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Research article

Revealing the spatial variation in vehicle travel time with weather and driver travel frequency impacts: Findings from the Guangdong–Hong Kong–Macao Greater Bay Area, China

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Abstract: Vehicle travel time information is an essential location-based services that can be used to assess highway traffic conditions and provide valuable insights for transit agencies and travelers. To reveal the spatial variation in vehicle travel time with multiple factors, a multiple regression model and a geographically weighted regression model are used to investigate the associations between travel time and various factors. This study draws on freeway toll data in combination with local weather station records on Fridays over 12 months (286,406 travel information data points), and the Guangdong-Hong Kong-Macao Greater Bay Area (GBA), China, is used as a case study for examining the influence of weather and driver travel frequency on vehicle travel time. The results show that i) travel frequency along an origin-destination (OD) route has a significant effect on travel time, and this effect is approximately 3 to 100 times that of other explanatory variables; ii) rainfall significantly impacts travel time, with an effect that is 1.9 to 8.26 times that of other weather factors; and iii) both weather and driver travel frequency factors display spatial heterogeneity. These findings provide valuable insights for both traffic management and freeway travelers.

Keywords: travel time; spatial heterogeneity; geographically weighted regression; weather; travel frequency

1. Introduction

Travel time is an important performance indicator of the transportation system and is essential for travelers [1]. Numerous studies [2–4] have confirmed that travel time has a specific impact on travel behavior. Specifically, Li et al. [2] showed that travel time was significantly correlated with travel mode choice. Long et al. [3] revealed the influence of travel time information on travelers' route choices. Rasouli and Timmermans [4] suggested that increasing travel times might lead to the adaptation of activity-travel schedules. In summary, the study of travel time is of great value and can serve as a reference for travelers' activity schedules and improve travel satisfaction.

Travel time varies due to traffic flow, climatic conditions and other factors [5]. Some studies attach spatial labels to environmental impacts when studying travel time, but most of these spatial labels refer to adjacent areas (such as upstream and downstream roads) [6–8]. As a result, very little is known about how the impacts of various factors, such as the weather, on the travel time vary in different urban contexts. In addition, some researchers [9–11] have studied the effect of driving behavior (such as route familiarity and vehicle familiarity) on vehicle speed, which directly affects travel time. However, these studies focused on driving simulations or small road observation samples due to the lack of a complete dataset. Therefore, it is necessary to verify these experimental results with large sample data covering a wide geographical range.

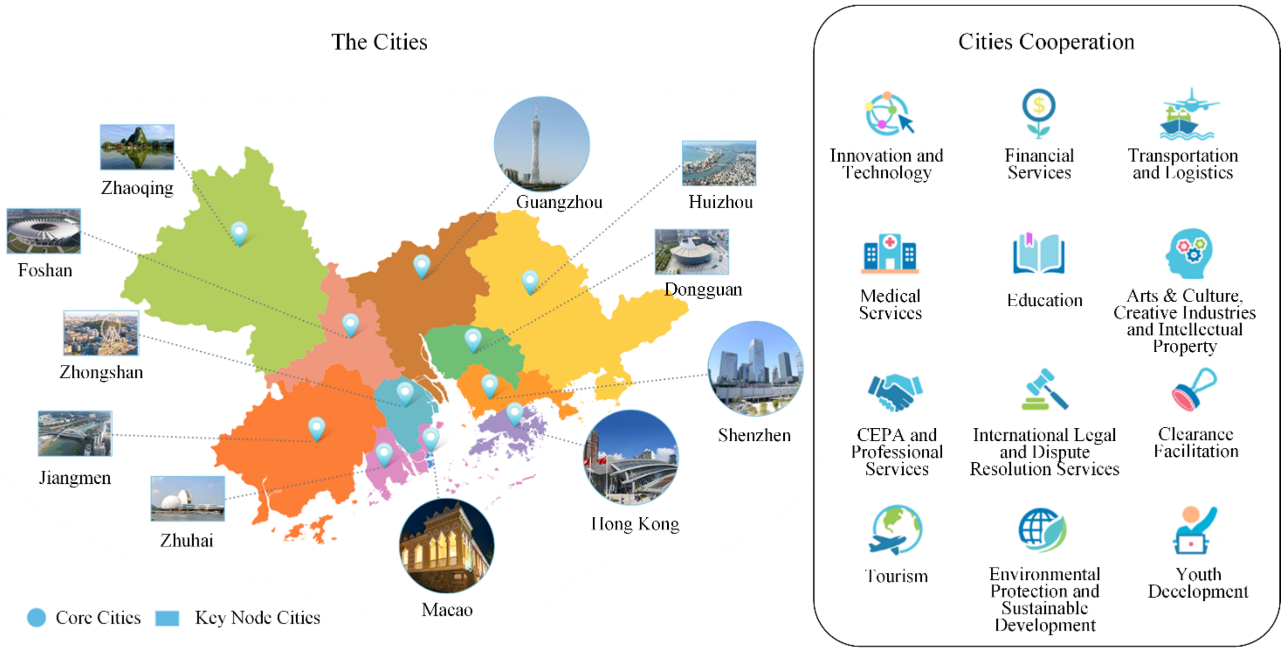


Figure 1. GBA city location and cooperation (source: https://www.bayarea.gov.hk/).

With a total population of more than 86 million and a GDP of USD 1668.8 billion in 2020 [12], the Guangdong-Hong Kong-Macao Greater Bay Area (GBA) is a mega-urban region in China's Pearl River Delta, comprising two special administrative regions and nine municipalities in Guangdong Province (see Figure 1). The development of the GBA is part of critical strategic planning in the national development blueprint to promote in-depth regional integration and coordinated economic growth to develop a world-class megacity area suitable for living, working, and tourism [12]. The cooperation between cities in the GBA covers many aspects, such as innovation and technology, financial services, transportation and logistics, and tourism (see Figure 1). As of the end of 2017, the freeway mileage in the GBA had exceeded 4000 kilometers, making it one of the areas with the highest freeway network density in China [13]. The freeway network density in the core area of the GBA has exceeded that of the New York Bay Area in the U.S. and the Tokyo Bay Area in Japan [13].

With its high-density traffic network and vast population base, the GBA has generated massive demand for transportation [14], drawing widespread attention. Many researchers [15–17] have researched the economy, environment, and transport in the region. However, few studies have focused on travel times in the GBA. A closed and managed freeway network can provide a large amount of travel data for the GBA with its large population and well-developed freeway network. These data are refined to the individual vehicle level, including the departure place and time of the vehicles, making it possible to study travel time comprehensively. In addition, the GBA has a broad spatial scope, creating an opportunity to explore the spatial impact of travel time. Therefore, taking the GBA as the research area to study how different factors affect travel time in different regions has the advantages of a complete dataset and a wide geographical range and can provide valuable insights for travelers in the GBA.

The rest of this paper is organized as follows. Section 2 gives a literature review of relevant studies. Section 3 presents the study area and related data. Section 4 provides our models and elaborates on our analytical approaches. Section 5 discusses the analysis results and summarizes the significant findings of the research. Section 6 includes conclusions and future directions.

2. Literature review

There has been a considerable amount of research into travel time. Various methodologies have been used in previous studies, which have obtained valuable research results (see Table 1). These studies mainly considered three aspects: traffic flow parameters, traffic environmental factors, and spatial information.

Many studies [1,18–20] have focused on predicting or estimating travel time by analyzing traffic flow parameters such as historical travel times, speed, and volume. Zhang and Rice [20] developed a time-varying coefficient linear model to describe the relationship between the anticipated travel time and a travel time estimate using currently available data. To estimate the expected travel time using speed and volume data, Yeon et al. [19] developed a model using discrete-time Markov chains (DTMCs) in which the states corresponded to whether the links were congested. Fei et al. [18] predicted online short-term travel time using a Bayesian inference-based dynamic linear model (DLM), which considered that the expected freeway travel time consisted of the median of historical travel times, time-varying random variation in travel time, and a model evolution error. Yildirimoglu and Geroliminis [1] used a congestion search algorithm that combined real-time and historical traffic data to predict the experienced travel times.

Table 1. Summary of the factors considered in existing studies.

Author	Main factors	Method	Results
Traffic flow parameters			
Zhang and Rice [20]	• Anticipated trip travel time • Travel time estimated using current data	Time-varying coefficient linear model	Propose a method to predict freeway travel times
Yeon et al. [19]	• Speed and volume	Discrete-time Markov chains considering the probability of breakdown, and freeway links	Propose a method to predict freeway travel times
Fei et al. [18]	• Median historical travel times • Time-varying random variation in travel time • Model evolution error	Bayesian inference-based dynamic linear model	Present a model to predict online short-term travel time on a stretch of freeway
Yildirimoglu and Geroliminis [1]	• Historical and real-time traffic information (5-min volume, occupancy, and speed averages)	Development of stochastic congestion maps and an online congestion search algorithm	Propose a method to predict travel times
Traffic environment factors			
Wang et al. [21]	• Traffic factors (traffic volume, speed, event) • Weather (rainy, cloudy, or sunny)	Exclusive disjunctive soft set theory	Propose a method to predict travel times
Li et al. [22]	• Objective factors (traffic volume, vehicle speed) • Weather (rain intensity, visibility)	Exclusive disjunctive soft set theory	Propose a method to predict travel times
Caceres et al. [23]	• Different roadway types • Weather (normal weather, adverse weather) • Time of day	Travel time distribution	Adverse weather clearly shows negative impacts on the travel time reliability of urban corridors
Zou et al. [24]	• Time of day • Day of week • Inclement weather • Traffic incidents	Probabilistic model	Weather conditions, except for snow, incur a minor impact on off-peak and weekend travel times, whereas peak travel times are highly variable under different weather conditions
Sophia et al. [5]	• Aerosol optical depth • Precipitation • Temperature • Night light data	Linear regression, ridge regression, random forest regression, and elastic net regression	Propose a method to predict travel times
Wan et al. [25]	• Travel information service level • Drivers' road selections	Bayesian methods	Improving travel information services can help drivers to travel more effectively and allow travel information systems to achieve the expected targets and benefits
Pirc et al. [26]	• Indirect travel time estimation • Level of service	Multiple linear regression	Propose a method to predict travel times
Spatial information			
Zou et al. [8]	• Travel time of the upstream links	Space-time diurnal (ST-D) method	The ST-D method is more robust than the traditional vector autoregressive models
Lee et al. [6]	• Travel time of the upstream links	Spatiotemporal algorithm based on a gated recurrent unit (GRU), the recurrent neural network, long short-term memory, and GRU models with the conventional algorithm	The spatiotemporal GRU predicted link and route travel times most accurately among the four models
Yang and Qian [7]	• Incident features, speed, volume, and other characteristics with location information	LASSO linear regression, stepwise regression, and random forest	Features that include speed, incidents, travel demand level, visibility, precipitation intensity, weather type, wind speed/gust, and pavement conditions are helpful in predicting travel time
Parent and LeSage [27]	• Freeway expenditures and lane miles • Gasoline taxes and traffic volumes	Spatial dynamic panel data model Log-linear relationship	The impact of some factors on travel time could spread to neighboring regions due to the substantial spatial spillovers

Traffic environmental factors that lead to travel time variations have also been considered in some research. Many studies [21–24] have indicated that weather conditions affect travel time. Specifically, when establishing a travel time model based on soft set theory, Wang et al. [21] classified the weather conditions into rainy, cloudy, and sunny categories. Li et al. [22] focused on the impacts of rain intensity and visibility when studying the influence of weather conditions on freeway travel time predictions. It has been demonstrated that only adverse weather can cause a significant effect on traffic conditions, and detailed weather conditions were further aggregated according to their severity in some research [23,24]. In addition to the weather, these studies have also considered factors including time, traffic events, and roadway types [21,23,24]. Moreover, Sophia et al. [5] used a machine learning algorithm and big data to understand how weather and night light data (as a measurement of economic activity) help predict travel times. Wan et al. [25] analyzed the effect of different travel information service levels on travel time prediction error. Pirc et al. [26] used multiple linear regression to combine direct travel time measurements, indirect travel time estimation, and qualitative data regarding the level of service.

Despite abundant approaches that have been proposed in travel time prediction, spatial information has rarely been considered in prediction models [8]. Geographically dispersed travel times, such as the travel times of upstream links, have been used as predictors to obtain accurate travel time predictions [6,8]. Incident features, speed, volume, and other characteristics with location information (e.g., upstream or downstream, alternative routes, the opposite direction) have been shown to increase understanding of the correlations between freeway congestion and various spatiotemporal features and to predict travel time [7]. The limitation of these studies is that they focused only on the spatial impact between sections. Parent and LeSage [27] estimated the relationship between statewide average work commute times and other factors, including freeway expenditures and lane miles, gasoline taxes, and traffic volumes. The results demonstrated that the impact of some factors on travel time might spread to neighboring regions due to substantial spatial spillovers.

The geographically weighted regression (GWR) model can explain the spatial heterogeneity of the research object because it allows the regression coefficient of the dependent variable to change with space [28,29]. In recent years, the GWR model has been widely used to solve complicated spatially heterogeneous problems in transport research, such as modeling annual average daily traffic [30,31], analyzing the causes of spatial regionality in traffic accident black spots [32], capturing the spatial heterogeneity in travel demand [33], and exploring the effects of the built environment on vehicle crashes [34], traffic states [29] and the average travel speed of road sections [35]. These studies have proven the effectiveness of GWR in studying spatial characteristics in the transportation field.

Three issues from previous studies can be summarized as follows:

i) Most studies assessing the impact of spatial information on travel time consider only the spatial impact between sections, such as upstream or downstream, alternative routes, and opposite directions. Few studies have examined the spatial heterogeneity of travel time from a broader perspective (e.g., urban agglomeration). Existing research in the field of transportation has indicated that the traffic situation is spatially heterogeneous based on the inherent shape of the examined city. Therefore, it is necessary to explore the spatial influence of various factors on travel time considering a very large geographical scope.

ii) There was no significant spatial difference in weather in previous studies due to their small study areas. Although the weather has been proven to affect travel time, the spatial heterogeneity of the impact of weather on travel time has not been discussed. Whether the effect of weather on travel time is spatially unstable is an area worth exploring.

iii) Existing studies on travel time were primarily focused on improving traffic management, so they explored only the impact of environmental factors on travel time. Driver influences (e.g., the driver's familiarity with the route) were not incorporated into these studies. The extent to which the environment and the driver affect travel times could thus not be compared.

In summary, this study contributes to the literature in the following aspects:

- This study analyzes the spatial heterogeneity of vehicle travel time in the GBA using large-scale freeway toll data. It provides a comprehensive understanding of various factors affecting vehicle travel time at the level of the urban agglomeration.
- We explore the impact of the number of times travelers use the route and freeway network on travel time, comparing the extent to which environmental factors such as weather, traffic volume, and travel frequency affect travel time.
- GWR is utilized to investigate the spatial divergences of crucial factors, such as the impact of real-time weather on travel time, which can help better understand the spatial heterogeneity of travel time determinants.

3. Data preparation

3.1. Study area

The study area is the GBA, including nine cities (Guangzhou, Shenzhen, Zhuhai, Foshan, Huizhou, Dongguan, Zhongshan, Jiangmen, and Zhaoqing) and the two Special Administrative Regions of Hong Kong and Macau. This area is one of the most competitive urban agglomerations worldwide and one of the areas with the highest density of freeway networks in China. Utilizing large-scale traffic data to explore the influencing factors of vehicle travel time will contribute to improving the traffic management of this notable urban agglomeration. In addition, as it is located between 21.3–24.2°N and 111.2–115.3°E and covers a total area of 56,000 square kilometers, the GBA has a complex topography and varying natural conditions [36], which makes it an excellent case study for exploring the spatial impact of weather on vehicle travel time. The GBA can be divided into forty-three research units according to their administrations, connections, and data source rules according to the studies by Lin et al. [14,16]; this division performs effectively in studying the transportation flow of the GBA city group. The zoning results and the abbreviations of the corresponding regions in the study are shown in Figure 2.

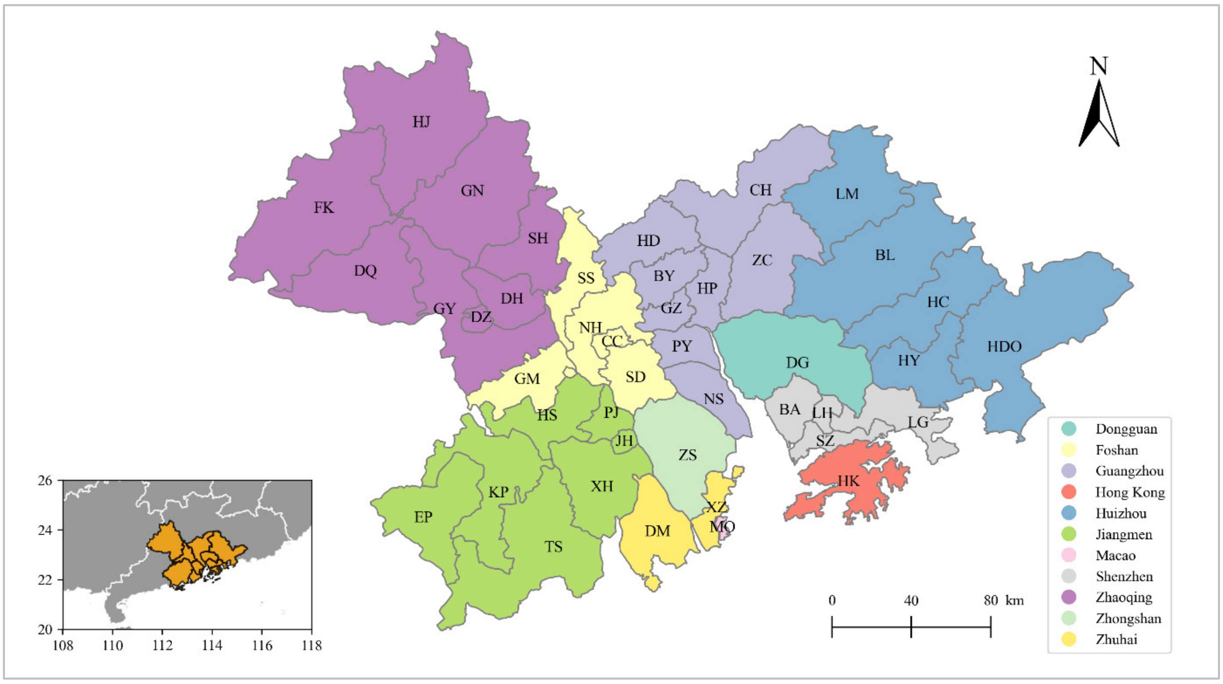


Figure 2. Geographical location and research units in the GBA.

3.2. Data sources and data processing

The primary data used in this study, the toll data, are obtained from the Guangdong Provincial Department of Transportation. The obtained dataset has various types of trip information, such as origins and destinations, departure and arrival times, vehicle types, and encrypted plate indices. According to the zoning results, a toll station is randomly selected as the origin or destination for each district. In particular, due to the lack of data on Hong Kong and Macao, freeway toll stations close to Hong Kong and Macao are used as alternatives. The dataset covers 304,228 trip information points of 169,160 cars recorded by 43 toll stations on all Fridays in 2019. In addition, the weather data (including temperature, wind, visibility, and rainfall) contained 11,230 records from the National Meteorological Administration of China.

Data outliers are filtered based on the following principles. Data with abnormal time information, such as arrival times earlier than or equal to departure times, are excluded. Records of departures and arrivals at the same toll station or data with zero mileage are considered unreasonable. Travel records corresponding to nonstandard encrypted license plate indices are not used. After data cleaning, 286,406 trip information points are used for the final analysis. For weather data processing, the very rare evident abnormalities must be replaced by the average value of the nearest three stations.

Summary statistics for the study variables included in this study are described in Table 2. The classification of explanatory variables and the visual description of the data features are shown in Figure 3. The dependent variable of this study is the log-transformed travel time of cars on all Fridays in 2019. The explanatory variables are mainly divided into four categories: weather, traffic volume, travel frequency, and travel distance. A detailed description of the dependent and explanatory variables is as follows.

Table 2. Definitions and descriptive statistics of variables.

Variables	Definitions	Unit	Min	Max	Mean	Sd.
Dependent variables						
Log travel time	Log-transformed travel time.		5.34	14.72	7.48	0.85
Independent variables						
Weather						
Temperature_O	The hourly highest temperature at the origin.	℃	8.7	37.1	24.87	5.81
Rainfall_O	Cumulative hourly precipitation at the origin.	mm	0	38.3	0.20	1.53
Visibility_O	Hourly minimum visibility at the origin.	km	0.2	50.0	20.77	9.87
Windspeed_O	Hourly average wind speed at the origin.	m/s	0	11.7	2.36	1.27
Temperature_D	The hourly highest temperature at the destination.	℃	8.7	37.1	24.88	5.75
Rainfall_D	Cumulative hourly precipitation at the destination.	mm	0	38.3	0.21	1.59
Visibility_D	Hourly minimum visibility at the destination.	km	0.2	50.0	20.85	9.83
Windspeed_D	Hourly average wind speed at the destination.	m/s	0	11.7	2.36	1.27
Traffic volume						
Volume_O	Hourly traffic volume at the departure toll station.		1	3492	435.1	442.08
Volume_D	Hourly traffic volume at the arrival toll station.		2	2939	431.2	391.56
Travel frequency						
Frequency_network	The frequency of the car traveling on the freeway network in 2019.		1	6241	181.8	223.22
Frequency _OD	The frequency of the car traveling between the OD pair in 2019.		1	1055	18.63	45.28
Travel distance						
Mileage	The travel mileage between OD pairs.	km	10.6	523.1	53.7	45.56

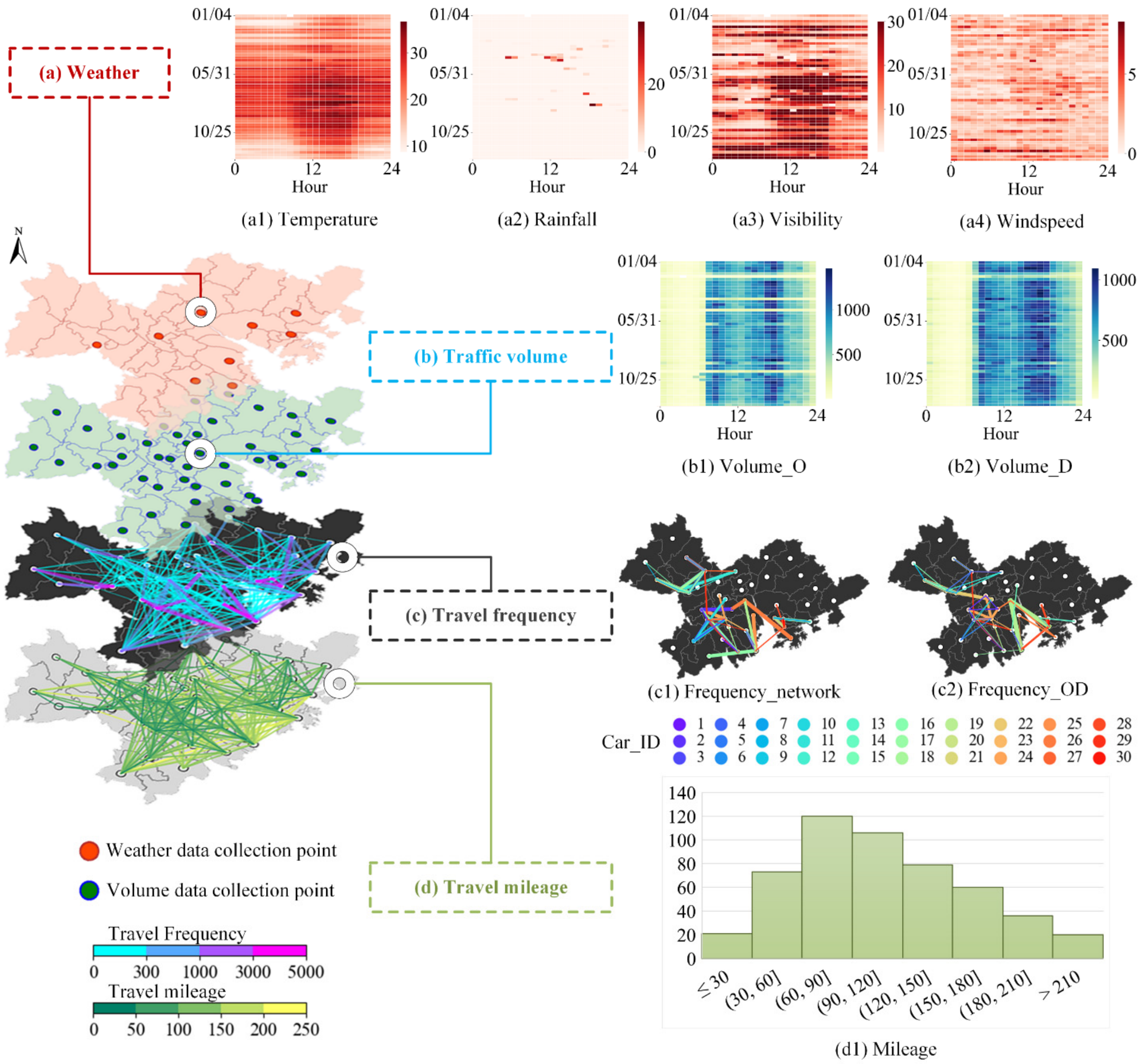
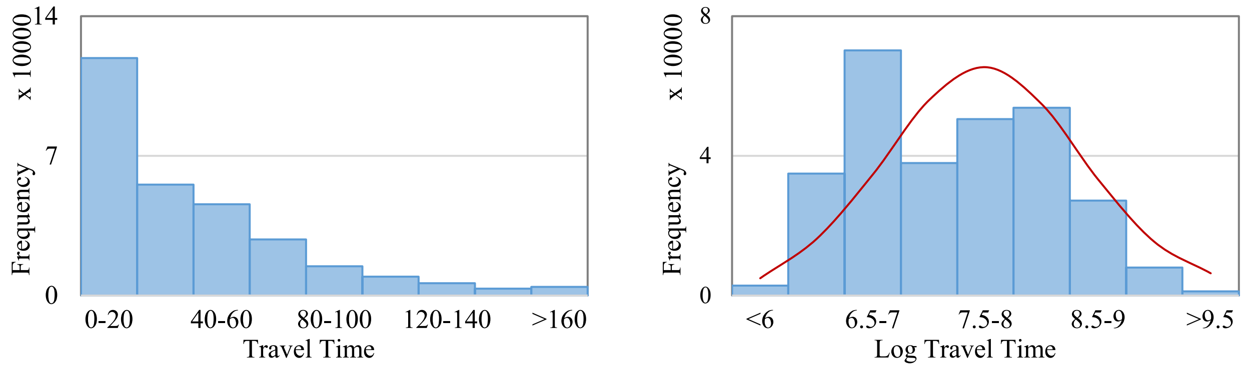


Figure 3. The classification of explanatory variables and the visual description of data features.

3.2.1. Dependent variables

The travel time of the cars is calculated according to the departure and arrival times recorded in the toll data. Most people travel short and medium distances depending on their need to commute on Fridays. Consequently, the histogram of the travel time is highly skewed, which violates the normality assumption of the regression model. It is necessary to perform a logarithmic transformation of the travel time data to achieve a normal distribution of the sample mean and improve the interpretability. The logarithmic transformation result is presented in Figure 4.



(a) Before Log Transformation (b) After Log Transformation

Figure 4. Data transformation of travel time.

3.2.2. Candidate explanatory variables

We refer to many previous studies on the selection of candidate variables. Many studies [21–24] have confirmed that environmental factors have a certain impact on travel time. For example, weather factors change the travel time by affecting the driver's speed selection [37]. Increased traffic volume will lead to longer travel time [27]. Other studies [9–11] mainly focus on drivers' factors, which report the correlation of drivers' familiarity with speed selection. Furthermore, these studies did not compare the effects of environmental factors and driver factors on travel time. We also do not know the difference between the interference degree of environmental factors and driver factors on travel time. Other studies take historical traffic information, such as historical travel time and historical speed, as variables to predict travel time [1,18]. However, the main purpose of this study is to explore the influencing factors of travel time from the perspective of drivers, only real-time environmental factors are considered while historical factors are not the focus of our current study. Therefore, weather, traffic volume, travel frequency, and mileage, which are closely related to travel time, are selected as candidate explanatory variables in this paper. Weather and traffic volume vary with time and location, showing significant spatial variability in the study area. Travel frequency and distance are the main indicators of driver familiarity and travel mileage, respectively, from the perspective of individuals.

Weather data (temperature, wind, visibility, and rainfall) are collected at hourly intervals. Due to the broad geographical scope involved in this study, there are usually different weather conditions at the origin and destination. Travelers may be affected by a combination of origin and destination conditions [38]. Therefore, the weather conditions of both the origin and destination are considered in the model. Temperature_O (Temperature_D) refers to the hourly highest temperature at the origin (destination) when the vehicle starts (arrives). Rainfall_O (Rainfall_D) represents the cumulative precipitation at the origin (destination) when the vehicle starts (arrives). Visibility_O (Visibility_D) refers to the lowest value per hour at the origin (destination) when the vehicle starts (arrives). Moreover, Windspeed_O (Windspeed_D) is defined as the average wind speed in that hour at the origin (destination) when the vehicle starts (arrives).

The traffic volume and travel distance data can be obtained from the toll data. The traffic volume includes the hourly traffic volume at the departure toll station (represented by Volume_O) and the hourly traffic volume at the arrival toll station (represented by Volume_D). Mileage refers to the travel distance between OD pairs.

Driver familiarity with the route plays a vital role in driving behavior [39]. This paper explores the impact of driver familiarity with the road network and fixed routes on the travel time by studying the travel frequency between the freeway network and the OD. According to statistics from the Chinese Ministry of Public Security, by the end of 2018, the number of cars in China reached 240 million, and the number of car drivers reached 359 million [40], which means that an ordinary car corresponds to approximately 1.5 drivers. Therefore, one vehicle can be considered to correspond to approximately one main driver; that is, the travel behavior associated with a vehicle can correspond to the driving behavior of its driver. Therefore, travel frequency can be extracted from the toll data by the encrypted license plate index. The travel frequency of the freeway network (represented by Frequency_network) is defined as the frequency of a specific vehicle entering the freeway network in the current year. Likewise, the driver's trip frequency on the OD route (represented by Frequency_OD) is defined as the number of times a specific vehicle passes through the same pair of ODs in the current year.

4. Methodology

A multilinear regression model is first developed to determine the explanatory variables significantly affecting travel time and calculate the variance inflation factor (VIF) of these variables. Second, the spatial autocorrelation test for each selected explanatory variable is carried out by calculating Moran's I index. Finally, GWR is performed to account for different impacts of significant variables on the travel time in different regions. Simultaneously, the performance of the GWR is compared with the global model to verify its effectiveness and applicability for travel time modeling.

4.1. Model variable selection

A multilinear regression model based on ordinary least squares (OLS) is first used to identify the variables that are significantly related—at a 95% confidence level—to travel time among the candidate variables. The formula is shown in Eq (1):

$$\mathbf{y}_i = \beta_0 + \sum_{j=1}^{p} \beta_j \boldsymbol{\vartheta}_{ij} + \boldsymbol{\varepsilon}_i \tag{1}$$

where $\mathbf{y}_i$ denotes the dependent variable vector, representing the vehicle travel time $i \in \{1,2, \dots n\}$. $\boldsymbol{\vartheta}_{ij}$ is the vector of explanatory variable j of vehicle i, β_j denotes the estimated coefficient $j \in \{1,2, \dots p\}$, and $\boldsymbol{\varepsilon}_i$ is the residual term.

The highly linear correlation of several explanatory variables in the regression model, also called multicollinearity, can lead to bias in interpreting the significance and impact of a specific explanatory variable without affecting the accuracy of the model estimation [41]. In this study, the severity of multicollinearity is determined by calculating the VIF. The calculation formula for the VIF is shown in Eq (2):

$$VIF = \frac{1}{1 - R^2} \tag{2}$$

where R^2 denotes the goodness of model fit. Generally, explanatory variables with a VIF more significant than 10 must be eliminated from the model.

4.2. Spatial autocorrelation test

Using the spatial model first requires a spatial autocorrelation analysis of the explanatory variables [42]. Moran's I index is commonly used to evaluate the spatial autocorrelation of explanatory variables and is calculated in Eq (3):

$$I = \frac{n}{\sum_{i=1}^{n}\sum_{k=1}^{n} a_{ik}} \cdot \frac{\sum_{i=1}^{n}\sum_{k=1}^{n} a_{ik}(\vartheta_i - \bar{\vartheta})(\vartheta_k - \bar{\vartheta})}{\sum_{i=1}^{n}(\vartheta_i - \bar{\vartheta})^2} \tag{3}$$

where n is the number of vehicles, $\bar{\vartheta}$ is the mean value of the explanatory variable ϑ, and a_{ik} refers to the spatial weight between the origin of vehicle *i* and the origin of vehicle $k \in \{1,2, \dots n\}$. Positive and negative Moran's I values indicate that the explanatory variables have spatial clustering and discrete spatial patterns, respectively. If Moran's I value is 0, the variable is randomly distributed.

4.3. Geographically weighted regression

Compared to global regression, which assumes that the effects of explanatory variables are spatially fixed, GWR can fully explain the spatial nonstationarity and heterogeneity of variables by associating independent variables with geographic locations. Many studies have demonstrated that using GWR in spatial analysis yields better results than OLS [43,44]. In this study, GWR is used to model the spatial relationship between vehicle travel time and various factors, as shown in Eq (4):

$$\mathbf{y}_i(u_i, v_i) = \beta_{i0}(u_i, v_i) + \sum_{j=1}^{p} \beta_{ij}(u_i, v_i)\boldsymbol{\vartheta}_{ij}(u_i, v_i) + \boldsymbol{\varepsilon}_i(u_i, v_i) \tag{4}$$

where (u_i, v_i) refers to the coordinate of the origin of vehicle i. $\mathbf{y}_i$ denotes the vehicle travel time, which is the dependent variable vector. $\boldsymbol{\vartheta}_{ij}$ denotes the value of the j^{th} explanatory variable vector, and β_{i0} denotes the intercept parameter. $\beta_{ij}(j = 1,2, \dots, p)$ denotes the estimated coefficient for the j^{th} explanatory variable vector. $\boldsymbol{\varepsilon}_i$ denotes the residual term.

Regions that are spatially close tend to show similar traffic patterns [45]. The GWR model fully obeys the first law of geography [42], which means that the shorter the distance between the origins of the vehicles is, the more influence they are considered to have on each other. Therefore, when estimating parameters, a spatial weight matrix is introduced so that nearby samples have a considerable weight, while distant samples have a small weight. The Gaussian function is a common method for estimating the spatial weight matrix [44], written as Eq (5):

$$w_{ik} = exp\left[-\frac{1}{2}\left(\frac{d_{ik}}{b}\right)^2\right] \tag{5}$$

where d_{ik} is the distance between locations *i* and *k* and *b* is the bandwidth. The size of the bandwidth greatly influences the results of GWR, which is reflected in an excessively large bandwidth leading to a large deviation in the regression parameters. In contrast, a minimal bandwidth will lead to a significant variance in the regression parameters [46]. The cross-validation (CV) score, or the corrected Akaike information criterion (AICc) approach, is commonly used for optimal bandwidth determination [47]. The optimum bandwidth is determined by the CV score approach in this study. In evaluating the model's quality, a lower AICc and higher adjusted R2 values indicate better model performance [46].

5. Results and discussion

5.1. Results of the global models

An OLS model was first built to simulate the association between travel time and candidate explanatory variables. Each candidate explanatory variable was initially screened based on significance. Explanatory variables with a statistically significant linear correlation with travel time ($p < 0.05$) were selected as final variables. After selection, the remaining 11 variables were Temperature_O, Rainfall_O, Visibility_O, Windspeed_O, Rainfall_D, Windspeed_D, Volume_O, Volume_D, Frequency_network, Frequency_OD, and Mileage. To ensure that the model was not affected by multicollinearity, a multicollinearity test was also performed on these 11 variables. The results show that all VIF values were less than 10, the minimum value was 1.06, and the maximum value was 1.62. The hypothesis of multicollinearity among independent variables was therefore rejected.

The final OLS results are presented in Table 3. The adjusted R^2 of the estimated model was 0.7611, which means that the selected variables explained 76.11% of the travel time. All explanatory variables were significant at the 0.01 confidence level. Overall, according to their degree of influence, the explanatory variables ranked in the following descending order: Mileage, Frequency_OD, Volume_O, Volume_D, Frequency_network, Rainfall_O, Rainfall_D, Visibility_O, Windspeed_O, Windspeed_D, and Temperature_O. The following is a detailed analysis.

Table 3. OLS regression results.

Variables	Coefficient	Std. Error	t statistics	p-value	VIF
Intercept	6.686	0.003	2231.684	< 0.0001 ***	
Weather					
Temperature_O	-0.020	0.004	-4.909	< 0.0001 ***	1.17
Rainfall_O	0.166	0.020	8.144	< 0.0001 ***	1.10
Visibility_O	0.087	0.005	18.885	< 0.0001 ***	1.39
Windspeed_O	-0.083	0.009	-9.198	< 0.0001 ***	1.62
Rainfall_D	0.149	0.019	7.753	< 0.0001 ***	1.06
Windspeed_D	-0.072	0.009	-8.034	< 0.0001 ***	1.57
Traffic volume					
Volume_O	0.717	0.007	107.301	< 0.0001 ***	1.19
Volume_D	0.705	0.006	113.339	< 0.0001 ***	1.15
Travel frequency					
Frequency_network	0.545	0.025	22.201	< 0.0001 ***	1.28
Frequency_OD	-2.111	0.021	-102.000	< 0.0001 ***	1.32
Travel distance					
Mileage	7.499	0.009	819.051	<0.0001 ***	1.10
Diagnostic statistics					
Observations	286394				
Multiple R-squared	0.7611				
Adjusted R-squared	0.7611				
Residual sum of squares	49201.78				
F-statistic	82940				
p-value	< 0.0001				
AIC	308312.4				
AICc	308312.4				

Note: *** denotes significance at a confidence level of 99.9%. All variables were normalized before the regression analysis.

The influence degree of Mileage on travel time is the highest among all variables, and the influence degree of traffic volume is second only to Mileage and Frequency_OD. As expected, the estimated mileage parameter is positive, indicating that travel time increases with miles. In addition, in line with previous studies, the estimated effects are related to the traffic volume, suggesting that increasing these variables would lead to longer travel times [27]. Volume_O has nearly the same degree of impact on the travel time as Volume_D.

An interesting result about travel frequency is that the impact of Frequency_OD on travel time is three times that of traffic volume. Compared with the weather, both Frequency_OD and Frequency_network have a higher impact on travel time. In particular, the influence of Frequency_OD is even 12–105 times that of weather. Furthermore, the results related to travel frequency indicate that Frequency_OD and Frequency_network have opposite influences on travel time. The absolute value of the coefficient of Frequency_OD (2.111) is much higher than the coefficient of Frequency_network (0.545), showing that the former is the more decisive factor. A higher Frequency_OD, as expected, is associated with a shorter travel time. Previous studies have noted that vehicle speed increases with driver familiarity [9,10], which explains why greater familiarity with fixed routes contributes to a shorter travel time. However, a higher familiarity with vehicles and driving, as determined by the Frequency_network, unexpectedly corresponds to a longer travel time. This negative impact, albeit unexpected, was also reported in the study conducted by Zolali et al., who found that drivers' tendencies toward higher speed decrease as their driving experience increases [11].

Compared with other variables, the influence of weather variables is the smallest. Among the weather variables, rainfall has the greatest impact on travel time, approximately 1.9 to 8.26 times that of other weather factors. In addition, the weather conditions at the origin and destination have different effects on travel time. All four weather variables at the origin station significantly affect travel time, whereas only rainfall and wind speed at the destination significantly affect travel time. Regarding the influence degree, the impact of rainfall and wind speed at the destination on the travel time is not as great as that at the origin. The absolute values of the coefficients are 10 and 13% lower than those at the origin, respectively. Moreover, different weather variables have different effects on travel time. Rainfall and visibility positively impact the travel time, whereas temperature and wind speed show the opposite effect. The positive coefficient of the rainfall variable reveals that rainfall prolongs travel time, which has also been mentioned in previous studies [22]. Followed by visibility and wind speed, the coefficient is four times that of temperature, which has the lowest degree of influence. Some previous studies have pointed out that low visibility and high wind speed can reduce the travel speed, that is, increase the travel time [48–50]. However, in this study, visibility has a negative impact, while wind speed has positive effects on travel time. A possible reason is that the influence of weather variables on travel time is spatially heterogeneous, which cannot be captured by global models, leading to biased conclusions.

5.2. Results of the GWR models

While the global model explains the relationship between the travel time and the variables, it also provides counterintuitive estimates because it assumes that the independent variables are spatially homogeneous. Therefore, GWR was used to further explore the different spatial effects of the explanatory variables on travel time. Before the GWR analysis, the global Moran's I test was performed to determine the spatial autocorrelation correlation of explanatory variables, as shown in Table 4. All the variables estimated Moran's I values that were not equal to 0. All p values were less than 0.01, and Z-scores were less than -2.58 or higher than 2.58, indicating that the 11 variables were spatially autocorrelated. Therefore, there was sufficient evidence to support using the GWR.

Table 4. Results of Moran's I test.

Variables	Moran's I index	Expected index	Sd.	Z-score	p-value
Temperature_O	0.031	0	0.0004	78.367	<0.001
Rainfall_O	0.003	0	0.0004	7.609	<0.001
Visibility_O	0.020	0	0.0004	49.575	<0.001
Windspeed_O	0.026	0	0.0004	64.620	<0.001
Rainfall_D	0.002	0	0.0004	4.001	<0.001
Windspeed_D	-0.001	0	0.0004	-3.408	<0.001
Volume_O	0.822	0	0.0004	1950.801	<0.001
Volume_D	0.315	0	0.0004	784.968	<0.001
Frequency_network	0.045	0	0.0004	115.503	<0.001
Frequency _OD	0.048	0	0.0004	119.161	<0.001
Mileage	0.447	0	0.0004	1110.077	<0.001

The results of the GWR estimations are shown in Table 5. The adjusted R2 obtained using the GWR model was 0.8594, which was 0.098 higher than that of the OLS model. The value of the AICc of the GWR was 48.9% lower than that in the OLS model, suggesting the superiority of the GWR model. Except for mileage, the estimated coefficients of the other variables had both negative and positive coefficients, revealing that these variables were inversely associated with travel time in different regions. The degree of nonstationarity of all explanatory variables could be examined by comparing the positive and negative percentages of the local coefficients. A proportion of approximately 70% was considered a sign that an explanatory variable had a uniform influence on travel time and a dominant direction (positive or negative) [34]. Details will be provided in the following section.

Table 5. Estimation of the GWR models.

Variables	Coefficient					Percentage of regions with positive/negative coefficients	
	Min.	25%	Median	75%	Max.	Positive	Negative
Intercept	3.88	6.58	6.64	7.09	7.71		
Temperature_O	-0.14	-0.05	0.02	0.07	0.50	53.49%	46.51%
Rainfall_O	-0.48	-0.15	0.06	0.34	0.64	69.77%	30.23%
Visibility_O	-0.17	-0.04	-0.02	0.02	0.15	65.12%	34.88%
Windspeed_O	-0.30	-0.03	0.00	0.07	0.43	58.14%	41.86%
Rainfall_D	-0.19	0.08	0.19	0.30	1.08	88.37%	11.63%
Windspeed_D	-0.24	-0.03	0.02	0.07	0.43	41.86%	58.14%
Volume_O	-4.57	-0.48	0.40	0.83	3.48	79.07%	20.93%
Volume_D	-0.33	0.03	0.31	0.72	3.13	81.40%	18.60%
Frequency_network	-0.87	-0.40	-0.13	0.24	3.10	27.91%	72.09%
Frequency _OD	-5.94	-1.27	-0.84	-0.46	1.35	16.28%	83.72%
Mileage	3.37	6.03	7.65	9.84	11.81	100.00%	0.00%
Multiple R-squared	0.8594						
Adjusted R-squared	0.8592						
Residual sum of squares	28950.16						
AIC	156904						
AICc	157422.1						

5.3. Discussion on spatially varying effects

The estimated coefficients of explanatory variables vary with space in the GWR models. The studied regions are mapped in different colors based on their estimated coefficients to better clarify the spatially varying effects of the explanatory variables. Some critical explanatory variables are discussed below.

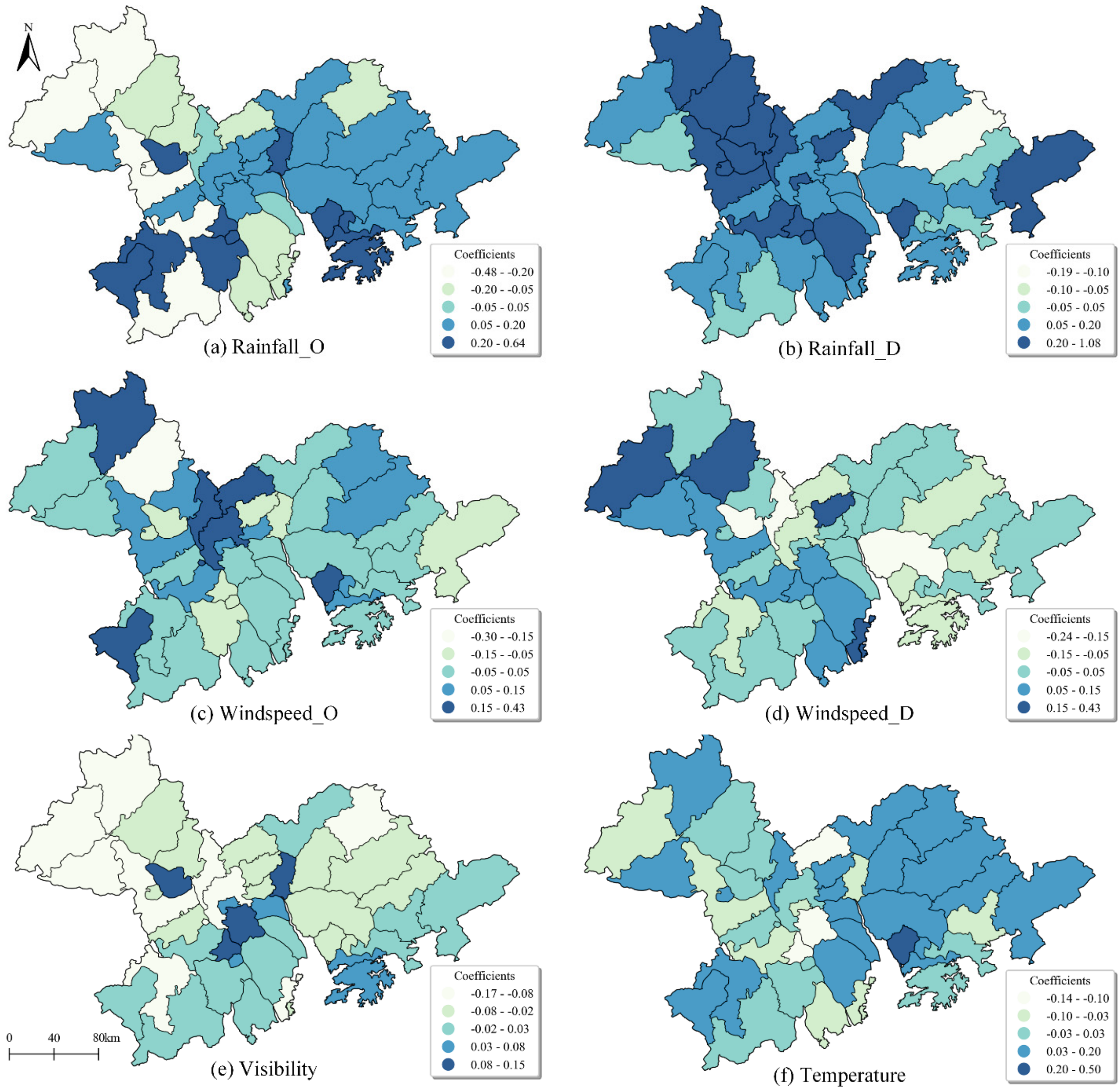


Figure 5. Spatial distribution of the estimated coefficients of weather variables.

Figure 5 depicts the distribution characteristics of the coefficients for weather variables. Rainfall_O and Rainfall_D were positively correlated with travel time in most regions (approximately 70 and 90%, respectively). These results are consistent with the global model and research [22]. Interestingly, we observed counterintuitive results in a few areas. As shown in Figure 5(a), the regions (colored in white) where Rainfall_O negatively affected travel time were clustered in the western part of the GBA. However, Rainfall_D positively impacted these regions to a greater extent than Rainfall_D (see Figure 5(b)). The statistical data on rainfall were further examined to understand the reason for this result. It was found that the average rainfall in the western part of the GBA was the smallest. One explanation for the anomalous coefficients is that vehicles originating from areas with less rainfall tend to be more negatively affected by rainfall at their destinations.

As shown in Figure 5(c),(d), the effect of wind speed on most areas is minimal, reflected by the coefficient close to 0. In some areas, the impact of wind speed, most of which was positive, cannot be ignored. However, wind speed in a few areas significantly negatively impacted travel time. The reasons for these differences may be complex. For example, the impact of wind speed variables on travel time may be nonlinear, with some literature pointing out that wind speeds above a certain threshold negatively affect vehicle speed [51].

In terms of visibility (see Figure 5(e)), the increase in Visibility_O reduces travel time in most regions (65%), which differs from the conclusion of the global model but is consistent with previous studies [48–50]. The travel time of some areas (shown in white) was more obviously affected by the negative impact of visibility, which was mainly concentrated in the northwestern GBA, that is, Zhaoqing. The statistical data on visibility in this area were further examined to understand the reason for this result. The standard deviation of the visibility in these areas was significantly higher than that in other areas. Therefore, the higher visibility may have a more apparent negative impact on the travel time in areas with less stable visibility.

The travel time in the core area (near the estuary) and the east (Huizhou) of the GBA will increase with increasing temperature (see Figure 5(f)). Although the temperature has a minimal effect on travel time in the global model, it is interesting that the GWR results show that temperature has a nonnegligible, positive impact on travel time in approximately half of the regions. These areas were mainly distributed in the core area (near the estuary) and the east (Huizhou) of the GBA, with abundant summer resorts, such as beaches and river rafting sites. Previous studies have shown that the choice of travel destination is affected by temperature [52]. Additionally, it has been proven that seasonal changes play an essential role in leisure activities [53]. Therefore, higher summer temperatures are likely to promote the travel demand in these places, and the increased traffic volume increases travel time. The difference in the impact of temperature on travel time in different regions reflects the seasonal attraction of summer tourism in the core area (near the estuary) and the east (Huizhou) of the GBA to tourists to a certain extent.

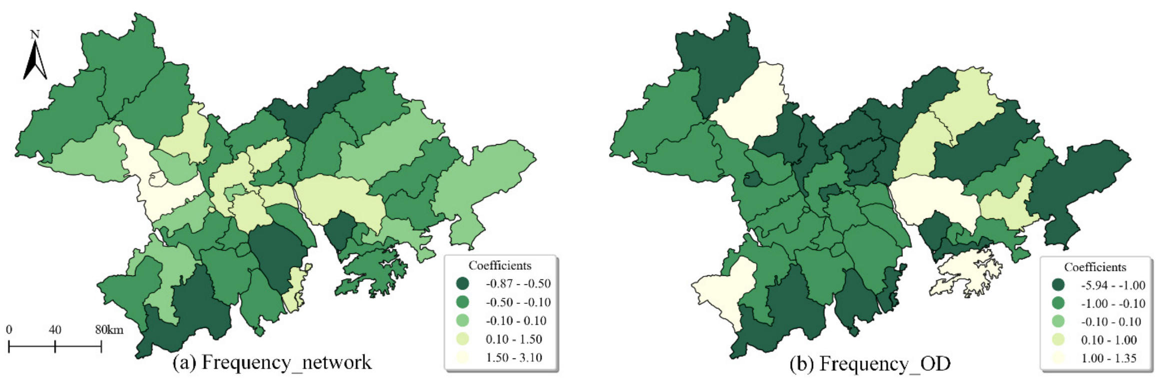


Figure 6. Spatial distribution of the estimated coefficients of travel frequency variables.

The influence of Frequency_network on travel time is quite opposite in different regions (see Figure 6(a)). In contrast to the results of the global model, the GWR results show that the Frequency_network is negatively correlated with the travel time in most regions (approximately 70%). Although previous studies have demonstrated that experienced drivers have a lower desire to drive fast [11], this result is consistent with our usual perception that increased driving frequency can reduce travel time. Because driving skills usually improve with increased driving frequency, drivers with a high driving frequency on the freeway network are more skilled in dealing with the complex road conditions of the freeway network. However, in the remaining 30% of the regions, such as Guangzhou, Dongguan, and other central areas of the GBA, the coefficient of the Frequency_network was positive. One possible reason is that these areas are located in the Pearl River delta plain in the coastal area, which has a flat and low-lying terrain [54], making it a better driving environment than the northern mountainous areas. Under these circumstances, driving skills have a more negligible effect on reducing the travel time than drivers' willingness to reduce high-speed driving. Hence, drivers with a higher driving frequency have longer travel times.

The spatial difference in the impact of Frequency_OD on travel time is reflected in different degrees, which generally shows the characteristics of a large impact in the edge areas and a small impact in the central areas. Frequency_OD had a negative impact on travel time in most regions (over 80%) (see Figure 6(b)), which is consistent with the global regression and previous findings [9,10]. In terms of spatial distribution, the degree of negative impact at the fringes of the GBA was higher than that in the central part, similar to the distribution of the average mileage across the GBA (see Figure 7). A possible explanation for this result is that the higher the driving mileage is, the more pronounced the effect of the OD driving frequency on reducing travel time.

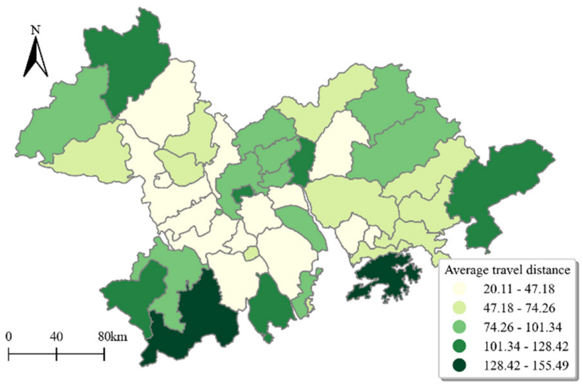


Figure 7. Spatial distribution of average travel distance.

For Volume_O, as shown in Figure 8(a), there are a few counterintuitive results on the western and eastern edges of the GBA; that is, the greater the traffic volume is, the shorter the travel time. Both Volume_O and Volume_D were positively correlated with travel time in most regions (approximately 80%), with a few exceptions (approximately 20%). Using the coefficient of Volume_O as an example (see Figure 8(a)), these areas were concentrated in the western periphery and eastern periphery of the GBA, characterized by low traffic volume. A possible explanation is that since the traffic volume in these places does not reach saturation, the increase in traffic volume has little effect on the road traffic state. From the time-varying characteristics of traffic volume, the volume during the day is often greater than at night. Furthermore, drivers tend to drive at higher speeds during the day than at night due to better visibility [55], which may explain the counterintuitive result in this study that higher traffic volumes result in shorter travel times. Furthermore, in conjunction with the coefficient plots for Volume_D (see Figure 8(b)), Volume_D tends to have the opposite effect to Volume_O in these regions. This suggests that these vehicles originating from low traffic volume areas are likely to be headed to regions where traffic volume is heavy enough to affect travel time.

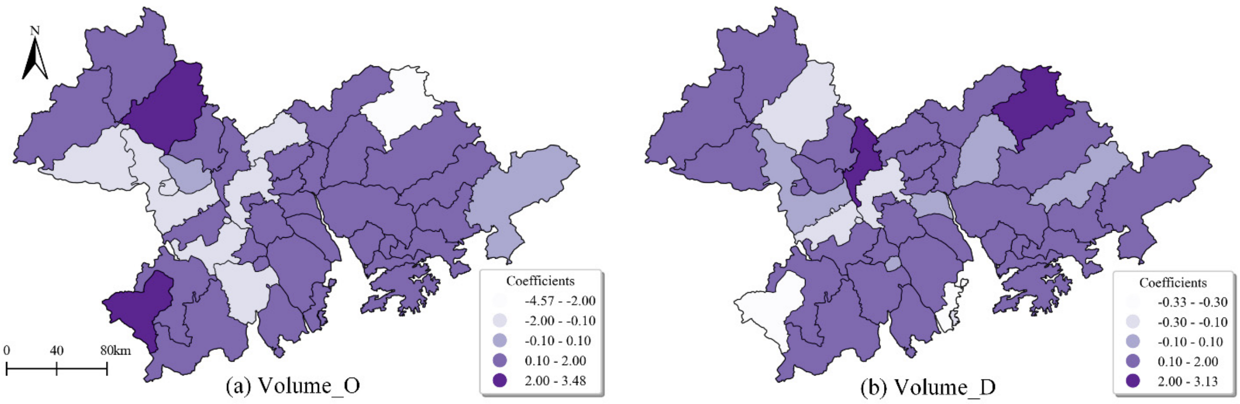


Figure 8. Spatial distribution of the estimated coefficients of traffic distance variables.

Finally, typical regions significantly affected by each variable are summarized in Table 6.

Table 6. Typical regions significantly affected by each variable.

Variables	Significant, positive effect	Significant, negative effect
Rainfall_O	Jiangmen and the east of the Pearl River Estuary	The western GBA
Rainfall_D	Eastern Zhaoqing	-
Windspeed_O	Foshan	-
Windspeed_D	The central and western GBA	-
Visibility_O	LM, HJ, FK, GY	-
Temperature_O	The central and eastern GBA	-
Frequency_network	-	BA, ZS, TS, CH
Frequency_OD	-	The fringes of the GBA
Volume_O	GN, EP	The central and western GBA
Volume_D	LM, SS	-

6. Conclusions

Travel time information is closely related to travel behavior. Understanding the factors that affect travel time can provide valuable insights into travel plans. However, few studies have quantified and compared the impact of travel frequency and other environmental factors on travel time simultaneously. Moreover, limited efforts have been made to investigate the spatial variations of factors affecting travel time from the perspective of an urban agglomeration. Therefore, this study analyzed vehicle travel time in the GBA based on comprehensive freeway toll data, revealed the determinants of travel time, and quantified their impacts. First, vehicle travel time and various influencing factors, including weather, traffic volume, travel frequency, and distance, are obtained from freeway toll data and meteorological data. Second, the influences of weather, traffic volume, travel frequency, and travel distance on travel time are explored by multiple linear regression. Finally, GWR is performed to further reveal spatial divergences in the effects of these factors on travel time and to provide more accurate travel time modeling in various contexts. The main findings can be summarized as follows:

i) The results of multiple linear regressions show that, in addition to travel distance, travel frequency on the OD route has the most considerable impact on travel time, approximately 3 to 100 times that of the traffic volume and weather variables.

ii) In regard to the weather variables, not only do different variables impact travel time to varying degrees, but the same variable at the origin and destination also has different degrees of influence. Rainfall significantly impacts travel time by approximately 1.9 to 8.26 times that of other weather factors. Four weather variables at the origin have significant effects on travel time, whereas only rainfall and wind speed at the destination significantly affect travel time. Compared with the weather at the origin, the weather at the destination is slightly less influential.

iii) The results of the GWR models further reveal that the effects of the critical variables on travel time vary with space. Moreover, the impact of a single factor on travel time has large spatial variability. For example, the travel time in the northwestern GBA is more susceptible to a negative visibility impact. Although the travel time is minimally affected by temperature in the global model, the temperature has a nonnegligible promoting effect on travel time in the eastern part of the GBA in the GWR results. In addition, the negative impact of the OD travel frequency on travel time in the periphery of the GBA is greater than that in the central region.

Overall, this study enriches the literature on the spatial impact of vehicle travel time and obtains empirical evidence directly associated with various factors. The findings will help provide a reference for travelers in different regions to better plan their trips. For example, the travel time in the eastern part of the GBA in summer is expected to be longer than that in other seasons, so drivers should choose an earlier departure time. However, there are still some limitations that require further improvement. First, there are still some abnormal results of weather factors that cannot be well explained. One reason may be that there are few collection points for weather data. The next step will be to obtain more detailed weather data to compensate for the existing deficiencies. Second, this study considers only the traffic volume at the origins and destinations of trips but lacks information on the traffic volume along the way. Therefore, in future research, we will collect the traffic volume of road sections and further explore the spatial influence of traffic volume on travel time. Third, we assume a linear relationship between the explanatory variables and travel time, which could be inaccurate. Therefore, in follow-up research, it is necessary to further explore the linear and nonlinear relationships between the explanatory variables and travel time to provide a deeper understanding of the impact of various factors on travel time. Fourth, limited by data privacy protections, this study does not consider the personal characteristics of drivers, such as gender, age, income, etc., which may have a great impact on vehicle travel time. In future research, we will further study the impact of these factors on vehicle travel time.

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Conflicts of interest

The authors declare there are no conflicts of interest.

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