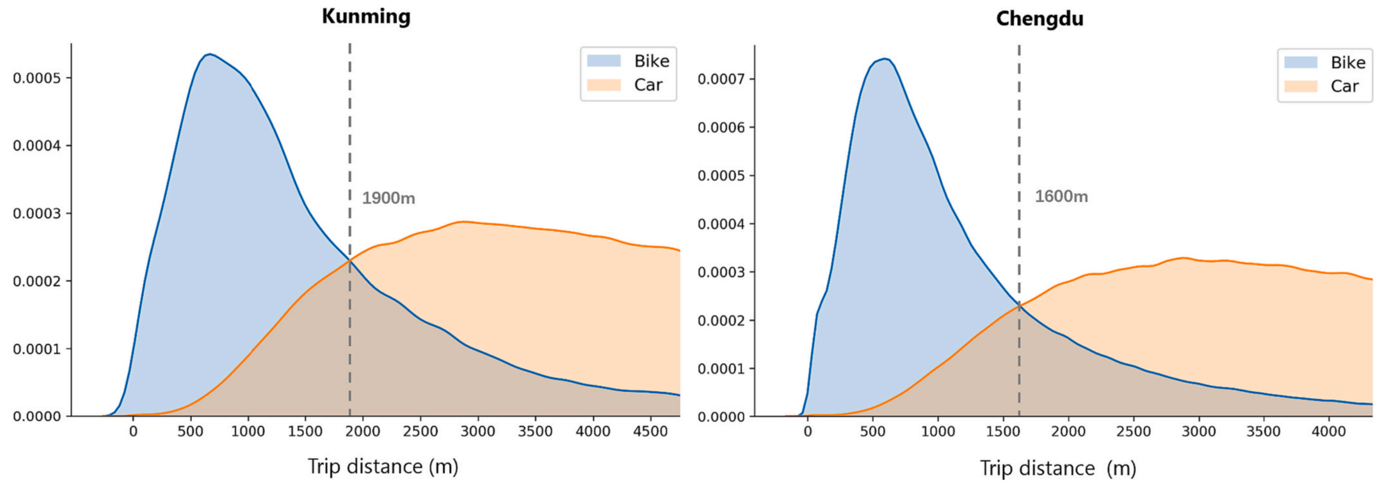

Fig. 8. Distribution of the trip distances of bikes and cars in Kunming and Chengdu (The data is from Meituan and DiDi).

probability of people using motorised vehicles such as cars is higher. Similarly, In Kunming, such critical value is a travel distance of around 1900 m. Therefore, this paper initially set 1600 m as the threshold (D_{t1}) in Chengdu and 1900 m in Kunming. To make the result more convincing, the following sensitivity analysis has been conducted under different threshold parameters in the travel mode substitution model.

5.2. Spatial patterns of emission changes

The result from the travel mode substitution model shows that in Kunming 5.5% of e-bike sharing trips replaced walking, 49.1% of the trips replaced bike trips, 16.0% replaced public transits, and 29.4% replaced car trips, while in Chengdu the percentage of shared e-bike trips that replaced walking, bicycles, buses, and cars was 6.4%, 40.4%, 19.9%, and 33.3%, respectively. The average net emissions reduction per kilometre are 119.9 g in Kunming and 108.1 g in Chengdu. Dividing the urban space of two cities into relatively high population density areas and low population density areas, it can be found that shared e-bikes in high-density areas have a higher substitution rate for public transportation than in low-density areas, but a lower substitution rate for cars compared to low-density areas in both cities (Fig. 9). Although a larger proportion of e-bike sharing trips substitute green modes than high carbon emission vehicles, the net emissions are reduced. This is because the travel distances of shared e-bike trips that replace cars are longer than those of the trips replacing low carbon modes, such as walking or cycling, and shared e-bikes themselves are a low-carbon transportation mode and the carbon emission parameter is small. Therefore, the emissions reduced by replacing one car trip are far greater than the emissions increased by replacing one bike/walking trip.

The net carbon emissions change of Kunming and Chengdu has been measured based on the result of the travel mode substitution model. To better understand the impact of the location of e-bike sharing trips on the net emissions, we analysed the spatial patterns of net emissions changes. We allocated the carbon emissions of each trip to its start point (since the origin of a trip generally reflects the demand for travel and provides the location information of where to deploy the shared e-bikes). This section assesses the carbon emission reduction effect of shared e-bikes using two approaches. The first measure provides insights into the scale of carbon emissions reduced by shared e-bikes. The scale of carbon emissions represents the net carbon emissions of all trips in each grid. The second measure emphasizes the efficiency of carbon emission reduced by shared e-bikes, which is the average net carbon emission per kilometre travelled in each grid. Carbon emissions per km in each grid is calculated by dividing the net carbon emissions of all trips in the grid by the total distance travelled by these trips. The value of carbon emissions per km in each grid is assigned to the centre point of each grid for visualization. The visualization process for the scale of carbon emissions is also the same. The study shows the visualization results of 100*100 m and 500*500 m level grids (Fig. 10, Fig. 11, Fig. 12, Fig. 13).

The carbon emissions reduction effect of shared e-bikes exhibits significant spatial heterogeneity. The spatial pattern of net emissions at the 100*100 m level is relatively complex and not intuitive, so we also

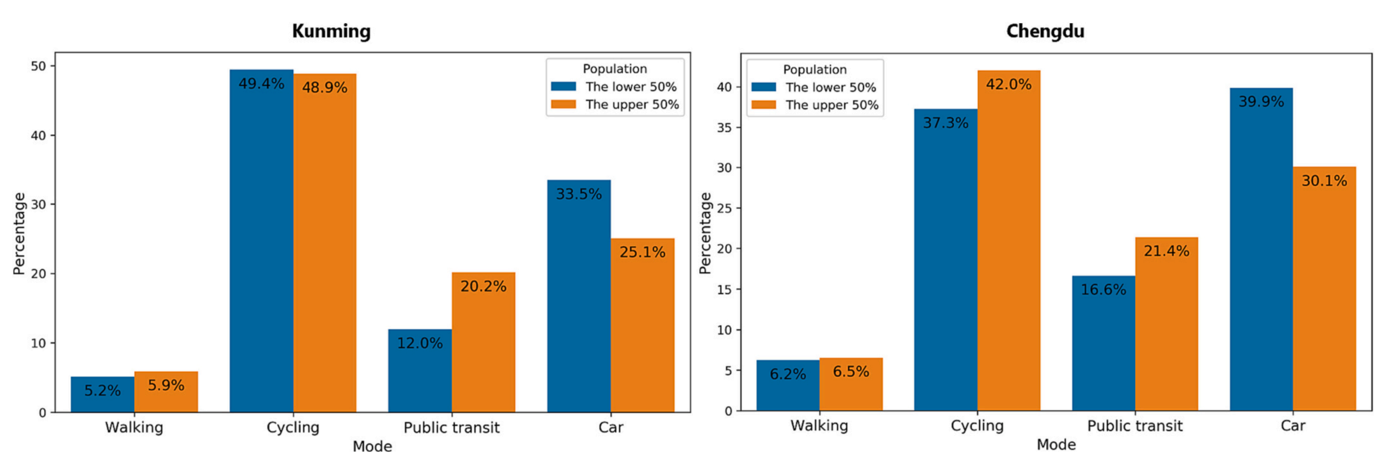

Fig. 9. Percentage of substituted travel modes in relatively high and low population density areas (the lower 50% and upper 50% of the population distribution in Kunming and Chengdu, respectively).

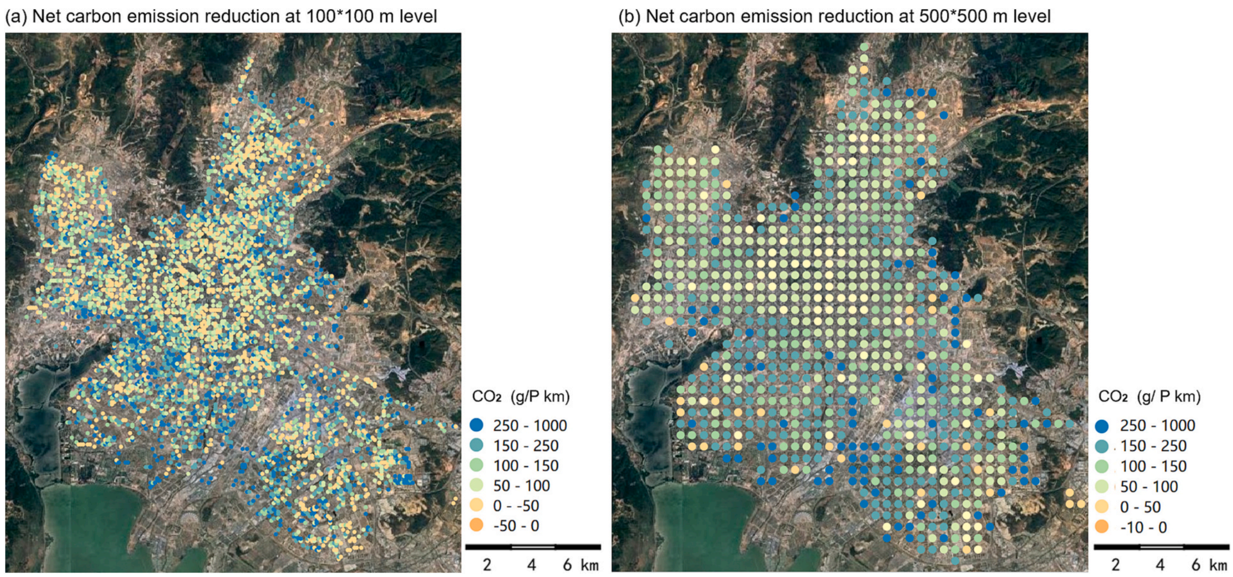

Fig. 10. The spatial distribution of carbon emissions reduction per kilometre in Kunming (The base map is from satellite map of Google).

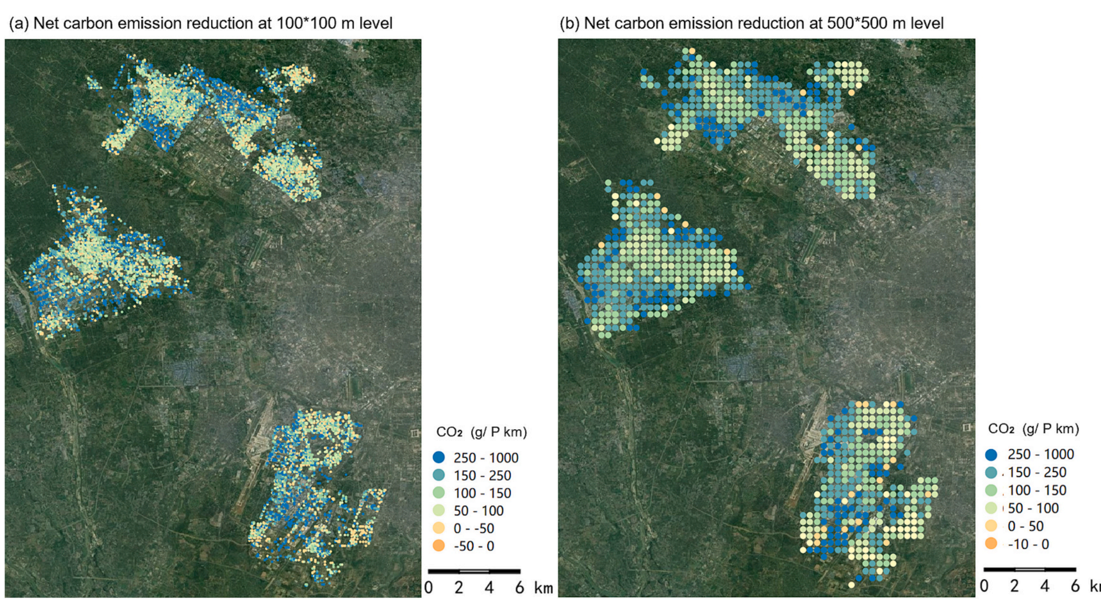

Fig. 11. The spatial distribution of carbon emissions reduction per kilometre in Chengdu.

plotted net emissions at the 500*500 m level. In the map, the higher the net CO_2 emission reduction, the colder the colour, and orange represents the increase in CO_2 emissions attributable to shared e-bikes. It can be observed that e-bike sharing does not decrease carbon emissions everywhere, but increases CO_2 in certain places. In 86% of spatial grids, the launch of shared e-bikes could help to reduce carbon emissions. Shared e-bikes in non-central areas exhibit a higher carbon reduction per kilometre than those in central areas, so the emission reduction efficiency of shared e-bikes in non-central areas is higher. However, the central areas have a higher volume of shared e-bike trips. As a result, the total emission reduction from shared e-bike trips in the central areas is higher than in the non-central areas. The relationship between the typical urban features of shared e-bike placement and emission reduction efficiency is explored in the following analysis.

5.3. Which built environments are conducive to carbon emission reductions?

To explore the relationship between features of the built environments and reductions in the carbon emissions attributable to shared e-bikes, this study conducts regressions to assess the influence of land use, accessibility, and socioeconomic factors on the efficiency of emission reduction in e-bike sharing. The dependent variable in the regressions is carbon emission reduction per kilometre, which takes into account the distance travelled, helps mitigate the influence of confounding factors and allows for better standardization and comparability across diverse geographic areas. In the OLS model, all independent variables have VIF between 1 and 3, so the multi-collinearity is insignificant. Regarding the results of the OLS model, the coefficients of land-use diversity, land-use intensity, road density, public transport stops, and economic activities are all significantly negative in both cities (cf. Table 4). This indicates that the carbon reduction efficiency of shared e-bikes is much stronger in underdeveloped non-central areas with lower building density, less

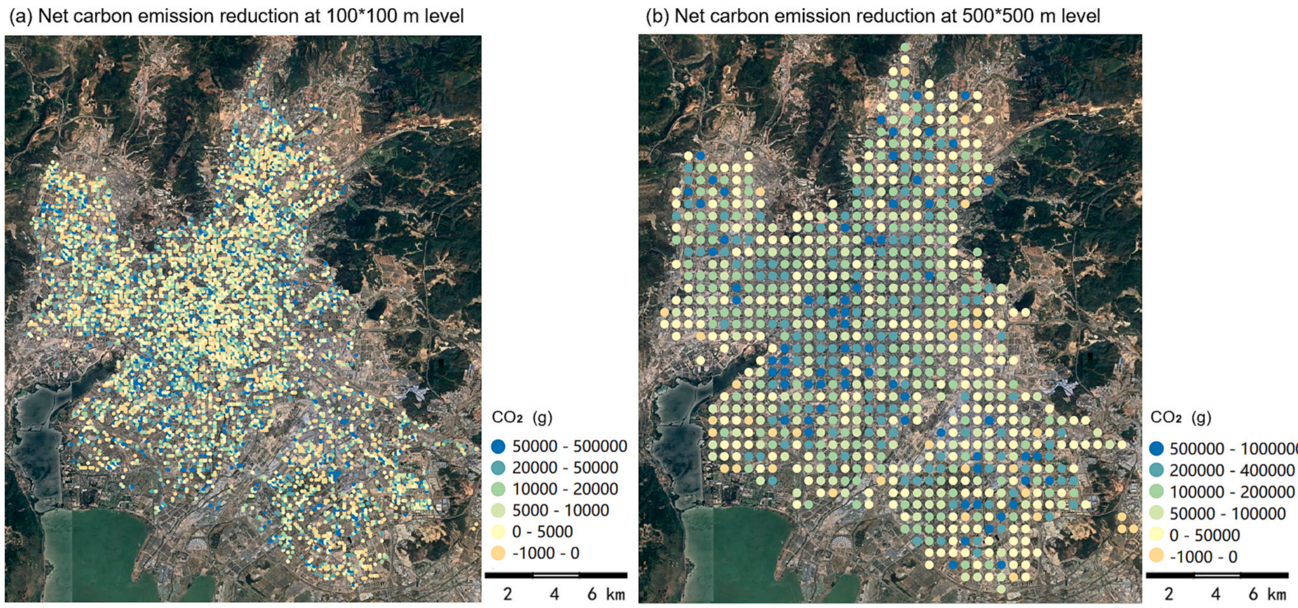

Fig. 12. The spatial distribution of total carbon emissions reduction in Kunming.

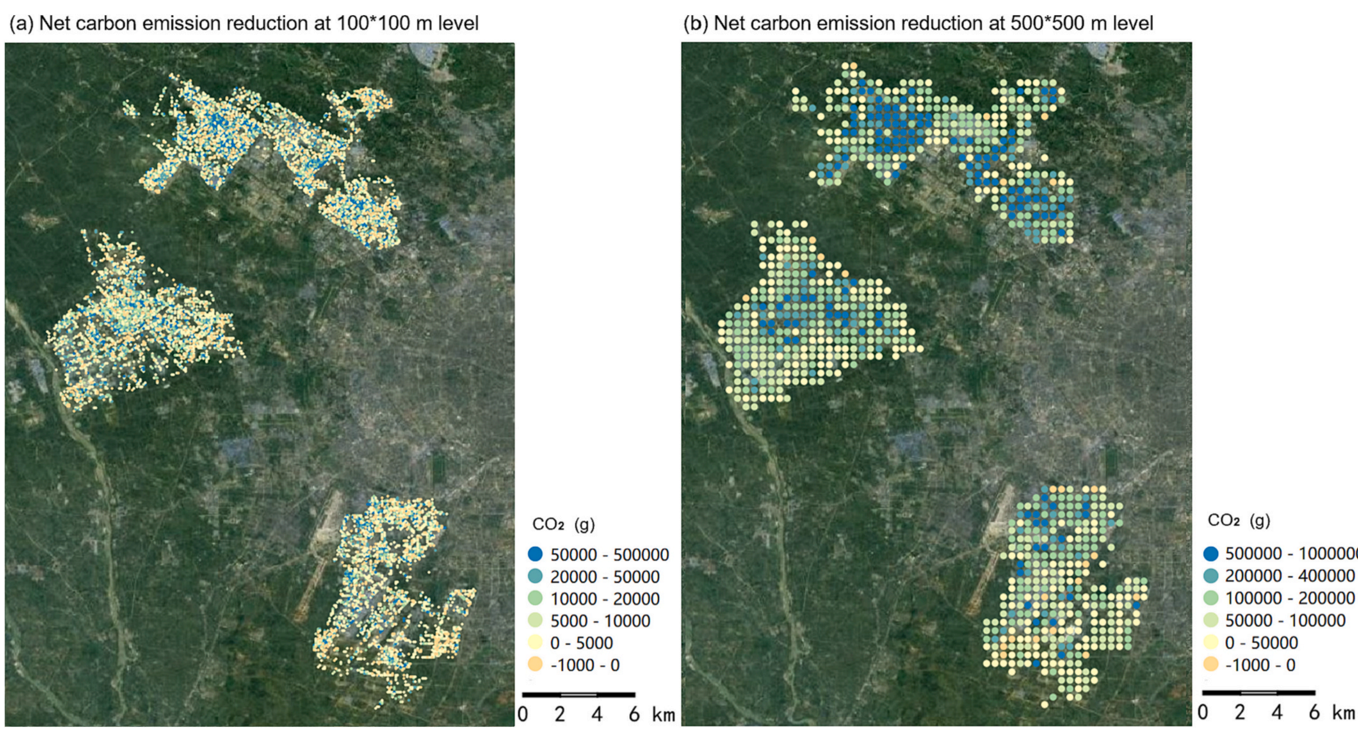

Fig. 13. The spatial distribution of total carbon emissions reduction in Chengdu.

diverse land use, and lower accessibility, potentially because shared e-bikes in these regions are more likely to replace transport modes that rely on fossil energy. This result demonstrates the environmental preference for the deployment of shared e-bikes. To avoid errors caused by spatial interdependence, the study also uses Spatial Durbin Model to accommodate spatial dependence between carbon emissions reduction effect of shared e-bikes and the spatial lags of both the outcome and urban feathers. After considering spatial lags of variables, most fixed characteristics become insignificant, while many spatial lags of the explanatory variables are significant, indicating that these characteristics of adjacent areas affect the carbon emissions reduction effect. To be more specific, the spatial lag of land use diversity and economic activities are significantly negative in both cities. The spatial lag coefficient of public transport stops and road density are significantly negative in one city case, and insignificant in another one, indicating the dependence between carbon emissions reduction effect and these urban features of adjacent areas is unstable, with certain randomness. Among all variables, land use diversity, public transport facilities, and economic activities are the relatively stable determinants relating to the carbon emissions reduction efficiency of shared e-bikes.

This is potentially because when the function of a place is monotonous, and transport service facilities density is low, people need to travel long distances to meet the needs of daily life, and a long e-bike sharing trip are more likely to replace a previous car trip. At the same time,

Table 4
Testing the correlation between features of the build environment and shared e-bikes' carbon emissions reduction: Regression results.

	Dependent variable: Carbon emissions reduction (g/p·km)			
	Kunming	Kunming	Chengdu	Chengdu
	OLS	SD	OLS	SD
	(1)	(2)	(3)	(4)
Independent Variables				
Land Use Diversity	−0.508***	0.010	−0.387***	−0.109*
	(0.089)	(0.103)	(0.042)	(0.058)
Land Use Intensity	−0.079**	−0.024	−0.062**	0.001
	(0.040)	(0.051)	(0.030)	(0.038)
Economic activity	−0.207***	0.240	−0.190***	0.080
	(0.067)	(0.181)	(0.022)	(0.098)
Public Transport	−0.194***	−0.133***	−0.193***	−0.043*
	(0.027)	(0.031)	(0.018)	(0.024)
Road Density	−0.227***	−0.081***	−0.039***	−0.016
	(0.022)	(0.026)	(0.011)	(0.014)
Control Variables				
Trip Duration	0.080***	0.074***	0.021***	0.019***
	(0.004)	(0.004)	(0.002)	(0.002)
Population	−0.104***	−0.017	−0.021***	−0.017*
	(0.020)	(0.024)	(0.008)	(0.010)
Lag Variables				
lag. Land Use Diversity		−0.735***		−0.192***
		(0.150)		(0.073)
lag. Land Use Intensity		0.017		−0.073
		(0.066)		(0.050)
lag. Economic activity		−0.337*		−0.180*
		(0.193)		(0.100)
lag. Public Transport		−0.042		−0.128***
		(0.045)		(0.030)
lag. Road Density		−0.164***		−0.010
		(0.037)		(0.018)
lag. Duration		−0.001		0.0001
		(0.007)		(0.003)
lag. Population		−0.072**		0.009
		(0.033)		(0.013)
Constant	5.846***	4.151***	5.521***	3.241***
	(0.252)	(0.302)	(0.073)	(0.113)
Observations	4073	4073	7105	7105
R^2	0.141		0.085	
Log Likelihood		−5692.789		−8477.601
Akaike Inf. Crit.		11,419.580		16,989.200

Note: *$p < 0.1$, **$p < 0.05$, ***$p < 0.01$.
Economic activity is night light index in log form; Public Transport is public transport stops density in log form; Population is population density in log form.

many characteristics of places often come together. Specifically, attributes like relatively low land use density are always accompanied by low road density, undeveloped public transport systems, and low economic level. People living in these areas may not be rich enough to afford taxis or private cars. The emergence of shared e-bikes provides more low-carbon travel options for people in these areas, so e-bike sharing is more likely to replace high-carbon vehicles in those areas. When the function of land use is relatively mixed, facilities like workplaces, residences, shopping, eating and entertainment areas are located around the neighbourhood. Most trips that occur in these areas are relatively short because residents can meet most of their needs travelling only a short distance. Thus, people may choose cycling or walking to reach their destination instead of cars. Therefore, e-bike sharing trips in places with highly mixed land use replace cars at a lower rate than in places with single land function. These findings could potentially help the decision making about where to launch and deploy e-bike sharing systems.

5.4. Sensitivity analysis

In the travel mode substitution model, the distance threshold between non-motorised travel and motorised travel may affect the carbon emission results so, in this section, we check the sensitivity of results to alternative distance threshold parameters (D_{t1}) in the substitution model (Fig. 3). As mentioned in the results, travel distances from 1 km to 3 km are the primary competition interval of different travel modes. When the travel distance of an e-bike trip is <1 km, the probability of the trip replacing motorised vehicles is low; when the travel distance is >3 km, the probability of the trip replacing non-motorised vehicles is pretty small. Therefore, we set two extreme scenarios by using the lowest and the highest values of the competition interval as the distance thresholds to generate the lowest and highest estimates for the carbon emissions reduction effect of shared e-bikes. The lowest estimate of carbon reduction from e-bikes occurs in the extreme scenario where all e-bike sharing trips with distances below 3 km replaced non-motorised travel modes, and the highest carbon reduction effect occurs when all trips with distances above 1 km replaced motorised travel modes. This paper then conducts regressions separately to check whether the variables are still significant and have the same negative correlations under extreme scenarios. It is found that the average carbon emissions reduction per kilometre lies between 53 g to 196 g. Additionally, even based on the upper limit of distance threshold (3 km) or the lower limit (1 km), the variables mentioned above are still significantly negatively correlated with the carbon emissions reduction effect (Table 5). Besides distance sensitivity analysis, the study varies the parameters from 50% to 150% of the original value for the travel time difference threshold (Tt) to generate the lowest and highest carbon reducation estimates. A time range of 10 to 30 min is set for the sensitivity testing. It shows that the average carbon emissions reduction per kilometre lies between 52 g to 190 g and all the variables mentioned are significantly negatively (Table 6). We also explored the effect of distance threshold D_{t2} on the model by varying the parameters from 50% to 150% of the original distance, which ranged from 250 m to 750 m. This analysis helped us evaluate how sensitive the proportions are to the threshold. In Kunming, the proportion of replaced walking ranged from 3.0% to 10.6%, and the proportion of cycling ranged from 44.0% to 51.6%. Similarly, in Chengdu, the proportion of replaced walking and cycling trip ranged from 2.9% to 12.8% and from 41.3% to 51.2%, respectively. The

Table 5
Testing the sensitivity of carbon emission results to alternative distance parameters.

	Dependent variable: Carbon Emissions Reduction:			
	$D_{t1} = 1$ km		$D_{t1} = 3$ km	
	Kunming	Chengdu	Kunming	Chengdu
	OLS	OLS	OLS	OLS
	(1)	(2)	(3)	(4)
Independent Variables				
Land Use Diversity	−0.355***	−0.289***	−0.556***	−0.705***
	(0.071)	(0.038)	(0.109)	(0.054)
Land Use Intensity	−0.066**	−0.017	−0.021	−0.165***
	(0.032)	(0.027)	(0.048)	(0.038)
Economic activity	−0.006	−0.128***	−0.270***	−0.219***
	(0.053)	(0.020)	(0.082)	(0.028)
Public Transport Stops	−0.156***	−0.172***	−0.206***	−0.195***
	(0.022)	(0.016)	(0.033)	(0.023)
Road Density	−0.171***	−0.018*	−0.222***	−0.109***
	(0.017)	(0.010)	(0.026)	(0.013)
Control Variables				
Trip Duration	0.037***	0.014***	0.120***	0.059***
	(0.003)	(0.002)	(0.005)	(0.003)
Population	−0.097***	−0.026***	−0.087***	−0.035***
	(0.016)	(0.007)	(0.024)	(0.010)
Constant	5.786***	5.561***	4.890***	4.782***
	(0.200)	(0.065)	(0.303)	(0.097)
Observations	4073	7105	4073	7105
R^2	0.074	0.053	0.214	0.224

Note: *$p < 0.1$, **$p < 0.05$, ***$p < 0.01$.
Economic activity is night light index in log form; Public Transport is public transport stops density in log *form; Population is population density in log form.*

Table 6
Testing the sensitivity of carbon emission results to alternative time parameters.

	Dependent variable: Carbon Emissions Reduction:			
	$T_t = 10$ min		$T_t = 30$ min	
	Kunming	Chengdu	Kunming	Chengdu
	OLS	OLS	OLS	OLS
	(1)	(2)	(3)	(4)
Independent Variables				
Land Use Diversity	−0.224***	−0.312***	−0.640***	−0.547***
	(0.054)	(0.025)	(0.100)	(0.048)
Land Use Intensity	−0.055**	−0.047**	−0.142***	−0.099***
	(0.024)	(0.018)	(0.044)	(0.035)
Economic activity	−0.088**	−0.037***	−0.254***	−0.187***
	(0.041)	(0.013)	(0.075)	(0.025)
Public Transport Stops	−0.071***	−0.043***	−0.119***	−0.187***
	(0.017)	(0.011)	(0.031)	(0.020)
Road Density	−0.114***	−0.084***	−0.226***	−0.072***
	(0.013)	(0.006)	(0.024)	(0.012)
Control Variables				
Trip Duration	0.047***	0.008***	0.100***	0.038***
	(0.003)	(0.001)	(0.005)	(0.002)
Population	−0.022*	−0.017***	−0.141***	−0.032***
	(0.012)	(0.005)	(0.023)	(0.009)
Constant	5.471***	5.667***	4.950***	4.474***
	(0.153)	(0.044)	(0.282)	(0.084)
Observations	4073	7105	4073	7105
R^2	0.112	0.094	0.164	0.118

Note: *p < 0.1, **p < 0.05, ***p < 0.01.
Economic activity is night light index in log form; Public Transport is public transport stops density in log form; Population is population density in log *form.*

findings of the sensitivity analysis make the results of the paper more convincing.

6. Conclusions and policy implications

This is the first study, to the best of our knowledge, that analyses the potential carbon emissions reduction effect of shared e-bikes based on a large collection of shared e-bike trip data. In a sharing economy, e-bikes represent a new form of public transportation, and their potential for reducing emissions is worth exploring. In our study, we develop a travel mode substitution model to measure which mode is most likely to be substituted by shared e-bike trips, estimate the net carbon emissions change, and employ OLS and spatial lag models to explore how the environmental benefits of shared e-bikes can be boosted in which kinds of urban context. In terms of the proportion of replacement, shared e-bikes are more prone to reduce public transit and bike trips than car trips. However, the emissions reduction effect of shared e-bikes is stronger than the emissions increase effect resulting in a net reduction following the introduction of shared e-bikes. On average, shared e-bikes result in a reduction in carbon emissions by 108–120 g per kilometre in the two cities.

Regarding the spatial distribution of carbon emissions, although e-bike sharing reduces carbon emissions in most areas, it still increases carbon emissions in some urban contexts, especially for places with mixed and compact land use and easy accessibility. Therefore, when planning the spatial coverage of e-bike sharing schemes with the aim of enhancing carbon emission reduction efficiency, priority should be given to implementing shared e-bikes programs in areas characterized by single land use, low density, low income, and poor public transportation services. However, if the goal is to maximize the overall carbon emission reduction achieved through e-bikes, it would be advisable to deploy more e-bikes in densely populated central areas.

Our results provide a reference for policy makers to promote the substitution of cars and inhibit the substitution of active travel by shared e-bikes. Nowadays, it is still controversial whether cities should allow the entry of shared e-bikes. Some big cities in China, like Beijing and Guangzhou, have forbidden the usage of shared e-bikes because of safety issues, while some cities like Kunming allow them. Chengdu forbids the usage of shared e-bikes in the urban centre, but permits them in the suburb. Places that will benefit from shared e-bikes could be identified from the perspective of reducing net carbon emissions. The corollary of this study for government and businesses for managing e-bike sharing schemes is that they need to be deployed in suitable locations with appropriate cycling infrastructure, especially in suburbs.

Although this study develops an innovative and quantitative calculation of the carbon emissions reduction effect of shared e-bikes based on big data analysis, there are some limitations. First, this study estimates the emissions change primarily based on the shared e-bike trip dataset, and does not take into account the potential complementary effect on public transit and bikes, and the indirect substitution of cars by facilitating public transit in the last-mile connection, when calculating the net carbon emissions estimation. Secondly, the paper calculates the carbon emissions changes during the use of shared e-bikes, and does not consider the whole life-cycle carbon emissions of shared e-bikes, such as fleet manufacturing, recycling and re-distribution. Thirdly, shared e-bikes may be likely to save additional carbon emissions compared to a scenario where people would make these trips with private e-bikes. Fourthly, the method uses the distance distribution of shared bikes and ride-hail trip to represent the distance distribution of bikes and cars. The absence of private vehicles is not solely due to data availability constraints. Shared e-bikes are considered as a form of public transportation, with the ability to be shared by the public rather than privately owned. Their primary competitors are other public transportation options that also possess a public/shared nature, such as shared bikes, shared ride-hail trips, and public transit. Shared e-bikes mainly serve as substitutes for these modes of transportation with shared attributes, hence private vehicles are not considered in this method. Besides, there are still many unobserved factors that influence people's choices, including travel cost, comfort, safety, crowdedness, privacy, varying levels of car ownership and mode splits between urban and rural areas. Limited by the availability of these data, the mode substitution model used in this study did not incorporate these factors, which could potentially introduce some inaccuracies into the outcomes. When the relevant data sources become available, such as the combination of survey data about the travel choice of citizens under different situations, a more accurate analysis will be carried out. Fifthly, as of the end of 2020, conventional vehicles comprised 98.25% of the total national automobile stock, while electric vehicles (EVs) accounting for the remaining 1.75%. Due to the low market share of EVs, the method used to calculate the carbon emissions reduction resulting from the replacement of cars with e-bikes did not consider the carbon emissions reduction specifically from EVs, which may slightly overstate the carbon reduction effect of e-bike sharing. Finally, this paper has focused on the spatial heterogeneity of the carbon emissions of shared e-bikes, and did not analyse the changing characteristics of carbon emissions over time during a day. Subsequent studies might explore the carbon emissions reduction effect of shared e-bikes in more depth, to further unravel the impact of shared e-bikes on carbon emissions. These discussions may make the findings more comprehensive and give more precise policy and business implications.

CRediT authorship contribution statement

Qiumeng Li: Conceptualization, Data curation, Methodology, Formal analysis, Software, Visualization. **Franz Fuerst:** Supervision, Writing – review & editing. **Davide Luca:** Supervision, Writing – review & editing.

Data availability

The authors do not have permission to share data.

Acknowledgements

Many thanks to Meituan company for providing the invaluable data that fueled this study. Additionally, we wish to express our sincere appreciation to Professor Xun Li and Dr. Weipan Xu for their invaluable guidance and support.

Appendix A. Appendix

Table A1

Points-of-interest categories.

ID	Category	Examples
1	Commercial sites	Retail, food, restaurant, shopping mall
2	Office building/space	Company, bank, health service, travel agency
3	Residence communities	Real estate, lodging, hotel
4	Education	University, school
5	Government	City hall, embassy, police
6	Transport facilities	Airport, transit station, parking, energy supply station
7	Green space	Green parks
8	Others	Others

References

Berjisian, E., Bigazzi, A., 2019. Summarizing the Impacts of Electric Bicycle Adoption on Vehicle Travel, Emissions, and Physical Activity. REACT Research on Active Transportation Lab. University of British Colombia.

Bieliński, T., Kwapisz, A., Ważna, A., 2021. Electric bike-sharing services mode substitution for driving, public transit, and cycling. Transp. Res. Part D: Transp. Environ. 96, 102883.

Bigazzi, A., Wong, K., 2020. Electric bicycle mode substitution for driving, public transit, conventional cycling, and walking. Transp. Res. Part D: Transp. Environ. 85, 102412.

Boarnet, M.G., Greenwald, M., McMillan, T.E., 2008. Walking, urban design, and health: toward a cost-benefit analysis framework. J. Plan. Educ. Res. 27 (3), 341–358.

Bucher, D., Buffat, R., Froemelt, A., Raubal, M., 2019. Energy and greenhouse gas emission reduction potentials resulting from different commuter electric bicycle adoption scenarios in Switzerland. Renew. Sust. Energ. Rev. 114 (OCT.), 109298.1-109298.11.

Cairns, S., Behrendt, F., Raffo, D., Beaumont, C., Kiefer, C., 2017. Electrically-assisted bikes: potential impacts on travel behaviour. Transp. Res. A Policy Pract. 103, 327–342.

Cervero, R., 2002. Built environments and mode choice: toward a normative framework. Transp. Res. Part D: Transp. Environ. 7 (4), 265–284. https://doi.org/10.1016/S1361-9209(01)00024-4.

Cervero, R., Kockelman, K., 1997. Travel demand and the 3Ds: density, diversity, and design. Transp. Res. Part D: Transp. Environ. 2 (3), 199–219. https://doi.org/10.1016/S1361-9209(97)00009-6.

Cherry, C., Cervero, R., 2007. Use characteristics and mode choice behaviour of electric bike users in China. Transp. Policy 14 (3), 247–257. https://doi.org/10.1016/j.tranpol.2007.02.005.

Cherry, C.R., Yang, H., Jones, L.R., He, M., 2016. Dynamics of electric bike ownership and use in Kunming, China. Transp. Policy 45, 127–135. https://doi.org/10.1016/j.tranpol.2015.09.007.

D'Almeida, L., Rye, T., Pomponi, F., 2021. Emissions assessment of bike sharing schemes: the case of just eat cycles in Edinburgh, UK. Sustain. Cities Soc. 71, 103012 https://doi.org/10.1016/j.scs.2021.103012.

De Haas, M., Kroesen, M., Chorus, C., Hoogendoorn-Lanser, S., Hoogendoorn, S., 2022. E-bike user groups and substitution effects: evidence from longitudinal travel data in the Netherlands. Transportation 49 (3), 815–840.

De Sá, T.H., Parra, D.C., Monteiro, C.A., 2015. Impact of travel mode shift and trip distance on active and non-active transportation in the São Paulo Metropolitan Area in Brazil. Prev. Med. Rep. 2, 183–188.

Demetsky, M.J., Bin-Mau Lin, B., 1982. Bus stop location and design. Transp. Eng. J. ASCE 108 (4), 313–327.

Eren, E., Uz, V.E., 2020. A review on bike-sharing: the factors affecting bike-sharing demand. Sustain. Cities Soc. 54, 101882 https://doi.org/10.1016/j.scs.2019.101882.

Ermagun, A., Samimi, A., 2018. Mode choice and travel distance joint models in school trips. Transportation 45 (6), 1755–1781. https://doi.org/10.1007/s11116-017-9794-y.

Ewing, R., Cervero, R., 2010. Travel and the built environment. J. Am. Plan. Assoc. 76 (3), 265–294. https://doi.org/10.1080/01944361003766766.

Fishman, E., Washington, S., Haworth, N., 2014. Bike share's impact on car use: evidence from the United States, Great Britain, and Australia. Transp. Res. Part D: Transport Environ. 31, 13–20. https://doi.org/10.1016/j.trd.2014.05.013.

Fitch, D.T., Mohiuddin, H., Handy, S.L., 2021. Examining the effects of the Sacramento dockless E-bike share on bicycling and driving. Sustainability 2021 (13), 368.

Frank, L., Bradley, M., Kavage, S., Chapman, J., Lawton, T.K., 2008. Urban form, travel time, and cost relationships with tour complexity and mode choice. Transportation 35 (1), 37–54. https://doi.org/10.1007/s11116-007-9136-6.

Fukushige, T., Fitch, D.T., Handy, S., 2021. Factors influencing dock-less E-bike-share mode substitution: evidence from Sacramento, California. Transp. Res. Part D: Transp. Environ. 99, 102990 https://doi.org/10.1016/j.trd.2021.102990.

Fyhri, A., Heinen, E., Fearnley, N., Sundfør, H.B., 2017. A push to cycling—exploring the e-bike's role in overcoming barriers to bicycle use with a survey and an intervention study. Int. J. Sustain. Transp. 11 (9), 681–695. https://doi.org/10.1080/15568318.2017.1302526.

Gehl, J., Koch, J., 2011. Life between Buildings: Using Public Space. Island Press.

Harvey, J., Guo, A., 2018. Cycling and Other Active Modes in the UK: How and Why Are They Changing? https://eprints.ncl.ac.uk.

Haustein, S., Moller, M., 2016. Age and attitude: changes in cycling patterns of different E-bike user segments. Int. J. Sustain. Transp. 10 (9), 00.

Hawas, Y.E., Hassan, M.N., Abulibdeh, A., 2016. A multi-criteria approach of assessing public transport accessibility at a strategic level. J. Transp. Geogr. 57, 19–34.

Hellobike, 2020. https://www.helloinc.com/detail.html?guid=e2d858578a1343528d0546619581026f&type=news.

Hiselius, L.W., Svensson, S., 2017. E-bike use in Sweden – CO2 effects due to modal change and municipal promotion strategies. J. Clean. Prod. 141, 818–824.

Johnson, M., Rose, G., 2013. Electric bikes–cycling in the New World City: An investigation of Australian electric bicycle owners and the decision making process for purchase. In: Paper presented at the Proceedings of the 2013 Australasian Transport Research Forum.

Jones, T., Harms, L., Heinen, E., 2016. Motives, perceptions and experiences of electric bicycle owners and implications for health, wellbeing and mobility. J. Transp. Geogr. 53, 41–49. https://doi.org/10.1016/j.jtrangeo.2016.04.006.

Kim, H., Seok, H., Iris You, S., Lee, C., 2020. An empirical analysis for mode choice in a short-distance trip with personal rapid transit. J. Adv. Transp. 2020, e7436710 https://doi.org/10.1155/2020/7436710.

Kong, H., Zhang, X., Zhao, J., 2020. How does ridesourcing substitute for public transit? A geospatial perspective in Chengdu, China. J. Transp. Geogr. 86, 102769 https://doi.org/10.1016/j.jtrangeo.2020.102769.

Kou, Z., Wang, X., Chiu, S.F., Cai, H., 2020. Quantifying greenhouse gas emissions reduction from bike share systems: a model considering real-world trips and transportation mode choice patterns. Resour. Conserv. Recycl. 153, 104534 https://doi.org/10.1016/j.resconrec.2019.104534.

Kr-asia, 2020. Forget bike-sharing, e-bikes to become the next trend in China's sharing economy. https://kr-asia.com/forget-bike-sharing-e-bikes-to-become-the-next-trend-in-chinas-sharing-economy.

Lee, M., Chow, J.Y., Yoon, G., He, B.Y., 2021. Forecasting e-scooter substitution of direct and access trips by mode and distance. Transp. Res. Part D: Transp. Environ. 96, 102892.

Li, Q., Zhou, S., Wen, P., 2019. The relationship between centrality and land use patterns: empirical evidence from five Chinese metropolises[J]. Comput. Environ. Urban. Syst. 78, 101356.

Li, A., Zhao, P., Huang, Y., Gao, K., Axhausen, K.W., 2020. An empirical analysis of dockless bike-sharing utilization and its explanatory factors: case study from Shanghai, China. J. Transp. Geogr. 88, 102828.

Liao, Y., 2021. Ride-sourcing compared to its public-transit alternative using big trip data. J. Transp. Geogr. 95, 103135.

Lin, X., Wells, P., Sovacool, B.K., 2017. Benign mobility? Electric bicycles, sustainable transport consumption behaviour and socio-technical transitions in Nanjing, China. Transp. Res. A Policy Pract. 103, 223–234.

Liu, X., Long, Y., 2016. Automated identification and characterization of parcels with OpenStreetMap and points of interest. Environ. Plan. B Plan. Des. 43 (2), 341e360.

MacArthur, J., Dill, J., Person, M., 2014. Electric bikes in North America: results of an online survey. Transp. Res.Rec. J. Transp. Res. Board 2468, 123–130.

MacArthur, J., Cherry, C., Harpool, M., Scheppke, D., 2018. A North American Survey of Electric Bicycle Own-ers. NITC-RR-1041. Transportation Research and Education Center (TREC), Portland, OR.
Mattson, J., Godavarthy, R., 2017. Bike share in Fargo, North Dakota: keys to success and factors affecting ridership. Sustain. Cities Soc. 34, 174–182. https://doi.org/10.1016/j.scs.2017.07.001.
McQueen, M., MacArthur, J., Cherry, C., 2020. The E-bike potential: estimating regional e-bike impacts on greenhouse gas emissions. Transp. Res. Part D: Transp. Environ. 87, 102482 https://doi.org/10.1016/j.trd.2020.102482.
Mellander, C., Lobo, J., Stolarick, K., Matheson, Z., 2015. Night-time light data: a good proxy measure for economic activity? PLoS One 10 (10), e0139779.
Moilanen, M., 2010. Matching and settlement patterns: the case of Norway. Pap. Reg. Sci. 89 (3), 607–623. https://doi.org/10.1111/j.1435-5957.2009.00264.x.
Montgomery, B.N., 2010. Cycling trends and fate in the face of bus rapid transit: case study of Jinan, Shandong Province, China. Transp. Res. Rec. 2193 (1), 28–36.
Moser, C., Blumer, Y., Hille, S.L., 2018. E-bike trials' potential to promote sustained changes in car owners mobility habits. Environ. Res. Lett. 13 (4), 044025 https://doi.org/10.1088/1748-9326/aaad73.
Murray, A.T., Davis, R., Stimson, R.J., Ferreira, L., 1998. Public transportation access. Transp. Res. Part D: Transp. Environ. 3 (5), 319–328. https://doi.org/10.1016/S1361-9209(98)00010-8. Pucher, J.E., Buehler, R.E., 2012. City cycling. MIT Press, Cambridge, MA.
Nankervis, M., 1999. The effect of weather and climate on bicycle commuting. Transp. Res. A Policy Pract. 33 (6), 417–431. https://doi.org/10.1016/S0965-8564(98)00022-6.
Peng, Z.-R., 1997. The jobs-housing balance and urban commuting. Urban Stud. 34 (8), 1215–1235. https://doi.org/10.1080/0042098975600.
Philips, I., 2020. E-Bike Carbon Savings – How Much and where?, p. 7.
Ramos, El Elliott Ramos, 2021. Nbcnews. https://www.nbcnews.com/news/us-news/covid-fueled-rise-e-bike-see-where-ridership-grew-u-n1272127.
Rérat, P., 2021. The rise of the E-bike: towards an extension of the practice of cycling? Mobilities 1–17.
Salonen, M., Toivonen, T., 2013. Modelling travel time in urban networks: comparable measures for private car and public transport. Journal of transport Geography 31, 143–153.
Schwieterman, J.P., 2019. Uber economics: evaluating the monetary and travel time trade-offs of transportation network companies and transit service in Chicago, Illinois. Transportation Research Record 2673 (4), 295–304.
Shannon, Claude E., 1948. A mathematical theory of communication. Bell Syst. Tech. J. 27 (3), 379–423. https://doi.org/10.1002/j.1538-7305.1948.tb01338.x (July–October).
Sloman, L., Hopkinson, L., 2020. The carbon impact of the national roads programme. https://tps.org.uk/news/the-carbon-impact-of-the-national-roads-programme.
Spencer, P., Watts, R., Vivanco, L., Flynn, B., 2013. The effect of environmental factors on bicycle commuters in Vermont: influences of a northern climate. J. Transp. Geogr. 31, 11–17. https://doi.org/10.1016/j.jtrangeo.2013.05.003.
Sun, Q., Feng, T., Kemperman, A., Spahn, A., 2020. Modal shift implications of e-bike use in the Netherlands: moving towards sustainability? Transp. Res. Part D: Transp. Environ. 78, 102202 https://doi.org/10.1016/j.trd.2019.102202.
United Nations, Department of Economic and Social Affairs, Population Division, 2019. World Urbanization Prospects: The 2018 Revision (ST/ESA/SER.A/420). United Nations, New York.
Wamburu, J., Lee, S., Hajiesmaili, M.H., Irwin, D., Shenoy, P., 2021. Ride substitution using electric bike sharing: feasibility, cost, and carbon analysis. Proc. ACM Interact. Mobile Wearable Ubiquitous Technol. 5 (1), 1–28.
Wang, Y., Sun, S., 2022. Does large scale free-floating bike sharing really improve the sustainability of urban transportation? Empirical evidence from Beijing. Sustain. Cities Soc. 76, 103533 https://doi.org/10.1016/j.scs.2021.103533.
Wegener, M., Fuerst, F., 2004. Land-use transport interaction: state of the art. Urban/regional 3–16.
Winters, M., Brauer, M., Setton, E.M., Teschke, K., 2010. Built environment influences on healthy transportation choices: bicycling versus driving. J. Urban Health 87 (6), 969–993. https://doi.org/10.1007/s11524-010-9509-6.
Yang, W., Zhou, S., 2020. Using decision tree analysis to identify the determinants of residents' CO2 emissions from different types of trips: a case study of Guangzhou, China. J. Clean. Prod. 277, 124071.
Zhang, Y., Mi, Z., 2018. Environmental benefits of bike sharing: a big data-based analysis. Appl. Energy 220 (JUN.15), 296–301.