Analyzing Spatiotemporal Daily Travel Source Carbon Emissions Based on Taxi Trajectory Data

MAOPENG SUN\(^1,2\), CHENLEI XUE\(^1\), YANQIU CHENG\(^1\), LING ZHAO\(^3\), AND ZHIYOU LONG\(^1,2\)

\(^1\)College of Transportation Engineering, Chang’an University, Xi’an 710064, China
\(^2\)Engineering Research Center of Highway Infrastructure Digitalization, Ministry of Education, Chang’an University, Xi’an 710064, China
\(^3\)Nanjing Vocational Institute of Transport Technology, Nanjing 211188, China

Corresponding author: Maopeng Sun (sunmp@chd.edu.cn)

This work was supported in part by the Ningbo Transportation Science and Technology Project under Grant 220123180075, and in part by the Natural Science Research Program of Shaanxi Province under Grant 2020JQ-360.

ABSTRACT Analyzing the spatial-temporal distribution of travel carbon emissions will help government departments to develop effective policies and strategies for carbon emission management. This research proposes a trajectory-based analysis method to identify sources of high travel carbon emissions and the relationship between car use and travel carbon emissions. The vehicle-specific power model (VSP), which considers the effect of the vehicle operating speed on emissions, was used to estimate emissions from the travel origin to the destination. The research area was divided into grids according to the population distribution, and the grid carbon emissions (GCE) and grid average carbon emissions (GACE) were calculated. This article used several spatial measurement models to investigate the spatial-temporal trend and influencing factors of travel emissions. A case study using one month of Ningbo taxi data showed the following. 1) The concentration of emission sources was significantly reduced during the evening peak, but the proportion of the contribution was relatively high. 2) Many areas in the suburbs had a high proportion of high emitters throughout the day and not only during the commuting period. 3) Population density and car use ratio were used to explain the quantitative relationship between car use and travel emission sources. This study can guide travel carbon emission monitoring and local carbon emission reduction strategies.

INDEX TERMS Carbon emissions, daily travel, car use, vehicle-specific power model, trajectory data.

I. INTRODUCTION Climate change leading to global warming resulting from fossil energy use has become an urgent topic [1]. According to a research report on fuel combustion released by the International Energy Agency, transportation accounts for nearly a quarter of the global energy-related greenhouse gas emissions, representing the primary carbon emission driver [2]. The proportion of carbon emissions from daily car use exceeds half of the total emissions from the transportation sector, and the balance is even higher in some cities [3]. In the past ten years, China’s urbanization rate has increased by more than 20%, and private cars have grown at an average annual rate of nearly 19 million. The leading energy efficiency technologies to reduce passenger cars’ carbon emissions include enhancement of fuel quality, engine technology improvement [4], encouraging the use of hybrid electric vehicles and energy-efficient cars [5], as well as urban public transport promotion [6]. According to statistics from the Transportation Administration of the Ministry of Public Security of China, the number of motor vehicles in China in 2020 was 280 million, while new energy vehicles comprised less than 5 million. The most direct result is that the increased demand for daily car use cannot be matched by new energy vehicles [7]. Increasing urban population and car service will prevent meeting the transportation carbon abatement targets [8].

Many studies have shown that technology and market solutions combined with targeted promotion policies can effectively improve emission reduction [9]–[11]. The Chinese management department mainly uses undifferentiated government intervention to reduce the emission of vehicle pollutants, such as license plate restrictions. However, high-emission areas and people producing high emissions do
not bear higher costs in urban emission reduction, although this strategy is very effective. It even adds an extra burden to low emitters [12]. It has also been shown that matching needs and optimizing resource allocation by building smart cities is an excellent way to promote the rapid implementation of low-carbon transportation technologies [13], such as fostering convenience and individual incentive mechanisms for accelerating low-carbon travel modes in high-emission areas [14]. However, whether implementing intervention measures or optimizing resource allocation methods, it is necessary to identify the spatial distribution of high travel carbon emissions and determine the relationship between population growth and car use dependence and carbon emissions in urban development [15].

The accurate estimation of individual travel emissions is the basis of regional analysis [16]. The existing literature shows the following two research gaps. First, most studies on individual emissions are based on survey data, which have limitations, such as small coverage, low time accuracy, and time-consuming collection, making this approach unsuitable for dynamic monitoring and analysis [17]. This method cannot measure the impact of traffic congestion and changes in the operating speed on the emissions [18]. Second, the traffic emission calculation method based on the speed and density of the traffic network has the advantage of real-time analysis of the spatial distribution of traffic carbon emissions. However, this method typically does not correlate car driving with travel demand to analyze daily travel emissions [19]. Specifically, this method does not explain the spatial distribution of travel emissions from the perspective of the source of travel demand [20].

Using the vehicle travel information recorded in trajectory data to calculate the emissions from the origin to the destination can overcome the drawbacks of the sampling survey, making this approach the primary method for calculating network emissions. Among various vehicle trajectory data, taxi GPS data has the advantages of comprehensive coverage, easy access, and low maintenance cost; thus, these data are widely used in urban travel activity monitoring [21]–[23]. Due to privacy protection issues, private car trajectory data are usually not available, and taxis can be regarded as a proxy to reflect human mobility by vehicles [21], [24], [25]. Taxi emissions are also higher than emissions from other transportation modes and are considered a high-emission travel mode [26]. However, vehicle-based GPS emission research has not been used to analyze the spatial distribution of daily travel sources. The main focus is on emissions at the administrative district scale and emissions from transportation networks.

This paper proposes a trajectory-based method to analyze the spatio-temporal trends of traffic emissions and the relationship with travel demand. The vehicle-specific power (VSP) model is used to account for individual car travel emissions to consider the effect of the vehicle operating speed on emissions. The target city is divided into grids based on population density (PD), and the grid carbon emissions (GCE) and grid average travel emissions (GACE) are calculated. A geographically weighted regression (GWR) model considering PD and taxi use ratio (TU) as independent variables is employed to explore the relationship between travel demand and carbon emissions in an urban environment.

This study contributes to existing studies in two aspects. First, this research identifies the source of carbon emissions from daily travel at a finer scale than the administrative area. This method has higher temporal accuracy and better spatial coverage than questionnaire surveys, enabling the management department to perform efficient dynamic monitoring. Second, the PD and the relative proportion of taxi trips were used to calculate the taxi (car) utilization rate, to obtain the relationship between PD and the car utilization rate and travel emissions at fine temporal and spatial scales, which was lacking in existing methods. Our research demonstrates the spatial heterogeneity of the impact of PD and car use on traffic emissions.

This paper is structured as follows. Section 2 discusses existing research demonstrating the proposed methods’ applicability. Section 3 and Section 4 introduce the research data and research methods, respectively. Section 5 presents a case study, and Section 6 is an in-depth discussion of the research results. Section 7 concludes the research. Figure 1 shows the flow diagram and research approach.

### Table 1. The abbreviations are used in this research.

| Abbreviation | Description |
|--------------|-------------|
| VSP          | The vehicle-specific power model |
| GCE          | Grid carbon emissions |
| GACE         | Grid average travel emissions |
| PD           | Population density |
| TU           | Taxi use ratio |
| GWR          | Geographically weighted regression |

This paper proposes a trajectory-based method to analyze the spatio-temporal trends of traffic emissions and the relationship with travel demand. The vehicle-specific power (VSP) model is used to account for individual car travel emissions to consider the effect of the vehicle operating speed on emissions. The target city is divided into grids based on population density (PD), and the grid carbon emissions (GCE) and grid average travel emissions (GACE) are calculated. A geographically weighted regression (GWR) model considering PD and taxi use ratio (TU) as independent variables is employed to explore the relationship between travel demand and carbon emissions in an urban environment.

This study contributes to existing studies in two aspects. First, this research identifies the source of carbon emissions from daily travel at a finer scale than the administrative area. This method has higher temporal accuracy and better spatial coverage than questionnaire surveys, enabling the management department to perform efficient dynamic monitoring. Second, the PD and the relative proportion of taxi trips were used to calculate the taxi (car) utilization rate, to obtain the relationship between PD and the car utilization rate and travel emissions at fine temporal and spatial scales, which was lacking in existing methods. Our research demonstrates the spatial heterogeneity of the impact of PD and car use on traffic emissions.

This paper is structured as follows. Section 2 discusses existing research demonstrating the proposed methods’ applicability. Section 3 and Section 4 introduce the research data and research methods, respectively. Section 5 presents a case study, and Section 6 is an in-depth discussion of the research results. Section 7 concludes the research. Figure 1 shows the flow diagram and research approach.
II. LITERATURE REVIEW

The research methods of transportation carbon emissions are divided into direct measurements and indirect statistics. Direct measurements are carried out at roadside locations or following individual vehicles using portable emission measurement systems [27]. Due to the high cost and susceptibility to environmental disturbances, the most significant contribution of direct measurement methods is to simulate and measure emission factors and suitable for regional analysis [28]. The indirect statistics method is more widely used and can be further divided into top-down and bottom-up approaches [2].

Top-down indirect approaches are widely used to analyze regional emission dynamics and influencing factors, but it is difficult to reflect individual differences within the region using this method [29]. Wang et al. (2019) used the factor reversible structural decomposition method of input-output analysis, focusing on sectoral carbon emissions, and discussed the impact of urbanization and changes in consumption patterns on household carbon emissions [30]. Ali et al. (2019) used time-series data from 1972 to 2014 to determine the one-way short-term causal relationship between urbanization and carbon emissions. They pointed out the necessity of government intervention in promoting the adoption of green technology in urban industrial and residential sectors [31]. Wang and Zhang (2020) analyzed transportation carbon emissions and their influencing factors based on traffic emissions and economic and social data of 286 cities in China [12]. These studies provide essential information for policy-making to reduce transportation emissions on the macro-level [32]. Nevertheless, top-down approaches are challenging for analyzing and assessing the difference in travel carbon emissions from downscaling from administrative scales, mainly because energy consumption statistics are at the city and administrative areas.

Bottom-up indirect methods are usually based on concrete evidence of citizen behavior and responses for evaluating the travel emission characteristics and influencing factors from a micro perspective [33]. Rong et al. (2018) calculated residential travel emissions based on questionnaire surveys and found that high-emission areas were mainly distributed in new urban areas and rapidly expanding built-up areas on the outer layer of the city [13]. Yang et al. (2018) investigated travel emissions of the working class based on travel survey data and found that people producing high emissions were typically male with a high income that owned a car and were 30-40 years old [18]. Brand et al. (2021) compared the impact of car travel and active travel (walking or cycling for transport) on travel emissions using travel activity data [34]. Calculating the residents’ carbon emissions based on traditional travel surveys, questionnaires, or interviews is the principal means of bottom-up methods. These methods are considered expensive, time-consuming, subjective, and arbitrary [17]. Although the reliability of the questionnaire survey method requires more discussion, these studies have limited coverage and are not conducive to real-time monitoring and evaluation. In detail, most analyses only reflect the local characteristics of the survey area. It is often difficult to distinguish specific periods because surveys do not describe travel times accurately. Besides, the travel distance is usually the main parameter for calculating travel emissions without considering the impact of traffic and road conditions on emissions.

Vehicle-based GPS data has received increasing attention since these data accurately reflect the driving state of motor vehicles [20]. The VSP model is based on the measured emission data of cars and can be used to establish the relationship between the average emission rate and the GPS-based driving parameters using regression fitting; it is a primary method for studying road emissions. Simulation results for public vehicles [35], taxis [36], and light-duty vehicles [37] have demonstrated that the VSP model has high accuracy for estimating fuel consumption. Scholars have begun to apply this method to the study of urban travel activities and related emissions. For example, Zhang et al. (2018) used taxi trajectories to calculate fuel consumption and carbon emissions and applied a visualization method to obtain the spatial distribution of carbon emissions in a transportation network [38]. Xia et al. (2020) proposed an approach combining taxi records to calculate carbon emissions from daily travel and explored the relationship between urban forms and carbon emissions at the administrative region scale [17]. Chen et al. (2020) analyzed the temporal characteristics of multimodal travelers and discussed the effect of shifting to low-carbon travel modes on urban traffic emission reduction [36]. However, vehicle-based GPS emission research has not been applied to investigating the spatial distribution of daily travel sources. The main focus has been on emissions at the administrative district scale and emissions from transportation networks.

In summary, the top-down approach is not suitable to reveal the source and spatial distribution of carbon emissions from daily travel inside the city. The questionnaire-based bottom-up methods have limited coverage and are not conducive to real-time monitoring and evaluation. This research derived inspiration from the transportation network emission model and calculated vehicle emissions from the travel origin to the destination for individual vehicles based on taxi trajectory data. The origin of the travel trajectory was used to identify the distribution of emissions due to travel demand at a finer scale than the administrative area.

III. DATA SOURCES AND PROCESSING

A. TAXI TRAJECTORY DATA

This research utilized taxi trajectory data from more than 4300 taxis in Ningbo for one month (July 2017). The taxi trajectory data were obtained from the Ningbo Municipal Transportation Bureau. The taxi trajectory data included approximately 25.7 million records per day, containing longitude and latitude information for the taxi ID, status (vacant or occupied), timestamp, and velocity. A sample record is listed in Table 2. Moreover, the taxi trajectory data were recorded...
TABLE 2. A sample record of the taxi trajectory data.

| ID     | Longitude | Latitude | Timestamp       | Velocity | State  |
|--------|-----------|----------|-----------------|----------|--------|
| BT0**6 | 121.5844  | 29.8817  | 2017-07-30T15:59:57 | 0        | vacant |
| BT0**6 | 121.53835 | 29.9000  | 2017-07-30T15:59:57 | 49       | occupied |

TABLE 3. A sample of the taxi trip data.

| Vehicle number | Pick-up time     | Pick-up Location | Drop-off Location | Distance (km) | Duration (s) |
|----------------|------------------|------------------|-------------------|---------------|--------------|
| BT0**6         | 2017-09-31T15:47:00 | 121.59758       | 121.62026         | 5.2           | 720          |
| BT0**6         | 2017-09-31T19:28:00 | 29.89233       | 29.90005          | 6.6           | 600          |

TABLE 4. A sample of the Tencent user data.

| Longitude | Latitude | Location (2019-04-28T07:00) | Location (2019-04-28T07:30) | Location (2019-04-28T08:00) |
|-----------|----------|-----------------------------|-----------------------------|-----------------------------|
| 121.36    | 29.76    | 17                          | 12                          | 21                          |
| 121.36    | 29.77    | 12                          | 10                          | 15                          |

TABLE 5. NFCR according to the average speed interval [38].

| Average Speed (km/h) | NFCR | Average Speed (km/h) | NFCR |
|----------------------|------|----------------------|------|
| 0-2                  | 1.085137 | 36-38                | 2.361389 |
| 2-4                  | 1.258708 | 38-40                | 2.395369 |
| 4-6                  | 1.311138 | 40-42                | 2.441831 |
| 6-8                  | 1.477515 | 42-44                | 2.470396 |
| 8-10                 | 1.573123 | 44-46                | 2.538255 |
| 10-12                | 1.64575 | 46-48                | 2.566097 |
| 12-14                | 1.729985 | 48-50                | 2.581801 |
| 14-16                | 1.807417 | 50-52                | 2.595986 |
| 16-18                | 1.841056 | 52-54                | 2.6796 |
| 18-20                | 1.922954 | 54-56                | 2.715854 |
| 20-22                | 1.996735 | 56-58                | 2.755036 |
| 22-24                | 2.045498 | 58-60                | 2.809524 |
| 24-26                | 2.092286 | 60-62                | 2.864735 |
| 26-28                | 2.163184 | 62-66                | 2.926168 |
| 28-30                | 2.186922 | 66-70                | 3.049095 |
| 30-32                | 2.25144  | 70-80                | 3.289347 |
| 32-34                | 2.328849 | 80-90                | 3.550955 |

IV. METHODS

A. CARBON EMISSION ACCOUNTING BY TAXI TRAVEL

The VSP model has been used to estimate the output power of light-duty vehicles and has been employed to simulate the relationship between the vehicle’s operational state and fuel consumption [41]. The earliest VSP models used vehicle speed, vehicle acceleration, and road type to estimate fuel consumption. It is challenging to obtain the operating state of vehicles due to the high data requirements [38]. Scholars conducted large-scale experiments to find alternative solutions to simplify the calculations. Song and Tu conducted experiments to determine the relationship between the average vehicle speed and fuel consumption at each timestamp to improve the VSP model [42]. We use this method to calculate fuel consumption. The fuel consumption of each segment was determined as follows:

\[ f_{i,l} = ER_0 \times NFCR_l \times T_{i,l} \]  

where \( f_{i,l} \) is the actual fuel consumption of segment \( l \) of taxi \( i \); \( ER_0 \) represents the average fuel consumption rate of the taxi, which is set as 0.274 in Song and Tu’s experiments [43]; \( NFCR_l \) represents the normalized fuel consumption rate in the average speed interval \( l \) (see Table 5); \( T_{i,l} \) represents the driving duration (seconds) in the intermediate speed interval \( l \) of taxi \( i \).

The total fuel consumption of taxi \( i \) from the origin \((x_{oi}, y_{oi})\) to the destination \((x_{di}, y_{di})\), representing the total fuel consumption of a representative sample of intra-urban movement, can be expressed as follows:

\[ F_{i,j} = \sum_{l=1}^{n} f_{i,l} \]  

where \( F_{i,j} \) represents the total fuel consumption of taxi \( i \) from the origin to the destination; \( n \) represents the number of all records from the origin to the destination.
Since there is no noticeable difference in the vehicle type and engine size of taxis, the same emission factor and fuel consumption were used to calculate emissions. The total carbon emissions of a taxi journey were obtained according to Equations (1)-(2).

\[
C_{ij} = EF_{\alpha} * F_{i,j} = EF_{\alpha} \sum_{i=1}^{n} ER_{0} * NFCR_{1} * T_{i,j} \quad (3)
\]

where \( C_{ij} \) (kg) represents the trip’s carbon emissions by taxi \( i \), and \( ER_{\alpha} \) represents exhaust emission \( \alpha \), which is 2.18 kg/L [17].

The algorithm of travel emissions can be summarized as follows:

Step 1. Sort the Trajectory data are sorted according to the ID and timestamp.

Step 2. Use Equation (1) to calculate the emissions generated by the vehicle driving at 15-s intervals (the timestamp interval is 15 s).

Step 3. Determine the origin and destination record of the trip according to the vehicle’s driving state field.

Step 4. Calculate the total carbon emissions of the trip using Equation (3).

Step 5. Repeat steps 3 and 4 until there are no more origin records of the trip.

Methods for downscaling the travel behavior from the administrative scale include using traffic analysis zones, the grid-based method, and Tyson polygons. The fine-scale population downscaling approach is usually based on the grid-based method [39]. This study uses a 0.01 × 0.01 degree grid unit to match the population data.

**Definition 1:** Grid carbon emissions (GCE) are defined as all emissions generated by the travel demand in each research unit. The most critical factor in carbon emissions from daily travel is the travel demand, although travel trajectories may be distributed across multiple areas or roads. Therefore, computing the GCE requires that the trip’s origin is located in the grid, and not all trajectories fall entirely within this grid. The GCE is expressed as:

\[
C_{E} = \sum_{(x_{o},y_{o}) \in [x_{o},y_{e}]} C_{i,j} \quad (4)
\]

where \( \{x_{o},y_{o}\} \) represents the latitude and longitude range of each grid.

**Definition 2:** Grid average carbon emissions (GACE) are the weighted average of the trip emissions within each grid, reflecting the proportion of high emitters. The weight coefficient of the GACE is obtained based on the relationship between the number of trips and distance and is not the average value. The GACE is expressed as:

\[
\bar{C}_{E} = \frac{\sum_{(x_{i},y_{i}) \in [x_{o},y_{e}]} C_{i,j} \times f\left(x_{i,j}\right)}{\sum f\left(x_{i,j}\right)} \quad (5)
\]

where \( f\left(x_{i,j}\right) \) represents the weight coefficient.

In reality, travel costs increase with increasing travel distance, and there is a distinct distance decay when people travel by car [44]. Therefore, the decay function is considered a reliable parameter. After calculations, the relationship between the observed travel distance and the number of trips can be fitted using an exponential function, as demonstrated in other studies [45]. The weight coefficient is defined in Equation (6):

\[
f\left(d_{i,j}\right) = e^{\beta d_{i,j}} \quad (6)
\]

where \( d_{i,j} \) is the travel distance, and \( \beta \) is the decay coefficient.

**Definition 3:** The taxi TU reflects the relationship between the number of taxis and the total number of trips in each grid. Location entropy was used to determine the dominant regional factors and obtain the factors’ spatial concentrations. A significant advantage of this method is that it can calculate the aggregation degree of some aspects spatially without considering the number of other elements. The Tencent user density per hour was used to measure the population per grid. For each grid unit, the TU is defined as:

\[
u_k = \frac{e_k}{e_p} \quad (7)
\]

where \( e_k \) is the ratio of taxi gravel in grid \( k \) to all taxi trips, and \( e_p \) is the ratio of the number of residents in grid \( k \) to the number of all residents.

**B. NATURAL BREAKS MODEL FOR CLASSIFICATION**

The natural breaks method divides the research objects into groups with similar properties by calculating the natural break of the sequence. This method determines the optimum arrangement by iteratively comparing the sum of the squared differences between the element’s mean value and the observed value in each group, i.e., the variance goodness-of-fit. The calculated optimal classification threshold is the breakpoint in the ordered distribution of the sequence. The variance goodness-of-fit is defined in Equations (8)-(10).

\[
VGF_{j} = \frac{SDAM - SCDM_{j}}{SDAM} \quad (8)
\]

\[
SDAM = \sum_{i=1}^{n} \left( \frac{x_i - \bar{X}_j}{n} \right)^2 \quad (9)
\]

\[
SCDM_{j} = \sum_{i=1}^{k} \left( x_i - \bar{X}_{j,k} \right)^2 \quad (10)
\]

where \( VGF_{j} \) represents the variance goodness-of-fit of the jth iteration, \( SDAM \) represents the sum of squared deviations of the sequence, \( SCDM_{j} \) represents the sum of squared deviations of the category means of the jth iteration, \( n \) represents the sum of the series, \( x_i \) represents the ith value in the series, and \( \bar{X}_{j,k} \) represents the average value of all values in the kth combination of the jth iteration.

ArcGIS software was used to calculate the natural breaks and its verification indicators. The natural breaks method can estimate the breakpoint of the sequence to determine the optimal number of groups. The range of the variance goodness-of-fit is 0-1, and its value is proportional to the number of groups. However, too many clusters are not conducive to visualization and analysis. The optimum number of clusters occurs when the variance goodness-of-fit has stabilized [46].
C. SPATIAL AUTOCORRELATION METHOD

The Moran’s I was used to evaluate the spatial distribution characteristics of the travel emission sources. It is an indicator of spatial correlation. The Moran’s statistics is expressed as:

\[
I = \frac{n \sum_{i=1}^{n} \sum_{j=1}^{n} W_{ij} z_i z_j}{\sum_{i=1}^{n} \sum_{j=1}^{n} W_{ij} \sum_{i=1}^{n} z_i^2}
\]

where \( z_i \) represents the deviation of the attribute of element \( i \) from its average value, \( W_{ij} \) represents the spatial weight between element \( i \) and element \( j \), and \( n \) is the sum of the elements.

The statistical z-score is calculated as follows:

\[
Z = \frac{I - E[I]}{\sqrt{V[I]}}
\]

where \( E[I] \) is the weighted mean of the total emissions, and \( V[I] \) in the standard deviation.

ArcGIS software was used to calculate Moran’s I and the verification indicators. The Moran’s I value ranges from –1 to 1. When the value is close to 1, it indicates a positive correlation, and when the value is equal to 0, it means no correlation. \(|Z| > 2.58\) is regarded as statistically significant, and the confidence level of statistical significance is set to 99% (less than 0.01).

D. GEOGRAPHICALLY WEIGHTED REGRESSION MODEL

The GWR model is typically used to analyze spatial differences, including the spatial attributes of the data in the regression model. It is expressed as follows:

\[
y_i = \beta_{0(u_i,v_i)} + \beta_{k(u_i,v_i)} x_{ik} + \epsilon_i
\]

where \( y_i \) is a dimensional interpretation variable, \( x_{ik} \) is a dimensional interpretation variable matrix, \( \beta_{k(u_i,v_i)} \) is the regression coefficient of factor \( k \) at the regression point, \((u_i, v_i)\) represents the coordinates at the ith observation point, and \( \epsilon_i \) is the random error term of the independent distribution.

Existing studies have confirmed that population, trip distance, land use and the built environment affect traffic emissions [17]. The PD and vehicle use intensity are considered the main driving factors affecting emissions in the transportation sector in urban areas [47]. In this study, the explanatory variables were the PD (100 population) and the taxi TU in each grid, and the response variable was the carbon emissions by taxi travel in each grid.

The Gaussian kernel was chosen to calculate the spatial weighting coefficient, and the cross-validation method was selected to calculate the optimal bandwidth.

V. RESULTS

Ningbo is located on the southeast coast of China, 150 km from Shanghai. Ningbo’s per capita GDP was 143,157 RMB (around 20,752 USD) and ranked 13th of the 35 major cities across China in 2019. There are one central business district (CBD) and two sub-CBDs in the urban area. The proportion of new energy and clean energy in urban buses was 90% in 2020. Ningbo, one of the most representative large and medium-sized towns in China, is an excellent case for studying transport-related carbon emissions in China. The study area is located in the central urban district of Ningbo (light red color in Figure 2). The resolution of the research unit in this study is 0.01 × 0.01 degrees. The study area contains 731 grids (black grid in Figure 2).
TABLE 6. Comparison of travel information in each period.

| Time      | Trip volume | Distance(km) | Time(min) | Speed(km/h) | Emission(kg) |
|-----------|-------------|--------------|-----------|-------------|--------------|
|           |             |              |           | Average     | 1st Quantile | 3rd Quantile |
| 7:00-8:00 | 167162      | 5.93         | 13.6      | 24.9        | 24.9         | 30.25        |
| 8:00-9:00 | 152400      | 6.03         | 14.6      | 23.96       | 23.96        | 29.98        |
| 9:00-10:00| 172905      | 5.83         | 16.3      | 21.01       | 21.01        | 26.97        |
| 10:00-11:00| 171128     | 5.45         | 14.1      | 22.69       | 22.69        | 28.65        |
| 11:00-12:00| 183294     | 5.26         | 12.4      | 24.22       | 24.22        | 30.33        |
| 12:00-13:00| 197828     | 5.32         | 12.5      | 24.58       | 24.58        | 30.75        |
| 13:00-14:00| 184362     | 5.48         | 12.1      | 26.25       | 26.25        | 31.28        |
| 14:00-15:00| 178606     | 5.71         | 11.4      | 28.69       | 28.69        | 32.85        |
| 15:00-16:00| 179485     | 5.66         | 10.9      | 29.75       | 29.75        | 33.81        |
| 16:00-17:00| 170051     | 5.58         | 10.7      | 30.13       | 30.13        | 34.81        |
| 17:00-18:00| 136949     | 5.54         | 10.5      | 30.33       | 30.33        | 35.05        |
| 18:00-19:00| 91665      | 5.38         | 10.2      | 30.25       | 30.25        | 34.85        |

TABLE 7. Distance attenuation fitting in each period.

| Time      | Trip volume | decay coefficient | R²  |
|-----------|-------------|-------------------|-----|
| 7:00-10:00| 492467      | -0.136            | 0.9478|
| 10:00-13:00| 552250    | -0.142            | 0.9437|
| 13:00-16:00| 542453    | -0.140            | 0.9491|
| 16:00-19:00| 397765     | -0.144            | 0.9599|

TABLE 8. Spatial autocorrelation analysis results.

| Time      | Moran’s I | Variance | Z-score | P-Value |
|-----------|-----------|----------|----------|---------|
| GCE       | 7:00-10:00| 0.5904216 | 0.001190 | 17.26819 | p<0.001 |
|           | 10:00-13:00| 0.598889 | 0.001179 | 17.39334 | p<0.001 |
|           | 13:00-16:00| 0.599624 | 0.001113 | 18.01731 | p<0.001 |
|           | 16:00-19:00| 0.487547 | 0.001100 | 14.74432 | p<0.001 |
|           | 7:00-10:00| 0.490715  | 0.001271 | 13.80394 | p<0.001 |
|           | 10:00-13:00| 0.442703 | 0.001271 | 12.45668 | p<0.001 |
|           | 13:00-16:00| 0.478461 | 0.001271 | 13.45799 | p<0.001 |
|           | 16:00-19:00| 0.494230 | 0.001271 | 13.90135 | p<0.001 |

all less than 0.01, demonstrating that the travel emission data have a positive spatial autocorrelation (Moran’s I > 0). The total emissions from travel are more spatially clustered than the average emissions from travel because the Moran’s I is relatively high.

Figure 3 shows the number of groups obtained from the natural break method and the variance goodness-of-fit. The variance goodness-of-fit is close to 0.9 for 4 groups, at which point the fitting curve begins to stabilize. As mentioned, a large number of groups is not conducive to discovering data discontinuity and visualization; thus, 4 groups are used.

The values of 731 grids are divided into four groups according to natural breaks from high (group 1) to low (group 4). Table 9 lists the number of grids in each group and the proportion of total emissions. Although there are differences in the number of grids in different groups, the emission sources are concentrated in a few areas. During the morning peak period, the emissions from 14 grid areas account for about one-third of the total emissions. In the evening, the emissions of eight grids account for 40% of the total emissions. About 2.5%-6% of the region contributes approximately 45%-60% of the total emissions from travel.

Figure 4 and Figure 5, respectively, show the spatial distribution of the GCE and GACE. The color of the grid indicates high (red) and low (green) values. Specifically, the red grid in Fig. 4 represents the spatial distribution of the first group in Table 9, the orange grid represents the second group, the light green grid represents the third group, and the green grid represents the fourth group. The high carbon emissions sources by taxi travel occurred primarily in the CBD and sub-CBDs, and the core-periphery structure of carbon emissions represented a sharp gradient (Fig. 3). The airport (southwest of the city) is an isolated high travel emissions source area. However, high average travel carbon emissions areas are found in the suburbs, showing the opposite distribution characteristics.

C. GEOGRAPHICALLY WEIGHTED REGRESSION ANALYSIS

Figure 10 shows the results of the geographically weighted regression. The variance inflation factors (VIF) of the PD and TU are less than 10, indicating that the two independent variables do not exhibit multicollinearity and can be used for regression analysis. The adjusted $R^2$ of the GWR is about 0.979, showing that the PD and TU explain the quantitative relationship between car use and the emission sources.
from a spatial perspective. The Moran’s I index of the GWR residual is less than 0.001, indicating that the spatial effect of the residual is eliminated. Figure 6 shows the spatial distribution of the PD and TU regression coefficients. To compare the impact of different variables on regional traffic emissions, we used the same interval (500kg) to present the visual display. The color of the grid indicates high (red) and low (green) values. For every unit increase in the PD or car TU, the traffic emissions in the red grid area increases by more than 2000 kg per month, and those in the orange area increase by more than 1500-2000 kg per month. However, in the low-impact area (dark green grid), for every additional unit of PD or car TU, the increase in traffic emissions is less than 500kg per month. The highest value of the urban residential density coefficient occurs in the city center, exhibiting a peak. The TU coefficient has multiple peaks.

VI. DISCUSSION
Our results demonstrate that the sources of travel emissions are not randomly distributed. The proposed method provides new insights into the spatial distribution of emissions from daily travel.

TABLE 9. The number of grids in each group and the proportion of total emissions.

| Time     | Group 1(highest) | Group 2 | Group 3 | Group 4(lowest) | None data |
|----------|------------------|---------|---------|-----------------|-----------|
| 7:00-10:00 | 14grid (32.65%)  | 30grid (24.97%) | 92grid (29.09%) | 355grid (13.29%) | 240grid   |
| 10:00-13:00 | 5grid (18.59%)   | 14grid (25.44%) | 63grid (27.37%) | 402grid (11.21%) | 247 grid   |
| 13:00-16:00 | 6grid (26.11%)   | 15grid (25.29%) | 56grid (30.33%) | 367grid (18.27%) | 287 grid   |
| 16:00-19:00 | 8grid (41.08%)   | 17grid (23.46%) | 47grid (22.06%) | 289grid (12.85%) | 370grid   |

FIGURE 4. Spatial distribution of GCE. The color of the grid indicates high (red) and low (green) values.

FIGURE 5. Spatial distribution of GACE. The color of the grid indicates high (red) and low (green) values.

TABLE 10. The regression results of the geographically weighted regression.

| VIF(PD) | VIF(TU) | R²     | Adjusted R² | Residual Moran’s I |
|---------|---------|--------|-------------|-------------------|
| 1.063   | 2.540   | 0.98953| 0.97876     | p<0.001           |

A. SPATIAL CHANGES IN HIGH TRAVEL CARBON EMISSIONS
The kernel range of the travel emission sources has shrunk, but the contribution rate has increased significantly from the morning peak to the evening peak. There is a significant spatial difference between the distribution of daily travel emission sources and the distribution of the road network traffic emissions. Many studies on road emissions have shown that high vehicle emissions are clustered in the urban circle composed of urban expressways due to the high traffic volume and low-speed driving caused by congestion during peak travel times [20], [38], [48]. Travel carbon emissions are rooted in travel demand, although the travel
trajectories are distributed in multiple areas. The travel carbon emission sources in this study are mainly concentrated in the urban centers and suburban centers (see Figure 4). A significant spatial agglomeration (see Table 8) exhibiting a core-peripheral gradient is observed. The main reason is the dense population, with a high travel demand, which is consistent with existing research results [17]. However, the range of the source emissions has decreased, and the proportion of total emissions has increased significantly from the morning peak to the evening peak. The Moran’s I index dropped from 0.6 to 0.5, indicating that the spatial autocorrelation characteristics decreased. The classification obtained from the natural breaks indicates that 14 grids contributed one-third of total emissions and 8 grids contributed two-fifths of total emissions from morning peak to evening peak. The taxi (car) use during the evening rush hour shows more significant spatial aggregation. Table 6 shows that the average trip emissions during the evening rush hour are much lower than at other times. Encouraging low-carbon travel in high-emission source areas by increasing charging facilities and granting additional rights will significantly reduce emissions from urban travel. During the evening peak period, the use of taxis by residents within 5-10 km of the gathering center decreased. Maybe other modes of travel are suitable substitutes for cars.

The average travel emissions of suburban residents are significantly higher than that of densely populated urban centers. Residents close to the city center will avoid high emission trips during the morning peak. There are multiple high average emission kernels and significant spatial autocorrelation characteristics (see Table 8). High average travel emissions mean that the proportion of high emissions are high. Specifically, the weight of long-distance travel in the distance attenuation function is lower than that of short-distance travel. The 20% highest emitters produced approximately 40% of emissions. While many households have relocated to suburban areas, most job opportunities and amenities are still located downtown. The evidence is that most of these travelers’ destinations were in the center of the city. Similar studies showed that residents far away from urban centers emit high emissions from travel, but the results showed that only carbon emissions from commuting were affected [49], [50]. This result is inconsistent with our results. Many areas in the suburbs always have a high proportion of high emitters throughout the day and not only during the commuting period (see Figure 5). In China’s large and medium-sized cities, the suburban areas have lower land costs and enjoy more flexible policies, leading to the construction of many high-end residential spaces. High-income residential areas are generally considered areas with high car dependence and high emissions, explaining the suburbs’ persistently high average travel emissions. The urban center and its periphery continue to exhibit low-emission characteristics of moderate travel, especially in the morning peak period, covering a more comprehensive range. Relevant studies have shown that people in the city center will avoid long delays when traveling during the morning rush hour to reduce travel uncertainty [51], [52], which indirectly reduces the emission cost of travel.

B. REGRESSION ANALYSIS OF TRAVEL EMISSIONS

The PD and taxi (car) use ratio (TU) were used to explain the quantitative relationship between car use and travel emission sources, indicating spatial heterogeneity (see Table 9). The PD and TU regression coefficients show different spatial characteristics. The PD regression coefficient for travel emissions gradually decreases from the downtown area to the periphery, indicating that the travel carbon emissions are much higher in areas of dense population than in other regions. This conclusion is consistent with the results of previous studies because a high PD in those areas will lead to increased urban congestion and more car travel [17], [53]. Although scholars recognize that car usage plays a vital role in explaining car dependence and travel emissions, it is difficult to obtain accurate micro-scale data. The proportion of residents’ car use is usually obtained from questionnaire surveys, resulting in limited spatial coverage [18]. The analysis results show that the coefficient of taxi use has multiple peaks (see Figure 6b), which are located in populated urban centers.
areas, high-emission locations, and urban traffic bottlenecks. Improving public transport accessibility in these high-impact areas will help alleviate travel emissions. A comparison of Figure 4 and Figure 6 indicates that the concentration center of the emission source is the overlap area of the PD and TU coefficient peaks. This result demonstrates that despite the reduction in average travel emissions during the evening peak period, a slight increase in PD and car usage led to a significant increase in travel emissions.

C. SUGGESTIONS FOR POLICY IMPROVEMENT

Several government interventions could positively reduce daily travel carbon emissions. First, our research results show the spatial distribution of high emissions. Government intervention aimed at low-carbon travel in these areas will improve the efficiency of energy-efficient technologies. Densely populated areas are high-emission sources, but the proportion of high emissions is relatively low because the proportion of long-distance travel is relatively low. Providing more convenient shared bicycle services will help people choose low-carbon trips. Second, many high emitters are concentrated in the suburbs of the city. The promotion of services such as customized buses in the identified areas could reduce emissions and alleviate congestion. Ningbo City has a single urban center despite attempts to create two new districts in urban planning. Transportation carbon emissions are much lower in urban areas with multiple employment centers than in scattered urban areas with single employment centers. Third, there are apparent spatial differences in the effect of PD and car use on travel emissions. It is recommended to increase employment opportunities and the residential population in areas with high PD coefficients. It is also suggested to evaluate the convenience of public transportation in areas with high automobile use impact coefficients. Our research can be used to monitor changes in the spatial distribution of emission sources from daily trips during urban development.

D. LIMITATIONS

The method in this article can also be used to calculate the emissions of other pollutants such as NOX, although the current analysis was only conducted for carbon emissions. The results of this study indicate the need for further research. First, our case study considered only a single city in China. It is unknown if the results are similar for other areas, which has to be examined in the future. Second, the grid data classification methods may be controversial, but different classifications show the same results. Third, another potential limitation is that our only taxis were considered. Government authorities may have the power to utilize private car trajectory data to calculate the results using our method. Follow-up studies will further discuss the travel emissions of different vehicle types.

VII. CONCLUSION

Our study analyzed the sources of daily travel emissions within a city at a finer scale than the administrative level to examine the distribution of travel emissions sources and identify high-emission areas. The proposed method was then applied in a comprehensive case study in Ningbo, China. Grid-scale travel emissions were estimated, and the main influence factors were analyzed based on one-month taxi trajectory data. The research results revealed the spatio-temporal characteristics of the emission sources of car trips. In addition, the results also emphasize the spatial heterogeneity of the impact of PD and car use on emissions. Subsequent studies will further consider the calculation of emission values for different vehicle types. The effect of land use and space on travel emissions will also be the main objects of the authors’ follow-up research.

REFERENCES

[1] C. Wang, F. Wang, X. Zhang, Y. Yang, Y. Su, Y. Ye, and H. Zhang, “Examining the driving factors of energy related carbon emissions using the extended STIRPAT model based on IPAT identity in Xinjiang,” Renew. Sustain. Energy Rev., vol. 67, pp. 51–61, Jan. 2017, doi: 10.1016/j.rser.2016.09.006.

[2] C. Z. Zhu, M. Wang, and Y. R. Yang, “Analysis of the influencing factors of regional carbon emissions in the Chinese transportation industry,” Energies, vol. 13, no. 5, p. 1100, Mar. 2020, doi: 10.3390/en13051100.

[3] G. Fontaras, N.-G. Zacharof, and B. Ciuffo, “Fuel consumption and CO2 emissions from passenger cars in Europe—Laboratory versus real-world emissions,” Prog. Energy Combustion Sci., vol. 60, pp. 97–131, May 2017, doi: 10.1016/j.pecs.2016.12.004.

[4] Y. Geng, Z. Ma, B. Xue, W. Ren, Z. Liu, and T. Fujita, “Co-benefit evaluation for urban public transportation sector—A case of shanghai, China,” J. Cleaner Prod., vol. 58, pp. 82–91, Nov. 2013, doi: 10.1016/j.jclepro.2013.06.034.

[5] B.-B. Peng, Y. Fan, and J.-H. Xu, “Integrated assessment of energy efficiency technologies and CO2 abatement cost curves in China’s road passenger car sector,” Energy Convers. Manage., vol. 109, pp. 195–212, Feb. 2016, doi: 10.1016/j.enconman.2015.11.064.

[6] X. Luo, L. Dong, Y. Dou, N. Zhang, J. Ren, Y. Li, L. Sun, and S. Yao, “Analysis on spatial-temporal features of taxis’ emissions from big data informed travel patterns: A case of shanghai, China,” J. Cleaner Prod., vol. 142, pp. 926–935, Jan. 2017, doi: 10.1016/j.jclepro.2016.05.161.

[7] T. Huo, R. Cao, H. Du, J. Zhang, W. Cai, and B. Liu, “Nonlinear influence of urbanization on China’s urban residential building carbon emissions: New evidence from panel threshold model,” Sci. Total Environ., vol. 772, Jun. 2021, Art. no. 145058, doi: 10.1016/j.scitotenv.2021.145058.

[8] X. Zhou and T. Kuosmanen, “What drives decarbonization of new passenger cars?” Eur. J. Oper. Res., vol. 284, no. 3, pp. 1043–1057, Aug. 2020, doi: 10.1016/j.ejor.2020.01.018.

[9] W. R. Morrow, K. S. Gallagher, G. Collantes, and H. Lee, “Analysis of policies to reduce oil consumption and greenhouse-gas emissions from the US transportation sector,” Energy Policy, vol. 38, no. 3, pp. 1305–1320, Mar. 2010, doi: 10.1016/j.enpol.2009.11.006.

[10] S. Lee and B. Lee, “The influence of urban form on GHG emissions in the US household sector,” Energy Policy, vol. 68, pp. 534–549, May 2014, doi: 10.1016/j.enpol.2014.01.024.

[11] C. Brand, J. Anable, and C. Morton, “Lifestyle, efficiency and limits: Modelling transport energy and emissions using a socio-technical approach,” Energy Efficiency, vol. 12, no. 1, pp. 187–207, Jan. 2019, doi: 10.1007/s12051-018-9678-9.

[12] H. Wang and X. Zhang, “Spatial heterogeneity of factors influencing transportation CO2 emissions in Chinese cities: Based on geographically weighted regression model,” Air Qual. Atmos. Health, vol. 13, no. 5, pp. 977–989, Aug. 2020, doi: 10.1007/s12524-020-00854-2.

[13] P. Rong, L. Zhang, Y. Qin, Z. Xie, and Y. Li, “Spatial differentiation of daily travel carbon emissions in small-and medium-sized cities: An empirical study in Kaifeng, China,” J. Cleaner Prod., vol. 197, pp. 1365–1373, Oct. 2018, doi: 10.1016/j.jclepro.2018.06.205.

[14] D. Sun, Y. Zhang, R. Xue, and Y. Zhang, “Modeling carbon emissions from urban traffic system using mobile monitoring,” Sci. Total Environ., vol. 599, pp. 944–951, Dec. 2017, doi: 10.1016/j.scitotenv.2017.04.186.
X. Zhang, Z. Zhao, Y. Zheng, and J. Li, “Prediction of taxi destinations targeting high-emitting trips,” Transp. Res. Rec., Transp. Res. Board, vol. 2672, no. 25, pp. 11–20, Dec. 2018, doi: 10.1177/0361366618875514.

C. Y. Xia, M. Xiang, F. Kung, Y. Li, Y. Ye, Z. Shi, and J. Liu, “Spatial-temporal distribution of carbon emissions by daily travel and its response to urban form: A case study of Hangzhou, China,” J. Clean Prod., vol. 257, p. 11, Jun. 2020, Art no. 120797, doi: 10.1016/j.jclepro.2020.120797.

Y. Yang, C. Wang, and W. Liu, “Urban daily travel carbon emissions accounting and mitigation potential analysis using surveyed individual data,” J. Cleaner Prod., vol. 192, pp. 821–834, Aug. 2018, doi: 10.1016/j.jclepro.2018.05.025.

D. Sun and Y. Zhang, “Influence of avenue trees on traffic pollutant dispersion in asymmetric street canyons: Numerical modeling with empirical analysis,” Transp. Res. D, Transp. Environ., vol. 65, pp. 784–795, Dec. 2018, doi: 10.1016/j.trd.2017.10.014.

D. J. Sun, K. Zhang, and S. Shen, “Analyzing spatiotemporal traffic line source emissions based on massive Didi online car-hailing service data,” Transp. Res. D, Transp. Environ., vol. 62, pp. 699–714, Jul. 2018, doi: 10.1016/j.trd.2018.04.024.

M. Sun, C. Gao, C. Xue, S. Zhang, and C. Li, “A data-driven method for measuring accessibility to healthcare using the spatial interpolation model,” IEEE Access, vol. 9, pp. 64972–64982, 2021, doi: 10.1109/access.2021.3075494.

X. Zhang, Z. Zhao, Y. Zheng, and J. Li, “Prediction of taxi destinations using a novel data embedding method and ensemble learning,” IEEE Trans. Intell. Transp. Syst., vol. 21, no. 1, pp. 68–78, Jan. 2020, doi: 10.1109/TITS.2018.2888587.

D. J. Sun and X. Ding, “Spatiotemporal evolution of ridesourcing markets under the new restriction policy: A case study in Shanghai,” Transp. Res. A, Pract. Policy, vol. 130, pp. 227–239, Dec. 2019, doi: 10.1016/j.tra.2019.09.052.

F. Zhang, X. Zhu, W. Guo, X. Ye, T. Hu, and L. Huang, “Analyzing urban human mobility patterns through a thematic model at a finer scale,” ISPRS Int. J. Geo-Inf., vol. 5, no. 6, p. 78, Jun. 2016, doi: 10.3390/ijgi5060078.

F. Xia, J. Wang, X. Kong, Z. Wang, J. Li, and C. Liu, “Exploring human mobility patterns in urban scenarios: A trajectory data perspective,” IEEE Commun. Mag., vol. 56, no. 3, pp. 142–149, Mar. 2018, doi: 10.1109/MCOM.2018.1700242.

S. An, X. Hu, and J. Wang, “Urban taxis and air pollution: A case study in harbin, China,” J. Transp. Geog., vol. 19, no. 4, pp. 960–967, Jul. 2011, doi: 10.1016/j.jtrangeo.2010.12.005.

P. Hossain, M. K. E. Vardoulakis, L. Pirjola, and R. Britter, “Dynamics and dispersion modelling of nanoparticles from road traffic in the urban atmospheric environment—A review,” J. Aerosol Sci., vol. 42, no. 9, pp. 580–603, Sep. 2011, doi: 10.1016/j.jaerosci.2011.06.001.

M. P. Keucken, M. Moerman, M. Voogt, P. Zandveld, H. Verhagen, U. Stelwagen, and D. J. De, “Particle number concentration near road networks under the new restriction policy: A case study in Shanghai,” Transp. Res. D, vol. 7, pp. 149132–149141, 2019, doi: 10.1016/j.trd.2019.2945000.

Y. Yao, X. Liu, X. Li, J. Zhang, Z. Liang, K. Mai, and Y. Zhang, “Mapping fine-scale population distributions at the building level by integrating multisource geospatial big data,” Int. J. Geogr. Inf. Sci., vol. 31, pp. 1220–1244, Jun. 2017, doi: 10.1080/13658816.2017.1290252.

N. Cressie, “The origins of Kriging,” Math. Geol., vol. 22, no. 3, pp. 239–252, Apr. 1990, doi: 10.1007/BF00898887.

G. Song, “Study on traffic fuel consumptions and emissions model for traffic strategy evaluation,” Ph.D. dissertation, School Traffic Transp., Beijing Jiaotong Univ., Beijing, China, 2008.

T. Zhao, “On-road fuel consumption algorithm based on floating car data for light-duty vehicles,” M.S. thesis, School Traffic Transp., Beijing Jiaotong Univ., Beijing, China, 2009.

T. M. Oshan, “Potential and pitfalls of big transport data for spatial interaction models of urban mobility,” Prog. Geogr., vol. 72, no. 4, pp. 468–480, Oct. 2020, doi: 10.1080/03031242.2020.1787180.

J. W. Wang, F. Y. Du, J. Huang, and Y. Liu, “Access to hospitals: Potential vs. observed,” Cities, vol. 100, May 2020, Art no. 102671, doi: 10.1016/j.cities.2020.102671.

S. Golan, B. Saghaﬁan, S. Sheshangosht, and H. Ghalkhani, “Comparison of classiﬁcation and clustering methods in spatial rainfall pattern recognition at northern Iran,” Theor. Appl. Climatol., vol. 102, nos. 3–4, pp. 319–329, Nov. 2010, doi: 10.1007/s00704-010-0267-x.

Z. Zhang and W. Liu, “Determinants of CO2 emissions from household daily travel in Beijing, China: Individual travel characteristic perspectives,” Appl. Energy, vol. 158, pp. 292–299, Nov. 2015, doi: 10.1016/j.apenergy.2015.08.065.

Z. R. Wang, H. X. Zhou, Y. Si, and Y. H. Li, “Role of traffic emission on temporal and spatial characteristics of pollutant concentration on urban road network: A case of Beijing,” J. Adv. Transp., vol. 2020, Nov. 2020, Art no. 8883697, doi: 10.1155/2020/8883697.

C. Brand, A. Goodman, H. Rutter, Y. Song, and D. Ogilvie, “Associations of individual, household and environmental characteristics with carbon dioxide emissions from motorised passenger travel,” Appl. Energy, vol. 104, pp. 158–169, Apr. 2013, doi: 10.1016/j.apenergy.2012.11.001.

J. Ma, Z. Liu, and Y. Chai, “The impact of urban form on CO2 emission from work and non-work trips: The case of Beijing, China,” Habitat Int., vol. 47, pp. 1–10, Jun. 2015, doi: 10.1016/j.habitatint.2014.12.007.

S. D. Luo, “Departure and travel time model for the temporal distribution of morning rush-hour traffic congestion,” Int. J. Mod. Phys. C, vol. 20, no. 2, Feb. 2009, doi: 10.1142/S0129181409010082.

L.-L. Xiao, T.-L. Liu, and H.-J. Huang, “On the morning commute to urban human mobility patterns through a thematic model at a finer scale,” ISPRS Int. J. Geo-Inf., vol. 47, pp. 1–10, Jun. 2015, doi: 10.1016/j.habitatint.2014.12.007.

C. Brand, A. Goodman, H. Rutter, Y. Song, and D. Ogilvie, “Associations of individual, household and environmental characteristics with carbon dioxide emissions from motorised passenger travel,” Appl. Energy, vol. 104, pp. 158–169, Apr. 2013, doi: 10.1016/j.apenergy.2012.11.001.

M. Sun et al.: Analyzing Spatiotemporal Daily Travel Source Carbon Emissions Based on Taxi Trajectory Data
M. Sun et al.: Analyzing Spatiotemporal Daily Travel Source Carbon Emissions Based on Taxi Trajectory Data

MAOPENG SUN was born in Yanji, Jilin, China, in 1990. He received the B.S. degree in electronic commerce and the M.S. degree in transportation planning and management from Chang’an University, Xi’an, China, in 2013 and 2016, respectively, where he is currently pursuing the Ph.D. degree in transportation planning and management. His research interests include traffic data mining and transportation planning.

CHENLEI XUE was born in Xi’an, Shaanxi, China, in 1990. She received the B.S. degree in international business from Xi’an Jiaotong University City College, in 2013. She is currently pursuing the Ph.D. degree in transportation engineering with the School of Transportation Engineering, Chang’an University, China. Her research interest includes transportation planning.

YANQIU CHENG received the bachelor’s and master’s degrees from the Highway College, Chang’an University, China. He is currently pursuing the Ph.D. degree with the Department of Traffic Engineering, Chang’an University. From September 2018 to July 2020, he was a Visiting Scholar with Missouri University of Science and Technology. His research interests include urban transportation analysis and planning and transportation system modeling.

LING ZHAO was born in Nanjing, Jiangsu, China, in 1992. She received the B.S. degree in electronic commerce and the M.S. degree in transportation planning and management from Chang’an University, Xi’an, China, in 2014 and 2017, respectively. She is currently a Lecturer with Nanjing Vocational Institute of Transport Technology. Her research interests include traffic data mining and transportation planning.

ZHIYOU LONG received the B.S. degree in logistics management from Southwest Minzu University, Chengdu, China, in 2020. He is currently pursuing the master’s degree in transportation engineering with the School of Transportation Engineering, Chang’an University, Xi’an, China. His research interests include traffic big data mining and intelligent perception road data calibration.